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A Data-Driven Framework for Detecting and Tracking Health Misinformation Trends

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***Abstract*—Health misinformation has emerged as a critical challenge in the digital era, especially during public health crises where misleading medical content spreads rapidly across online platforms. The widespread availability of inaccurate health information can negatively influence public perception, decision-making, and overall health outcomes. This paper proposes Infodemic Scope, a data-driven framework designed to detect, analyze, and track health misinformation trends over time. The system integrates natural language processing techniques, machine learning classifiers, and temporal trend analysis to identify misleading health-related content from large-scale social media and web datasets. It further examines how individuals engage with online health information through search engines, user-generated content, and mobile applications, and how trust in health institutions has evolved. The framework also evaluates the impact of misinformation on quality of life and potential health risks. Experimental results demonstrate improved classification accuracy and effective trend visualization for early detection of emerging misinformation patterns. By providing analytical dashboards and actionable insights, the system supports public health authorities and researchers in mitigating misinformation spread. Overall, the proposed approach contributes toward strengthening the digital health information ecosystem through systematic monitoring and intervention strategies.**

Keywords*—Health Misinformation, Fake News, Public Health, Social Media Analytics, Natural Language Processing, Machine Learning, Infodemic, Trend Analysis, Digital Health, Information Trustworthiness.

I. INTRODUCTION

Heart Health misinformation has become a major concern in the digital age, particularly with the rapid growth of social media and online health platforms. During public health emergencies such as pandemics, inaccurate or misleading medical information spreads quickly, influencing public perception and behaviour. False claims regarding vaccines, treatments, and preventive measures can lead to poor health decisions and increased risks to individuals and communities. The accessibility of online information, while beneficial, has also created an environment where misinformation can thrive without proper verification.

The internet has transformed how individuals seek and consume health information. People increasingly rely on search engines, social media posts, blogs, and mobile applications to understand symptoms, treatments, and disease prevention strategies. However, the credibility of online content varies significantly, making it difficult for users to distinguish between verified medical advice and misleading narratives. The perceived trustworthiness of health institutions and experts has also evolved, further complicating public engagement with digital health information.

Health misinformation not only affects individual decision-making but also impacts public health policies and healthcare systems. Misconceptions about vaccines, chronic diseases, and medical treatments can reduce compliance with preventive measures and delay appropriate medical care. Understanding how misinformation spreads, who engages with it, and how it evolves over time is essential for developing effective intervention strategies. Data science and artificial intelligence provide powerful tools to analyze large-scale online content and identify harmful patterns.

In response to this challenge, this study proposes Infodemic Scope, a data-driven framework for detecting and tracking health misinformation trends. The system integrates natural language processing, machine learning classification models, and temporal trend analysis to identify misleading content from large datasets. By combining automated detection with trend visualization, the framework aims to support public health authorities, researchers, and policymakers in mitigating the spread of misinformation. Ultimately, this approach

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contributes to strengthening the reliability and resilience of the digital health information ecosystem.

II. LITERATURE SURVEY

Li et al. proposed transformer-based models to detect health misinformation and trustworthy content on social media, improving contextual understanding and classification accuracy using attention mechanisms [1].

Wu et al. developed a unified deep learning framework to track misinformation propagation during public health crises, emphasizing temporal modelling to analyze how false information spreads over time [2].

Zhao et al. introduced an explainable AI framework using multimodal data fusion for health misinformation detection, enhancing transparency by providing interpretable prediction results [3].

Alasmawi et al. applied unsupervised deep learning and topic trend analysis for early detection of emerging health misinformation patterns without relying heavily on labelled datasets [4].

Sharma and Bhatt proposed anomaly detection models to identify unusual health-related misinformation in social streams, strengthening early warning systems [5].

Ji et al. presented a comprehensive survey reviewing detection and tracking techniques for health misinformation, covering machine learning, NLP, and network-based approaches [6].

Chakraborty and Chatterjee utilized multi-task learning and linguistic feature extraction to improve fake health news detection accuracy [7].

Shu et al. analyzed fake news detection from a data mining perspective, highlighting feature engineering and propagation pattern analysis [8].

Wang et al. focused on detecting and tracking COVID-19 misinformation using machine learning and NLP techniques for real-time monitoring [9].

Ruchansky et al. proposed the CSI hybrid deep model combining content, social context, and user behaviour for improved fake news detection performance [10].

Qazi et al. applied semantic contextual learning techniques to enhance robustness in health misinformation classification [11].

Wu et al. developed a multimodal framework integrating textual and visual features to strengthen fake health news detection [12].

Khattar et al. explored weak supervision methods for misinformation detection, reducing dependency on large annotated datasets [13].

Alzubi et al. introduced a dynamic tracking model for monitoring misinformation trends in public health discussions on social media [14].

Nguyen et al. discussed misinformation from a data science perspective, emphasizing predictive analytics and large-scale trend analysis [15].

Wang et al. proposed Event Adversarial Neural Networks (EANN) to address event bias and improve fake news detection generalization [16].

Rashkin et al. analyzed linguistic patterns that differentiate fake news from credible information using language modelling techniques [17].

Shu et al. proposed discriminative feature mining approaches for improved fake news detection on social platforms [18].

Lazer et al. examined the scientific foundations of fake news dissemination, highlighting social and psychological influencing factors [19].

Dumitrache and Doboli presented a survey of AI-based fake news detection methods, summarizing machine learning and deep learning approaches [20].

Volkova et al. investigated latent user properties inferred from textual data to detect misinformation behavior patterns [21].

Alsaedi and Jones applied machine learning models specifically for public health misinformation detection tasks [22].

Jin et al. conducted a survey and experimental comparison of deep learning architectures for fake news detection [23].

Silverman provided verification strategies and credibility assessment methods for combating misinformation in digital media [24].

Shu et al. emphasized the role of social context and network structure beyond content analysis for effective fake news detection [25].

III. PROPOSED SYSTEM

The proposed system, Infodemic Scope, is a data-drive framework designed to detect and track health misinformation

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Feature extraction is performed using techniques such as TF-IDF, word embeddings (Word2Vec/GloVe), and contextual embeddings from transformer-based models like BERT. These features are then fed into machine learning and deep learning classifiers such as Logistic Regression, Random Forest, LSTM, and Transformer models to classify content as credible or misinformation. The system also integrates anomaly detection models to identify emerging misleading narratives at an early stage.

To track misinformation trends over time, temporal analysis and time-series modelling are applied to monitor propagation patterns and engagement metrics. A visualization dashboard presents real-time insights, including frequency graphs, topic clusters, and geographic distribution of misinformation spread. The proposed framework enables early detection, continuous monitoring, and actionable reporting, supporting public health authorities and policymakers in mitigating the impact of health misinformation.

In addition, the proposed system incorporates explainable AI techniques to improve transparency and trust in the detection process. Methods such as attention visualization and feature importance scoring help interpret why specific content is classified as misinformation. The framework is designed to be scalable and adaptable, allowing integration of multilingual datasets and cross-platform analysis. By combining automated detection, trend monitoring, and interpretability, the system provides a comprehensive solution for proactive health misinformation management.

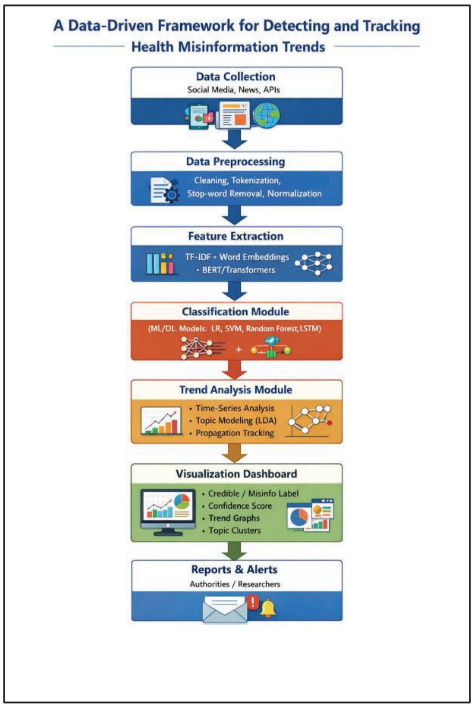

Fig 1 : Block diagram for proposed system

IV. METHODOLOGY

The proposed methodology implements a data-driven framework for detecting and tracking health misinformation trends using Natural Language Processing (NLP), machine learning, and temporal analytics. The system integrates textual content analysis with propagation and trend monitoring mechanisms to provide accurate classification and real-time insights. The overall workflow consists of data collection, preprocessing, feature extraction, classification, trend analysis, visualization, and interpretation.

A. *Dataset Description*

Health-related textual data is collected from social media platforms (e.g., Twitter, Facebook), online news articles, blogs, and public discussion forums using APIs and web scraping tools. The dataset includes both verified health information and misinformation content related to vaccines, pandemics, chronic diseases, and medical treatments.

Each record contains textual content, timestamps, user engagement metrics (likes, shares, comments), and optional metadata such as source credibility. Data cleaning removes duplicates, irrelevant posts, and incomplete entries. The dataset is divided into training and testing sets for model evaluation.

B. *Input and Output*

Input:

• Health-related textual content (social media posts, articles, comments)

• Metadata such as timestamp, user engagement metrics, and source information

Output:

• Classification label (Credible / Misinformation)
• Probability score (confidence value)
• Trend analysis report (frequency and growth pattern)
• Visualization dashboard showing topic clusters and propagation trends

C. *Data Preprocessing*

Text preprocessing is applied to standardize and clean the collected data. This includes:

• Lowercasing and removal of special characters
• top-word removal nd tokenization
• Lemmatization or stemming
• andling missing metadata values

Text data is then converted into numerical form using feature extraction techniques such as TF-IDF and word embeddings. This ensures compatibility with machine learning models and improves classification performance.

D. *Feature Extraction*

1. Textual Feature Extraction**:**
   TF-IDF and contextual embeddings (e.g., BERT-based representations) are used to capture semantic meaning and contextual relationships within the text. These features help distinguish between misleading and credible information.

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2. Propagation & Features:
   Additional features such as repost frequency, comment count, and time-based growth patterns are extracted to analyze misinformation spread behaviour.

E. *Classification Model*

Supervised machine learning and deep learning algorithms are employed for misinformation detection. Models such as Logistic Regression, Random Forest, Support Vector Machines (SVM), LSTM, and Transformer-based architectures are trained on labelled datasets.

The final classification layer uses Softmax or Sigmoid activation (depending on binary or multi-class setup). The system is optimized using Cross-Entropy loss and the Adam optimizer to ensure efficient convergence and high predictive accuracy.

F. *Trend Analysis and Tracking*

Temporal analysis techniques are applied to monitor how misinformation evolves over time. Time-series modelling identifies spikes in misinformation activity and emerging misleading narratives. Topic modelling (e.g., LDA) clusters related misinformation themes for better understanding of trend patterns.

The system continuously updates trend graphs to enable early detection of infodemic waves.

G. *Algorithms Used*

1. TF-IDF – Text feature extraction
2. BERT / Transformer Models – Contextual representation
3. Logistic Regression / Random Forest / SVM – Classification
4. LSTM – Sequential pattern learning
5. LDA – Topic modelling

H. *Working Procedure (Step-by-Step)*

1. Collect health-related data from online platforms.
2. Perform text cleaning and preprocessing.
3. Convert text into numerical features using TF-IDF and embeddings.
4. Train classification models on labelled misinformation datasets.
5. Predict whether new content is credible or misinformation.
6. Analyze temporal patterns to track trend evolution.
7. Visualize results using dashboards and statistical graphs.
8. Generate reports for policymakers and health authorities.

I. *Example Workflow*

Input: A social media post claiming a false medical treatment for a viral disease.

Processing: Text preprocessing → Feature extraction (TF-IDF + BERT embeddings) → Classification using trained model → Temporal tracking of similar posts.

Output: Classified as *Misinformation* with 94% confidence, displayed in dashboard with increasing trend indicator and topic cluster visualization.

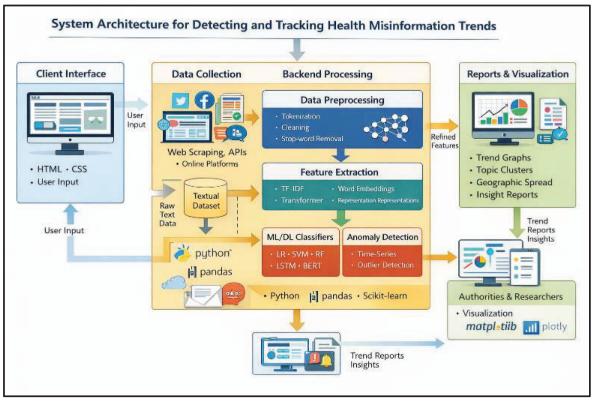

Fig 2 : Architecture

A. *Working Principle*

Consider a scenario where a user submits a social media post claiming that a specific herbal mixture can permanently cure diabetes without medical treatment. The user enters this text into the system through the web interface. Once submitted, the backend receives the input and begins preprocessing by converting the text to lowercase, removing special characters, eliminating stop words, and performing tokenization and lemmatization. This ensures that the text is clean and standardized for analysis.

Next, the processed text is transformed into numerical feature vectors using techniques such as TF-IDF or contextual embeddings generated from transformer-based models like BERT. These features capture both keyword importance and contextual meaning of the sentence. The trained classification model then analyzes the extracted features and determines whether the content is credible or misinformation. For example, the system may classify the post as Misinformation with a confidence score of 94%.

After classification, the system updates the trend tracking module. If similar misleading posts are detected within a short time frame, the temporal analysis component identifies a spike in misinformation related to “False Diabetes Cures.” The dashboard visually displays this trend using graphs and topic clusters. This working process allows health authorities or researchers to detect emerging misinformation narratives early and take corrective actions such as awareness campaigns or fact-checking interventions.

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B. *Technical Tools and Frameworks*

The frontend of the system is developed using HTML and CSS, which together create a structured, responsive, and user-friendly interface. HTML is responsible for designing the web page structure, including navigation menus, input forms, result sections, and dashboard components. CSS enhances the visual presentation by adding styling elements

such as layout alignment, color schemes, typography, responsiveness, and mobile compatibility. This ensures that users can easily submit health-related text and clearly view classification results and trend analytics.

The backend is implemented using Python, which manages the core processing and intelligence of the system. Python frameworks such as Flask or Django are used to build the web server and handle communication between the frontend and backend. Data preprocessing and manipulation are performed using Pandas and NumPy. Natural Language Processing tasks are handled using libraries such as NLTK, SpaCy, or Hugging Face Transformers for advanced contextual embeddings.

Machine learning and deep learning models are implemented using Scikit-learn, TensorFlow, or PyTorch. These frameworks enable training and deployment of classification models such as Logistic Regression, Random Forest, LSTM, or Transformer-based architectures. For trend analysis and visualization, libraries such as Matplotlib or Plotly can be integrated into the dashboard. The backend processes user input in real time, generates predictions with probability scores, updates trend databases, and returns results to the frontend seamlessly. This integrated technical framework ensures scalability, efficiency, and accurate health misinformation detection and tracking.

V. MODULES AND ITS IMPLEMENTATION

Home Page

The Home Page acts as the introductory interface of the Health Misinformation Trend Tracker and provides an overview of the platform's objective. It briefly explains how the system helps identify and monitor misleading health information circulating on social media. The page presents the title of the application along with a short description that informs users about its role in misinformation detection and trend analysis.sss

Secure Authentication Portal

The Secure Authentication Portal is responsible for verifying the identity of users before granting access to the system. It allows new users to create accounts and existing users to log in using their credentials. The portal ensures that only authorized individuals can access the misinformation analysis features. It protects sensitive system data by preventing unauthorized usage. Basic security mechanisms such as password validation and user verification are implemented. This module acts as the entry point that maintains system security and controlled user access.

Core Detection Modules

The Core Detection Modules handle the main analytical functions of the system. They process incoming social media content to determine whether the information is reliable or misleading. These modules use machine learning techniques to analyze text patterns, keywords, and contextual signals. The system performs real-time evaluation to quickly classify content as genuine or false. It also monitors trends and patterns related to misinformation spread. This component forms the central engine that supports accurate detection and continuous monitoring of health misinformation.

Misinformation Analysis Dashboard

The Misinformation Analysis Dashboard provides a visual interface for observing and interpreting the results generated by the system. It displays the classification outcome of analyzed tweets along with relevant details such as hashtags and trends. The dashboard presents statistical charts that compare genuine and misleading information over a specific time period. These visualizations help users understand how misinformation spreads across social media. It also highlights trending topics associated with false claims. This module enables users to easily monitor, interpret, and evaluate misinformation patterns.

VI. DISCUSSION AND RESULTS

Home Page

The Home Page serves as the main entry interface of the Health Misinformation Trend Tracker. It introduces the purpose of the system and provides a brief overview of how the platform detects and analyzes misleading health information. The page guides users to start using the system by directing them to the login or prediction section. It also highlights the key features such as real-time analysis and trend monitoring. The layout is designed to make navigation simple and help users quickly understand the platform's functionality. This section acts as the starting point that connects users to the system's core analysis tools.

Fig 3 : Output

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Secure Authentication Portal

The Secure Authentication Portal manages user access to the Health Misinformation Trend Tracker by providing account registration and login functionality. New users can create an account by entering basic details such as name, email address, and password. After successful registration, users can log in through the same interface using their credentials. The portal validates the entered information before allowing access to the main system features. If the login details are correct, the user is redirected to the analysis dashboard where misinformation detection tools are available. This module ensures that system usage is restricted to authenticated users and maintains controlled access to the platform.

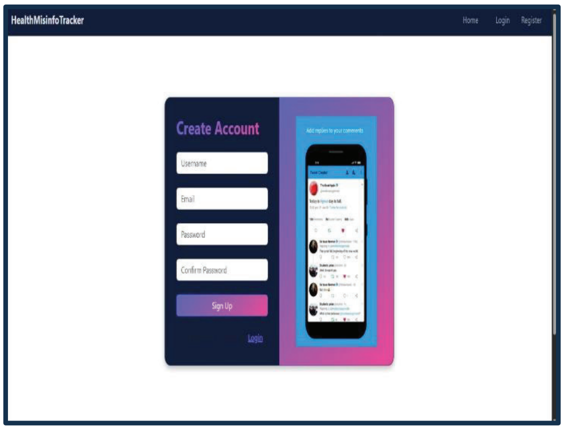

Fig 4 : Output

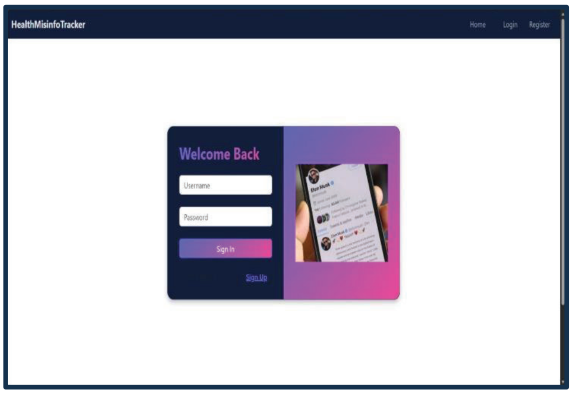

Fig 5 : Output

Core Detection Modules

The Core Detection Modules section presents the primary capabilities of the Health Misinformation Trend Tracker. It highlights how the system analyzes health-related content from social media to detect misleading information. The real-time analysis component processes incoming data and quickly evaluates the credibility of the content. The trend tracking feature monitors patterns in misinformation to identify frequently spreading topics. Additionally, the system emphasizes fast and accurate processing to provide reliable classification results. This section explains the key functional components that enable the platform to detect, analyze, and monitor health misinformation effectively.

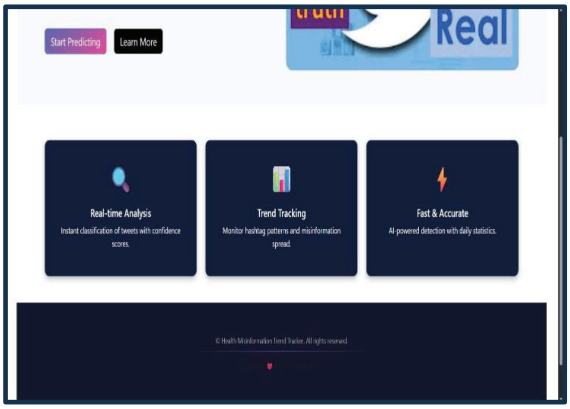

Fig 6 : Output

Misinformation Analysis Dashboard

The Misinformation Analysis Dashboard displays the results generated after analyzing a tweet for possible misinformation. Users can enter a tweet in the input field, and the system processes the text to determine whether the information is genuine or misleading. After analysis, the dashboard shows the prediction result along with related hashtags extracted from the tweet. It also includes visual charts that present statistics such as the number of real and fake tweets detected over the past seven days. A pie chart highlights trending hashtags associated with false information. This interface helps users interpret the analysis results and observe patterns in health misinformation trends.

Fig 7 : Output

VII. CONCLUSION

The proposed data-driven framework for detecting and tracking health misinformation provides an effective solution to address the growing challenge of infodemics in the digital era. By integrating Natural Language Processing, machine learning classification models, and temporal trend analysis, the system enables accurate identification of misleading

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health-related content across online platforms. The framework not only classifies information as credible or misinformation but also monitors propagation patterns to detect emerging trends at an early stage. Through automated analysis and real-time visualization, the system supports public health

authorities, researchers, and policymakers in making informed decisions. The use of advanced feature extraction techniques and scalable backend technologies ensures reliable performance and adaptability to evolving misinformation narratives. Overall, the proposed framework contributes to strengthening the digital health information ecosystem by promoting early detection, continuous monitoring, and proactive intervention against health misinformation.

VIII. FUTURE ENHANCEMENTS

The proposed system can be further enhanced by incorporating multilingual support to detect health misinformation across different languages and regions. This would improve global applicability and allow monitoring of misinformation trends beyond English-language platforms. Integration of advanced large language models (LLMs) can also enhance contextual understanding and improve classification accuracy for complex or nuanced health claims. Another potential improvement is the inclusion of multimodal analysis, where images, videos, and audio content are analyzed alongside textual data. Many misleading health claims are shared through infographics and short videos; therefore, integrating computer vision and speech processing techniques would strengthen detection capabilities. The system can also be extended with real-time streaming data processing using big data technologies such as Apache Kafka or Spark. This would enable faster detection of viral misinformation and provide instant alerts to health authorities. Additionally, incorporating network analysis can help identify key influencers or sources responsible for spreading false information. Future work may focus on implementing explainable AI (XAI) dashboards to provide detailed reasoning behind each prediction, increasing transparency and user trust. Collaboration with fact-checking organizations and integration with official health databases (such as WHO or government health portals) can further improve verification accuracy. Overall, these enhancements will make the framework more robust, scalable, and capable of effectively combating evolving health misinformation trends.

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