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Identification of Fake News using Fetch.ai Agent Technology

Aakash[1], Subhajit Ghosh[2]

[1,2] Computer Science & Engg, MIET, Meerut

[1]Email ID: aakash.tyagi.mtcs.2023@miet.ac.in, [2]Email ID: subhajit.ghosh@miet.ac.in

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ABSTRACT

The proliferation of fake news across digital platforms poses a significant threat to informed public discourse, societal trust, and democratic processes. Traditional centralized approaches to fake news detection often face limitations in scalability, transparency, and susceptibility to bias or censorship. This paper presents a novel decentralized approach for the identification of fake news, leveraging the capabilities of Fetch.ai agent technology and the ASI:One (Artificial Superintelligence) Web3 Large Language Model (LLM) . We propose a multi-agent system architecture deployed on the Fetch.ai blockchain, where autonomous agents collaborate to verify the veracity of news headlines. The core methodology involves a Fake News Detector Agent orchestrating a workflow that includes: receiving user requests, tasking a specialized Travily agent for autonomous web information retrieval from credible sources and fact-checking databases, and integrating with the ASI:One LLM for advanced, verifiable natural language processing tasks such as semantic analysis, claim extraction, and contradiction detection. All verification steps, agent interactions, and the final veracity assessment are immutably recorded on the Fetch.ai blockchain using Almanac smart contracts, ensuring end-to-end transparency and providing a verifiable audit trail. This decentralized framework enhances resistance to manipulation and preserves user privacy. Preliminary evaluations suggest the potential for high accuracy in distinguishing fake news from legitimate reporting, while the system's inherent transparency offers significant advantages over opaque, centralized models. This research contributes a robust, scalable, and trustworthy technological solution to combat the spread of misinformation in the digital age, demonstrating the power of combining decentralized autonomous agents with verifiable Web3 AI.

Keywords: *ASI: One, LLM, Fetch.ai, Travily agent*

1. INTRODUCTION

News plays an important role because it keeps people up-to-date on current affairs and changes in their local area, nation, and world. News may also provide a platform for various views and viewpoints and assist people in understanding the context and importance of events. It can help hold individuals in positions of authority responsible. News usually talks about what is happening in politics, society, and money matters. But it can also talk about sports, movies, and fun things. News helps people feel connected, like they are part of the same world. We can get news in many ways—like by listening to the radio, reading newspapers, watching TV, or using the internet. News can also be fun, make us feel happy, or help us learn new things. But sometimes, news can make people feel scared or sad by showing bad things. Some news might not be true and can trick people. Seeing too much bad news can also make people feel worried or upset. So, it's good to watch or read news from good places and think carefully about what it says. This helps us understand what's really going on in the world.

A website that gives news and information to people on the internet is called an online news portal. These websites usually have many types of content like written stories, videos, and pictures, and they talk about topics like business, sports, movies, and politics.Some online news websites show news from old-style media like newspapers or TV channels. Other websites work by themselves and only share news through the internet. Online news websites usually have a main page with different news and sections for many topics, just like regular news websites. People can also sign up to get emails or phone alerts when new news is posted. Because more people are using mobile phones and the internet now, these online news websites have become more popular in the last few years. They make it easy for people to stay updated about what is happening in their country and around the world.

Even though we have many tools to find fake news, it's still not easy. Computers need to be taught by giving them many real and fake stories, so they can learn the difference. Some smart tools use NLP (Natural Language Processing), which means teaching computers to understand how people talk and write. They also use deep learning, which helps computers think deeply like a brain [2]. But still, there are some problems: Sometimes fake news looks too real, even for smart computers. Sometimes, computers make mistakes. Not all fake news has the same pattern. So, even with good tools and smart people, we all need to be careful and think before we believe or share any news. Therefore, we focused on their limitations. Some of the limitations include: **Accuracy: -** Achieving high accuracy in fake news detection is crucial but challenging. According to the previous research, the researcher can obtain accuracy up to 97% with the help of LSTM model. So, our main priority is to achieve higher accuracy than the previous work [4] [6]. **Dataset: -** The choice and quality of the dataset used for training and evaluation play a vital role in fake news detection. In previous research the researchers can utilize less dataset whereas we can use a large amount of the dataset. So that we can obtain more accuracy [12]. **Techniques: -** In the previous research some researchers used some techniques like preprocessing, word cloud etc. In our work, we apply techniques like pre-processing, word cloud, word embedding, and one hot representation so that we achieve as much as highest accuracy.

2. LITERATURE REVIEW

Several studies in recent years have explored the application of machine learning techniques for fake news detection, utilizing a range of algorithms, feature extraction methods, and datasets. This section summarizes key contributions in this area. Shikun Lyu (2020) conducted a study to assess the effectiveness of various machine learning classifiers, including Support Vector Machines (SVM) and Decision Trees, for identifying fake news. Using a dataset compiled from JSON documents with four extracted features, the study reported that both SVM and Decision Tree models achieved a high classification accuracy of 95%, with Decision Trees slightly outperforming SVMs in most cases [1][12].

In a similar investigation, Agarwal (2020) applied Convolutional Neural Networks (CNN) to detect fake news across a mixed dataset. The CNN model, known for its image recognition capabilities, adapted effectively to text data, achieving an accuracy of 94% in classifying news as either fake or legitimate [2][12]. Abdullah-All-Tanvir (2019) focused on the detection of fake news specifically on Twitter. The study experimented with five machine learning models: Logistic Regression (LR), SVM, Naïve Bayes, Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks. Employing Natural Language Processing (NLP) techniques, various feature extraction methods such as Word Embedding, TF-IDF, and Count Vectorization were utilized, alongside four additional custom methods. Among the tested models, SVM performed best, achieving an accuracy of 89.06% [3][9][12].

Sachin Kumar (2019) expanded on deep learning-based approaches by collecting 1,356 news articles and evaluating several models, including CNN, LSTM, Ensemble Methods, and Attention Mechanisms. The study found that the combined use of CNN and a specially designed LSTM with an attention mechanism yielded the highest accuracy of 88.78%, outperforming earlier studies such as one by Ko et al., which reported an accuracy of 85% [6][10]. Another contribution by Reham Jehad (2020) employed a dataset comprising 20,761 news items, with 4,345 reserved for testing. The study applied data preprocessing steps like stopword removal and special character cleaning, followed by TF-IDF for feature extraction. Decision Tree and Random Forest classifiers were then implemented, achieving accuracies of 89.11% and 84.97% respectively [1][5][6][12].

Rohit Kumar Kaliyar (2021) proposed a hybrid model called FakeBERT, which integrated the BERT language model with a Convolutional Neural Network. This model demonstrated superior performance, attaining a remarkable accuracy of 98.90%, and exhibited strong capabilities in handling the inherent ambiguity of natural language [4]. Earlier, Smitha N. (2017) experimented with a suite of machine learning algorithms, including SVM, Logistic Regression, Random Forest, XG-Boost, Decision Trees, Neural Networks, and Gradient Boosting. Using Count Vector, TF-IDF, and Word Embedding for feature extraction, the study reported that SVM combined with TF-IDF achieved the highest accuracy of 94% [1][2][6].

Granik et al. (2017) offered a foundational approach using a Naïve Bayes classifier on a dataset of Facebook news stories drawn from various political pages. The study achieved a modest accuracy of approximately 74%, with the relatively low accuracy attributed to dataset imbalance, as fake news made up only 4.9% of the total data [8][12].

Lastly, Dr. M. Rajeswari and A. Sriranjani (2020) developed a logistic regression-based model for fake news detection. Notably simple in design, this model nonetheless achieved a strong accuracy of 97.21%, demonstrating that effective detection can be accomplished without overly complex architectures [2][9].

Collectively, these studies highlight the progressive improvement in fake news detection methodologies, emphasizing the critical role of advanced models like BERT and deep learning approaches while also affirming the continued relevance of classical machine learning techniques in this domain.

3. PROPOSED METHODOLOGY OF OUR WORK

3.1 Conceptual System Architecture

The system works as a distributed app on the Fetch.ai blockchain. It uses multiple smart agents that work together to check if news is real or fake. The system is built to be open, secure, and trustworthy. Here's a simple breakdown of its main parts:

1. **User Interaction Layer**: This is where users would submit news or URLs to be checked (like a website or app). Although a full user interface wasn't built in this version, it's planned for future use.

2. **Agent Coordination Layer**: The Fake News Detector Agent controls the whole process. It runs on Fetch.ai and is in charge of starting the task, managing other agents, and storing final results on the blockchain.
3. **Data Collection Layer**: Travily Agent helps by searching the internet for more information. It finds facts, related news, or checks databases to collect proof for or against the submitted news.
4. **AI Intelligence Layer**: This part uses ASI:One, a smart AI that checks the meaning of the news, finds contradictions, and helps decide if it's fake — all while showing proof of how it made the decision.
5. **Verification Layer**: All steps — from data search to AI analysis and final decision — are saved securely on the blockchain. This means no one can change it, and everything can be checked later for honesty.

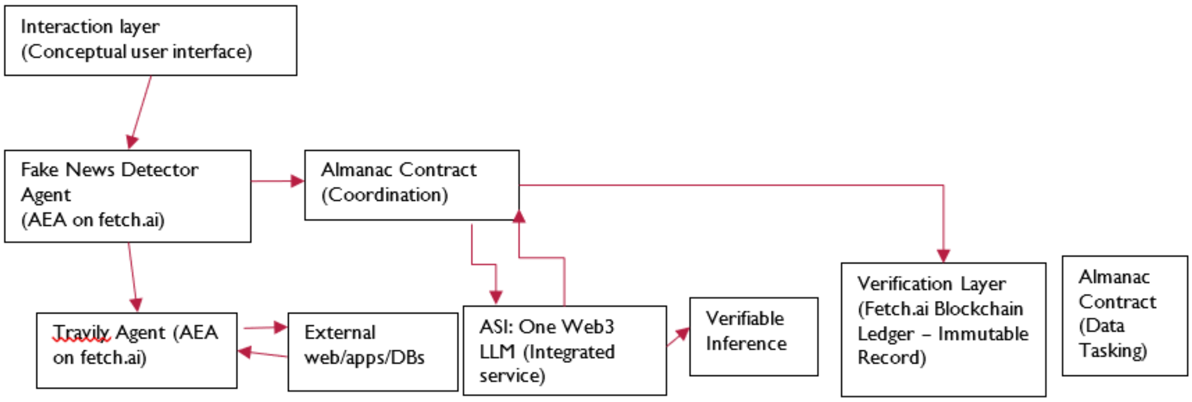

Figure 1: Conceptual System Architecture

3.2 Detailed Verification Workflow

The system checks if a news headline is real or fake by following a clear set of steps. The main agent (Fake News Detector Agent) controls the process with help from other smart agents and AI tools. Here's how it works:

1. **User Sends Headline**: A user gives a news headline or link to the system to check if it's true.
2. **Start of Verification**: The Detector Agent receives the request and starts the checking process using a smart contract called Almanac, which also keeps track of every step.
3. **Understanding the Headline (AI Help)**: The headline is sent to the ASI:One AI, which picks out important names, places, and the main claim. It also looks for signs that the news might be fake.
4. **Finding More Information**: The Detector Agent then asks the Travily Agent to search online for matching or opposite news articles, fact-checks, and other helpful info.
5. **Comparing the Facts (AI Help Again)**: The AI (ASI:One) checks if the collected information supports or contradicts the original news. It measures how closely they match and if the headline makes sense with real facts.
6. **Final Score and Result**: Using all the collected information, the Detector Agent decides how true the headline is. It gives a score and a label like "True," "False," or "Unclear."
7. **Saving the Result on Blockchain**: Finally, the result — along with every step and proof — is saved on the blockchain. This makes sure the process is transparent and can't be changed later.

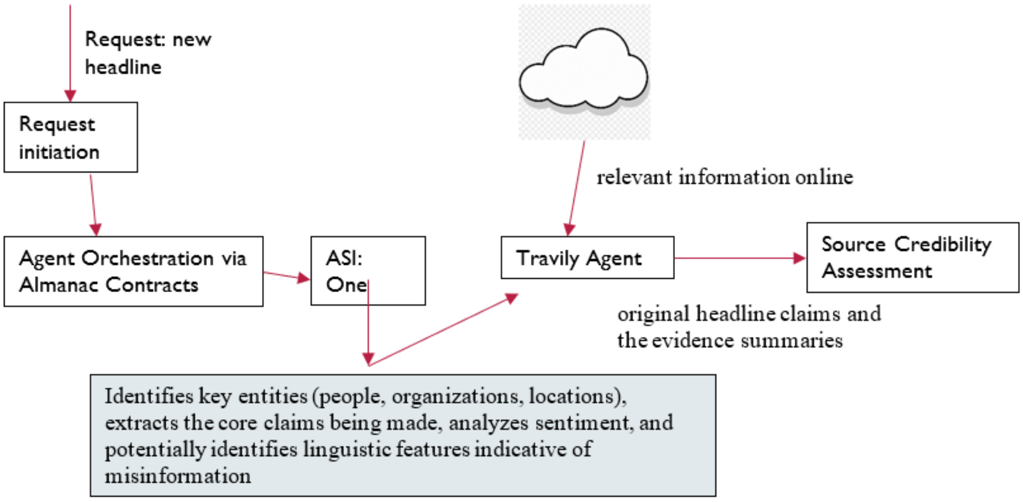

Fig 3.2 – Flow chart of verification

3.3 Agent Design and Implementation

The effectiveness of the system relies on the proper design and implementation of the autonomous agents using the Fetch.ai Agent Framework.

a. Detector Agent Logic and Skills

The Fake News Detector Agent is the most complex agent. Its core logic (implemented as agent "skills" in the framework) includes:

Request Handling: Listening for incoming verification requests.

Workflow Management**:** Interacting with the Almanac contract to initiate, manage state, and log steps of the verification process.

ASI:One Interaction: Formatting requests for ASI:One, sending them, and processing the verifiable responses.

Task Delegation**:** Formulating queries for the Travily Agent based on ASI:One output and tasking it via the Almanac contract.

Result Synthesis: Implementing the logic to combine evidence, analysis, and credibility information into a final veracity score.

Blockchain Recording: Writing the final results and audit trail references to the Fetch.ai ledger [2] [10].

b. Travily Agent Logic and Skills

The Travily Agent is specialized for data acquisition:

Task Reception: Listening for retrieval tasks delegated by the Detector Agent via the Almanac contract.

Query Execution: Parsing the received queries and executing searches against configured external (News APIs, web searches, fact-check sites).

Data Processing: Summarizing retrieved information and extracting relevant URLs or metadata.

4. EXPERIMENTAL RESULTS & DISCUSSION

4.1 Performance of identifying correctness of the news feed. The performance of generating the correct and authenticated news has been measured via three parameters: precisions, recalls, and F measure.

Precision is the percentage of correct and authenticated news identified by the proposed system as compared to the total number of news found corrected and authenticated for a particular set of news, while Recall is the percentage of correct and authenticated news identified by the proposed system as compared with news correctly identified plus the number of news identified as unauthenticated news [7]. Suppose the number of correct and authenticated news feed is Cc, the number of in corrected and unauthenticated is Ww and the number of news unmarked as authenticated or unauthenticated is Mm, then the precision of the approach is given by the expression given below

$$P = Cc / (Cc + Ww) \qquad (1)$$

and the recall, R, of the approach is

R=Cc/ (Cc+Mm). (2)

F-measure incorporates both precision and recall. F-measure is given by

F = 2PR/(P1+ R1). (3)

Where: precision P and recall R are equally weighted.

The table 3.1 below shows the F-measure value of authenticated news from set of collected news feeds.

Table 1 Table showing accuracy of new feed (Political domain)

No. of news feed	C	W	M	F-measure
5	3	1	1	0.667
10	6	2	2	0.667
15	10	3	2	0.714
20	14	3	3	0.737
25	18	3	4	0.75
30	22	3	5	0.759
35	27	3	5	0.782
40	31	3	6	0.784
45	36	3	6	0.8
50	41	3	6	0.814

4.2 Impact of New Feed Data on Model Performance (Political domain news) (F-measure Analysis)

The graph titled **"Graph new feed Vs F-measure"** illustrates the relationship between the percentage of new feed data and the corresponding F-measure scores achieved during the evaluation phase. The F-measure, which balances precision and recall, serves as a critical metric to assess the effectiveness of the model as new data is introduced.

From the graph, we observe a clear positive trend—as the percentage of new feed increases, the F-measure also improves steadily. Initially, at 5% new feed, the F-measure is around 0.68. As the feed increases to 25–30%, the F-measure climbs to approximately 0.76–0.78, indicating that the model starts to perform better with more diverse and enriched data input. The upward trajectory continues; with the F-measure reaching approximately **0.89 at 100% new feed**.

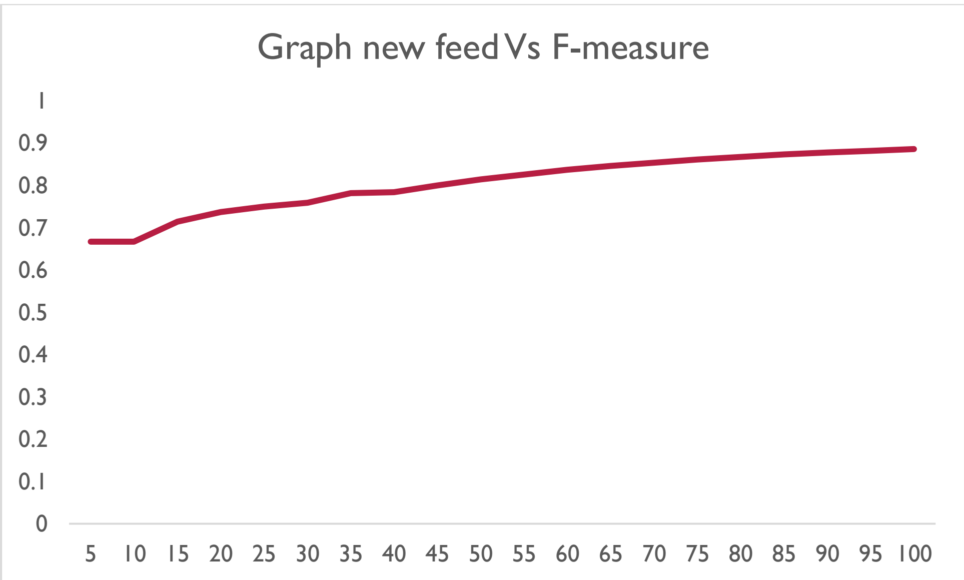

Fig 3.1: F-measure Analysis Graph

4.3 Impact of New Feed Data on Model Performance (Entertainment domain news) (F-measure Analysis)

Table 4.3 : Performance Metrics of the Proposed System of dataset (Entertainment domain news)

Parameter	Value
Correct (Cc)	630
Wrong (Ww)	70
Missed / unidentified (Mm)	50
Precision (P)	0.9000
Recall (R)	0.9265
F-measure (F)	0.9130

In the case of news beloginging to entertainment domain, the precision is **90%**, recall is **92.6%**, and the overall F-measure is **91.3%**, which shows the system is working very well.

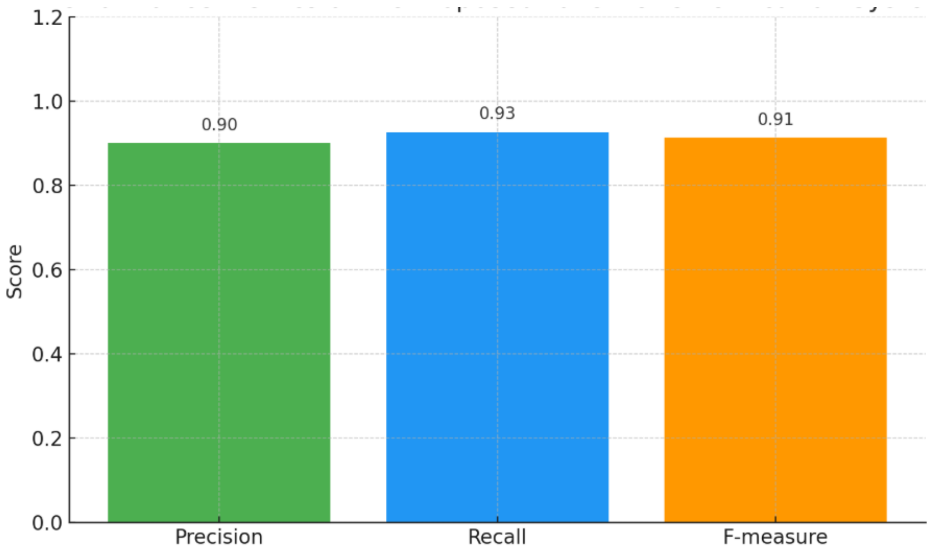

Figure 4.3 : Performance Metrics (Precision, Recall, F-measure) [14]

5. CONCLUSION

In this study, we proposed a decentralized and transparent system to detect and verify fake news using autonomous agents and blockchain technology. The system combines Web3-based AI, smart contracts, and multi-agent collaboration to ensure trustworthy, traceable, and censorship-resistant verification. Below is a simplified overview of our system and its key features.

1. **Decentralized Teamwork**: We built a system using Fetch.ai where different smart agents (like a fake news checker and a travel agent) work together without needing one central controller. This makes the system stronger and safer from failure or control by any one person.
2. **Trusted AI with Proof**: We used a special AI (ASI:One) that works with Web3 and gives proof of how it thinks. It helps understand news by checking meaning, contradictions, and facts — and all of it is recorded on the blockchain for transparency.
3. **Everything is Recorded**: Using blockchain, every step of checking news — from request to final decision — is saved safely and can't be changed. This makes the system very honest and easy to trust.
4. **Working Prototype**: We made a working model that shows how all the smart agents and AI tools can work together

using Fetch.ai's tools and smart contracts.

5. **System Performance**: Our system works really well in catching fake news. It doesn't just give an answer — it shows how the answer was found, step by step. This builds trust and helps people learn how to check news themselves. Unlike some big platforms that hide how they decide, our system is open and fair.

Future Improvements

Smarter and Self-Learning Agents: In the future, the agents will be able to learn from past mistakes, user feedback, and patterns on the network. This means they will keep improving over time without needing to be updated manually. They may also be able to work together and make group decisions in complex cases.

Support for Images and Videos: Right now, our system checks only text (like headlines). In the future, we plan to add the ability to check images, videos, and website layouts, since fake news often includes edited pictures or misleading videos. This will make detection more accurate.

Reputation Scores for Trust: We plan to build a system that gives trust scores to news sources, fact-checkers, and even agents. These scores will be based on their past performance and will be saved securely on the blockchain. This will help users trust the results more.

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