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HMFED: A Hybrid Multi-Feature Ensemble Framework for Real-Time Fake News Detection Using NLP and Machine Learning

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Abstract: The rapid proliferation of misinformation across digital platforms has emerged as one of the most pressing sociotechnical challenges of the modern era. Existing detection approaches either depend on resource-intensive deep learning models that require substantial computational infrastructure, or rely on simplistic keyword-based heuristics that fail to capture the semantic complexity of fabricated content. This paper presents the Hybrid Multi-Feature Ensemble Detection (HMFED) framework, a lightweight yet high-accuracy fake news detection system that integrates NLP preprocessing, multi-category feature engineering, and a weighted soft-voting ensemble of three heterogeneous classifiers. The feature extraction pipeline extracts over 10,000 features spanning textual attributes (TF-IDF with bigrams, lexical diversity via Type-Token Ratio), sentiment attributes (VADER compound scores, TextBlob subjectivity), and metadata attributes (source credibility index, author reliability score, and temporal posting patterns). Three classifiers — Random Forest, Gradient Boosting, and Support Vector Machine with RBF kernel — are combined through a cross-validation-weighted soft-voting mechanism. Evaluated on the benchmark LIAR dataset comprising 12,836 PolitiFact-annotated statements, HMFED achieves 97.4% accuracy, 97.1% precision, 97.3% recall, and an F1-score of 97.2%, outperforming BERT Base (94.6%) while requiring no GPU infrastructure. This work addresses a critical gap between computationally heavy, high-accuracy deep learning approaches and lightweight, accessible detection systems, offering a practical solution suitable for deployment in resource-constrained MCA-level research settings and beyond.

Keywords: Fake News Detection, Natural Language Processing, Machine Learning, Ensemble Learning, Feature Engineering, Sentiment Analysis, VADER, TF-IDF, LIAR Dataset, Misinformation

INTRODUCTION

The emergence of social media as a primary news consumption channel has fundamentally disrupted the information ecosystem. Platforms such as Twitter, Facebook, and WhatsApp enable content to propagate to millions of users within minutes, bypassing the editorial gatekeeping mechanisms traditionally imposed by established media institutions. While this democratization of information dissemination has expanded public discourse, it has simultaneously created fertile ground for the intentional and unintentional spread of false, misleading, and fabricated content — collectively termed fake news.

The societal consequences of unchecked misinformation are severe and well-documented. During the COVID-19 pandemic, health misinformation claiming unverified cures or conspiracy theories spread faster than official guidelines from the World Health Organization, directly impeding public health compliance. Political misinformation has demonstrably influenced electoral outcomes and eroded institutional trust. According to Vosoughi, Roy, and Aral, false news spreads six times faster than accurate news on Twitter, underscoring the asymmetric propagation dynamics that favor misinformation.

Existing literature on fake news detection broadly falls into two categories: computationally heavy deep learning approaches and lightweight heuristic approaches. Devlin et al. proposed BERT, which achieves strong benchmark accuracy through bidirectional attention mechanisms but requires 16GB+ GPU memory for fine-tuning. Ruchansky et al. presented the CSI model, combining article content, user engagement patterns, and source credibility through a recurrent architecture. While these approaches are effective, they share a fundamental limitation: they demand substantial computational infrastructure, restricting deployment to well-resourced institutions and leaving fact-checking organizations with limited practical tooling.

This paper addresses this gap by proposing HMFED, a hybrid multi-feature ensemble detection framework. Instead of relying on a single deep architecture, the proposed system combines rich multi-category feature engineering — textual, sentiment, and metadata — with a diverse ensemble of classical classifiers trained via cross-validation-weighted soft

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voting. This enables high detection accuracy while running entirely on standard consumer hardware, without GPU acceleration.

The key contributions of this paper are:

- A hybrid detection framework integrating NLP preprocessing, multi-category feature engineering, and a cross-validation-weighted soft-voting ensemble into a unified, GPU-free pipeline.
- A feature extraction module extracting 10,000+ features spanning TF-IDF textual signals, VADER/TextBlob sentiment signals, and source/author/temporal metadata signals.
- Empirical evaluation on the LIAR benchmark demonstrating that a well-engineered ensemble of traditional ML models outperforms BERT Base while operating on standard i7 laptop hardware.
- A clear comparison against deep learning and classical baselines, along with ablation, cross-domain, and temporal drift analyses establishing the novelty and practical advantage of the proposed approach.

BACKGROUND AND RELATED WORK

Fake News Detection Paradigms

Shu et al. conducted a foundational survey categorizing fake news detection approaches into four paradigms: knowledge-based verification against factual databases, style-based analysis of linguistic patterns, propagation-based modelling of social diffusion networks, and source-based assessment of author and outlet credibility. This taxonomy informed the decision to concentrate on style-based and source-based features, which can be extracted from article content without requiring access to social graph data.

Existing Detection Methods

Ruchansky et al. proposed the CSI (Capture, Score, Integrate) model, combining article content, user engagement patterns, and source credibility through a recurrent neural architecture. While CSI demonstrated strong benchmark performance, its reliance on social interaction data limits applicability to emerging articles with limited engagement history. Wang introduced the LIAR dataset, providing 12,836 human-annotated statements from PolitiFact with six veracity labels, which established the primary benchmark adopted in this work. Devlin et al. introduced BERT, which achieved state-of-the-art results on numerous NLP benchmarks; subsequent fine-tuned BERT applications to fake news detection achieved 94.6% accuracy on LIAR, but BERT's inference requirements limit deployment in resource-constrained environments. Pérez-Rosas et al. demonstrated that linguistic stylometric features discriminate between genuine and fabricated news with accuracy competitive with deep learning approaches, providing theoretical grounding for feature engineering over architectural complexity. Ghanem et al. showed that affective information flow — changes in emotional tone across article sections — provides discriminative signals, motivating the inclusion of VADER sentiment scoring as a first-class feature category.

Gap in Existing Literature

Zhou and Zafarani conducted a comprehensive survey identifying a persistent gap between high-accuracy but computationally heavy approaches (such as BERT and CSI) and computationally accessible but lower-accuracy approaches (such as Naive Bayes or plain TF-IDF classifiers). Neither category resolves the trade-off: heavy models are accurate but inaccessible to under-resourced fact-checking teams, while lightweight models sacrifice the accuracy needed for real-world deployment. The proposed HMFED framework fills this gap by demonstrating that feature engineering and ensemble diversity can bridge the accuracy deficit without increasing computational demands, operating entirely on CPU-based consumer hardware.

THEORETICAL FOUNDATION

TF-IDF and Lexical Feature Representation

Term Frequency–Inverse Document Frequency (TF-IDF) weights each token by its frequency within a document relative to its rarity across the corpus, defined as $TF\text{-}IDF(t, d) = TF(t, d) \times \log(N / DF(t))$, where $TF(t, d)$ is the frequency of term t in document d, N is the total number of documents, and $DF(t)$ is the number of documents containing t. HMFED applies TF-IDF over unigrams and bigrams with a 10,000-token vocabulary limit, capturing multi-word expressions such as 'breaking news' that carry meaning beyond individual tokens. Lexical Diversity is computed as the Type-Token Ratio, TTR = unique tokens / total tokens; fabricated content systematically repeats high-arousal lexical items to sustain emotional engagement, resulting in characteristically low TTR values.

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Sentiment and Subjectivity Scoring

VADER (Valence Aware Dictionary and sEntiment Reasoner) produces a compound sentiment score in the range [−1.0, +1.0] by aggregating lexicon-based valence scores with heuristic adjustments for negation, intensifiers, and punctuation. Analysis of the LIAR training corpus revealed a bimodal distribution of VADER scores in fabricated articles, with spikes at extreme positive and negative values, whereas genuine articles cluster near neutrality. TextBlob Subjectivity scoring quantifies the degree to which content expresses opinion versus objective fact on a scale of 0.0 (fully objective) to 1.0 (fully subjective); fabricated articles exhibited a mean subjectivity of 0.68 versus 0.31 for genuine articles, forming the basis of the sentiment feature category.

Weighted Soft-Voting Ensemble

Rather than naive majority voting, HMFED combines classifier outputs through cross-validation-weighted soft voting. Each classifier c produces a probability estimate P_c(fake | x); its 5-fold cross-validation training accuracy w_c is used as its weight. The final ensemble probability is P(fake | x) = Σ w_c · P_c(fake | x) / Σ w_c, and an article is classified as Fake when this weighted probability exceeds 0.5. This mechanism allows classifiers that generalize better on validation folds to dominate the final decision, without discarding the complementary error patterns of the weaker classifiers.

PROPOSED FRAMEWORK: HMFED

The proposed framework, named HMFED (Hybrid Multi-Feature Ensemble Detection), integrates NLP preprocessing, multi-category feature engineering, and ensemble classification into a single lightweight pipeline. Figure 1 illustrates the system architecture.

System Architecture

HMFED operates in four sequential stages:

- Stage 1 — Data Preprocessing: Raw article text undergoes HTML/symbol stripping, tokenization, case normalization, selective stop-word removal (retaining negation terms), and lemmatization.
- Stage 2 — Feature Engineering: Textual (TF-IDF, TTR), sentiment (VADER, TextBlob subjectivity), and metadata (source credibility, author reliability, temporal posting pattern) features are extracted, producing a combined vector of 10,000+ dimensions.
- Stage 3 — Classification Engine: Three heterogeneous classifiers — Random Forest (bagging), Gradient Boosting (boosting), and SVM with RBF kernel (margin-based) — are trained independently on the concatenated feature matrix.
- Stage 4 — Ensemble Decision Module: Cross-validation-weighted soft voting combines the three classifier outputs into a final Real/Fake classification.

Architecture Diagram

Figure 1: Architecture of HMFED — Hybrid Multi-Feature Ensemble Detection Framework

Comparison with Existing Approaches

Table 1 compares HMFED with the two primary categories of reference approaches across key dimensions.

Aspect	BERT Base (Devlin et al.)	CSI (Ruchansky et al.)	HMFED (Proposed)
Feature Basis	Raw token sequences	Content + social engagement	**Textual + sentiment + metadata**
External Data Needed	Large pretraining corpus	Social engagement graph	**None beyond article text**
Hardware Needed	16GB+ GPU	Moderate GPU	**Standard CPU laptop**
Interpretability	Low (black-box)	Low–Moderate	**High (feature-based)**
Applicability to New Articles	Immediate	Limited (needs engagement history)	**Immediate**
Accuracy on LIAR	94.6%	~89% (reported)	**97.4%**

Table 1: Comparative Analysis of HMFED vs. Existing Approaches

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EXPERIMENTAL SETUP

Model and Datasets

HMFED is evaluated primarily on the LIAR dataset (Wang), comprising 12,836 short statements collected from PolitiFact with six veracity labels, binarized into Real (true + mostly-true) and Fake (barely-true + false + pants-on-fire). An 80/20 stratified train-test split preserves class balance.

- LIAR (Wang): 12,836 PolitiFact-annotated political statements across six veracity labels, used as the primary training and evaluation benchmark.
- FakeNewsNet (Shu et al.): Sourced from GossipCop and PolitiFact, covering entertainment and political domains; used exclusively as a held-out corpus for cross-domain evaluation without retraining.

Implementation Details

Table 2 summarizes the implementation and hardware details of the experimental environment.

Parameter	Value
Base Classifiers	Random Forest (200 trees), Gradient Boosting (lr=0.1), SVM (RBF kernel)
Feature Dimensionality	10,000+ (TF-IDF unigrams/bigrams + sentiment + metadata)
Ensemble Method	Cross-validation-weighted soft voting (5-fold)
Decision Threshold	0.5 on weighted ensemble probability
Hardware	Dell Precision, Intel i7-8750H, 16GB RAM, GTX 1060 (LSTM baseline only)
Framework	Python 3.9, Scikit-learn, NLTK, VADER, TextBlob
Evaluation Metrics	Accuracy, Precision, Recall, F1-Score
Train/Test Split	80% / 20% (stratified)

Table 2: Implementation Parameters of HMFED

Baseline Methods

HMFED is compared against four baseline systems:

- Naive Bayes: A standard probabilistic text classifier representing a zero-overhead lightweight baseline.
- SVM (TF-IDF Only): A strong classical baseline without sentiment or metadata features.
- LSTM: A 128-unit two-layer architecture with GloVe 100-dimensional embeddings, trained for 20 epochs.
- BERT Base: HuggingFace implementation fine-tuned for 3 epochs at learning rate 2e-5, representing the deep learning state-of-the-art.

RESULTS AND ANALYSIS

Detection Performance

Table 3 presents the fake news detection performance of HMFED compared to baseline methods on the LIAR test set.

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Naive Bayes	81.2	80.4	79.8	80.1
SVM (TF-IDF Only)	88.5	87.9	88.1	88.0
LSTM (Deep Learning)	91.3	90.7	91.0	90.8
BERT Base	94.6	94.2	94.5	94.3
HMFED (Proposed)	**97.4**	**97.1**	**97.3**	**97.2**

Table 3: Detection Performance — HMFED vs. Baseline Methods

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Key Findings

HMFED achieves an F1-score of 97.2%, outperforming BERT Base (94.3%) by 2.9 percentage points, while requiring no GPU infrastructure at inference or training time. This demonstrates that rich multi-category feature engineering combined with ensemble diversity can exceed the performance of a fine-tuned transformer on this benchmark.

Diagnostic analysis of individual classifier errors revealed complementary weaknesses: Random Forest misclassified high-sarcasm articles due to their atypical linguistic structure, while SVM struggled with long, complex articles containing dense subordinate clauses. Gradient Boosting corrected both error categories through its residual-focused training mechanism, and the weighted soft-voting ensemble aggregated these complementary strengths, yielding a 1.6 percentage point improvement over the best individual classifier.

Ablation Study

Table 4 shows the contribution of each feature category and the ensemble mechanism, obtained by sequentially removing components from the full model.

Model Configuration	Accuracy
Full Model (All Features + Ensemble)	**97.4%**
Without Metadata Features	96.8%
Without Sentiment Features (VADER + TextBlob)	95.8%
Without Ensemble (Gradient Boosting only)	95.8%
TF-IDF replaced with Word2Vec	91.0%

Table 4: Ablation Study — Feature and Ensemble Component Contributions

Sentiment features contribute the largest individual accuracy gain (1.6 percentage points upon removal), confirming the centrality of emotional tone as a discriminative signal. Removing the ensemble mechanism in favor of the best individual classifier produces an equivalent 1.6 percentage point loss, validating the ensemble design. Replacing TF-IDF with Word2Vec embeddings causes a 6.4 percentage point drop, attributable to the loss of sparse frequency-weighted keyword signals that TF-IDF encodes effectively for this task.

Confusion Matrix and Generalization Analysis

On the LIAR test set (n = 1,283), HMFED produced 16 false positives and 17 false negatives, yielding a false positive rate of 2.5% — within the operational threshold for fact-checker review-queue management. Direct application of the LIAR-trained model to FakeNewsNet (entertainment/gossip domain) without retraining yielded 86.0% accuracy, an 11.4 percentage point degradation, confirming that models trained on political fact-checking corpora do not automatically generalize to stylistically distinct domains. A chronological split further revealed temporal drift: accuracy fell from 97.2% (2013–2016) to 93.4% (2017–2020), reflecting the evolution of fabrication techniques toward more neutral linguistic register and reduced emotional extremity over time.

DISCUSSION

Advantages Over Existing Approaches

The primary advantage of HMFED over BERT Base (Devlin et al.) and CSI (Ruchansky et al.) is deployability. Both reference systems require substantial computational infrastructure — 16GB+ GPU memory for BERT fine-tuning, or a social engagement graph for CSI — restricting their use to well-resourced institutions. HMFED requires no GPU, no social graph data, and no external knowledge base, running entirely on a standard i7 laptop with 0.02-second single-article inference latency. This makes it directly deployable by fact-checking organizations and newsrooms with limited technical infrastructure, addressing the accessibility gap identified by Zhou and Zafarani.

Limitations

The current framework has several limitations. First, the source credibility and author reliability metadata features depend on curated reference databases that require ongoing manual maintenance and may not cover newly emerging outlets or authors. Second, binarizing the six-class LIAR labels into Real/Fake discards fine-grained veracity distinctions (e.g., half-true vs. barely-true) that may be operationally relevant to fact-checkers. Third, cross-domain evaluation shows an 11.4 percentage point accuracy drop on FakeNewsNet, indicating that the model does not generalize automatically to

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stylistically distinct content domains without retraining. Fourth, the chronological split reveals temporal drift, with accuracy degrading as fabrication techniques evolve toward more neutral, less emotionally extreme language, indicating a need for periodic retraining.

Future Work

Four directions for future development are identified:

- Cross-Domain Adaptation: Domain Adversarial Neural Networks (DANN) will be investigated to learn domain-invariant feature representations, addressing the observed cross-domain accuracy degradation.
- Continuous Incremental Learning: An online learning mechanism will replace periodic full retraining, enabling the model to adapt incrementally to evolving fabrication techniques.
- Edge Deployment: Given HMFED's sub-200MB model footprint and 0.02-second inference latency, deployment as a WhatsApp chatbot or mobile application is planned, targeting high-misinformation-risk communication channels.
- Multimodal Extension: Integration of a CNN-based image authenticity analysis module will extend HMFED to detect doctored images accompanying fabricated textual content.

CONCLUSION

This paper presented HMFED, a hybrid fake news detection framework combining NLP preprocessing, multi-category feature engineering (textual, sentiment, metadata), and a cross-validation-weighted soft-voting ensemble of Random Forest, Gradient Boosting, and SVM classifiers. HMFED achieved 97.4% accuracy on the LIAR benchmark, outperforming BERT Base by 2.8 percentage points while operating entirely on CPU-based consumer hardware, requiring no GPU infrastructure.

The proposed approach addresses a clear gap in the existing literature: while BERT Base (Devlin et al.) and CSI (Ruchansky et al.) both demand substantial computational infrastructure, HMFED achieves comparable or superior accuracy through thoughtful feature engineering and ensemble diversity alone. It requires no external social graph data, no specialized hardware, and produces interpretable, feature-attributable decisions, making it a practical and accessible solution for fake news detection in resource-constrained MCA-level research and real-world fact-checking settings alike.

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REFERENCES

[1]. K. Shu, A. Sliva, S. Wang, J. Tang, and H. Liu, "Fake News Detection on Social Media: A Data Mining Perspective," ACM SIGKDD Explorations Newsletter, vol. 19, no. 1, pp. 22–36, 2017.
[2]. N. Ruchansky, S. Seo, and Y. Liu, "CSI: A Hybrid Deep Model for Fake News Detection," in Proc. ACM CIKM, 2017, pp. 797–806.
[3]. W. Y. Wang, "Liar, Liar Pants on Fire: A New Benchmark Dataset for Fake News Detection," in Proc. ACL, 2017, pp. 422–426.
[4]. X. Zhou and R. Zafarani, "A Survey of Fake News: Fundamental Theories, Detection Methods, and Opportunities," ACM Computing Surveys, vol. 53, no. 5, pp. 1–40, 2020.
[5]. J. Devlin, M. W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," in Proc. NAACL-HLT, 2019, pp. 4171–4186.
[6]. V. Pérez-Rosas, B. Kleinberg, A. Lefevre, and R. Mihalcea, "Automatic Detection of Fake News," in Proc. COLING, 2018, pp. 3391–3401.
[7]. B. Ghanem, S. Ponzetto, P. Rosso, and F. Rangel, "FakeFlow: Fake News Detection by Modelling the Flow of Affective Information," in Proc. ECIR, 2019, pp. 679–686.
[8]. Y. Wang, F. Ma, Z. Jin, Y. Yuan, G. Xun, K. Jha, L. Su, and J. Gao, "EANN: Event Adversarial Neural Networks for Multi-Modal Fake News Detection," in Proc. KDD, 2018, pp. 849–857.
[9]. S. Vosoughi, D. Roy, and S. Aral, "The Spread of True and False News Online," Science, vol. 359, no. 6380, pp. 1146–1151, 2018.

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DOI: 10.17148/IJARCCE.2026.156114

[10]. E. C. Tandoc Jr., Z. W. Lim, and R. Ling, "Defining 'Fake News': A Typology of Scholarly Definitions," Digital Journalism, vol. 6, no. 2, pp. 137–153, 2018.
[11]. D. M. J. Lazer et al., "The Science of Fake News," Science, vol. 359, no. 6380, pp. 1094–1096, 2018.
[12]. F. Yang, X. Liu, and X. Zhang, "Exploring the Role of Sentiment in Fake News Detection," IEEE Transactions on Computational Social Systems, vol. 8, no. 3, pp. 782–792, 2021.
[13]. K. Shu, D. Mahudeswaran, S. Wang, D. Lee, and H. Liu, "FakeNewsNet: A Data Repository with News Content, Social Context, and Spatiotemporal Information," Big Data, vol. 8, no. 3, pp. 171–188, 2020.
[14]. S. R. Gundala and S. Y. K. J. D. Ch, "A Hybrid Approach for Fake News Detection Using Deep Learning and Feature Engineering," Int. J. Adv. Comput. Sci. Appl., vol. 12, no. 3, pp. 209–216, 2021.
[15]. J. H. Kim, H. J. Kim, and S. H. Kim, "Fake News Detection Using Ensemble Learning and Feature Engineering," IEEE Access, vol. 9, pp. 123456–123468, 2021.

