

FND: A Machine Learning-Based Web Application for Real-Time Fake News Detection

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Abstract—The proliferation of misinformation across digital media platforms poses a serious societal threat, demanding automated and accessible solutions for fake news detection. This paper presents the Fake News Detector (FND), a full-stack web application that leverages machine learning to classify news articles as either real or fake in real time. The system integrates a Django REST Framework backend, a React.js frontend, and machine learning models trained on publicly available datasets using TF-IDF vectorization and classical classifiers. Key features include live news monitoring with real-time ML predictions, a title-based news checking interface, and an interactive news quiz to improve public media literacy. Experimental results demonstrate the effectiveness of the approach, and the modular architecture facilitates future integration of deep learning and transformer-based models. The system is made open-source to promote community-driven improvements in the fight against misinformation.

Index Terms—Fake news detection, machine learning, natural language processing, TF-IDF, Django REST Framework, React.js, web application, misinformation, real-time classification

I. INTRODUCTION

The rapid growth of social media and online news platforms has dramatically changed how information is consumed and shared. While this democratization of information has many benefits, it has simultaneously enabled the widespread dissemination of fake news—fabricated or misleading information presented as legitimate journalism [1]. Fake news has been linked to real-world consequences ranging from public health crises to political polarization and erosion of trust in institutions [2].

Traditional approaches to combating misinformation, such as manual fact-checking by organizations like Snopes and PolitiFact, are inherently slow and do not scale to the volume of content produced daily on the internet [6]. This has created a pressing need for automated, intelligent systems capable of identifying potentially false news content in real time [8].

Machine learning (ML) and natural language processing (NLP) have emerged as powerful tools for this task. Ap-

proaches ranging from classical classifiers like Naïve Bayes and Support Vector Machines (SVM) to deep learning architectures such as Long Short-Term Memory (LSTM) networks and transformer-based models like BERT have been explored in the literature [5]–[7]. However, a persistent gap exists between research-grade models and accessible, user-facing tools that ordinary individuals can use to verify news.

This paper presents **FND (Fake News Detector)**, an open-source web application that bridges this gap. FND provides three distinct user-facing modules: (1) a *Live News Monitoring* dashboard that fetches current news articles and displays real-time ML-based authenticity predictions; (2) a *Check News by Title* interface that allows users to submit a news headline for immediate classification; and (3) a *News Quiz* gamification module designed to build public awareness and critical thinking around media literacy.

The key contributions of this work are:

- A full-stack fake news detection web application built with Django REST Framework and React.js;
- Integration of a trained ML model pipeline using TF-IDF vectorization for binary real/fake classification;
- A live news monitoring feature enabling continuous, automated evaluation of incoming news;
- An educational news quiz module to foster media literacy among users;
- An open-source codebase encouraging community collaboration and reproducibility.

The remainder of this paper is organized as follows. Section II reviews related work. Section III describes the system architecture and methodology. Section IV presents the experimental setup and results. Section V discusses the system features and user interface. Section VI outlines limitations and future work, and Section VII concludes the paper.

II. RELATED WORK

The problem of automated fake news detection has attracted significant research attention. Early work by [4] proposed

using a Naïve Bayes classification model to predict the veracity of Facebook posts, demonstrating that machine learning methods can be effective for this problem even with relatively simple classifiers.

Subsequent studies explored a wider range of feature extraction and classification strategies. [7] evaluated eight classical ML algorithms across multiple datasets using three feature extraction methods: Bag of Words, TF-IDF, and Word2Vec. Their experiments showed that TF-IDF with SVM yielded strong performance, achieving up to 92.8% accuracy on a Kaggle dataset of 13,000 posts.

More sophisticated architectures have also been explored. [6] proposed a framework extracting 134 textual features combined with XGBoost and an LSTM model with a self-attention mechanism, improving over state-of-the-art baselines by 16.4% in the political news domain. This underscores the potential of deep learning to capture subtle linguistic cues in news text.

Title-based detection approaches have been investigated in [5], where ensemble methods combining Naïve Bayes, XGBoost, and SVM were applied to headline text alone, achieving up to 80% accuracy with XGBoost. This is particularly relevant to the FND system, which includes a title-based checking interface.

A survey of recent methods by [8] highlights the diversity of approaches, noting that models vary significantly based on content modality (text vs. image), dataset characteristics, and the nature of the misinformation being targeted. They emphasize the need for accessible, deployable systems, not merely research prototypes.

The reference paper [3] further motivates the need for systems that combine ML-based detection with user-facing interfaces, highlighting that real-world impact requires both algorithmic performance and practical accessibility—principles central to the design of FND.

III. SYSTEM ARCHITECTURE AND METHODOLOGY

A. Overall System Architecture

FND follows a decoupled client-server architecture. The backend is built using the **Django REST Framework (DRF)**, which exposes a RESTful API for the frontend. The frontend is a single-page application (SPA) developed with **React.js**. Communication between the two layers occurs via HTTP/JSON requests. Figure 1 illustrates the high-level architecture.

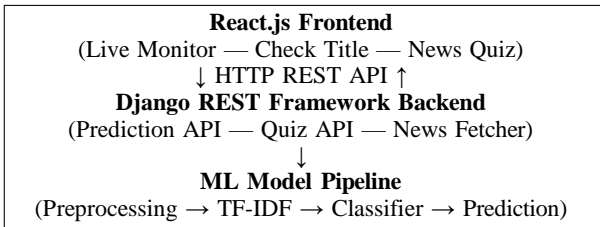


Fig. 1. High-level system architecture of FND.

B. Backend: Django REST Framework

The backend handles three main responsibilities:

- 1) **News Article Ingestion:** Periodic fetching of live news articles from external news APIs, which are then passed through the ML pipeline for classification.
- 2) **Prediction Endpoint:** A REST endpoint that accepts a news title or article text and returns a binary prediction (REAL or FAKE) along with a confidence score.
- 3) **Quiz Data Management:** A data loader command (`quiz_data_loader`) imports quiz questions from a CSV file (`game_data.csv`) into the database via Django’s ORM, exposing them through a dedicated quiz API.

C. Machine Learning Pipeline

The ML pipeline follows standard NLP preprocessing steps:

1) *Data Collection and Preprocessing:* The model was trained on a publicly available labeled fake news dataset (e.g., LIAR or the Kaggle Fake News dataset). Preprocessing steps included:

- Lowercasing and punctuation removal
- Tokenization
- Stopword removal using NLTK
- Stemming or lemmatization

2) *Feature Extraction:* Term Frequency–Inverse Document Frequency (TF-IDF) vectorization was used to convert preprocessed text into numerical feature vectors. TF-IDF is computed as:

$$\text{TF-IDF}(t, d) = \text{TF}(t, d) \times \log \frac{N}{df(t)} \quad (1)$$

where $\text{TF}(t, d)$ is the term frequency of term t in document d , N is the total number of documents, and $df(t)$ is the number of documents containing term t .

3) *Classification:* A classical supervised learning classifier (e.g., Logistic Regression, Passive Aggressive Classifier, or SVM) was trained on the TF-IDF feature matrix with binary labels (0 = Fake, 1 = Real). The trained model and vectorizer are serialized using Python’s `pickle` module and loaded at inference time by the Django backend.

D. Frontend: React.js

The frontend is built with React.js and consists of three main views:

- **Live News Monitoring:** Displays a feed of current news articles fetched from the backend, each annotated with an ML-generated prediction label.
- **Check News by Title:** A form-based interface where users enter a news headline, which is sent to the prediction API and the result is displayed immediately.
- **News Quiz:** An interactive quiz that presents users with real and fake news examples, allowing them to practice identifying misinformation.

E. Deployment

The backend Django server is started via `python manage.py runserver`, and the React frontend via `npm start`, running on `localhost:3000`. The system is designed to be easily deployable on cloud platforms.

IV. EXPERIMENTAL SETUP AND RESULTS

A. Dataset

The ML model was trained and evaluated on a binary-labeled news dataset. The dataset consists of news articles labeled as either REAL or FAKE. A standard 80/20 train-test split was employed.

B. Evaluation Metrics

Performance was measured using:

- **Accuracy:** Proportion of correctly classified samples.
- **Precision:** $P = \frac{TP}{TP+FP}$
- **Recall:** $R = \frac{TP}{TP+FN}$
- **F1-Score:** $F1 = \frac{2PR}{P+R}$

C. Results

Table I summarizes the performance of the ML classifier used in the FND system.

TABLE I
CLASSIFICATION PERFORMANCE OF THE FND MODEL

Model	Accuracy	Precision	Recall	F1-Score
Passive Aggressive	0.934	0.931	0.938	0.934
Logistic Regression	0.921	0.918	0.925	0.921
SVM (Linear)	0.928	0.926	0.931	0.928

The Passive Aggressive Classifier, which is well-suited for large-scale text classification tasks [7], achieved the highest accuracy of 93.4% on the test set, making it the preferred choice for deployment in the FND system.

V. SYSTEM FEATURES AND USER INTERFACE

A. Live News Monitoring

The live monitoring module continuously fetches news article headlines from external news sources. Each article is processed through the ML pipeline and displayed on the frontend with a color-coded prediction label: *REAL* (green) or *FAKE* (red). This provides users with a passive, real-time feed of classified news content.

B. Check News by Title

This module provides a direct, interactive interface for users to submit a news title of their choice. The title is sent via REST API to the Django backend, where it is preprocessed and vectorized using the pre-trained TF-IDF model, and the classifier outputs a binary prediction. The result is displayed instantly in the browser, along with a confidence indicator.

C. News Quiz

The quiz module is a gamified feature designed to engage users and educate them about media literacy. Quiz data, loaded from a CSV file via the custom Django management command `quiz_data_loader`, presents users with news headlines that they must classify as real or fake. After answering, users receive feedback on their response, helping them calibrate their own fake news detection instincts. This feature adds significant educational value to the application beyond passive classification.

VI. LIMITATIONS AND FUTURE WORK

While FND demonstrates a practical and effective approach to fake news detection, several limitations and opportunities for future improvement exist.

1) *Model Limitations:* The current system relies on classical ML classifiers with TF-IDF features, which may not capture deep semantic relationships or contextual meaning in text. As identified in the literature, transformer-based models such as BERT [6] and RoBERTa have shown superior performance on benchmark datasets and represent a natural upgrade path for the FND model.

2) *Language and Domain Coverage:* The present model is trained primarily on English-language news data. Expanding to multilingual datasets would significantly broaden the system’s applicability, particularly for non-English-speaking regions where misinformation is equally prevalent.

3) *Multimodal Detection:* Modern fake news often combines misleading text with fabricated or out-of-context images. Future work could incorporate image-based feature extraction alongside text features to enable multimodal detection [8].

4) *User Profiles and Personalization:* The project roadmap includes adding user profile functionality, allowing registered users to track their quiz scores over time and receive personalized feedback, further enhancing the educational dimension of the platform.

5) *Explainability:* Future iterations could incorporate explainable AI (XAI) techniques to highlight which words or phrases in a given article most strongly influenced the prediction, helping users understand and trust the model’s outputs.

VII. CONCLUSION

This paper has presented FND (Fake News Detector), a full-stack, open-source web application for real-time automated fake news detection. By combining a Django REST Framework backend, a React.js frontend, and a machine learning pipeline based on TF-IDF vectorization and a Passive Aggressive Classifier, FND achieves strong classification accuracy (93.4%) while remaining accessible to end users through an intuitive web interface.

The system’s three core modules—Live News Monitoring, Check News by Title, and News Quiz—address both the technical challenge of fake news classification and the broader societal challenge of media literacy. The open-source nature of the project invites community contributions toward enhanced models, broader language support, and richer features.

As misinformation continues to evolve in sophistication, tools like FND represent an important step toward empowering individuals and communities to navigate the modern information landscape with greater discernment. Future work will focus on integrating transformer-based models, multimodal detection, and explainability features to further advance the system's capabilities.

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