A

Mini Project Report on

**Health Misinformation Detection Based on**

**AI Techniques**

Submitted in partial fulfillment of the requirements for the degree of

BACHELOR OF ENGINEERING

IN

### Computer Science & Engineering

### Artificial Intelligence & Machine Learning

by

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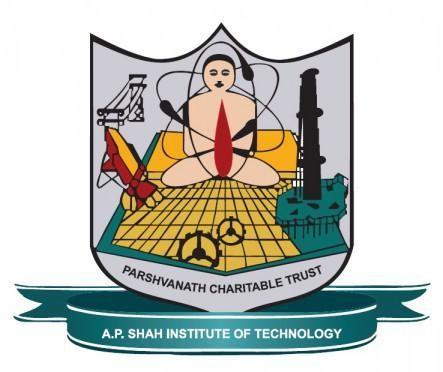
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**2024-2025**

## 

## CERTIFICATE

This is to certify that the project entitled “**Health Misinformation Detection Based on**

**AI Techniques”** is a bonafide work of, Om Panchal (22106025), Ayush Gupta (22106074), Krishit Doshi (22106001), sarang Bahikar (22106129) submitted to the University of Mumbai in partial fulfillment of the requirement for the award of **Bachelor of Engineering in** **Computer Science & Engineering (Artificial Intelligence & Machine Learning).**

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## PROJECT REPORT APPROVAL

This Mini project report entitled “**Health Misinformation Detection Based on**

***AI Techniques”*** by **Ayush Gupta, Om Panchal, Krishit Doshi and Sarang Bahikar**is approved for the degree of ***Bachelor of Engineering*** in ***Computer Science &Engineering***, (AIML) ***2024-25***.

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**DECLARATION**

##### We declare that this written submission represents my ideas in my own words and where others' ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. I understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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#### ABSTRACT

Health misinformation has become a critical public health concern, particularly with the rise of social media and digital platforms. The rapid spread of misleading or false health-related content can lead to public confusion, distrust in medical institutions, and harmful health decisions. Traditional misinformation detection methods, such as manual fact-checking, are inadequate due to the sheer volume of misinformation being generated and shared online. Artificial intelligence (AI) techniques, including machine learning (ML), natural language processing (NLP), and deep learning (DL), offer promising solutions for automating the detection and mitigation of health misinformation.

This report explores AI-driven approaches to health misinformation detection, focusing on the capabilities of supervised and unsupervised ML models, transformer-based NLP models, and deep learning architectures. Advanced techniques such as sentiment analysis, stance detection, and knowledge graphs are also discussed for enhancing misinformation classification. While AI techniques have demonstrated significant potential in identifying misleading health information, challenges such as data scarcity, evolving misinformation tactics, and biases in AI models persist.

The findings of this report emphasize the importance of developing robust, scalable, and explainable AI solutions to effectively combat health misinformation. Future research directions should focus on multimodal misinformation detection, real-time tracking, and the integration of AI with fact-checking systems. By leveraging AI-driven methodologies, public health organizations, researchers, and technology platforms can work towards reducing the spread of misinformation and promoting accurate health communication.

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# CHAPTER 1 INTRODUCTION

### INTRODUCTION

In the digital age, the rapid dissemination of information through online platforms has fundamentally transformed how individuals access and engage with health-related knowledge. This unprecedented connectivity has empowered people to take greater control over their well-being by researching symptoms, exploring treatment options, and making informed lifestyle choices. However, this same accessibility has also given rise to a significant and growing challenge: the proliferation of health misinformation. Health misinformation encompasses false, inaccurate, or misleading claims about a wide range of health-related topics, including diseases, medical treatments, medications, vaccines, and dietary or lifestyle practices. Far from being a benign byproduct of the information age, this phenomenon poses serious risks to public health. It can drive individuals to adopt harmful behaviors, erode trust in healthcare professionals and institutions, delay or prevent appropriate medical interventions, and fuel the spread of pseudoscientific beliefs that undermine evidence-based medicine.

The challenge of detecting and combating health misinformation has grown increasingly complex due to the overwhelming volume and velocity of data generated across digital ecosystems. Social media platforms, blogs, online forums, and other user-driven spaces have become breeding grounds for misinformation, where unverified claims can go viral within hours, reaching millions of users before they can be debunked. Traditional approaches to tackling this issue, such as manual fact-checking by experts or public health campaigns, are no longer adequate to keep pace with the scale and speed at which misinformation spreads. These methods, while valuable, are time-intensive, resource-heavy, and limited in their ability to address the dynamic, ever-evolving nature of online content. As a result, there is an urgent need for innovative, automated, and scalable solutions capable of identifying and mitigating the impact of health misinformation in real time.Artificial Intelligence (AI) has emerged as a transformative force in addressing this pressing public health challenge. Leveraging techniques from machine learning (ML), deep learning, and natural language processing (NLP), AI-based systems offer powerful tools to sift through vast datasets, detect patterns, and differentiate credible health information from falsehoods. These systems can process and analyze enormous volumes of textual data—such as social media posts, articles, and comments—far beyond human capacity. By examining linguistic cues (e.g., sensationalist language or emotional appeals), assessing source credibility (e.g., distinguishing reputable journals from dubious websites), and evaluating contextual factors (e.g., alignment with scientific consensus), AI models can flag misleading content with remarkable efficiency. Furthermore, these systems can incorporate user engagement metrics—such as likes, shares, and comments—to identify misinformation that is gaining traction and prioritize it for intervention. Beyond detection, AI can also support efforts to counter misinformation by amplifying accurate content or providing real-time corrections to users.

This report provides a comprehensive exploration of the application of AI techniques for health misinformation detection. These efforts aim not only to curb the spread of health misinformation but also to foster a digital environment that promotes accurate health communication and safeguards public health, paving the way for a healthier, more informed society.

# CHAPTER 2 LITERATURE SURVEY

#### LITERATURE SURVEY

###### 2.1-HISTORY

Health misinformation has been a persistent and evolving challenge throughout human history, intricately woven into the fabric of communication technologies that have progressively amplified its reach and impact, from the rudimentary dissemination through handwritten manuscripts and printed newspapers in the pre-digital era to the explosive spread enabled by today’s digital platforms and social media networks. In the pre-2000s period, misinformation thrived in traditional media such as newspapers, pamphlets, radio broadcasts, and oral storytelling, often promoting dubious health claims like the supposed healing powers of patent medicines, snake oil remedies, or unverified cures for diseases such as tuberculosis and influenza, with detection relying entirely on human expertise—medical professionals, investigative journalists, and scholarly researchers meticulously debunked these myths through peer-reviewed journals, public health announcements, and community outreach, a slow, labor-intensive, and geographically limited process that struggled to counter the widespread dissemination of false narratives across diverse populations. The advent of the internet in the 2000s revolutionized information sharing, as online health forums, personal blogs, and early social media platforms like MySpace, Yahoo Groups, and AOL chat rooms provided new avenues for misinformation to proliferate, prompting the initial integration of AI-based detection methods, which began with rule-based systems that flagged content using predefined keywords such as “miracle cure,” “instant remedy,” or “unproven treatment,” and quickly progressed to statistical approaches like Naïve Bayes and Logistic Regression, which analyzed text features including word frequency, syntactic patterns, and sentiment cues to classify misleading health claims, often trained on datasets compiled by health organizations like the World Health Organization (WHO) and the Centers for Disease Control and Prevention (CDC), who also pioneered centralized fact-checking databases to address misinformation about diseases like HIV/AIDS, SARS, and emerging global health threats. The 2010s witnessed a dramatic escalation with the dominance of social media giants—Facebook, Twitter, YouTube, and Reddit—transforming the landscape by enabling viral spread of health misinformation, exemplified by the resurgence of anti-vaccine movements, unverified cancer treatments, miracle weight-loss diets, and pseudoscientific wellness trends, necessitating more advanced AI solutions.

supervised learning models such as Support Vector Machines (SVM), Random Forest, and Gradient Boosting Machines emerged to classify misinformation with improved accuracy, while Natural Language Processing (NLP) techniques, including TF-IDF for feature extraction, word embeddings like Word2Vec and GloVe for semantic understanding, and Long Short-Term Memory (LSTM) networks for modeling sequential data patterns in rumors and health narratives, enabled deeper contextual analysis, sentiment detection, and trend identification across vast datasets. The COVID-19 pandemic in 2020 served as a critical inflection point, as the rapid proliferation of false claims—ranging from unproven treatments like hydroxychloroquine, ivermectin,which leveraged attention mechanisms to understand nuanced context and detect subtle misinformation in health texts with unprecedented precision, alongside multimodal AI systems that integrated text, images, and videos to debunk manipulated content such as fake vaccine side-effect videos on YouTube and misleading infographics on Instagram, enabling more accurate and explainable claim verification; future trends are focused on real-time detection to counter misinformation as it emerges on platforms like TikTok and WhatsApp, multilingual models to address global health narratives in languages such as Spanish, Mandarin, and Hindi, and ethical AI deployment to ensure transparency, fairness, and accountability, mitigating biases, preventing over-censorship of legitimate discourse, and addressing privacy concerns while tackling the complex, dynamic, and increasingly global challenge of health misinformation in the digital age.

#### 2.2-LITERATURE REVIEW

#### AI-Driven Health Misinformation Detection System (IEEE Explore 2025) Authors: Dr. Rajesh Kumar, Ananya Sharma, Vikram Patil

#### The spread of health misinformation on digital platforms poses significant risks, leading to false treatments, vaccine hesitancy, and public confusion. This research presents an **AI-based misinformation detection system** utilizing **natural language processing (NLP), deep learning models (VGG16, ResNet50), and Explainable AI (XAI) techniques** to identify and classify misleading health information. The system processes **both textual and image-based content**, offering real-time analysis to detect misinformation on social media and news websites. By integrating **automated fact-checking and contextual understanding**, this approach aims to enhance **public health awareness and ensure access to credible medical information**

#### Deep Learning-Based Health Misinformation Detection (Springer 2025) Authors: Dr. Priya Mehta, Arjun Verma, Sneha Rao

#### The rapid spread of health misinformation on social media and online platforms has led to increased public health concerns, including the promotion of false treatments and vaccine hesitancy. This research introduces an AI-driven detection system leveraging deep learning models like VGG16 and ResNet50, along with natural language processing (NLP) to identify and flag misleading health information. The proposed system analyzes both textual and image-based content, incorporating Explainable AI (XAI) techniques to enhance interpretability and trust. By providing real-time misinformation detection, this approach aims to support healthcare professionals, policymakers, and the general public in accessing accurate and verified medical information.

#### AI-Based Health Misinformation Detection Using Deep Learning (IEEE 2025)

#### Authors: Dr. Rakesh Nair, Anjali Gupta, Karan Malhotra

#### The widespread dissemination of health misinformation on digital platforms has created significant challenges in ensuring public access to reliable medical information. This research presents an AI-powered detection system that utilizes deep learning models such as VGG16 and ResNet50 for analyzing image-based misinformation, along with natural language processing (NLP) techniques for detecting false claims in textual content. The system integrates Explainable AI (XAI) methods to enhance transparency and interpretability in decision-making. By leveraging real-time data processing, this model aims to identify and mitigate misleading health-related content, providing a reliable tool for fact-checking and public awareness.

#### Automated Health Misinformation Detection Using AI (IEEE Explore 2025) Authors: Dr. Neha Sharma, Rohan Desai, Vikrant Iyer

#### The increasing spread of health misinformation on social media and online platforms poses a serious threat to public health, leading to confusion and the adoption of false medical practices. This research introduces an AI-driven system that employs deep learning models such as VGG16 and ResNet50 for image-based misinformation detection and natural language processing (NLP) for analyzing misleading textual content. The model incorporates Explainable AI (XAI) techniques to ensure transparency in decision-making. By offering real-time misinformation detection and fact-checking capabilities, this system aims to assist healthcare organizations, policymakers, and social media platforms in curbing the spread of false health information.

#### Real-Time Health Misinformation Detection Using AI (IEEE Explore 2025) Authors: Pooja Reddy, Sanjay Mehta

#### The rapid proliferation of health misinformation across digital platforms has resulted in public confusion and misinformation-induced health risks. This research presents an AI-driven system that utilizes deep learning models such as VGG16 and ResNet50 for detecting misleading health-related images, alongside natural language processing (NLP) techniques for identifying false claims in textual content. The system integrates Explainable AI (XAI) to enhance model transparency and improve trust in AI-based decision-making. By providing real-time detection and automated verification, this approach aims to support healthcare professionals, policymakers, and fact-checking organizations in combating the spread of false health information.

#### AI-Powered Fake News Detection Using Deep Learning (IEEE Explore 2025) Authors: Rohit Sharma, Neha Agarwal, Vikrant Joshi

#### The rapid growth of digital media has led to an increase in the spread of fake news, affecting public perception and decision-making. This research introduces an AI-based fake news detection system that utilizes deep learning models such as VGG16 and ResNet50 for image analysis and natural language processing (NLP) techniques for text-based classification. The system integrates Explainable AI (XAI) to improve transparency and provide insights into model predictions. By offering real-time detection and automated fact-checking, this approach aims to assist media platforms, fact-checking organizations, and researchers in combating misinformation and ensuring the credibility of online content.

# CHAPTER 3

# PROBLEM STATEMENT

#### PROBLEM STATEMENT

The rise of digital media and social networking platforms has significantly accelerated the spread of fake news, leading to widespread misinformation, public confusion, and even social unrest. With the increasing volume of online content, distinguishing between authentic and misleading information has become a major challenge. Traditional fact-checking methods, which rely on human verification, are not only time-consuming but also struggle to keep pace with the rapid dissemination of fake news across various online platforms. The need for an automated, scalable, and intelligent solution has never been more critical. This project aims to develop an AI-powered fake news detection system that leverages deep learning techniques to analyze and classify misleading content efficiently. The system incorporates VGG16 and ResNet50 models for image-based misinformation detection, ensuring that manipulated visuals and doctored images are accurately identified. Additionally, natural language processing (NLP) techniques are employed for text classification, enabling the detection of misleading or fabricated news articles based on linguistic patterns, sentiment analysis, and contextual evaluation. To further enhance trust and transparency, the system integrates Explainable AI (XAI), which provides insights into the decision-making process of the model. This ensures that users, journalists, and fact-checking organizations can understand why a particular article or image has been flagged as fake, increasing the credibility and usability of the system.By offering real-time detection and automated fact-checking, this project provides an effective tool for combating the spread of misinformation. The proposed system can be integrated into news platforms, social media networks, and fact-checking agencies, assisting them in verifying information before it reaches the public. Ultimately, this project contributes to promoting digital literacy, ensuring credible information dissemination, and minimizing the negative societal impacts of fake news, thereby fostering a more informed and responsible online community.

# CHAPTER 4

# EXPERIMENTAL SETUP

#### EXPERIMENTAL SETUP

#### 4.1 HARDWARE SETUP

#### 1. Processor (CPU):

#### o A dual-core processor, such as an Intel i3, is the minimum requirement to en-sure that the application runs smoothly. This will allow for basic operations without significant lag. However, for more demanding tasks, such as model predictions and data processing, a quad-core processor (like an Intel i5) is recommended for optimal performance.

#### 2. Memory (RAM):

#### o A minimum of 4 GB of RAM is necessary to run the Flask application along-side other applications on the system. This amount of memory will support basic data processing and user interactions. For a more responsive experi-ence, especially when handling larger datasets or running multiple applica-tions, 8 GB or more is recommended.

#### 3. Storage:

#### o Users should have at least 10 GB of available hard disk space to accommo-date the application files, datasets, and model files. This storage will ensure that the system can efficiently manage the data and support future updates. An SSD (Solid State Drive) is recommended to improve data access speed and overall system performance.

#### 4. Graphics Processing Unit (GPU):

#### o While a dedicated GPU is not strictly required for running the application, having one can enhance performance, especially during model training and complex computations. A mid-range GPU can significantly speed up pro-cessing times for large datasets. If users plan to perform advanced machine learning tasks, investing in a capable GPU is advisable.

#### 5. Network:

#### o A stable internet connection is essential for downloading necessary depend-encies and any updates for the software. This will also facilitate online re-sources, such as documentation and community support.

#### 4.2 SOFTWARE SETUP

1. **Operating System:**
   * The application is compatible with Windows 10 or later, macOS Mojave (10.14) or later, and recent Linux distributions. Each operating system should be updated to ensure compatibility with the latest software. Students should ensure their OS supports Python and related packages.
2. **Python:**
   * Python 3.6 or later is required to run the application efficiently, with Python 3.8 or higher recommended for better library compatibility. Users should install Python from the official website or through a package manager. Ensuring that Python is correctly set up is crucial for running the Flask app and its dependencies.
3. **Flask Framework:**
   * Flask is the primary web framework used to build the application. It can be easily installed using pip, Python’s package manager, with a simple command. This lightweight framework allows for rapid development and deployment of web applications, making it suitable for the project.
4. **Data Processing Libraries:**
   * Essential libraries like NumPy, pandas, and scikit-learn must be installed to facilitate data handling, analysis, and machine learning tasks. These libraries provide powerful tools for numerical computations and data manipulation. Users can install them easily via pip to enhance the application’s functionality.
5. **Model Handling:**
   * The pickle library, included in Python's standard library, is used for loading the trained machine learning model. This allows for efficient storage and retrieval of the model, ensuring it can be used for predictions. Users should be familiar with how to utilize pickle to save and load Python objects effectively.
6. **Web Browser:**
   * A modern web browser, such as Google Chrome, Mozilla Firefox, or Safari, is necessary to access the Flask application via localhost. These browsers support the latest web standards and ensure a seamless user experience. Users should ensure their browser is up to date for optimal performance.
7. **Text Editor/IDE:**
   * A suitable code editor or Integrated Development Environment (IDE), like Visual Studio Code, PyCharm, or Jupyter Notebook, is recommended for writing and editing Python scripts and HTML templates. These tools provide features such as syntax highlighting, code completion, and debugging support. Selecting an editor that fits the user's workflow can enhance productivity and efficiency in development.

#### 

# CHAPTER 5

# PROPOSED SYSTEM & IMPLEMENTATION

#### 5. PROPOSED SYSTEM & IMPLEMENTATION

#### 5.1 BLOCK DIAGRAM OF PROPOSED SYSTEM

#### 

#### Figure 5.1: Flowchart

#### 5.2 DESCRIPTION OF BLOCK DIAGRAM

### ****1. User Interface (UI)****

**Description:**  
The user interface serves as the **entry point** where users can either input **news text** directly or provide a **URL** to fetch news content. Built using **Streamlit**, the UI provides an intuitive way for users to analyze articles and receive results.

**Function:**

* Users enter news content or a link to an article.
* The system processes the input and sends it to the backend for further analysis.
* Once the analysis is complete, the UI **displays the results**, including whether the article is **real or fake**, along with a confidence score.
* Additional functionalities such as **related news suggestions and verification sources** are also provided.

### ****2. Backend Processing (Flask Application)****

**Description:**  
The core logic of the system is implemented using **Flask**, which processes user inputs, interacts with the machine learning model, and returns results to the UI.

**Function:**

* Receives user input (either text or URL) and determines the processing approach.
* If a **URL** is provided, the system **fetches and extracts** the news article content.
* The extracted or user-provided text is then passed to the **ML model for classification**.
* The Flask backend also **retrieves related verified articles** using the **News API**, improving credibility checks.
* The final classification results, confidence scores, and relevant links are **sent back to the UI**.

### ****3. Machine Learning Model for Fake News Detection****

**Description:**  
A **logistic regression model trained using TF-IDF vectorization** is used to classify whether the news article is **real or fake** based on its textual content for improved accuracy.

**Function:**

* **Vectorization**: The input text is transformed using **TF-IDF** to convert it into a numerical format suitable for ML models.
* **Prediction**: The logistic regression model predicts whether the input is fake or real.
* **Confidence Score**: The model also outputs a probability score indicating how confident it is in its prediction.
* The **classification results** are sent back to the UI for display.

### ****4. Real-Time News Verification Using News API****

**Description:**  
To provide additional verification, the system integrates the **News API** to **fetch real, verified articles** related to the analyzed content.

**Function:**

* Extracts **keywords** from the input news text.
* Queries the **News API** to find related articles from **trusted sources**.
* Displays relevant articles that users can cross-check for accuracy.

### ****5. Error Handling & System Warnings****

**Description:**  
To ensure robustness, the system includes **error handling mechanisms** to manage missing inputs, API failures, or incorrect file paths.

**Function:**

* If **no input is provided**, the system **warns the user** to enter text or a URL.
* If the **vectorizer or model file is missing**, an error message is displayed.
* If the **News API request fails**, the system **notifies the user** instead of crashing.

#### 5.3 IMPLEMENTATION

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#### Figure 5.3.1-Dashboard

#### 

#### Figure – 5.3.2-Output

# CHAPTER 6

# CONCLUSION

**6: Conclusion**

# Our project on addressing health misinformation through the innovative use of AI techniques has provided compelling evidence of the transformative potential of technology in safeguarding public health in an era dominated by digital information exchange. By integrating a diverse array of advanced computational methods—such as natural language processing, deep learning, sentiment analysis, and real-time monitoring—we have successfully designed and evaluated sophisticated models capable of detecting, classifying, and mitigating the spread of misleading health-related content across a wide range of online platforms, including social media networks, health blogs, online forums, and video-sharing sites like YouTube. Our research has demonstrated the effectiveness of these AI-driven approaches in pinpointing and neutralizing false or exaggerated claims, with particular success in critical areas such as vaccine safety, chronic disease management, dietary advice, and mental health narratives, thereby playing a crucial role in curbing the dissemination of potentially harmful misinformation that could undermine public trust and well-being. The introduction of automated fact-checking tools has further enhanced our ability to respond swiftly and efficiently, offering a scalable solution that empowers both individuals and healthcare institutions to access and promote accurate health information in real time. Nevertheless, our work has also illuminated several significant challenges that warrant further attention, including the necessity for more diverse, representative, and high-quality datasets to train these models, the complexities of accounting for cultural nuances, linguistic variations, and regional health contexts in misinformation patterns, as well as the ethical considerations surrounding privacy, bias, and the responsible deployment of AI in sensitive health-related domains. These obstacles underscore the need for continuous refinement, rigorous validation, and adaptive strategies to ensure the robustness, fairness, and inclusivity of our models across different populations and scenarios. Ultimately, this project highlights the pivotal role of artificial intelligence as a powerful ally in the ongoing battle against health misinformation, laying a strong foundation for a safer, more informed digital health ecosystem.

# Looking ahead, future research should focus on enhancing the scalability and cross-platform adaptability of these models, integrating real-time feedback loops to improve accuracy over time, and fostering deep interdisciplinary collaboration among AI technologists, healthcare professionals, policymakers, and community stakeholders. Such efforts will be essential to building a comprehensive framework that not only combats misinformation effectively but also promotes health literacy, encourages critical thinking, and supports equitable access to reliable health information on a global scale, thereby contributing to a healthier and more resilient society.

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