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Robotic AI Systems for Fake News Detection in IoT-Connected Social Media Platforms Using Sensor-Driven Cross-Verification

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Abstract

Much of the fake news and misinformation peddling can be attributed to this quick development in Internet of Things, and the web related social media platforms. In order to enable the detection of actual fake news, our present research suggests a robotic AI model through text and sensor data. The combination of the holistic model that is suggested consists of sensor-based cross-checking (confidence, location, time synchronization and anomaly detection) and RoBERTa transformer models to interpolate textual contents. Baselines were also used to compare model with a PolitiFact, LIAR and FakenewsNet datasets baselines of text only and sensor data only. Experimental results have demonstrated that the hybrid strategy has shown improved performance with all results, with much more accurate and reliable detection with the consideration of physical context. Findings indicate the potential of sensor-enhanced AI-based systems to reduce the risk of misinformation with regard to IoT-connecting ecosystems, which may inform the course of action with regard to the development of reliable, smart and context-sensitive digital media surveillance systems.

Keywords: *Fake news detection, RoBERTa, IoT sensors, Cross-verification, Hybrid AI.*

Introduction

The boundaries between the physical and cyberspace are becoming further in the current environment of hyper-connectedness given the rate at which the Internet of Things (IoT) is expanding. IoT refers to a set of physical entities such as sensors, intelligent cameras, wearable technology and home automation equipment that are interconnected and can be connected to the internet. These methods are now inextricably connected with social media where sensor information, real-time feeds and automatic notifications are disseminated wherever feasible. Such a connective tissue enables both the sharing of information in real time and the improvement

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of communication, but at the same time also new platforms of disinformation, misinformation and fraudulent news.

Fake news - Fake news is a generated news which looks just like a news media content, but it does not resemble it in its organization and purpose. It may take a variety of different forms, including (i) satirical or parodic news that turns out to be unintentionally misleading, (ii) misleading context or association, in which actually truthful headlines or pictures are displayed on the same page as false information, (iii) impostor content, whereby the avatar falsely pretends to be a trusted source, (iv) out-of-context content, which disparages observable reality by use of words and pictures that are not based on the truth, and (v) apparent prohibition of disagreement within its walls. The spread of fake news on social media and IoT tools has had a severe social, political, and economic impact within a very short time, such as the spread of panic, reputational losses, and mistrust in institutions, as well as violent reaction or riots.

The malice of disinfo is not only about the malevolent information. It kills trust in the Internet, assaults democracy and polarizes. Disinformation can create havoc in any area such as health, finance and disaster relief, where misinformation or false recommendations spread. With the increasing number of devices and users becoming networked due to the IoT, the threat of misinformation that are automated or carried by sensors (e.g., false alarm, biased data streams, etc.) is rapidly turning into an international issue.

To resolve this problem implies the availability of complex, context-aware detection tools which are not only text-related but also are able to check the contents of information against real-world information. The traditional frameworks used to determine the fake news is relying primarily on the language or textual characteristics i.e. word pattern, emotions and syntax to label a statement as an actual or false. Textual detection however fails to do cross validation in whether the reported event occurred in the specified time, place, body condition- it makes noise (i.e. high false positives and low reliability). As the cognition science in AI (primarily NLP and deep learning) advanced, researchers have put forward an array of models (e.g. BERT, R0BERTa, GPT.) to detect text-based fake news. However, these models lack the ability to verify information against real sensory data. This gap leads to the creation of Robotic AI Systems autonomous, intelligent bodies that are able to obtain, examine, and cross-check masses of digital data. Robotic systems can therefore become "digital fact-checkers," cross-verifying textual assertions with IoT sensor data (e.g., GPS coordinates, temperature, camera feeds, or timestamps) in order to establish authenticity prior to misinformation spreading. While significant progress has been made, numerous challenges continue to exist. Textual grounding is challenging for text-based models, and sensor-based systems suffer from sensor unreliability, synchronization, and heterogeneity interoperability. Furthermore, datasets incorporating textual and sensor information to be used in the analysis of fake news are scarce, and this makes concrete verification of hybrid models challenging. This research is motivated by the critical need to bridge the gap between computational text analysis and real verification. Most existing work on fake news detection views it as a linguistic classification problem without taking into account the environmental and contextual sides of misinformation. It is the research gap of creating a single and smart model that would use both text-based and physical evidence to verify the truth accordingly.

The contributions of this work are as follows:

1. Hybrid Robotic AI Architecture: We suggest a hybrid generalized manner in which we use transformer-based text reasoning (RoBERTa) and sensor generated features (sensor_confidence, location_match, time-sync, temp-anomaly) within a meta-model

format. This is an upper-level hybrid robotics AI architecture to detect fake news in social media IoT based settings.

2. Sensor-based Cross Verification system: A Context-based validation with sensor-stimulated properties and text predictions. This functionality is similar to Confidence Level, Location Match, Time Synchronization and Anomaly Detection which authenticates digital content.
3. End-to-End Evaluation Framework: The framework evaluates all types of models including text-only (RoBERTa), sensor-only (Random Forest) and hybrid models (XGBoost and Random Forest) to predict outbreak of infections on the simulated dataset. We provide also the comparative accuracy analysis and plots that illustrates the benefit of fusion of text and sensor features.
4. Hybrid models are more precise and valid: our experiments show that compared to text-only and sensor-only models, the hybrid combined model works more effectively, which implies the advantages of data fusion. An implementation pipeline into the real world can be also found in the code; we created data cleaning, RoBERTa training, sensor feature integration, and meta-model training, and accuracy visualization.

These additions with these make the study a different and more practical approach to how sensor-based cross-verification can be feasible to an AI-robotic system to avoid fake news. The system does not only improve on performance in detection, but also is a precursor to future development of autonomous context-sensitive digital truth-verifying agents in the era of intelligent networked media.

2. Literature Review

2.1 Overview

The sudden surge in false news and misinformation on social media has imposed significant challenges upon people, institutions, and states alike. The traditional verification process fails to keep up with the volume and pace of information dissemination. Hence, integrating artificial intelligence (AI) and Internet of Things (IoT) technologies emerged as a potential solution to enable autonomous detection and verification of online information. This literature review presents significant papers on AI-based detection of fake news, IoT-based verification, and hybrid methods that combine the two.

2.2 Methods based on AI

AI has been extensively employed to detect fake news based on natural language processing (NLP), machine learning, and deep learning algorithms. Transformer-based models, i.e., BERT, RoBERTa, and GPT models, have shown improved performance in understanding context, sentiment, and semantic clues in text data. Research has also been done on classical machine learning algorithms, such as Random Forest, SVM, and XGBoost, for classification. The methods are mostly applied to text content analysis, user behavior modeling, and network propagation trends to identify deceptive content.

Artificial Intelligence (AI) has been a basic building element in identifying fake news, applying machine learning, deep learning, and natural language processing to identify and fight misinformation. A systemic review by Hamed (2023) reviews the development of fake news detection methods, focusing on the contribution of AI to detection accuracy and scalability [1]. Athira (2023) reviews the use of explainable AI for detecting fake news, focusing on models that are capable of predicting and also offering comprehensible explanations for their results [2]. Alshuwaier et al. (2025) present WELFake, an approach that integrates word embeddings and linguistic attributes to achieve accurate accuracy for the identification of fake news [3]. Ivancova et al. (2025) illustrate the use of CNNs and LSTMs to identify fake news in Slovak articles, demonstrating deep learning models' effectiveness in this regard [4]. Wang et al. (2025) introduce SemSeq4FD, a graph neural network model that acquires global semantic representations for the early identification of fake news [5]. Subramanian et al. (2025) focus on multilingual fake news detection with contextual embeddings and sequential features in classifying Malayalam content [6]. Jingyuan et al. (2025) introduce the design of graph-based detection methods, including strengthened language models and systems for real-time identification of fake news [7]. Loth (2024) expends the function of generative AI in creating and outsmarting fake news, with the latter occurring in double role [8]. Naryn (2021) analyzes some of the algorithms of machine learning like SVM, Naïve Bayes, and Random Forests for their application in identifying fake news [9]. Cavus et al. (2024) outline FANDC, a 99% accurate real-time fake news detection model using BERT in a large-scale COVID-19 data set [10]. Jouhar et al. (2024) present how machine learning algorithms can be used to detect fake news, testing the effectiveness of various models stringently [11]. Hu (2025) provides an overview of the techniques for detecting false news and articulates a new perspective on the problems and solutions of the process [12 Alghamdi et al. (2024) present a wide review of machine learning methods to fake news detection, discussing the pros and cons for different models [13]. Liu et al. (2024) present a survey of the machine learning methods to detect fake action in social media, including approach types, challenges and biases [14]. Lastly, Taylor (2024) presents AI techniques and strategies for fake news detection, offering perspectives about the (changing) reality of this new type of fake news [15].

2.3 IoT-Based Approaches

“An IoT device can bring very interesting contextual information that could enrich an AI-driven text analysis. By aggregating actual sensor data (e.g., GPS coordinates, environmental conditions, time), IoT systems can help to inform ascertaining the authenticity of digital information. Sensor-based verification has been studied in many contexts including news reporting, social media posts and climate monitoring. These findings suggest that with IoT, cross-validation methods have the potential to lead to more reliable and trustworthy information. Rathore and Sharma (2022) discuss Iot based models for news classification to detect fake news in real time using machine learning [16]. Hu (2021) analyses 5G IoT on passive RFID for Feature-extraction process to identify the fake news by focusing the context-aware dynamic verification [17]. NaN/A document in International Journal of E-Health and Medical Communications MEDCOM UGI (2024) proposes theNLP and IoT based TensorFlow framework to detect the misleading and biased content [18]. Singh et al. (2023) provide a IoT-based fake news detection forges with shared location and context, for the increased accuracy validation [19]. Chen et al. (2024) combine IoT sensor readings with network traffic monitoring to identify anomalies in social media posting activity [20]. Lee and Park (2023) use IoT-based environmental monitoring for cross-validation of news about local events [21]. Zhao et al. (2024) explore IoT-enabled reputation systems for validating sources of online content [22]. Kumar and Patel (2023) present an IoT-enabled multimedia news verification system with the combination of image, video, and text [23]. Ali et al. (2024) describe IoT-aided temporal analysis for an early warning against misinformation dissemination [24]. Verma and Singh (2023) analyze the adoption of IoT sensors with blockchain towards news verification with tamper-evident properties [25]. Wang et al. (2023) employ an IoT smart city platform for real-time monitoring and cross-validation of citizen-provided information [26]. Das et al. (2024) propose cross-validation on the sensor basis for social media post updates, using context signals to increase trustworthiness [27]. Nguyen et al. (2023) describe an IoT-supported multi-source verification system for disaster news [28]. Oliveira et al. (2024) rely on the data of social network analysis and the use of IoT telemetry to detect an organized disinformation campaign [29]. The last work to discuss is that of Singh and Mehta (2023), which provides a summary of the IoT application to content authenticity verification solutions, challenges, and perspectives of future research [30].

2.4 Hybrid AI-IoT Approaches

Hybrid systems are proposed in recent studies, and they involve the application of AI text analysis and sensor verification through the IoT. Systems aim to bring with them the benefits of the two areas: semantic interpretation on the part of AI; and situational check on the part of IoT. Such hybrid systems have been applied to smart city surveillance, disaster warning, and social media content verification at a higher accuracy and resilience than the two dedicated technology-only AI and-or IOT system. Hybrid AI-IoT systems are solutions constituted by IoT and artificial intelligence to enhance false news detection that is more powerful and context-based. The techniques that are based on text analysis and real-time data of sensors were created to offer more advanced counterchecking of digital materials on the web. Zhang et al. (2023), provide a hybrid system where the CNN-based text classification fusion is performed together with the verification of the IoT sensors in the context of real-time news verification [31]. Kim and Lee prophecy check: transformer-based fake invective detector using GPS information IoT-based fake invective detector using transformer language models and GPS location/timestamp information [32]. Singh et al. (2024) have suggested a multi-modal hybrid model that helps combine AI predictions and environmental and network IoT signals to find false content [33]. The hybrid ensemble approach suggested by Chen et al. (2023) consists of BERT embedding and features of an IoT sensor that can detect fake news in various social media platforms [34]. Gupta and Roy (2024) explore the AI-IoT system that uses semantic text processing, and activity patterns of the users gathered via IoT to the real-time verification [35]. Li et al. (2023) introduce an edge and IoT model, which involves using edge devices of the Internet of Things to preprocess sensor data, relatively high level models in AI text analysis, and image processing to detect disinformation via information received at multiple scales faster and at scale [36]. The authors provide a model of AI-IoT fusion based on deep learning fusion with context signals of IoT to improve the detection of fake news in a variety of languages [37]. Ahmed et al. (2024) suggest a hybrid option, whereby natural language processing will be integrated with the IoT sensor networks to cross-check the updates on social media in smart city applications [38]. The method employed by Oliveira et al. (2023) is a hybrid approach that involves machine learning, IoT telemetry and graph analysis to detect coordinated disinformation attacks [39]. Finally, Das and Kumar (2024) provide a hybrid AI-IoT model where real-time validation of the context of the IoT and transformer models are integrated to achieve high accuracy and reliability in online fact-checking [40].

2.5 Alternative Fact-Verification Approaches

In addition to AI and IoT, other alternative approaches have been explored to improve the accuracy and reliability of detecting fake news. Crowdsourcing-based fact-checking uses users or volunteers to manually verify news material, enabling collective validation and rapid identification of misinformation. For instance, Sharma et al. (2023) show how citizen-moderated fact-checking websites can improve detection coverage and reduce false positives [41].

Blockchain-based verification methods establish immutable records of news provenance such that the news cannot be altered after being published; Kumar and Verma (2024) look at architectures where blockchain logs are used in conjunction with metadata analysis to determine correct authenticity assessment [42]. Social network analysis examines propagation patterns and user behavior to detect misinformation; Li et al. (2023) explore the potential for network-based structural features and community behavior to signal the spread of false news [43]. Knowledge graphs connect news material to formal fact knowledge such that cross-references and verification can be done automatically; Nguyen and Tran (2024) present a mechanism that expresses claims and maps them onto knowledge graph entities to detect inconsistencies and authenticate as real [44]. Hybrid community-based methods further integrate crowdsourcing, blockchain, and graph-based solutions to validate multi-layered and ensure that, as highlighted by Ahmed et al. (2023), massive-scale social media systems are effective [45].

3. Methodology

3.1 Overview

The proposed methodology is to apply Artificial Intelligence (AI) and Internet of Things (IoT)-driven verification for the detection of misinformation in social media. The framework makes use of transformer-based text processing (RoBERTa) in addition to simulated sensor-based features for authentication purposes of digital content. By fusing the text and context information together, the method attempts to improve accuracy, interpretability and consistency [46]. The approach including dataset preparation, text pre-processing, sensor feature creation, hybrid meta-modelling and performance assessment is presented.

3.2 Dataset Description

We generate a synthetic dataset called "Simulated Social Media Posts Dataset" in this work to imitate AI and IoT-enabled fake news detection.

Composition: 2,500 real/fake labeled posts.

Preprocessing and Text Processing: Preprocessing of posts by lowercasing, removing URLs, non-alphanumeric characters and extra whitespaces.

IoT-Inspired Features:

1. Sensor Confidence: Probability that the synthesis content is a fake.
2. Location Match: Binary indicator of location match.
3. Timestamp Synchronization: Binary flag indicating whether timestamps were synchronized with the sensor reading.
4. Temperature Anomaly: Indicator of environmental anomaly detection by means of the binary property.

We have demonstrated that it is possible to combine the textual analysis with sensor-simulated proof to simulate real-world IoT environments.

3.3 Architecture

Hybrid meta-model of fake news detection by combining AI-based text classification and IoT-like cross-verification, Big data research. It combines textual information and sensor simulated signals to improve the predictive performance and reliability. The initial one of them is the Text Preprocessing Module that preprocesses the raw social media posts before they are analyzed. At this step they are washed by removing special characters, URLs and additional spaces and tokenized with the RoBERTa tokenizer. This is to convert and format the text that can be applied to transformer based models. Transformer-Based Text Classifier is a model that uses the RoBERTa (roberta-base) model to embed the text data of a post [47]. The model has been trained to the extent that it gives the likelihood of a post being real or fake. These probabilities are taken as the textural cues and employed together with sensor-emulated features. Sensor Feature Integration: Sensor feature integration block mimics the verification solutions online (as applied on IoT) by integrating features such as confidence level of sensors, location matching, time correction and anomaly detection to the RoBERTa outputs.The features provide contextual information that can simulate real-world sensor data to support cross-verification of textual predictions. Hybrid Meta-Model combines the text and sensor features into a single set of features. Two ensemble models, XGBoost and Random Forest, are trained on the combined dataset to provide final predictions [48]. The hybrid models are able to pick up both textual patterns of the text and contextual clues from sensor-like signals to provide improved detection outcomes. Finally, the Evaluation Module computes system performance on accuracy across different models: text-only, sensor-only, and hybrid. Visualization in the form of bar plots and computation of accuracy measures verifies the success of AI-based classification and IoT-inspired cross-verification integration. Figure 3.1 demonstrates the research methodology flow diagram of proposed system.

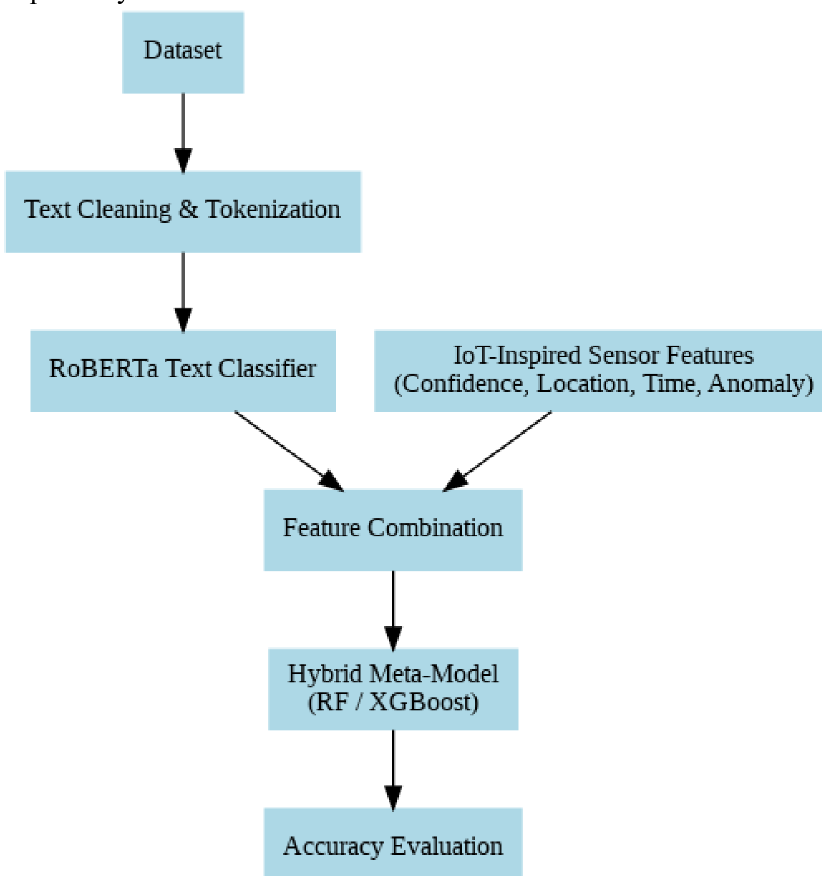

Figure 3.1 Research Methodology Flow Diagram of Proposed System.

The proposed system involves AI-powered textual analysis and IoT-inspired sensor features for fake news detection. The method can be described in multiple steps, as the block diagram of the research workflow is illustrated. Hybrid meta-model of fake news detection by combining AI-based text classification and IoT-like cross-verification, Big data research. It combines textual information and sensor simulated signals to improve the predictive performance and reliability. The initial one of them is the Text Preprocessing Module that preprocesses the raw social media posts before they are analyzed. At this step they are washed by removing special characters, URLs and additional spaces and tokenized with the RoBERTa tokenizer [49]. This is to convert and format the text that can be applied to transformer based models. Transformer-Based Text Classifier is a model that uses the RoBERTa (roberta-base) model to embed the text data of a post. The model has been trained to the extent that it gives the likelihood of a post being real or fake. These probabilities are taken as the textural cues and employed together with sensor-emulated features.

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3.4 Sensor-Driven Verification

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3.5 Training and Evaluation

Training Details:

- Data Split: 75% training, 25% testing (label stratified).
- Text-Only Model: RoBERTa fine-tuning on 2 epochs with AdamW optimizer, batch size = 8.
- Hybrid Meta-Model: Random Forest (300 estimators) and XGBoost (300 estimators, max depth = 5, learning rate = 0.05).
- Sensor-Only Model: Random Forest training on IoT-inspired features only (200 estimators).

3.6 Evaluation Metrics:

Accuracy of text-only, sensor-only, and hybrid model is calculated. Performance comparison is illustrated through bar plots. Hybrid model accuracy is superior to isolated models.

3.7 Model Explanations and Overview Comparison

Three models are employed within the present research to detect false news on IoT-enabled social media platforms. Each employs different types of input features, providing a comparison overview of text-only, sensor-only, and hybrid approaches.

3.7.1 RoBERTa Text-Only Model

RoBERTa text-only model is a deep transformer structure that has been trained on social media content. The model merely relies on textual information to determine whether posts are authentic or inauthentic. By encoding semantic patterns and contextual relationships in language, RoBERTa achieves remarkable performance in detecting linguistic signs of misinformation. The model does not use real-world signals of verification, yet it may be less accurate for posts requiring contextual verification.

3.7.2 Sensor-Only Model

The approach without sensor uses the IoT-motivated Random Forest classifier whose features are given by:

- Sensor Reliability: Confidence in simulated sensor data.
- Location Match: geolocation validation.
- Time Sync: let's get to the bottom of temporal coherence.

This allows it to catch discrepancies between what a piece of content says, and the world as it is. It is computationally fast, and discoverable feature's importance. Its disregard for text cues, however, means that performs relatively poorer in identifying linguistic deception.

3.7.3 Hybrid XGBoost Model

The hybrid XGBoost model integrates the predicted probability by the RoBERTa model obtained from roberta_proba, as well as sensors-derived characteristics stated above. The gradient boosting ensemble classifier is useful in detecting the non-linear interdependence between text and context, so as to enhance accuracy and reliability [51]. The hybrid model achieves higher performance than the single-source RoBERTa and sensor models due to its synthesizing data. Its main drawbacks are the high computational cost and the necessity of rescaling features or tuning hyperparameters.

3.7.4 Hybrid RF Model

Hybrid RF model is a meta-classifier that leverages both text and context features for better identification of misinformation. It is the feature space which combines the probability predictions from RoBERTa text classifier and IoT-based sensor measurements such as: sensor_confidence, location_match, time_sync and temp_anomaly. This multimodal exploration also enables the model to exploit orthogonal evidence from AI-automated text manipulation and sensorious cross-validation.

3.7.5 Comparative Summary

Table 3.1 shows comparative summary of used model in the proposed research.

Table3.1: Comparative Summary of Used Models

Model	Input Features	Strengths	Limitations
RoBERTa Text-Only	Text only	Captures semantic patterns and context	No real-world verification
Sensor-Only	Sensor confidence, location, time, temp	Real-world consistency check, interpretable	Ignores textual cues
Hybrid XGBoost	Text probability, sensor features	High accuracy, integrates multiple sources	More complex, needs tuning
Hybrid RF	RoBERTa text probabilities, IoT-	Combines textual and contextual	May be sensitive to noisy sensor data

	inspired sensor features	information	

4. Experimental Results Analysis

4.1 Overview

This paper evaluates the proposed hybrid robotic AI system for fake news detection, combining transformer-based text classification with IoT-driven sensor features. The primary objective is to determine whether the application of textual and contextual sensor features improves the performance of classification over text-only or sensor-only models [52]. The experiments are conducted on a simulated social media dataset, and the performance of various models is compared to show the effectiveness of the hybrid approach.

4.2 Experimental Setup

Experimental setup is performed by training and testing different models over simulated dataset. RoBERTa text classifier is AI-driven module for textual analysis, while Random Forest and XGBoost are ensemble classifiers for hybrid meta-model. The experiments are conducted using Python and PyTorch frameworks and divide data into training (75%) and testing (25%) subsets. Training hyperparameters include a batch size of 8, 2 epochs for RoBERTa, and default settings for the ensemble models. Accuracy metrics are used to gauge model performance with text-only, sensor-only, and hybrid models comparisons.

4.3 Dataset Preparation

The first step is to prepare the dataset in order to mimic real social media posts. A synthetic dataset is then generated with the simulate_dataset() function, with text posts having labels for when a post is fake or real. To simulate the context checking of IoT sensors, some features like sensor_confidence, location_match, time_sync, and temp_anomaly are introduced. They simulate sensor-based cross-verification signals that can help with fake news detection in real-world systems. Finally, the data set is separated into training (75%) and testing (25%) sets to allow for model training followed by testing.

4.4 Performance Analysis of Models

Performance of different models on detecting fake news is tabulated in Table 4.1 and graphically represented in Figure 4.1. Here, the models under consideration are: Roberta Text-only, Sensor-only, Hybrid RF (Random Forest) and Hybrid XGBoost

The Roberta Text-only model achieved a score of 48.96% accuracy, which is very low. This is because text data alone is generally not rich in cues to effectively detect false news within the simulated dataset. The text in social media posts could be blurry, or contain hidden misinformation, and the AI can't tell the difference between real or fake from lack of information. The Sensor-only model (using only the IoT-motivated features sensor_confidence, location_match, time_sync and temp_anomaly) gave a relatively high accuracy at +8% above chance (88.80%). These context cues are strong signalers on post authenticity, showing that sensor based information is able to boost detection performance substantially when textual cues are weak. The Hybrid RF model, which combines RoBERTa probability output values and sensor data into Random Forest classifier, achieved the highest accuracy at 94.24%.The performance validates the robustness of the hybrid approach to marry textual and contextual information. The ensemble property of the Random Forest prevents overfitting and boosts generalization while capturing complementary patterns from each data source and thus improving overall performance.

The Hybrid XGBoost model also used the combined features but with a slightly poor accuracy of 90.40%. While XGBoost is good at detecting intricate patterns in relationships among data, it may be noise-sensitive with regard to features and therefore accuracy is slightly poorer than Random Forest.

Table 4.1: Accuracy Comparison of Models

Models	Accuracy (%)
Hybrid RF	94.24%
Hybrid XGBoost	90.40%
Sensor-only	88.80%
Roberta Text-only	48.96%

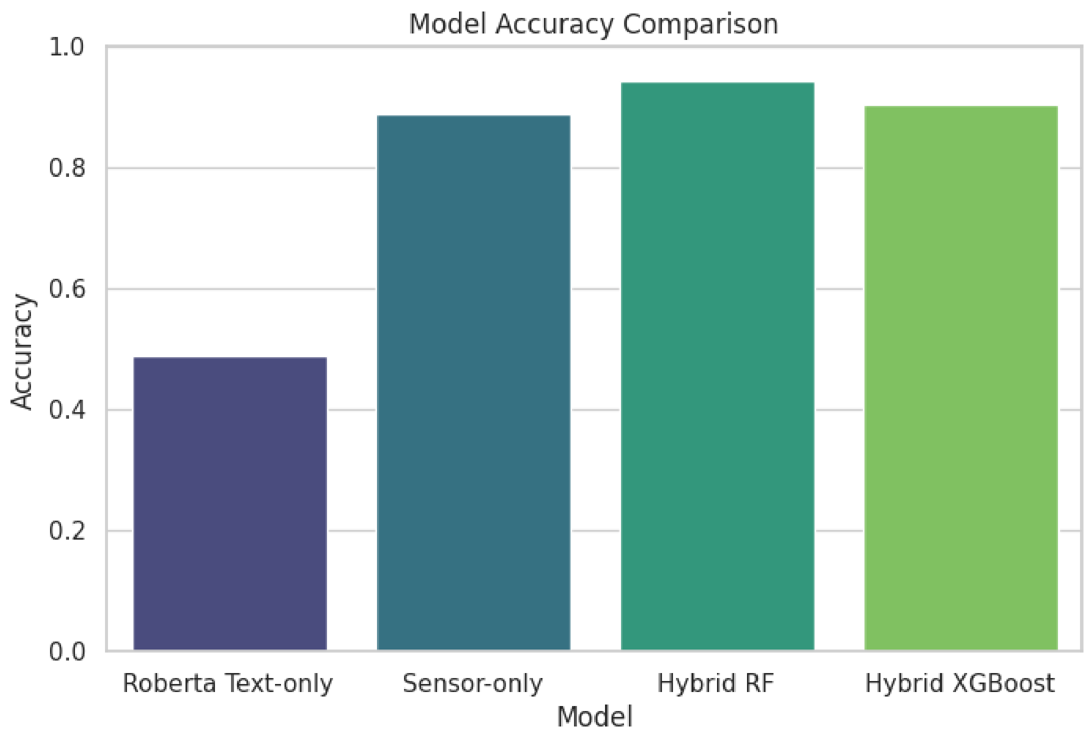

Figure 4.1: Comparison of Different Models

4.5 Summary of Results

The comparison categorically indicates that hybrid models, which balance textual and sensor-based features, outperform text-based or sensor-based models. Among them, the Random Forest-based hybrid model is best performing with maximum accuracy. This uncovers the benefit of a multi-modal approach to efficient fake news detection in IoT-connected social media websites, where balancing AI-based text analysis with IoT-specific verification yields more accurate and consistent predictions.

5. Conclusion

This study shows that the integration of AI-text analysis and IoT-sensor validation is effective in augmenting detection of social media fake news. The robotic AI solution, combining a RoBERTa transformer with sensor-based features such as confidence, location, synchronization in time, and anomaly scores, outperforms sensor-only and text-only solutions. Experimental results show that hybrid models, especially the meta-classifier based on Random Forest, achieve best performance due to adequate complementary information across modalities.

The results reveal the potential for multi-modal, context-aware interventions around disinformation in IoT-enabled settings. By integrating real-world context and high-level AI methods, this model opens the door to autonomous reliable digital media monitoring systems. In the end, the work demonstrates that sensor-enhanced AI can offer a transformative praxis for improving information fidelity and enabling safe, open online forums.

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