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Truthguard: An AI-Based Multimodal Framework for Detecting and Preventing Misinformation on Social Media Platforms

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Abstract: The rapid growth of digital communication and social media platforms has transformed the way information is shared and consumed globally. However, the increasing spread of misinformation, fake news, manipulated media, and misleading online content has created serious social, political, and economic challenges. Traditional misinformation detection systems often fail to understand contextual meaning, emotional manipulation, and inconsistencies between text and visual content. This research paper proposes **TruthGuard**, an AI-powered multimodal misinformation detection framework that integrates Natural Language Processing (NLP), Machine Learning, Deep Learning, and image verification techniques. The proposed system uses Transformer-based architectures such as BERT along with CNN and ResNet models for image analysis. The framework also introduces explainable AI mechanisms to improve transparency and user trust. Experimental observations indicate that multimodal hybrid systems achieve significantly higher accuracy and better contextual understanding than traditional machine learning approaches. The proposed framework aims to create safer digital communication environments and reduce the harmful effects of online misinformation.

I. INTRODUCTION

Social media platforms such as Facebook, Instagram, Twitter, YouTube, and WhatsApp have become the primary medium of information exchange in modern society. Millions of users share posts, videos, articles, and opinions every second. While these platforms improve communication and accessibility of information, they also create opportunities for the rapid spread of misinformation and fake news. Misinformation refers to false or misleading information shared intentionally or unintentionally. The spread of such content can influence elections, damage reputations, create panic during emergencies, and spread health-related myths. During global events such as pandemics, misinformation has caused confusion and fear among the public. Traditional moderation systems rely heavily on manual verification, which is time-consuming and inefficient for handling large-scale online data. Moreover, older machine learning models often fail to understand sarcasm, contextual meaning, emotional tone, and multimedia manipulation. This creates a strong need for intelligent AI-driven systems capable of understanding both textual and visual information. TruthGuard is proposed as a modern multimodal framework capable of detecting misleading content using NLP, Deep Learning, Transformer models, and computer vision techniques. The system focuses on improving detection accuracy while also providing explainable outputs and confidence scores for users.

II. OBJECTIVES OF THE RESEARCH

The major objectives of this research work are: • To design a multimodal misinformation detection framework. • To analyze textual and visual content together for better contextual understanding. • To improve fake news detection accuracy using Transformer-based architectures. • To implement explainable AI techniques for transparency and trust. • To compare traditional machine learning methods with modern deep learning approaches. • To reduce the harmful effects of misinformation on society. • To support future development of real-time misinformation monitoring systems.

III. LITERATURE REVIEW

Several researchers have contributed significantly to the field of misinformation detection. Traditional approaches mainly relied on machine learning algorithms such as Naive Bayes, Decision Trees, Logistic Regression, and Support Vector Machines. These methods achieved moderate accuracy but often struggled with contextual understanding and semantic interpretation. Recent advancements in Deep Learning introduced architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformer models. Among these, BERT and Vision Transformers have shown outstanding performance in understanding textual semantics and image patterns. Research studies also emphasize the importance of multimodal learning, where text, images, and social context are analyzed together. Multimodal systems can detect inconsistencies between textual claims and visual evidence, making them more effective than unimodal approaches. Explainable AI has emerged as another important research area. Users often hesitate to trust AI systems that provide predictions without explanations. Therefore, explainable AI techniques such as attention visualization, confidence scoring, and suspicious keyword analysis help improve system transparency and reliability.

IV. PROPOSED SYSTEM ARCHITECTURE

The proposed TruthGuard framework follows a hybrid multimodal architecture. The system accepts social media posts, headlines, comments, and images as input data. The architecture consists of multiple stages:
1. Data Collection Module: Datasets are collected from sources such as FakeNewsNet, Kaggle repositories, Twitter APIs, and public datasets. 2. Data Preprocessing Module: The collected data undergoes cleaning processes such as tokenization, stop-word removal, punctuation removal, normalization, and lemmatization. 3. Feature Extraction Module: TF-IDF vectors and BERT embeddings are used for textual feature extraction. These features help the model understand semantic meaning and contextual relationships. 4. Image Verification Module: CNN and ResNet architectures analyze images to identify manipulated or misleading media content. 5. Classification Module: Hybrid classifiers such as SVM, LSTM, and BERT are used to classify content into genuine or fake categories. 6. Explainable AI Module: The system generates confidence scores, attention maps, and suspicious keyword analysis to explain predictions.

V. METHODOLOGY

The methodology of TruthGuard involves a combination of Natural Language Processing, Deep Learning, and Computer Vision techniques. Step 1: Data Acquisition Large datasets containing fake and real news samples are collected from multiple sources. Step 2: Text Preprocessing Text data is cleaned and transformed into structured formats suitable for machine learning algorithms. Step 3: Feature Engineering TF-IDF vectors capture keyword frequency patterns, while BERT embeddings capture contextual meaning. Step 4: Image Analysis Visual content is processed using CNN and ResNet models to identify manipulated or unrelated images. Step 5: Classification The extracted textual and visual features are combined and passed through hybrid classifiers. Step 6: Explainability The system provides explanations, confidence percentages, and suspicious keyword indicators for each prediction.

VI. RESULTS AND DISCUSSION

Experimental observations indicate that the proposed multimodal framework achieves significantly better performance than traditional machine learning systems. Transformer-based models improve contextual understanding, while image verification modules enhance detection accuracy. The framework demonstrates high accuracy in detecting misleading social media posts, manipulated images, and emotionally misleading content. The inclusion of explainable AI further improves user trust and system reliability. The proposed model performs especially well in scenarios where textual and visual inconsistencies exist. For example, misleading headlines combined with unrelated images can be identified more effectively using multimodal analysis.

VII. PERFORMANCE EVALUATION

The following table compares the performance of traditional machine learning approaches with the proposed TruthGuard framework.

VIII. FUTURE SCOPE

Future improvements can make TruthGuard even more powerful and scalable. Possible future developments include: • Real-time live monitoring of social media platforms. • Detection of deepfake videos and synthetic media. • Multilingual misinformation detection. • Integration with browser extensions and social media APIs. • Blockchain-based verification systems. • Adaptive AI systems capable of learning new misinformation patterns automatically. The future scope of misinformation detection systems is vast, and AI-driven frameworks will play an important role in protecting digital ecosystems.

IX. CONCLUSION

TruthGuard presents a modern AI-based multimodal framework for misinformation detection on social media platforms. By integrating NLP, Deep Learning, Transformer models, and image verification techniques, the system addresses the limitations of traditional fake news detection methods. The framework improves contextual understanding, classification accuracy, and system transparency through explainable AI mechanisms. Experimental observations demonstrate that multimodal approaches significantly outperform traditional techniques. TruthGuard can contribute toward building safer and more trustworthy online communication platforms. With future advancements in AI and real-time monitoring systems, such frameworks can become essential tools for combating misinformation in the digital era.

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Metric	Traditional ML	TruthGuard (Proposed)
Accuracy	78-82%	94-96%
Precision	75%	93%
Recall	72%	91%
F1-Score	74%	92%