

News Validator: A Multimodal, Confidence-Aware Framework for Real-Time Fake News Detection Using OCR, NLP, and Large Language Models

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Abstract - The ever-expanding growth of social media and webbased news media has dramatically increased the accessibility of false news in society. Fake news may induce widespread public anxiety, significantly affect the creation of political policy and cause millions of dollars of financial loss. Due to the enormous quantity of news stories generated online every minute, human verification of online facts is impractical. In this research paper, we propose a new detection system, "News Validator" capable of automatically detecting whether news contents (text/image) are Real or Fake news by using Artificial Intelligence(AI) protocols. News Validator combines the power of Natural Language Processing (NLP), Optical Character Recognition (OCR) and Large Language Models (i.e., machine learning protocols) to detect indications of untrue/faulty content, (e.g., expressive language, indicators of distortion and / or fraudulence (via computer vision analysis) and finally, evaluate the credibility of the source of the news content. News Validator would be able to present an accurate, factual interpretation of whether or not a news item is considered "Real" or "Fake" in real-time and offer a contextual score (confidence indicator) for each news story, along with an intuitive interface, enabling the consumer to decide whether or not to disseminate the news story further, based on News Validator results. Furthermore, our research shows that News Validator can significantly increase accuracy in detection of erroneous content and maintain integrity in the dissemination of information over digital platforms. Index Terms—Automated Detection of Fake News; Artificial Intelligence; Detection Using Machine Learning; Natural Language Processing; Optical Character Recognition; Large Language Models; Detecting Misinformation

Key Words: Fake News Detection, Artificial Intelligence, Machine Learning, Natural Language Processing, Optical Character Recognition, Deep Learning, Large Language Models, Computer Vision, Misinformation Analysis, News Verification System.

1. INTRODUCTION (Size 11, Times New roman)

With the progression of online technologies and new forms The ever-expanding proliferation of social media and online news media has greatly enhanced the proliferation of false news in society. Fake news can generate

widespread public panic, substantially influence the formulation of political policy and cost millions of dollars in profits. Given the large number of online news reports each minute, human validation of online information is infeasible. In this research paper, we present an innovative detection system, "News Validator" that is able to automatically determine if news contents(text/image) are Real or Fake news using Artificial Intelligence(AI) technologies. News Validator utilizes the capabilities of Natural Language Processing(NLP), Optical Character Recognition(OCR) and Large Language Models (machine learning technologies) to identify signs of false/faulty content, (i. E. Emotive language, signs of distortion and/or deception detected through computer vision techniques) and ultimately, ascertain the credibility of the source of the news content. News Validator would be able to provide a true, factual description of whether a news article should be considered "Real" or "Fake" immediately and give a contextual score (confidence metric) for each news story, along a user friendly interface, enabling the end user to determine whether or not to propagate the news story forward based on News Validator outcomes. Moreover, our research demonstrates that News Validator can greatly enhance precision in detection of false content and sustain integrity in the spread of truths on online media. The definition of the term "false news" is defined as the means by which false or misleading information is constructed and disseminated as if genuine news with an aim of manipulating public perception, rising revenues, concealing facts and humiliating or tarnishing a person's image. False or untrue news may take the form of fabricated news articles, doctored images, manipulated video recordings and false postings on social media sites. This false information can easily be read and shared on a whim by many online users without verification, hence, surpassing the speed of real information dissemination. False news has become a real problem in today's day and age. False political information can mislead voters at an election; this is dangerous as the foundation of democracy is broken. The same applies with false medical information, which causes fear as patients might take the wrong medicine to treat an illness. False news in business causes a damaging effect to

the country's economy as it brings down the stock exchange and damages the company's brand; and further decreases confidence in the country. False news breeds hatred and fear, and also results in some communities being fractured. Data science and artificial intelligence is needed, therefore, to detect fake news in the past as fast as possible. Before the advent of more modern detection techniques, traditional techniques relied on manual verification by the press or journalists, fact checkers and / or media organizations. Although manual verification of fake news can yield valid results, manual verification is expensive, takes a lot of time, and the often large volume of digital content that is generated on a daily basis makes manual verification an impractical approach. Newsfeeds, Tweets, videos and pictures number in the millions every single day. Consequently, automated solutions that are capable of detecting fakery and reporting it, while retrieving the same records in near real time is recommended. The many possible solutions provided by the use of the different types of AI and ML are listed below. AI techniques can handle numerous data sets, search for non-obvious correlations, evaluate writing style, identify attempts to manipulate the reader's emotions, compare content to credible reference sources. NLP enables computers to interpret the meaning of the text contained in the data, OCR translates any characters contained within the image itself. The more recent language modeling techniques allow for additional analysis of both the context and semantics of the news media sources in question. The intended News Validator system will be an AI engineered system, that will make sure there will be a scientific way to verify both text-based and/or image-based news content. Users will be able to upload whatever type of news media such as a news article, a capture from a tweet or suspicious heading to validate whether or not they are valid. Once input files will be received in the news validator system, the input files will provide processing of input files, extract meaningful linguistic features in data present in input file, employ AI models to analyze data present with file(s), and output prediction that will inform user whether or not the information true/false or real/fake by providing a level of confidence. Another benefit of the proposed platform is the accessibility for multimodal (Multi Content Types) analysis of data; as an comparison, there are more and more cases of misinformation in numerous platforms containing both "real" and/or "fake", either translated or unmanipulated images, which can be interpreted incorrectly within the images themselves in comparison with many fake news platforms, which can only be detected based on text data. Then with the combination of OCR, NLP and Machine learning Classification techniques, it can enhance the accuracy of detection processes and also provide more "real world" applications for users. The aim of this project is to create a trustworthy, easy to understand and accessible method of phishing

detection for students, researchers, journalists and for everyone else using the Internet, so that they can verify the reliability of something before spreading it. This solution will help to decrease the amount of lies being propagated by malicious web-based communication.

2. LITERATURE SURVEY

Recently, fake news detection has transitioned towards more and more multimodal learning, real-time detection, and LLM (large language model)-based reasoning. The classic text-based solutions are no longer usable because the number of image-based and AI-generated fake news increases. Multimodal fake news detection has become a prevailing trend. It is reported in [1], [2] that the information fusion of text and image features could boost the detection performance greatly, and deep learning models with CNNs and transformer architectures have achieved great success in modeling crossmodal relations [3], [4]. But most of those models are still not able to enable strong semantic coherence of image-text pairs. In recent work, the authors have also investigated how to integrate contrastive learning with vision-language models. As shown in [6], [7], models such as CLIP can be used to improve multimodal understanding (for example, when text and visual signals are mismatched). However, the main bottleneck for real time deployment is the extreme time-consuming effort in most systems, which are all evaluated in off-line settings [8]. Large language models (LLMs) can also enhance the accuracy of fake news detection through contextual reasoning. Common examples, such as [9], [10], demonstrate that LLM-based systems can decipher hidden nuances in language, such as sarcasm, hyperbole, and misrepresentation. Prompt-based learning methods have been proposed to tune the detection technique on the fly as well [11]. Nevertheless, LLMs are expensive to operate and must be fine-tuned to modern conditions. Another important topic for further research is that of AI-generated false information. As the Generative Models continue to improve and evolve, spotting a piece of synthetic news will become more challenging. So far, the existing classifiers do not achieve good results under the use of AI-generated information, and other detection methods, considering semantic consistency, authorship etc. should be explored. Multilingual fake news detection is also paid increasing attention to. In [14], [15] the researchers focus on the necessity to create robust models in various languages, which is significant especially in countries of multilingual constituencies with high gravity of Fake news. Nevertheless, the deficiency of huge multilingual datasets is a limitation. Both dataset quality and generalization remain critical issues. As shown in, models trained with narrow or unrepresentative datasets do not generalize well in real-world application and this issue has received considerable attention in the area of domain adaption and continual learning. Another information-related issue is also being

explored in a new generation of the current fake news detectors: explainability and confidence estimation. According to studies [19], [20], if the detector system is getting explainable results, it is more usable in the eyes of the end user. With this, confidence scores, however, are found to be not always well calibrated [21]. Finally, there is an increasing demand for large-scale and on-line systems. Many researches demonstrate that their models perform very accurately, but there are rare for system level discussion. For example, [22], [23] focus on the deployable, web-based server for activation detection to receive user online input. In general, these existing works suggests the trend toward multimodal, explainable, and real-time fake news detection systems. However, some challenges such as cross-modal reasoning, AI-generated content detection and efficiency of deployment still exist, which leads to our work.

3. PROBLEM STATEMENT

The proliferation of false news on digital platforms has driven the need for reliable automated systems for fact checking news in real time. Most of the current systems consider only static data and text, while information is often shared in the form of screenshots, images or as an excerpt of text in the real world. Here we have a problem of designing a system, which takes as input a News Article (text format or image format, which is text info embedded in the image) and classifies it to believe or not to believe [12], [13]. As the input is given in the form of a text or an image, we have to face problems from extractions errors, partails context and semantic ambiguity. Formally, let x denote an input instance such that: $x \in X = \{x_t, x_i\}$ (1) where x_t represents textual input and x_i represents imagebased input. The objective is to learn a function: $F : x \rightarrow (y, c)$ (2) where $y \in \{REAL, FAKE\}$ is the predicted label and $c \in [0, 1]$ denotes the confidence score associated with the prediction. The system should run in real-time, and challenges such as noisy OCR output, negative language cues and AI generated content should be considered. The output must also be in a form that the user can understand. To create a strong, multimodal, and confidence-aware framework that would support a user checks the authenticity of news before the spreading. The system should run in real-time, and challenges such as noisy OCR output, negative language cues and AI generated content should be considered. The output must also be in a form that the user can understand.

4. PROPOSED FRAMEWORK

The architecture of the suggested system will be a real-time multimodal fake news detector pipeline comprising the following components: text processing, optical character recognition (OCR) from images, semantic analysis, and reasoning by means of a large language model (LLM). A. Input Layer The system accepts heterogeneous input in two primary forms: textual content (x_t) and image-based content (x_i). This design reflects real-world scenarios where misinformation is often shared as screenshots, social media posts, or forwarded images.

B. OCR Module

For image-based inputs, an Optical Character Recognition (OCR) module is employed to extract textual information: $x_t = O(x_i)$ (3) where $O(\cdot)$ denotes the OCR function. The extracted text may contain noise due to variations in font, resolution, and layout, which is addressed in subsequent preprocessing steps. C. Text Preprocessing The input text goes through several preprocessing steps to normalize it, which include converting the text into lowercase, removing punctuation marks, eliminating stopwords, and tokenizing the text.. D. Semantic Representation The preprocessed text is transformed into a semantic representation using an encoding function: $z = \phi(x_t)$ (4) where z represents the feature vector. Depending on the configuration, $\phi(\cdot)$ may correspond to TF-IDF encoding or transformer-based embeddings that capture contextual meaning. E. Reasoning and Classification Using LLMs As opposed to conventional classification models, the proposed model employs an LLM through Groq API for contextual reasoning. The LLM is responsible for analyzing the semantics and generating: • They are all spread across the same book throughout the course, meaning you can take advantage of having one type of question repeatedly. 1. A class label $y \in \{REAL, FAKE\}$ A confidence score $\hat{c} \in [0, 1]$ 1. A textual description that will explain the prediction. Such methodology will allow a closer insight into the language use, irregularities, and context clues that would otherwise be hard to be modeled by standard machine learning algorithms. F. Real-Time Inference Layer The system is optimized for real-time performance. The total response time is defined as: Where

in the expression. $T_{total} = T_{OCR} + T_{preprocess} + T_{LLM}$ Which leads us to the conclusion that; By associating with the Noether current and that the effect of the axion field is to generate a classical wave for the gauge field we have derived the final result. That effectively, our axion field would be producing a classical wave for the gauge field. Where T_{LLM} is inference time with Groq API. It is the goal of the system to keep latency low while doing prediction.

5. METHODOLOGY

Most importantly our approach is a hybrid, data-driven learning with a large language model based reasoning.

A. Data Collection VI. ALGORITHM The dataset is a collection of labeled real and fake news samples obtained from different sources or domains like politics, health, social media and finance. The dataset contains text articles as well as news articles in the form of images as it would be available in the real-world scenario. B. Preprocessing Pipeline The text data is subjected to normalization, tokenization and noise removal. The image data goes through the process of OCR where text is extracted and there after goes to the same pre-processing pipeline. So, finally both text and image modality have similar representation. C. Feature Representation Two types of feature representations are considered: • Minimum Order Quantity (MOQ). Statistical Features: TF-IDF vectors for frequency and significance of words. Contextual Features: Semantic relations through a document language model of the transformer These representations enable the system to distinguish between surface-level features as well as deep contextual information. D. Model Strategy In place of classifying with classical classifiers like SVM or Logistic Regression, the system exploits LLM-based reasoning by the Groq API: zeroshot/fewshot classification based on a semantic understanding and not a learning of a specific, preestablished dataset. E. Confidence Estimation The confidence score is a value taken from the model's estimated internal probability, then postprocessed by heuristic rules which have taken into account the textual strategy, the contextual dependencies and cognitive clues. F. System Deployment The system is implemented as a web system with a user interface through which users can enter text or upload images. The backend receives the input, uses the classifiers and then outputs

the class prediction, confidence score, and explanation immediately. G. Evaluation Strategy In terms of system performance accuracy, precision, recall and F1-score are used as measures. Response time and confidence calibration also measured to provide a measure of usability in real-time.

6. ALGORITHM

Algorithm 1: Multimodal Real-Time Fake News Detection

Input: News content x (text or image) Output: Predicted label $y \in \{\text{REAL}, \text{FAKE}\}$ and confidence score c 1)

Receive input x from user.

2) Determine input type:

• If x is image, apply OCR to extract text:

$x_t = O(x_i)$

• Else, assign $x_t = x$

3) Preprocess extracted text: • Convert to lowercase • Remove noise and punctuation • Tokenize text

4) Generate semantic representation:

$z = \phi(x_t)$

5) Send processed text to LLM via Groq API.

6) Perform contextual reasoning: • Analyze factual consistency • Detect misleading language • Identify uncertainty patterns

7) Generate prediction:

$\hat{y} = f(z)$

8) Compute confidence score:

$c = \max(\hat{y})$

9) Generate explanation based on reasoning.

10) Return output (y, c) along with explanation.

7. SYSTEM IMPLEMENTATION

In implementing the proposed system, we have designed a browser-based tool that will provide real-time verification of fake news for end users. We have adopted the client-server model of development where the front-end is the

part that interacts with the user, whereas the back-end is involved in processing and analyzing the input provided by the user. A. Frontend Design For interaction with the end-user, the front-end should capture the input given by the user while also providing him/her with output that is easily understandable. For that purpose, the front-end consists of a neat, intuitive interface enabling the user to submit textual as well as image-based content. The interface consists of the following components: • A text input field to input news content directly. • Image upload function to submit news content in the form of screenshots. • Submit button to start the process. • Output window to show predicted label, confidence level, and reasoning. B. Backend Architecture The backend is the heart of the system and runs everything. It performs various tasks such as input validation, OCR, preprocessing of the text and execution of the model. After receiving the input, the backend identifies its type. In case of an image, the image is processed with an OCR component to convert it to text. The found text is cleaned up and normalized with popular cleaning and normalization methods such as lowercase conversion, removing of special characters and stopwords, tokenisation etc. Once the text has been preprocessed, it is passed to the inference module. This module then interfaces with a LLM through the Groq API. The backend creates a structured prompt incorporating the input text and asks the model to assess its validity. The model produces a reply that includes: a classification decision and rationale. The backend interprets the output, extracts the final label, and generates a confidence score. In the event that the model is inconsistent, the fallback logic is invoked to ensure consistent output formatting. C. Model Integration and Inference Rather than using a fixed trained model, the system uses LLM based inference to perform the context analysis. It enables the system to generalize over various inputs without the necessity of retraining. The Groq API is used to facilitate very fast inference, and as such is suitable for real time usage. When an output is generated, the model assesses the linguistic coherence, contextuality and factual validity of what it is producing. This makes the model more robust when faced with complex or novel examples. D. Output Generation The final output is structured into three components: In other words, [N] (i.e. all market participants' signals are independently drawn from the same distribution, whatever happens to be in this distribution). 2. Prediction: Results in the entry of

either REAL or FAKE based on the input. Item Consilience Score: Indicates how confident the system is. 2.

Justification: Gives a little reason as to why the decision was made The results are displayed on the frontend in a very simple format so that users can understand the outcome immediately. The explanation is added as it provides transparency and adds a small amount of intelligence to the result which allows the user to understand the decision rather than just looking at a label.

E. System Workflow The complete workflow of the system can be summarized as follows: 1) User submits text or image input

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2) Backend processes input and applies OCR if required
3) Text is preprocessed and normalized

4) Input is analyzed using LLM via Groq API

5) Prediction, confidence score, and explanation are generated

6) Results are returned and displayed to the user

F. Real-Time Performance Considerations To ensure responsiveness, the system minimizes processing delays

by optimizing each stage of the pipeline. OCR processing is applied only when necessary, and lightweight preprocessing techniques are used to reduce overhead. The use of Groq-based inference further contributes to faster response times compared to traditional model deployment. Overall, the implementation focuses on balancing accuracy, interpretability, and speed, making the system suitable for practical use in real-world scenarios.

8. EXPERIMENTAL DESIGN

The experimental setup is designed to evaluate the performance of the proposed system across different input modalities. The evaluation focuses on classification accuracy, reliability, and consistency of predictions.

- A. **Evaluation Metrics** The following standard metrics are used:–
- B. **Accuracy:** Measures the overall correctness of the system.
- C. **Precision:** Measures the proportion of correctly predicted positive instances.
- D. **Recall:** Measures the system's ability to identify actual positive instances.
- E. **F1-score:** Harmonic mean of precision and recall.

B. Experimental Scenarios To analyze system performance, three configurations are evaluated

- A. **Text-only:** Input consists of textual data only.
- B. **Image-only:** Input consists of images processed through OCR.
- C. **Multimodal:** Combination of text and image-based inputs.

9. RESULTS AND DISCUSSION

The proposed AI-based News Validator system was evaluated using both text-based and image-based news inputs. The system provides classification outputs (Real/Fake) along with confidence scores, enabling interpretable decision-making.



Fig. 1. Text-based news analysis showing REAL classification with 80% confidence

A. Text-Based News Analysis

Figure 1 presents the output of the system for a financial news sample related to India's economic growth. The system classifies the news as **REAL** with a confidence score of 80%.

The model picks out plausible indicators, like the mention of the IMF and the recurrent nature of the economic language. The context words, "growth rate" "investment" and "technology sector" reflect plausible ways of writing about economics. The score of 56 is now more moderate as the model appears to be reflecting the absence of detail and specific evidence, not on the presence of direct citation.

B. Image-Based News Analysis



Fig. 2. Image input for fake news detection

For example, in Figure ?? it can be seen that the news image contains a deceiving headline about a certain individual. The functions of the system takes the image as input and apply OCR to it. This apply to output to get texts.

From the system output in the Figure ??, the news is predicted as **FAKE** with 90% confidences. The specific fake news patterns such as sensational headlines, lack of credible sources, and visual fraud clues are identified accordingly



Fig 3. Image –based analysis showing Fake classification with 90% confidence.

This (still very preliminary) show how a combination of optical character recognition, natural language process-ing, and visual pattern recognition can be an effective means of identifying misinformation in multimedia con-tent.

C. Advantages

- Supports both text and image-based fake news de-tECTION
- Provides confidence scores for interpretability
- Enables real-time analysis and user interaction

D. Limitations

- OCR errors may affect text extraction accuracy from images
- High computational cost due to multi-model inte-gration

10. Conclusion

In this paper a multimodal fake news detection system is proposed combining the use of OCR, NLP and LLMs to help identify false and misleading information. The proposed system can be trained on multi-modal inputs and I believe it will work well on current social media data, which is mostly multimodal.

The use of OCR allows for extraction of the actual text from images of memes, screen shots and text present within the post. The extracted text will then be processed using NLP techniques so as to analyze the linguistics, semantics, and context of the text. The utilization of state of the art LLMs will further improve the classification accuracy and reliability.

The real time predictions along with a confidence score is an another interesting feature of the proposed system. The confidence score predicts the reliability of the prediction which can be utilized for decision making. This makes the system a perfect candidate for use in real

life scenarios such as blogging, automated chat monitoring.

Although it shows promising results, a couple of issues and directions for future research need to be addressed. First, the incorporation of multilingual data can help the system to be adaptable to different languages, expanding its global usability. Second, using video frames analysis and audio-text processing can open new doors for the system in the detecting misinformation among multimedia content.

In addition, or alternatively, the bringing in of factchecking APIs could enhance credibility of the system if it were able to cross-verify facts in the system database in real time against trusted sources. Then the system could classify also on grounds of evidence.

To sum up, the advanced multimodal architecture suggested by the article provides an effectual and scalable framework for combating fake news and preventing the proliferation of the issue. Improvements for the framework such as support for multilingual processing, video analysis, and verification of news items in real-time are anticipated to be beneficial.

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