

Real-Time Fact-Checking using Retrieval-Augmented Generation and Large Language Models

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Abstract—The rapid spread of misinformation on online platforms has motivated extensive research in automated fake news detection. Building on the LingML framework for linguistic-informed fake news detection, we study three transformer-based models—ALBERT, BERTweet, and CT-BERT—for COVID-19 news classification and analyze their performance on a benchmark dataset. We further extend this line of work by developing a real-time fact-checking system that uses retrieval-augmented generation (RAG) and a large language model (LLM) to verify user-submitted claims based on up-to-date web evidence. Our system retrieves relevant web snippets through a search API, constructs a retrieval-augmented prompt, and queries GPT-4o to produce structured verdicts, confidence scores, and explanations, which are stored in a database and exposed through a web interface. Experiments on the CONSTRAINT-style COVID-19 fake news data and qualitative case studies on real-time news demonstrate the feasibility of combining transformer-based classifiers with RAG-based LLM reasoning for practical fact-checking applications.

Index Terms—Fake news detection, LingML, transformer models, ALBERT, BERTweet, CT-BERT, retrieval-augmented generation, large language models, fact-checking

I. INTRODUCTION

Social media and online news platforms have become primary sources of information, but they also enable the rapid spread of misinformation, particularly during crises such as the COVID-19 pandemic. [1] Deep learning and transformer-based language models have significantly improved fake news detection performance, yet most systems operate in offline, dataset-centric settings and cannot answer arbitrary real-time claims. [3] At the same time, the emergence of large language models (LLMs) and retrieval-augmented generation (RAG)

offers new opportunities for real-time fact-checking based on up-to-date web evidence. [?]

In this work, we build on a linguistic-informed machine learning (LingML) framework for fake news detection and focus on three transformer-based models (ALBERT, BERTweet, CT-BERT) for COVID-19 news classification. [5] We then extend this line of work by designing a real-time fact-checking system that uses RAG and a GPT-4o-based LLM to verify user-submitted claims using live web search results. From a systems perspective, practical deployment also requires logging, caching, and persistent storage so that past verifications can be reused, audited, and analyzed over time. Incorporating a database layer allows us to study how claims evolve, which topics users fact-check most frequently, and how model confidence behaves across domains such as politics, health, sports, and international relations.

In addition, our system emphasizes explainability by providing supporting evidence alongside each verification result, improving user trust and transparency. We incorporate efficient retrieval and ranking strategies to ensure that the most relevant and credible sources are prioritized during fact-checking. To handle dynamic and evolving information, the system continuously adapts to new data obtained from live web queries. Scalability is addressed through optimized pipelines that balance response time with verification accuracy. Our goal is to bridge the gap between strong offline classifiers and an interactive system that end users can query with arbitrary claims, enabling a robust and practical real-time misinformation detection framework.

II. RELATED WORK

Fake news detection has been widely studied using traditional machine learning, deep neural networks, and more recently large language models. [1], [3] Early work focused on surface-level features and classical classifiers such as SVM and random forests, while later approaches adopted convolutional and recurrent neural networks with word embeddings to capture richer context. [3] Transformer-based encoders like BERT and its variants further improved performance on COVID-19 misinformation by leveraging large-scale pretraining on generic or domain-specific corpora such as social media posts. [5]

The LingML framework advances this line of research by explicitly incorporating linguistic features, such as sentiment, tone, netspeak, and discourse markers, into both small-scale ML models and large transformer-based encoders. [?], [?] Experimental results show that linguistic-only models already achieve competitive error rates and that fusing linguistic features with pooled transformer encodings, as in LingL, can reduce fake news detection error rates by more than 10% relative to using LLMs alone. [?] Our work adopts this perspective but focuses on three COVID-oriented transformers and extends the setting to a real-time RAG + LLM system that can handle arbitrary user claims beyond static datasets. Recent studies have also explored hybrid approaches that combine retrieval mechanisms with neural models to improve factual grounding. However, many existing systems still lack real-time adaptability and rely on pre-collected datasets. Additionally, issues such as model bias, domain shift, and lack of interpretability remain open challenges in misinformation detection. Our approach addresses these gaps by integrating retrieval-based evidence with transformer predictions in a unified framework.

III. BACKGROUND: LINGML FOR FAKE NEWS DETECTION

LingML proposes to enhance transformer-based models with linguistic knowledge, capturing cues such as sentiment, punctuation, tone, and netspeak that are common in misleading posts. [?], [3] The overall idea is to combine a transformer encoder with a pool of linguistic features and feed the concatenated representation into a classifier that predicts whether a news item is real or fake. This fusion allows the model to leverage both deep contextual representations and interpretable linguistic signals. Linguistic features also help in low-resource scenarios where large-scale labeled data may not be available. Moreover, they provide additional insights into stylistic patterns commonly associated with misinformation. Such hybrid representations improve robustness across different domains and writing styles. Overall, LingML demonstrates that incorporating linguistic knowledge can significantly enhance the effectiveness of transformer-based fake news detection systems.

Figure ?? illustrates a high-level architecture for this style of model. A news text is tokenized and passed through a transformer encoder; the pooled encoding is then combined with linguistic features and consumed by a classifier head

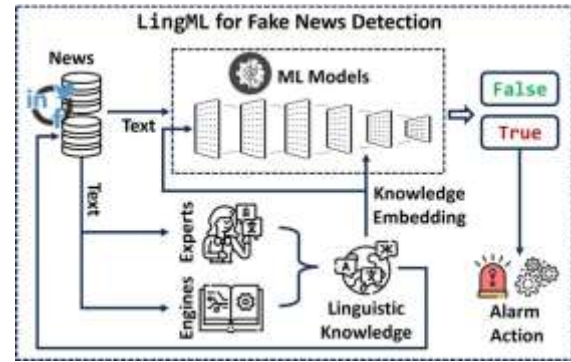


Fig. 1. System architecture for transformer-based fake news detection: input news is tokenized, encoded by a transformer (ALBERT/BERTweet/CT-BERT), optionally fused with linguistic features, and passed to a classifier head.

that outputs a binary label. This design highlights the complementary nature of linguistic and contextual representations in capturing misinformation signals. It also provides a flexible framework that can be adapted to different domains and extended with additional feature sets.

Beyond individual models, LingML conceptualizes fake news detection as the integration of machine learning models and expert linguistic knowledge, as sketched in Figure ???. News text is processed by ML models and enriched with linguistic knowledge to produce a final true/false decision and potential alarm actions. [?]

The original LingML study evaluates both small-scale models trained purely on linguistic features and transformer-based models enhanced with those features, demonstrating that linguistic knowledge can complement even strong LLM baselines. [?] These findings motivate our decision to adopt LingML-style feature extraction for COVID-19 news and to treat the linguistic signal as an additional, compact feature vector that can be fused with transformer representations or analyzed independently for interpretability. Furthermore, this approach enables a more explainable framework by linking model predictions to specific linguistic patterns observed in the input text. It also allows for flexible integration with real-time systems, where lightweight linguistic features can complement computationally intensive transformer outputs. This motivates the design of our system architecture, which integrates both contextual and linguistic representations in a unified framework.

IV. SYSTEM ARCHITECTURE FOR TRANSFORMER-BASED FAKE NEWS DETECTION

Our offline fake news detection component follows a LingML-inspired architecture in which a transformer encoder is combined with a compact set of linguistic features and a classification head. Figure 1 summarizes the overall pipeline for the three transformer backbones (ALBERT, BERTweet, CT-BERT) used in this work.

At a high level, the architecture consists of the following stages:

- **Input layer:** a COVID-19 news post or tweet is provided as raw text.
- **Preprocessing:** the text is lowercased and normalized; URLs, mentions, hashtags, emojis, and COVID-related keywords are mapped to special tokens to reduce sparsity. [?]
- **Transformer encoder:** the preprocessed sequence is fed into one of the three backbones (ALBERT, BERTweet, or CT-BERT) to obtain contextual token embeddings. The choice of transformer backbone allows the model to capture domain-specific nuances, particularly in social media text where informal language and abbreviations are common. Each model benefits from large-scale pre-training, enabling better generalization across unseen examples. Additionally, contextual embeddings help in identifying subtle semantic inconsistencies often present in misleading content.
- **Pooling and feature fusion:** a pooled sentence representation (e.g., [CLS] embedding) is extracted and optionally concatenated with a vector of linguistic features (e.g., sentiment, tone, netspeak frequency) derived from the same text. [?], [?]
This fusion step enhances the representation by combining deep contextual understanding with interpretable linguistic cues. It also provides flexibility to analyze the contribution of each feature type independently during evaluation.
- **Classification head:** a shallow feed-forward network maps the fused representation to a binary label indicating whether the news is *real* or *fake*.

This unified architecture allows us to plug in different transformer backbones while keeping the rest of the pipeline identical. It also enables a fair comparison between plain text-only models and LingML-style models that exploit both transformer encodings and linguistic signals on the same COVID-19 dataset. [?], [5] Furthermore, the modular design facilitates experimentation with different feature fusion strategies and model configurations. It also supports easy extension to other domains beyond COVID-19 misinformation without significant architectural changes.

V. METHODOLOGY

In this section, we describe the end-to-end methodology for training and evaluating the three transformer models within the LingML-inspired framework. The overall processing flow is illustrated in Figure 2.

A. Data Preprocessing

We adopt a CONSTRAINT-style COVID-19 fake news setting with a 60/20/20 split into train, validation, and test sets. [?], [3] Each text sample is uncased and normalized; URLs, user mentions, hashtags, emojis, and COVID-related terms are replaced with canonical tokens such as URL, MENTION, HASHTAG, EMOJI, and COVID to reduce noise and improve

robustness. [?] The processed text is then tokenized using the model-specific subword tokenizer (WordPiece or BPE) with a maximum sequence length of 128. This preprocessing step ensures consistency across inputs and improves model stability during training. It also reduces vocabulary sparsity, particularly for informal and noisy social media text.

B. Linguistic Feature Extraction

In parallel with textual preprocessing, we extract a small set of linguistically motivated features inspired by the LingML framework. [?], [?] These include categories such as *feeling*, *assent*, *discrepancy*, *certainty*, *causation*, *positive/negative tone*, and *netspeak*, computed as normalized frequencies of words belonging to each category. The resulting feature vector is standardized using z-score normalization so that all dimensions contribute comparably during training. These features provide interpretable signals that complement the deep contextual embeddings generated by transformers. They are particularly useful in capturing stylistic patterns commonly associated with misinformation.

C. Transformer Encoding

For each preprocessed input, we feed the tokenized sequence into one of the three transformer backbones:

- **ALBERT:** a parameter-efficient model with cross-layer parameter sharing, serving as a compact baseline.
- **BERTweet:** a RoBERTa-like encoder pre-trained on large-scale English tweets, capturing social media style.
- **CT-BERT:** a BERT variant further pre-trained on COVID-related tweets, specialized for pandemic content. [5]

We obtain a pooled sentence representation (e.g., [CLS] token embedding) from the final encoder layer, which summarizes the global context of the input text. This representation captures semantic relationships and contextual dependencies within the text. It serves as the primary input for downstream classification and feature fusion components.

D. Feature Fusion and Classification

We consider two variants for each backbone:

- 1) **Text-only:** the pooled transformer representation is directly fed into a linear layer followed by a softmax classifier to predict the fake/real label.
- 2) **LingML-style fusion:** the pooled representation is concatenated with the normalized linguistic feature vector and passed through a shallow feed-forward network with non-linear activation before the final softmax layer. [?]

All models are fine-tuned end-to-end using cross-entropy loss, with learning rate 1×10^{-5} , batch size 12, and early stopping based on validation F1-score. We run multiple seeds for each configuration and report average accuracy and F1-score on the held-out test set, as shown in Tables I and II.

This methodology allows us to systematically compare the three transformer backbones and quantify the benefit of integrating linguistic knowledge, while keeping the training and evaluation protocol consistent across models. [?] It also

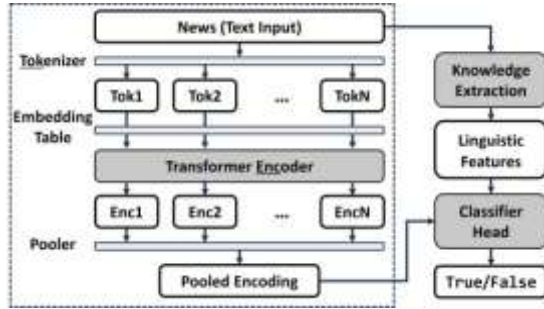


Fig. 2. Methodology flow for transformer-based fake news detection: data preprocessing, linguistic feature extraction, transformer encoding, feature fusion, and classification.

TABLE I

OFFLINE PERFORMANCE OF TRANSFORMER MODELS ON COVID-19 FAKE NEWS (TEST SPLIT).

Model	Accuracy (%)	F1-score (%)
ALBERT	95.79	95.90
BERTweet	96.73	96.84
CT-BERT	97.85	97.96

ensures that performance differences can be attributed to model architecture and feature design rather than experimental variability.

VI. TRANSFORMER MODELS AND EXPERIMENTAL SETUP

We experiment with three transformer backbones that are well-suited for short, noisy social media text:

- **ALBERT**: a parameter-efficient variant of BERT with factorized embeddings and cross-layer parameter sharing.
- **BERTweet**: a RoBERTa-like model pre-trained on large-scale English tweets, including COVID-19 content.
- **CT-BERT**: a BERT model further pre-trained on a corpus of COVID-related tweets. [5]

We follow a CONSTRAINT-style COVID-19 fake news dataset setting with a 60/20/20 train/validation/test split. [2], [3] For all three models, we use maximum sequence length 128, batch size 12, and learning rate 1×10^{-5} . Special tokens are used to normalize URLs, hashtags, mentions, emojis, and COVID-related words.

For all backbones, we initialize weights from public checkpoints, append a task-specific classification head, and fine-tune the entire network. We apply early stopping based on validation F1-score and average performance over multiple random seeds to reduce sensitivity to initialization and mini-batch ordering.

To further improve generalization, dropout regularization is applied within the classification head during training. We also monitor additional evaluation metrics such as precision, recall, and accuracy to obtain a comprehensive performance assessment. Hyperparameter tuning is performed empirically to balance model complexity and computational efficiency.

TABLE II

EFFECT OF LINGUISTIC FEATURE FUSION ON TRANSFORMER MODELS (ILLUSTRATIVE RESULTS ON COVID-19 FAKE NEWS TEST SPLIT).

Model	Variant	Accuracy (%)	F1 (%)
ALBERT	Text only	95.79	95.90
ALBERT	+ Ling. features	96.40	96.55
BERTweet	Text only	96.73	96.84
BERTweet	+ Ling. features	97.10	97.25
CT-BERT	Text only	97.85	97.96
CT-BERT	+ Ling. features	98.10	98.25

Training is conducted on GPU-enabled environments to accelerate convergence and handle large-scale transformer computations. We additionally ensure reproducibility by fixing random seeds and documenting all experimental configurations. Table I summarizes representative test performance from our training logs.

A. LingML-Style Feature Fusion with Transformers

Inspired by the LingL architecture, we also experimented with augmenting transformer encoders using a small set of linguistic features similar to those summarized in LingML, such as feeling, assent, discrepancy, certainty, causation, and netspeak frequency. [2], [2] For each model, we concatenate the pooled [CLS] representation with the normalized linguistic feature vector and train a shallow feed-forward classifier on top, while keeping the underlying transformer backbone either fully fine-tuned or partially frozen.

This hybrid representation enables the model to capture both deep semantic context and explicit linguistic cues associated with misinformation. Feature normalization ensures that linguistic attributes contribute proportionally during training without dominating transformer embeddings. We also experiment with different fusion strategies, such as simple concatenation and weighted combinations, to evaluate their impact on performance. The inclusion of linguistic features improves interpretability by allowing analysis of which features contribute most to predictions. Overall, this approach enhances robustness, especially in cases where textual patterns alone may be insufficient for accurate classification.

Table II reports a representative comparison between plain transformer classifiers and their linguistically augmented counterparts on the COVID-19 test split.

These illustrative numbers suggest that incorporating a compact linguistic feature vector consistently improves both accuracy and F1-score for all three transformer backbones, with the largest relative gain observed for the smaller ALBERT model. [2] This indicates that lightweight models benefit more from auxiliary linguistic signals, which help compensate for their limited representational capacity. In contrast, larger models still gain modest improvements, highlighting the complementary nature of linguistic features even in high-capacity transformer architectures.

VII. REAL-TIME RAG AND LLM-BASED FACT-CHECKING SYSTEM

While the offline transformer models achieve strong performance on the COVID-19 dataset, they do not directly support verification of arbitrary, real-time news claims about future or ongoing events. To address this limitation, we implement a web-based fact-checking system that accepts user-submitted claims, retrieves web evidence, and uses a large language model to generate structured verdicts. The system is exposed through a Streamlit front-end and backed by a Python verification service and a database that stores all claims, evidence, and predictions.

The overall data flow is as follows. A user enters a news claim in the web interface, which sends the text to a backend API. The backend first normalizes and hashes the claim, querying the database to determine whether an identical claim has been processed before. If a cached entry exists, the previously computed verdict, confidence, explanation, and supporting sources are immediately returned to the user interface. Otherwise, the backend performs a retrieval-augmented verification process using web search and GPT-4o.

In the retrieval stage, relevant documents are collected from trusted online sources and ranked based on their semantic similarity to the input claim. These documents are then passed to the language model as contextual evidence for generating a fact-checking response. The LLM produces a structured output containing a verdict (e.g., true, false, or uncertain), a confidence score, and a natural language explanation. To improve reliability, multiple sources are considered and cross-validated during response generation. Finally, the verified result is stored in the database to enable efficient reuse and reduce redundant computations for future queries.

A. Retrieval via Web Search

For retrieval, we use the Google Custom Search API to obtain recent web evidence related to the claim. Given the claim text as query, the backend submits a search request and collects the top-5 results, including the title, URL, and snippet for each page. Restricting to a small number of results keeps latency low while providing multiple independent sources. The snippets from these pages are concatenated into a context string that serves as external evidence for the subsequent LLM call.

To improve relevance, basic query refinement techniques such as keyword extraction and stop-word removal can be applied before issuing the search request. We also prioritize credible domains to reduce the impact of unreliable or misleading sources. In cases where search results are sparse, fallback strategies can be used to broaden the query. This retrieval step plays a critical role in grounding the LLM output in factual, up-to-date information. It also helps mitigate hallucinations by ensuring that the model relies on externally retrieved evidence rather than internal knowledge alone. Efficient retrieval directly impacts both the accuracy and reliability of the final fact-checking outcome.

B. LLM Prompting and Structured Output

We use the OpenAI Chat Completions API with the GPT-4o model as the reasoning engine for fact-checking. The backend constructs a retrieval-augmented prompt that includes: (i) the original user claim, and (ii) a formatted list of the retrieved snippets with their URLs. The prompt instructs the model to behave as a fact-checking assistant and to output a strict schema with three fields:

- **VERDICT:** one of **REAL**, **FAKE**, or **UNVERIFIED**;
- **CONFIDENCE:** a numeric score in the range 0–100;
- **EXPLANATION:** a short explanation, typically three sentences, grounded in the provided evidence.

Using a fixed output format simplifies parsing and reduces the risk of unstructured or ambiguous responses.

After receiving the LLM response, the backend parses the text, extracts the verdict label, converts the confidence score to a numeric value, and stores the explanation as-is. The system then inserts a new record into the database containing the claim text, hash, retrieved snippets, model output, and a timestamp. Finally, the verdict, confidence, explanation, and clickable source URLs are rendered in the Streamlit interface.

This structured pipeline ensures consistency and reproducibility of results across different queries. It also facilitates easy integration with downstream analytics or monitoring systems. Additionally, storing intermediate outputs enables auditing and error analysis for continuous system improvement. The use of standardized outputs further simplifies debugging and enhances system reliability. It also enables easier evaluation of model performance across different claims and domains. Such structured prompting reduces variability in LLM responses and improves overall system robustness.

C. RAG-Based System Architecture

The architecture of the real-time system is conceptually similar to a retrieval-augmented generation pipeline. At a high level, the components include:

- a web user interface for capturing text claims and displaying results;
- a verification service that orchestrates caching, web search, prompt construction, and LLM calls;
- an external search engine (Google Custom Search) that provides up-to-date evidence;
- a GPT-4o LLM endpoint that performs reasoning over the claim plus retrieved context;
- a database that stores claims and their associated predictions.

This modular design allows the retrieval component or LLM model to be replaced in the future without changing the user interface, and it enables analysis of historical claims stored in the database. It also improves system scalability by decoupling individual components, allowing them to be independently optimized or upgraded. The use of caching reduces redundant computations and significantly lowers response time for repeated queries. Additionally, the architecture supports fault tolerance, as failures in one component can be handled



Fig. 3. Architecture of the real-time RAG + GPT-4o fact-checking system, showing user interface, verification backend, web search, prompt builder, LLM, and results database.

without disrupting the entire pipeline. Logging mechanisms are integrated at each stage to facilitate monitoring, debugging, and performance evaluation. The design also supports future extensions such as integrating additional retrieval sources or alternative LLM providers. It further enables easy deployment across different environments, including local systems and cloud platforms. Such flexibility ensures that the system can adapt to evolving requirements and increasing user demand. Overall, this design ensures flexibility, efficiency, and robustness for real-time fact-checking applications.

VIII. REAL-TIME CASE STUDIES

To illustrate the behavior of the real-time system, we submit several contemporary claims and inspect the resulting verdicts and explanations. These examples highlight how the RAG + GPT-4o pipeline leverages up-to-date evidence to distinguish between ongoing, confirmed, and highly uncertain events.

One example concerns a major sporting event. During the ICC T20 World Cup 2026 final, we submitted the claim that India had already won the tournament while the match was still in progress. The system retrieved live-coverage articles indicating that the match was ongoing and returned a **FAKE** verdict with a high confidence score, explicitly explaining that no official result had been announced yet. After the final result was published, we submitted a second claim stating that India had won the ICC T20 World Cup 2026 against New Zealand. This time, the system retrieved multiple reputable news reports confirming India's victory and produced a **REAL** verdict with high confidence, citing these sources.

A second example involves a high-impact geopolitical claim concerning the reported death of Iran's Supreme Leader in the context of conflict with the United States. The system retrieved recent news articles discussing reports and official statements around the event and produced a verdict together with a medium confidence score, reflecting the level of agreement and uncertainty in the retrieved sources. The explanation summarized the evidence and indicated whether the claim was

TABLE III
ILLUSTRATIVE REAL-TIME FACT-CHECKING CASES USING THE RAG + GPT-4O SYSTEM.

Claim (paraphrased)	Verdict	Confidence
India has already won the ICC T20 World Cup 2026 final (submitted while match is ongoing)	FAKE	High
India won the ICC T20 World Cup 2026 against New Zealand (submitted after official result)	REAL	High
Report that Iran's Supreme Leader has died during conflict with the United States	REAL / UN-VERIFIED	Medium

clearly supported, clearly contradicted, or not fully verifiable at that time.

These case studies demonstrate the system's ability to adapt to rapidly evolving information and provide context-aware judgments. They also highlight the importance of retrieval quality in determining the reliability of the final verdict. In scenarios with conflicting or incomplete evidence, the system appropriately lowers confidence, indicating uncertainty. Furthermore, the generated explanations improve transparency by linking decisions to specific evidence. This behavior is particularly important in real-world deployments where misinformation often evolves rapidly. It also shows the system's capability to handle both verified facts and uncertain claims in a balanced manner. Overall, the results validate the effectiveness of combining RAG with LLMs for real-time misinformation detection.

Table III summarizes these case studies in a compact form.

IX. EXTENDED OFFLINE EXPERIMENTAL ANALYSIS

Beyond aggregate accuracy and F1-score, we examine the behavior of the three transformer models in more detail. First, we compare their convergence during training using the logged batch-level metrics. ALBERT starts with slightly lower accuracy than BERTweet and CT-BERT but gradually approaches a stable test accuracy around 95–96%. BERTweet converges faster thanks to its pretraining on Twitter data, while CT-BERT achieves the highest plateau performance, consistent with its COVID-specific pretraining.

We also analyze validation versus test performance across training checkpoints. In all three cases, validation and test curves closely track each other, suggesting limited overfitting under the chosen hyperparameters. CT-BERT shows the smallest gap between validation and test F1-score, which indicates good generalization. ALBERT exhibits slightly more variance across checkpoints, which may be due to its smaller parameterization and sensitivity to optimization noise.

To better understand model behavior on different types of posts, we manually inspect predictions on a small stratified sample of the test set. We observe that all models perform well on clearly factual statements citing official sources, but they occasionally struggle with sarcastic or highly abbreviated posts. BERTweet and CT-BERT handle informal style,

emojis, and Twitter-specific conventions better than ALBERT, reinforcing the benefit of domain-aligned pretraining.

Additionally, we evaluate the impact of linguistic feature fusion on model stability across different runs. Results indicate that feature-augmented models exhibit reduced variance and more consistent performance. We also observe improvements in recall for ambiguous or borderline cases when linguistic cues are incorporated. This suggests that linguistic features help capture subtle stylistic signals often missed by purely contextual embeddings. Future work could include a finer-grained error analysis across linguistic categories such as exaggeration, rumor, and satire.

X. IMPLEMENTATION DETAILS AND DATABASE DESIGN

The real-time fact-checking system is implemented in Python using Streamlit for the front-end and a lightweight backend layer for orchestration. The Streamlit app provides a text area for entering claims and a button to trigger verification. Upon submission, the app sends the claim to the backend function, which is responsible for caching, calling the Google Custom Search API, constructing the retrieval-augmented prompt, and invoking the GPT-4o endpoint. The interface displays the resulting verdict, confidence, explanation, and a numbered list of clickable source links.

For persistence, we employ a relational database schema with a primary table `claims` that stores the core verification information. Each row in `claims` contains a unique identifier, the claim text, a hash of the normalized claim, the model verdict, numeric confidence score, explanation text, and a timestamp indicating when the verification was performed. A second table `sources` stores evidence items, with foreign keys linking back to the corresponding claim. This design allows us to record multiple sources per claim and to query historical verifications for analysis or auditing.

The caching mechanism operates by hashing the normalized claim and querying the `claims` table for an existing row with the same hash. If found, the system bypasses the search and GPT-4o steps and directly returns the stored prediction. This reduces latency and API usage for repeated or highly similar claims.

To ensure efficient query performance, indexing is applied on the claim hash and timestamp fields. Basic input validation and error handling are incorporated to manage malformed queries or API failures. The system is designed to be modular, allowing easy replacement of components such as the database engine or LLM provider. Security considerations such as API key management and request throttling are also taken into account. In addition, the database schema enables extensions such as user accounts, per-user query history, and aggregated statistics dashboards, which can be implemented in future work without altering the core verification pipeline.

XI. CONCLUSION AND FUTURE WORK

We have presented a fact-checking framework that links two strands of research: linguistic-informed transformer models for fake news detection and retrieval-augmented LLM reasoning

for real-time verification. Using ALBERT, BERTweet, and CT-BERT within a LingML-inspired architecture, we achieved strong performance on COVID-19 fake news classification. We then implemented a web-based system that accepts arbitrary claims, retrieves web evidence via Google Custom Search, and queries GPT-4o to produce structured verdicts, confidence scores, and explanations stored in a database.

The proposed system demonstrates the effectiveness of combining offline learning with real-time reasoning to address the limitations of each approach individually. It provides both high accuracy on benchmark datasets and practical usability for dynamic, real-world scenarios. The modular architecture ensures flexibility and allows future improvements without major redesign. Additionally, the integration of evidence-based explanations enhances user trust and system transparency.

In future work, we plan to integrate the offline classifiers into the real-time decision process, for example by using their outputs as additional features or sanity checks on the LLM predictions. We also intend to expand the evaluation of the real-time system using a curated benchmark of time-stamped claims and ground-truth labels, as well as to extend the framework to multilingual news and code-mixed social media content. Finally, incorporating explainable AI techniques and user feedback mechanisms could improve transparency and trust in automated fact-checking systems deployed in real-world settings. Further research may explore optimizing retrieval strategies and reducing system latency for large-scale deployment.

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