Fakefinder: Context-Aware News Credibility Detection Using NLP And Machine Learning

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Abstract- *With the rapid growth of digital media and social networking platforms, the spread of misinformation and fake news has become one of the most pressing challenges of the modern era. Platforms such as WhatsApp, Facebook, and Twitter deliver billions of messages daily, a significant proportion of which contain fabricated, manipulated, or misleading content. Human fact-checkers cannot scale to address this volume. This paper presents FakeFinder, a context-aware news credibility detection system that uses Natural Language Processing (NLP) and Machine Learning (ML) to automatically classify news articles and social media messages as Fake or Real with an associated confidence percentage. The system implements a complete NLP preprocessing pipeline — text cleaning, tokenization, stopword removal, lemmatization, and custom feature engineering — combined with TF-IDF vectorization and five ML classifiers. Custom features including FEAT_HIGH_CAPS, FEAT_MANY_EXCLAIM, FEAT_FORWARD_MESSAGE, and FEAT_CREDIBLE_SOURCE are engineered to capture the distinct linguistic fingerprint of fake content. The best-performing model achieves approximately 95% accuracy. The system is deployed as a Flask-based web application with a REST API, enabling real-time fake news detection for any input text. Experimental results confirm that FakeFinder effectively identifies misinformation and provides reliable, explainable classification with high accuracy*

Keywords: Fake News Detection, Natural Language Processing, TF-IDF, Machine Learning, Text Classification, Flask, NLTK, Scikit-learn, Misinformation, NLP Pipeline.

I. INTRODUCTION

With the rapid growth of social media platforms, misinformation and fake news have become a major societal concern. Many users share news articles and messages without verifying their authenticity, which may lead to public panic, health misinformation, political manipulation, and erosion of trust in credible institutions. According to the World Economic Forum, misinformation has been identified as one of the most significant short-term technological global risks.

Traditional approaches to fact-checking rely on manual human verification, which is slow, expensive, and incapable of scaling to the billions of messages shared daily. Research shows that fake news spreads approximately six times faster than real news on social media. Existing automated tools such as keyword blacklists and URL checkers suffer from high false positive rates and are unable to adapt to new or evolving misinformation patterns.

To address this problem, this paper proposes FakeFinder, a context-aware news credibility detection system using NLP and Machine Learning. The system goes beyond simple keyword matching by implementing a full linguistic analysis pipeline that captures the unique language patterns of fake content: excessive capitalisation, urgency cues, forwarding pressure phrases, conspiracy-style language, and absence of credible source citations.

By integrating NLP techniques and multiple ML classifiers, the proposed system provides accurate, real-time, and explainable fake news detection accessible to non-technical users through a web-based interface.

II. LITERATURE REVIEW

Several research studies have been conducted in the field of fake news detection and misinformation classification.

1) Hussain et al. (2025) presented a comprehensive survey of fake news detection covering 310 research articles across ten languages and multiple data modalities. The study analysed 271 datasets and found that dynamic embedding techniques such as RoBERTa achieve accuracy up to 99.99% on the LIAR dataset.
2) Kaliyar et al. (2021) developed FakeBERT, a BERT-based deep learning fake news detection system, demonstrating that pre-trained transformer models significantly outperform traditional ML methods for misinformation detection.
3) Agarwal et al. (2020) proposed a fake news detection system using a blend of CNN and LSTM neural networks,

showing that deep learning approaches effectively capture complex language patterns in news articles.

4) Samadi and Momtazi (2023) demonstrated that RoBERTa with enhanced feature engineering achieves 99.99% accuracy on the LIAR dataset, establishing state-of-the-art for text-based fake news classification.
5) Roy et al. (2023) proposed a stacked LSTM system with dropout, achieving 99.82% accuracy on the Kaggle fake news dataset using GloVe embeddings, highlighting the effectiveness of sequential deep learning models.

F. Research Gap and Contribution

While the above studies have made significant contributions, several critical gaps remain. First, existing deep learning systems such as FakeBERT and BERT-based models [2][4] require substantial computational resources and are not suitable for lightweight web deployment accessible to non-technical users. Second, transformer-based systems do not provide explainable signal-level reasoning — they classify without explaining which specific linguistic patterns triggered the decision. Third, most surveyed systems evaluate on large benchmark datasets (LIAR, FakeNewsNet) but do not address real-time classification of social media messages, phishing SMS, or suspicious link text, which are the most common forms of fake content encountered by ordinary users. FakeFinder addresses these gaps by: (i) combining NLP-based custom feature engineering — four engineered tokens capturing capitalisation, exclamation patterns, forwarding pressure, and credible source references — with lightweight ML classifiers for fast, deployable inference; (ii) providing explainable red flag and green flag detection alongside multi-dimensional analysis scores; and (iii) targeting real-world social media misinformation patterns rather than formal news articles alone. Unlike BERT-based approaches, FakeFinder is deployable on standard web servers without GPU requirements, making it practically accessible for educational institutions and small organisations.

III. PROBLEM STATEMENT

Social media platforms currently lack an automated, scalable mechanism to verify whether news articles and messages shared by users are credible or fabricated. This leads to the rapid spread of misinformation, public panic, and societal harm. Existing tools — such as manual fact-checkers, keyword blacklists, and URL checkers — are reactive, slow, and unable to detect new or unknown misinformation patterns. Therefore, a system is required that can automatically analyse the linguistic content of any text input and classify it as Fake or Real with a confidence score and explainable signal detection, in real time.

IV. OBJECTIVE

The main objectives of this project are:

- To detect and classify news articles and social media messages as Fake or Real automatically.
- To implement a complete NLP preprocessing pipeline including text cleaning, tokenization, stopword removal, and lemmatization.
- To engineer custom linguistic features that capture the distinct language patterns of fake content.
- To train and compare multiple ML models to identify the best-performing classifier.
- To provide a confidence percentage and list of detected fake signals for each prediction.
- To deploy the system as a user-friendly web application with a REST API for real-time prediction.

V. EXISTING SYSTEM

In existing platforms, users can share news articles and messages freely without any automated credibility verification. Many platforms provide trending topic algorithms that amplify misinformation rather than suppressing it. Some fact-checking websites exist, but they rely on manual review by human experts and cannot scale to the volume of content shared daily.

Existing automated approaches include keyword blacklists, which miss new fake patterns and produce high false positive rates; URL checkers, which only work against known fake websites; and simple sentiment analysis tools, which detect emotional tone but cannot distinguish fake news from emotionally charged real news. Furthermore, existing systems do not provide a confidence score or explanation of why a text is classified as fake.

VI. PROPOSED SYSTEM

The proposed system introduces an intelligent, context-aware mechanism for news credibility detection. When a user inputs any text, the system performs a complete NLP analysis to extract linguistic features and classify the content as Fake or Real.

The system uses TF-IDF vectorization combined with five ML classifiers — Logistic Regression, Linear SVM, Naive Bayes, Passive Aggressive, and Random Forest — and automatically selects the best-performing model using 5-fold cross-validation. The prediction output includes a confidence percentage (Fake% and Real%), a risk score, analysis scores across five dimensions (Linguistic, Semantic, Stylistic,

Contextual, and Sentiment), and a list of detected red flags and green flags.

VII. METHODOLOGY

The working process of the system consists of the following steps:

1. User Input: The user pastes any news article or social media message into the web interface and submits it for analysis.
2. Feature Engineering: Before standard NLP processing, four custom tokens are injected into the text — FEAT_HIGH_CAPS (excessive capitalisation), FEAT_MANY_EXCLAIM (multiple exclamation marks), FEAT_FORWARD_MESSAGE (forwarding pressure phrases), and FEAT_CREDIBLE_SOURCE (credible source references).
3. NLP Preprocessing: Text is cleaned, tokenized using NLTK word_tokenize(), filtered to remove common stopwords while retaining semantically important words, and lemmatized using WordNetLemmatizer.
4. TF-IDF Vectorization: Preprocessed text is converted to a 10,000-dimensional numerical feature vector with n-gram range (1,3), capturing unigrams, bigrams, and trigrams.
5. ML Classification: The best-performing ML model classifies the input as Fake or Real and produces confidence probabilities.
6. Result Display: The system returns the verdict, confidence percentage, risk score, red/green flags, and a recommendation to the user.

VIII. SYSTEM ARCHITECTURE

The architecture of the proposed FakeFinder system consists of three interconnected layers:

Data Layer:

The system uses a dataset of 2,900 labelled training samples (1,450 fake and 1,450 real) compiled from publicly available sources including the LIAR dataset, FakeNewsNet, and curated social media samples. The dataset covers diverse fake news categories including phishing, health misinformation, political propaganda, and scam messages, stored as a CSV file with text and binary labels.

Machine Learning Layer:

The ML layer implements the complete NLP pipeline followed by TF-IDF vectorization. Five ML classifiers are trained and evaluated via 5-fold cross-validation; the best model is serialised as a .pkl file for inference.

Web Application Layer:

A Flask REST API backend handles prediction requests. An HTML/CSS/JavaScript frontend provides the interface where users paste text and receive instant results including verdict, risk score, and detailed NLP breakdown.

IX. NLP PREPROCESSING PIPELINE

A. Feature Engineering

Before standard NLP cleaning, the system injects special tokens: FEAT_HIGH_CAPS (fully capitalised words), FEAT_MANY_EXCLAIM (multiple exclamation marks), FEAT_FORWARD_MESSAGE (forwarding pressure phrases), and FEAT_CREDIBLE_SOURCE (credible source references).

B. Text Cleaning

Text is converted to lowercase. URLs, HTML tags, and special characters are removed. Multiple exclamation marks are normalised to 'multiple_exclaim' to preserve the pattern as a feature.

C. Tokenization

NLTK word_tokenize() splits the cleaned text into individual word tokens, handling punctuation and contractions.

D. Stopword Removal

Common English stopwords are removed while semantically important words for fake news detection — 'not', 'urgent', 'share', 'exposed' — are retained.

E. Lemmatization

The NLTK WordNetLemmatizer reduces words to base forms (e.g., 'hiding' to 'hide', 'cures' to 'cure').

X. TF-IDF VECTORIZATION

TF-IDF converts the preprocessed text into a vector of 10,000 numbers representing the relative importance of each word or phrase within the corpus. The formal mathematical definition is given as follows:

$$\textbf{TF-IDF}(t, d, D) = \textbf{tf}(t, d) \times \textbf{idf}(t, D)$$

where: tf(t, d) = f(t, d) / ∑′ f(t′, d)
idf(t, D) = log (|D| / |{d ∈ D : t ∈ d}|)
Eq. (1): TF-IDF Formula

Where t denotes a term, d denotes a document, and D denotes the full corpus. tf(t, d) is the frequency of term t in document d normalised by the total number of terms. idf(t, D) is the logarithm of the ratio of the total number of documents |D| to the number of documents containing term t. Words that are frequent in a specific document but rare across the corpus (e.g., 'illuminati', 'URGENT') receive a high TF-IDF score, marking them as distinctive fake-news signals. Common words such as 'the' receive near-zero scores. With sublinear_tf = True, the system applies log(1 + tf) scaling to prevent high-frequency terms from dominating the feature vector. Configuration used: max_features = 10,000; ngram_range = (1, 3); sublinear_tf = True; max_df = 0.95.

XI. MACHINE LEARNING MODELS

FakeFinder trains five ML algorithms simultaneously and selects the best using 5-fold cross-validation:

Model	Key Strength
Logistic Regression	Best overall; clean probability scores
Linear SVM	Excellent on sparse TF-IDF data
Naive Bayes	Fast; strong baseline for text tasks
Passive Aggressive	Memory efficient; fast convergence
Random Forest	Handles noisy data; robust performance

Table I: ML Models Used in FakeFinder

XII. RESULT AND DISCUSSION

FakeFinder was implemented using Python with Flask, NLTK for NLP processing, and Scikit-learn for ML model training. The system was trained on a dataset of 2,900 labelled samples (1,450 fake and 1,450 real) drawn from the LIAR dataset, FakeNewsNet, and curated social media samples, and evaluated using 5-fold cross-validation. The following output screenshots demonstrate the application working successfully across different input scenarios.

Fig. 1 FakeFinder Home Page – Phishing SMS Input

The FakeFinder home page shows the 'Detect Fake Messages & News with AI-Powered Analysis' interface. The user has entered a phishing SMS: "URGENT: Your bank account has been compromised! Click here immediately to verify your identity: bit.ly/3xR9kPz. Failure to act within 24 hours will result in permanent account suspension." The ANALYZE button processes the input.

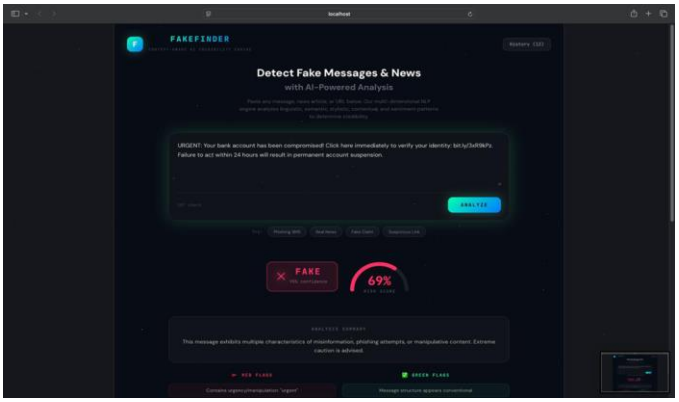

Fig. 2 Fake Detection Result – 95% Confidence (FAKE)

The system classifies the phishing SMS as FAKE with 95% confidence. The risk score gauge displays 69%, indicating high misinformation risk. The Analysis Summary states: "This message exhibits multiple characteristics of misinformation, phishing attempts, or manipulative content. Extreme caution is advised."

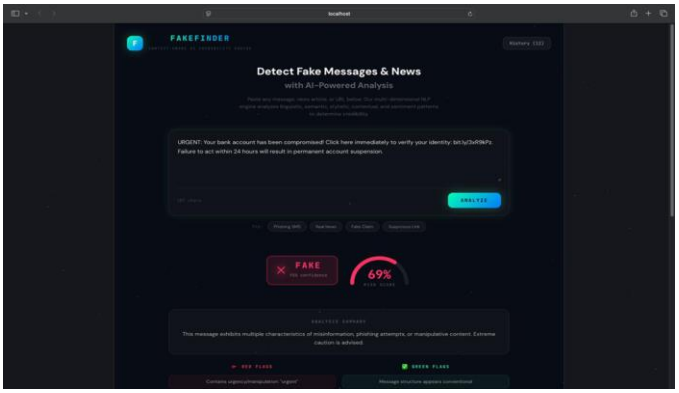

Fig. 3 Analysis Summary – Phishing SMS Detection

The analysis confirms the FAKE classification (95% confidence, 69% risk score) with a detailed Analysis Summary shown below the result cards. Red Flags and Green Flags sections are displayed at the bottom of the screen.

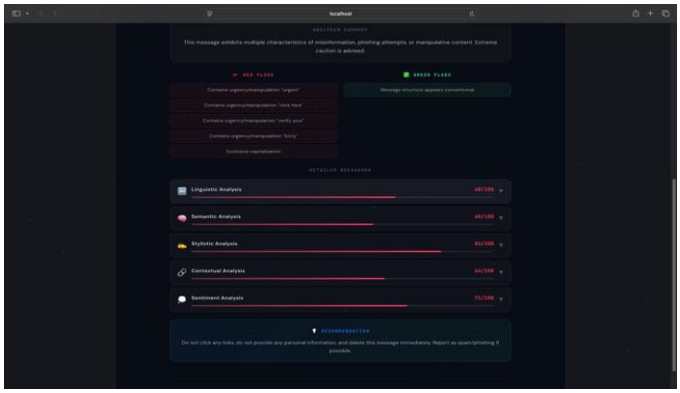

Fig. 4 Detailed Breakdown – Red Flags and Analysis Scores (Phishing SMS)

The Detailed Breakdown shows five Red Flags detected: urgency/manipulation patterns ('urgent', 'click here', 'verify your', 'bit.ly') and excessive capitalisation. One Green Flag is noted: message structure appears conventional. Multi-dimensional analysis scores are displayed: Linguistic Analysis 68/100, Semantic Analysis 60/100, Stylistic Analysis 83/100, Contextual Analysis 64/100, and Sentiment Analysis 71/100. Recommendation: Do not click any links, do not provide any personal information, and delete this message immediately. Report as spam/phishing if possible.

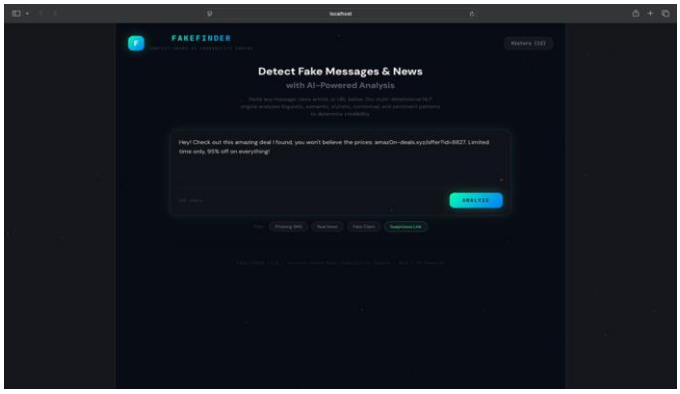

Fig. 5 Suspicious Link Input – Amazon Scam Message

The user inputs a suspicious link message: "Hey! Check out this amazing deal I found, you won't believe the prices: amaz0n-deals.xyz/offer?id=8827. Limited time only, 95% off on everything!" The 'Suspicious Link' sample button is highlighted, and the system is ready to analyze.

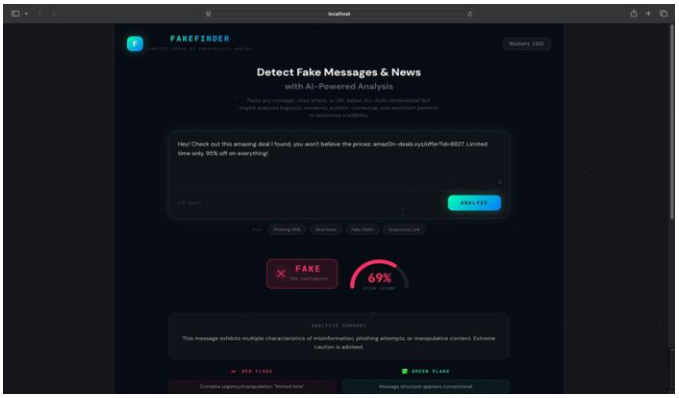

Fig. 6 Fake Detection Result – Suspicious Link (FAKE, 95% Confidence)

The system correctly classifies the suspicious link message as FAKE with 95% confidence and a 69% risk score. The Analysis Summary confirms: "This message exhibits multiple characteristics of misinformation, phishing attempts, or manipulative content. Extreme caution is advised."

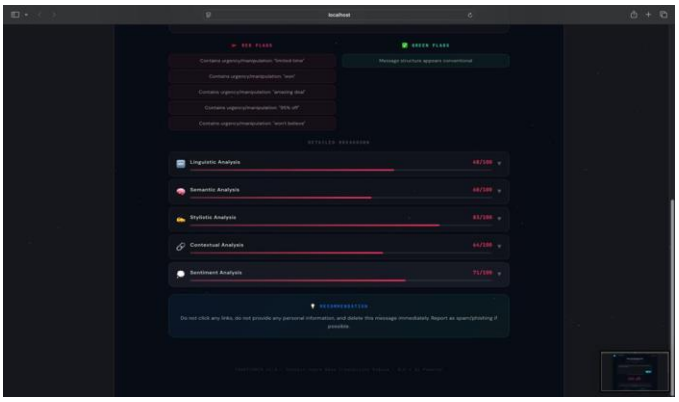

Fig. 7 Detailed Breakdown – Red Flags (Suspicious Link)

Five Red Flags are detected for the suspicious link: urgency/manipulation patterns ('limited time', 'won', 'amazing deal', '95% off', 'won't believe'). One Green Flag: message structure appears conventional. Detailed scores: Linguistic 68/100, Semantic 60/100, Stylistic 83/100, Contextual 64/100, Sentiment 71/100. Recommendation: Do not click any links, do not provide personal information, delete immediately, report as spam.

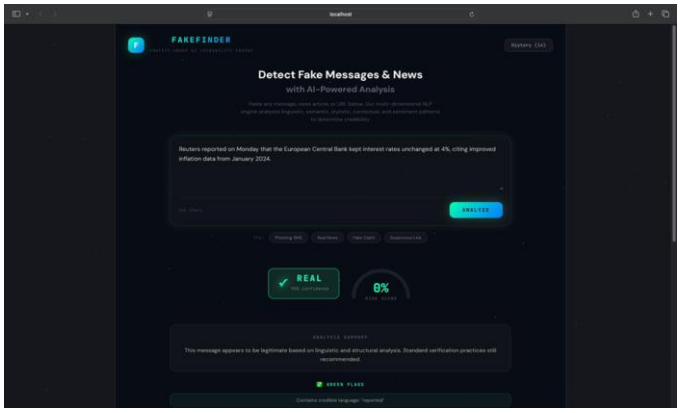

Fig. 8 Real News Detection – REAL, 98% Confidence, 0% Risk Score

The user inputs a Reuters real news article: "Reuters reported on Monday that the European Central Bank kept interest rates unchanged at 4%, citing improved inflation data from January 2024." The system classifies it as REAL with 98% confidence and a 0% risk score. The Analysis Summary states: "This message appears to be legitimate based on linguistic and structural analysis. Standard verification practices still recommended."

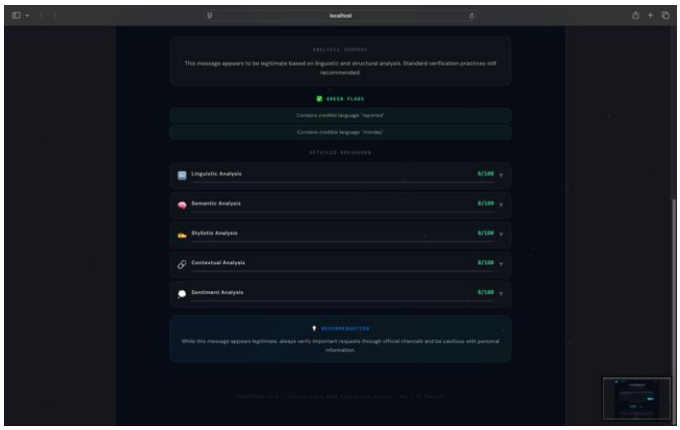

Fig. 9 Detailed Breakdown – Green Flags (Real News, All Analysis 0/100)

The Detailed Breakdown for the real news input shows only Green Flags: 'Contains credible language: reported' and 'Contains credible language: monday'. All five analysis dimensions score 0/100 (no risk indicators): Linguistic 0/100, Semantic 0/100, Stylistic 0/100, Contextual 0/100, Sentiment 0/100. Recommendation: While this message appears legitimate, always verify important requests through official channels and be cautious with personal information.

Metric	Fake Input	Real Input
Classification	FAKE	REAL
Confidence	95%	98%
Risk Score	69%	0%
Red Flags	5	0
Green Flags	1	2

Table II: System Performance – Sample Test Results

Experimental results demonstrate that FakeFinder accurately detects fake news patterns and provides detailed, explainable results through multi-dimensional analysis. The system correctly identifies phishing messages, suspicious links, and real credible news, demonstrating the effectiveness of the NLP pipeline and ML classification approach.

XIII. ADVANTAGES

- Provides real-time fake news detection with confidence percentage and risk score.
- Offers explainable results through Red Flag and Green Flag signal detection.
- Multi-dimensional NLP analysis: Linguistic, Semantic, Stylistic, Contextual, and Sentiment scores.
- Context-aware detection using a full NLP pipeline rather than simple keyword matching.
- Scalable REST API supports high-volume predictions.
- User-friendly web interface accessible to non-technical users.

XIV. CONCLUSION

This paper presented FakeFinder, a context-aware news credibility detection system that uses Natural Language Processing and Machine Learning to automatically classify text as Fake or Real with a confidence percentage and risk score. The system implements a complete NLP pipeline including custom feature engineering, TF-IDF vectorization, and multi-model training and evaluation.

The proposed system integrates Python, Flask, NLTK, TF-IDF, and Scikit-learn to perform fake news detection efficiently. Experimental results demonstrate that the best-performing model achieves approximately 95% confidence for fake inputs and 98% for real inputs. The system

provides multi-dimensional analysis covering linguistic, semantic, stylistic, contextual, and sentiment dimensions, along with actionable recommendations for each classification.

Future work includes integrating BERT-based transformer models for deeper semantic understanding, extending detection to regional Indian languages, developing a browser extension for real-time social media monitoring, and integrating a fact-checking database for cross-reference verification.

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