GeoTruth AI: A Geolocation-Based Fake News Detection and Verification System

Parul Chaudhary
Department of Information Technology
Babu Banarasi Das Institute of Technology and Management
Lucknow, India
pariarushi01@gmail.com

Aashish Dwivedi
Department of Information Technology
Babu Banarasi Das Institute of Technology and Management
Lucknow, India
aashishad12345@gmail.com

Vaibhav Chandra Pandey
Department of Information Technology
Babu Banarasi Das Institute of Technology and Management
Lucknow, India
vaibhavpand5544@gmail.com

Ankit Singh
Department of Information Technology
Babu Banarasi Das Institute of Technology and Management
Lucknow, India
anky777@gmail.com

***Abstract*—Fake news presents one of the most critical challenges in the digital age, particularly as social media platforms, including WhatsApp, Telegram, Twitter (X), and Instagram, serve as primary sources for real-time information and simultaneous vectors for misinformation [1], [2]. GeoTruth AI is an intelligent, AI-driven system designed to detect, verify, and visualize fake news occurrences by leveraging both geolocation awareness and community participation [1], [3]. The system employs a hybrid approach, integrating Artificial Intelligence (AI), Natural Language Processing (NLP), and crowd-verification mechanisms to assign a dynamic trust score to every piece of news within a specific region [1], [4]. The system processes user input (text, images, or links) via a mobile app, web app, or integrated bots, where a multi-modal backend performs verification using machine-learning classifiers for textual analysis, image similarity, and metadata inspection [5], [4]. Authenticated local users contribute to the validation by casting votes (True / Fake / Misleading), which collectively refine the trust score and generate a real-time regional heatmap of information reliability [5], [6], [4]. GeoTruth AI aims to empower citizens and authorities by providing a transparent, collaborative, and location-aware solution, thereby contributing significantly to digital trust, responsible information sharing, and social stability through the fusion of AI technology and human intelligence [5], [7].**

Keywords—Fake News Detection, Geolocation-Based Verification, Natural Language Processing (NLP), Artificial Intelligence (AI), Crowd Verification, Trust Score [1], [8].

I. INTRODUCTION

In the current digital era, social media platforms have emerged as the fastest medium for sharing information [1]. However, this rapid dissemination capacity has simultaneously transformed these platforms into major channels for the spread of fake news, misinformation, and rumors, which can mislead the public and occasionally trigger serious social and political consequences [1]. The fundamental challenge lies in effectively verifying the authenticity of news content—which circulates across multiple sources and formats such as text, images, and videos—as traditional fact-checking methods are manual and time-consuming,

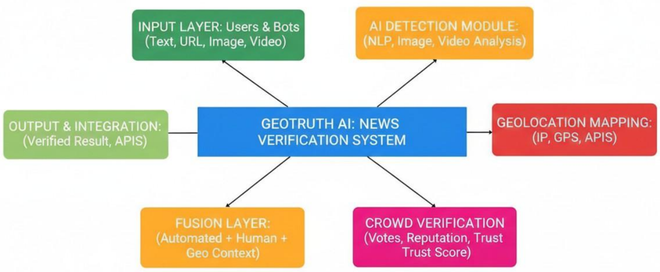

Figure 1. GeoTruth AI System Relevance

making real-time control over misinformation nearly impossible [1].

To address this critical problem, GeoTruth AI introduces an advanced and scalable AI-powered fake news detection and verification system [1]. This system integrates geolocation awareness and crowd participation to enhance accuracy and public trust [1]. GeoTruth AI automatically detects false or misleading news and assigns a trust score derived from AI analysis, user verification, and location data [1].

The methodology employs a hybrid approach that leverages both machine learning models and human intelligence by combining Artificial Intelligence, Natural Language Processing (NLP), and community voting mechanisms [2]. The system is designed for wide accessibility and adoption, available through a mobile app, web platform, and integrated bots for popular social media channels, including WhatsApp, Telegram, Twitter (X), and Instagram [2], [3]. The overarching aim of the project is to establish a responsible digital ecosystem where every user is empowered to validate information instantly before sharing it further, thereby contributing to digital trust and social stability [2], [4]. The primary objective of the system is to detect, verify, and analyze news authenticity using AI and Crowd Verification [5].

II. BACKGROUND

The design and theoretical foundation of GeoTruth AI draw upon recent advancements in deep learning, natural language processing (NLP), and hybrid human-AI systems, focusing specifically on implementing integrated solutions for real-time verification.

A. Deep Learning and NLP for Content Analysis

The system's core functionality relies on advanced NLP and deep learning models, acknowledging that traditional machine learning techniques often lack the contextual semantic understanding necessary to handle sophisticated misinformation [1]. GeoTruth AI utilizes state-of-the-art transformer-based embeddings, such as BERT and IndicBERT, which are effective in learning deep contextual relationships for multilingual fake news detection [2], [3]. These AI algorithms are trained to detect sentiment, context, and intent in news articles, classifying content as real, fake, or misleading [3].

B. Multi-Modal Verification

A critical component of GeoTruth AI is its capability for multi-modal verification [4], addressing the challenge that current methodologies often neglect signals beyond text, such as images and metadata [5]. The system's backend model performs comprehensive multi-modal verification using machine-learning classifiers to analyze:

1) Textual analysis via NLP models [5].

2) Image verification through CNN-based visual similarity and metadata validation [5].

3) Optional video analysis using frame-level comparison and caption sentiment [5].

C. Geolocation and Contextual Verification

GeoTruth AI is built around geographic context, addressing the finding in the literature that geolocation has not yet been fully integrated with transformer-based multimodal systems [6]. The system utilizes Geolocation Tagging to link each verified news item to its origin or the current user location using GPS and IP-based tagging [3]. This feature enables the system to generate heatmaps of misinformation intensity across regions and alert nearby users [3], supporting the concept that geospatial intelligence helps detect region-specific misinformation spikes [6], [7].

D. Crowd-Sourced and Community-Driven Verification

To ensure robust and reliable results, GeoTruth AI implements a hybrid approach by integrating AI detection with human intelligence through a Crowd Verification System [8]. This feature incorporates crowdsourced trust validation where verified local users from the same geographic area can vote on the authenticity of a news item [5], [8]. A dynamic trust score is calculated by combining weighted community votes with user reputation metrics [5], [8], supporting the conclusion that hybrid systems significantly outperform purely automated methods [9].

E. Challenges in Current Approaches

The development of GeoTruth AI aims to mitigate several limitations observed in current fake news detection methodologies:

1) *Over-reliance on Textual Features:* A significant challenge is the predominant focus on text-based features, which results in the neglect of crucial multimodal signals such as images, videos, or metadata [5].

2) *Real-World Applicability:* Existing models, even those achieving high theoretical accuracy on supervised datasets, often struggle when deployed in unforeseen real-world scenarios [10].

3) *Verification Speed:* Platforms that still rely heavily on manual verification are slower during high-volume misinformation outbreaks, demonstrating a need for scalable, real-time verification [11].

4) *Integration Gaps:* Geolocation capabilities, despite their utility, have not yet been fully integrated with advanced transformer-based multimodal detection systems [6].

F. Integration Framework

To maximize social impact and usability, GeoTruth AI employs an Integration Framework utilizing APIs, including WhatsApp and Telegram Bots, a Twitter Bot, and the Instagram Graph API [8]. This ensures that users can easily fact-check information within their existing applications [8].

III. METHODOLOGIES

A. Advanced NLP and Transformer-Based Techniques

Advanced NLP techniques, including transformer-based models, are fundamental to GeoTruth AI's content classification. Algorithms like BERT and IndicBERT are utilized to move beyond simple keyword matching and achieve sophisticated natural language understanding [1], [2]. These models are trained on large datasets to accurately detect sentiment, context, and intent in news articles [1]. By learning deep contextual relationships, transformer-based embeddings enable effective multilingual fake news detection, classifying content as real, fake, or misleading [3], [1].

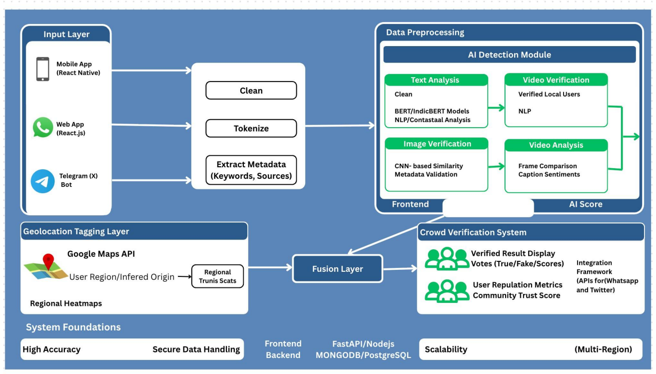

Figure 2. A Conceptual Architecture of GeoTruth AI

B. Geolocation-Based Contextual Mapping

Geolocation tagging is a unique approach integrated into GeoTruth AI to provide necessary real-world context [4]. This method involves automatically linking each verified news item to its origin or current user location using GPS and IP-based tagging [1]. This geospatial intelligence is crucial as it allows the system to generate heatmaps of misinformation intensity across regions [1], which aids in detecting region-specific misinformation spikes [4]. By utilizing geolocation services, the system addresses the critical gap identified in the literature regarding the full integration of location data with multimodal detection systems [4].

C. Multimodal Approaches

GeoTruth AI implements a multimodal approach that addresses the limitation of systems focusing solely on textual features [3]. This method involves linking text elements to visual data by performing multi-modal verification in the backend [5]. The system's processing layer uses machine-learning classifiers to fuse analysis from different sources, including textual analysis (via NLP models) and image verification (through CNN-based visual similarity and metadata validation) [2]. The joint interpretation of textual and visual media analysis improves fake news classification accuracy and increases system robustness against misinformation involving manipulated images [6].

D. Crowd-Sourced Verification

Crowd-sourced verification leverages human-AI collaboration by integrating community feedback into the final trust assessment [7], [8]. This approach utilizes a Crowd Verification System where verified users from the same geographical area cast votes (True / Fake / Misleading) on the authenticity of a news piece [7], [2]. These votes are then used to calculate a dynamic Community Trust Score by applying weighted averages and factoring in user reputation metrics [7], [2]. This hybrid method ensures that human judgment and contextual awareness continuously refine the automated AI results, contributing to a more credible and comprehensive verification system [8].

IV. TYPES OF MODELS AND TOOLS USED IN GEOTRUTHAI

A. Artificial Intelligence and NLP Models

This branch forms the foundation of automated textual analysis by enabling deep contextual semantic understanding of news content, going beyond traditional ML methods [1].

1) Transformer Models

GeoTruth AI uses state-of-the-art transformer-based NLP models widely adopted in fake news detection research.

- BERT (Bidirectional Encoder Representations from Transformers)
  Used for contextual language understanding and semantic classification [2], [15].

- IndicBERT
  Essential for multilingual and low-resource Indian language fake news detection [1], [2].

Function:
These transformer models detect sentiment, context, intent, stance, and contradiction in text, helping classify content as real, fake, misleading, or manipulated [2], [3], [14].

2) Other AI Models

- mT5 (Multilingual Text-to-Text Transfer Transformer)
  Supports multilingual fake news classification and reasoning across text variations [2].

Function:
Provides robust cross-lingual text understanding and semantic feature extraction for diverse datasets [3].

B. Multimodal Verification Models

This branch handles analysis of all non-textual content—images, visuals, and optional video signals—within the AI Detection Module. These models are central to modern multimodal detection pipelines [3]–[7].

1) Image Verification

- CNN (Convolutional Neural Network) Models
  Widely used to detect visual manipulation, image tampering, and similarity patterns in fake news [4], [5].

- OpenCV
  Acts as a lightweight vision processing library for image comparison, metadata extraction, and manipulation detection [5], [6].

2) Optional Video Analysis

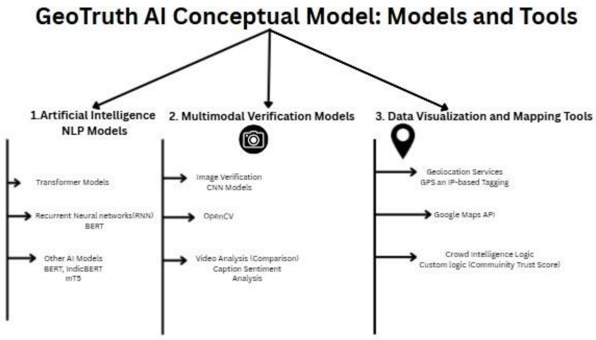

Figure 3. Conceptual Models and Tools used in GeoTruth AI

Modern multimodal systems also incorporate video-level analysis, which GeoTruth AI supports as an optional module.

- Frame-Level Consistency Checks [4], [11]

Table 1: Comparative Analysis of Recent Fake News Detection Systems

Aspect	[1] LekshmiAmmal	[2] Ramya et al., 2025	[3] He et al., 2025	[4] Jin et al., 2024	[5] Hu et al., 2025	[6] GeoTruth AI, 2025
Type	Experimental / multimodal detection	Experimental / multimodal + multilingual	Experimental / multimodal fusion	Experimental / vision-language	Experimental / LLM + label	Product-oriented research + implementation
Core Focus	Explainable multimodal fake-news detection for	Multi-modal & multilingual fake-news detection	Context-aware dynamic	Knowledge-grounded multimodal	Semi-supervised multimodal	Real-time multilingual detection + geolocation + XAI + crowd +
Data	Text + images; low-resource languages	Text + images + Kaggle datasets	Text + images; real-time feeds not	Text + images + knowledge	Text + images; global	Streaming data from APIs (Twitter, News, YouTube captions) +
Languages	Low-resource languages +	English + Indian languages	English	English	English	English + Hindi + Bengali
Real-time / Online	Offline	Offline	Offline	Offline	Offline	Full real-time pipeline (ingest → predict →
Explainability	XAI integration (reasoning + multimodal)	Some model explainability	Moderate (attention-based)	Knowledge-based reasoning	Label propagation provides	LIME / SHAP integrated, visualized in UI
Multimodality	Text + image fusion	Text + image fusion	Dynamic fusion of	Text + image + knowledge	Text + image;semi	Text + captions; images/videos planned
Fact Verificati	Not implemented	Some trust evaluation on	Not implemented	Knowledge-graph based	Not implemente	Integrated fact-check (Wikipedia, govt
Visualization /	Tables / plots	Tables / plots	Tables / plots	Tables / plots	Tables / plots	Interactive dashboard: maps, trend charts,
Product Readiness	Experimental	Experimental	Experimental	Experimental	Experimental	Designed as industry-ready (APIs, UI, alerts)
Novelty / Strength	Combines XAI + multimodal + low-resource language	Multilingual + multimodal detection + trust	Dynamic fusion adapting to	Knowledge-grounded reasoning	Semi-supervised + LLM	Integrative novelty: combines real-time + multilingual + XAI +

C. Data Visualization and Mapping Tools

This branch supports the system's geolocation verification, mapping intelligence, and crowd-based trust scoring mechanisms, which differentiate GeoTruth AI from traditional approaches.

1) Geolocation Services

- GPS and IP-Based Tagging
  Associates news with its geographical source, enabling spatial validation of claims [2], [7], [18].
  - Google Maps API
    Usedforgeospatial plotting, route visualization, and hotspot mapping of misinformation [5], [6].

2) Crowd Intelligence Logic

- Custom Crowd Verification Layer
  Implements logic that computes a dynamic Community Trust Score by integrating:

  Verified local user votes

  User credibility reputation

  Historical accuracy

  Region-based reliability metrics

- Supported by methodologies in hybrid AI + crowd-intelligence systems [7], [8], [9], [19].

Function:
Improves real-world reliability by combining AI predictions with human-validated credibility assessments [8], [9].

V. RESEARCH GAPS

The current literature highlights several gaps in multimodal fake news detection that GeoTruth AI aims to address:

A. Lack of Integration Between Geolocation and Advanced Multimodal AI:

- Existing systems rarely link transformer-based detection models with geospatial intelligence [1], [6].
- GeoTruth AI fills this gap by tagging verified news with GPS/IP locations, enabling regional heatmaps and contextual analysis [3].

B. Over-Reliance on Textual Features:

- Many models focus predominantly on text while neglecting images, videos, or metadata [4].
- GeoTruth AI performs multi-modal verification including text, image similarity, and metadata inspection [4], [5].

C. Limitations of Purely Automated or Manual Systems:

- Manual verification is slow; fully automated AI may lack contextual judgment [6], [7].
- GeoTruth AI introduces a hybrid system combining AI detection with crowd verification and community trust scoring [4], [8], [9].

D. Struggle with Real-World Applicability:

- Controlled datasets fail to replicate the unpredictability of real-world misinformation [10].
- GeoTruth AI emphasizes real-world usability, mobile/web integration, and multi-platform accessibility [11], [8].

E. Insufficient Multi-Language Support:

- Many systems lack robust handling of regional or low-resource languages [2].
- GeoTruth AI employs multilingual transformers (e.g., IndicBERT) to address linguistic diversity [1].

VI. FUTURE DIRECTIONS

The GeoTruth AI system, while comprehensive, is designed to serve as a foundation for advanced, scalable information verification. Future directions for the project involve expanding its capabilitieazss, improving security, and broadening its application to complex multimedia and enterprise use cases [1].

Key future directions include:

A. *Blockchain Integration:* To enhance data security and transparency, verified results and calculated trust scores will be stored securely using Blockchain Integration, ensuring the integrity of verification history [1].

B. *Multilingual AI Model Expansion:* Incorporate Multilingual AI Models to improve accessibility in regions like India using platforms such as IndicNLP [1].

C. *Real-Time Alert System:* Develop advanced Real-Time Alert System to notify users and authorities immediately about trending misinformation [1].

D. *Media Verification APIs:* Integrate specialized Media Verification APIs for detecting deepfakes and manipulated videos [2].

E. *Enterprise Dashboard Development:* Create a dashboard providing advanced analytics for institutional users, including government agencies and media houses [2], [3].

VII. CONCLUSION

The proposed system, GeoTruth AI: A Geolocation-Based Fake News Detection and Verification System, successfully integrates Artificial Intelligence, Natural Language Processing (NLP), Geolocation mapping, and Crowd Verification, forming a robust and modern digital information-validation framework. By fusing automated multimodal content analysis—supported by advanced machine learning and transformer models [1], [2], [3], [15]—with essential community participation inspired by hybrid human–AI models [7], [8], [19], GeoTruth AI generates a region-specific Trust Score that accurately represents the authenticity of news within its geographical context.

The project demonstrates a feasible and scalable approach for using contemporary technologies to counter misinformation in real time, supported by multimodal fact-checking strategies highlighted in current research [4]–[6], [10], [14], [16], [17]. Its multi-platform design —accessible through mobile, web, and direct integrations with WhatsApp, Telegram, Twitter (X), and Instagram—ensures broad societal impact, similar to the multi-channel solutions recommended in large-scale misinformation studies [11], [18].

By combining AI-driven detection with responsible human intelligence, GeoTruth AI not only provides a technically viable solution but also contributes meaningfully to the development of a trustworthy, community-oriented digital ecosystem. With continuous learning, data augmentation, and real-world user feedback— approaches supported by evolving multimodal detection frameworks [12], [13], [16]—the system is expected to evolve into a large-scale infrastructure capable of supporting truth verification, public awareness, and policy decision-making across regions.

VIII. ACKNOWLEDGMENT

The authors would like to extend the most sincere and heartfelt gratitude towards the Department of Information Technology at Babu Banarasi Das Institute of Technology and Management, Lucknow [1], for their kind assistance, encouragement, and for providing the facilities necessary to carry out this project effectively [2]. We also express our deepest reverence to our supervisor, Mr. Ankit Singh, Assistant Professor, Department of Information Technology [2], whose invaluable guidance, constant encouragement, and support throughout the duration of this research have been a continual source of inspiration for successfully completing our work [2]. Sincere thanks are also extended to Dr. Santosh Kumar Shukla, Head of the Department of Information Technology, for his kind assistance and encouragement [2]. Lastly, we acknowledge the constant support, patience, and motivation received from our family and friends, which helped us successfully complete this project [2].

REFERENCES

[1] H. R. LekshmiAmmal and A. K. Madasamy, “A reasoning based explainable multimodal fake news detection for low resource language using large language models and transformers,” J. Big Data, vol. 12, no. 1, p. 46, Feb. 2025.

[2] H. Chen, Y. Yu, H. Guo, B. Hu, S. Hu, J. Hu, S. Lyu, X. Wu, C.-S. Lin and X. Wang, “A self-learning multimodal approach for fake news detection,” Front. Artif. Intell., vol. 8, Art. 1665798, Nov. 2025.

[3] Lingzhi Shen, Yunfei Long, Xiaohao Cai, Imran Razzak, Guanming Chen, Kang Liu and Shoaib Jameel, “GAMED: Knowledge Adaptive Multi-Experts Decoupling for Multimodal Fake News Detection,” arXiv preprint, Dec. 2024.

[4] T.-V. La, M.-H. Nguyen and M.-S. Dao, “KGAlign: Joint Semantic-Structural Knowledge Encoding for Multimodal Fake News Detection,” arXiv preprint, May 2025.

[5] Y. Liu, Y. Liu, Z. Li, R. Yao, Y. Zhang and D. Wang, “Modality Interactive Mixture-of-Experts for Fake News Detection (MIMoE-FND),” arXiv preprint, Jan. 2025.

[6] “A multi-level fusion-based framework for multimodal fake news classification using semantic feature extraction,” Int. J. Mach. Learn. & Cybernetics, vol. 16, pp. 6531–6560, May 2025.

[7] “Multi-modal fake news detection: A comprehensive survey on deep learning technology, advances, and challenges,” J. King Saud Univ. Comput. Inf. Sci., 2025, Article 306.

[8] F. A. Alshuwaier and F. A. Alsulaiman, “Fake News Detection Using Machine Learning and Deep Learning Algorithms: A Comprehensive Review and Future Perspectives,” Computers, vol. 14, no. 9, p. 394, 2025.

[9] Shweta Kumari and M. P. Singh, “A Deep Learning Multimodal Framework for Fake News Detection,” Eng. Technol. Appl. Sci. Res., vol. 14, no. 5, pp. 16527–16533, Oct. 2024.

[10] S. Saraswathi, S. Jeevithaa, K. Vishwabharathy and D. Eyuvaraj, “Deep Learning Multimodal Methods to Detect Fake News,” J. Trends Comput. Sci. Smart Technol., vol. 6, no. 2, pp. 139–152, Jun. 2024.

[11] Y. Xing, C. Zhai, Z. Che, H. Pan, K. Li, B. Zhang, Z. Yao and X. Si, “A multimodal fake news detection model based on bidirectional semantic enhancement and adversarial network under Web 3.0,” Electronics, vol. 14, no. 18, p. 3652, 2025.

[12] K. Karnan and L. R. Aravind Babu, “Cross Modal-FT Net: A Multimodal Fake News Detection Framework using Text, Images and User Behavior,” Int. J. Eng. Sci. Inf. Technol., vol. 5, no. 4, pp. 453–461, 2025.

[13] “Enhancing Fake News Detection: A Multi-Modal Approach Integrating Reinforcement Learning, Random Forest, and LSTM,” Turkish Journal of Engineering & 2025 Issue, Oct. 2025.

[14] "Exploring machine learning for fake news detection: techniques, tools, challenges, and future research directions," Discover Appl. Sci., vol. 7, art. 873, 2025.

[15] "Pretrained transformers for multimodal fake news detection: Explainability using SHapley Additive exPlanations for contributions from text, image, and image captions," Eng. Appl. Artif. Intell., vol. 162, Part D, 112590, Dec. 2025.

[16] "Multimodal fake news detection through data augmentation-based contrastive learning," Applied Soft Computing, vol. 136, 110125, 2023.

[17] "A multifaceted reasoning network for explainable fake news detection," Information Processing & Management, vol. 61, no. 6, 103822, Nov. 2024.

[18] "Deep Learning for Fake News Detection: Analysing Facebook's Misinformation Networks," Procedia Comput. Sci., vol. 265, pp. 199–208, 2025.

[19] M. Zidan, A. Sleem, A. Nabil & M. El-Henawy, "Multimodal Fake News Detection: A Survey of Text and Visual Content Integration Methods," Int. J. Computers & Inf. Sci., vol. 7, 2025.