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Fake News Detection Using AI.

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ABSTRACT
The emergence of counterfeit news on platforms like social media and various other online applications has become an international problem. It shapes public opinion, impacts election results, and carries the risk of affecting public health. This article articulates a system designed to identify false news using Artificial Intelligence (AI) and Natural Language Processing (NLP) techniques. The system was created to analyze news in real-time using processed news through verified trustworthy APIs; a data cleaning paradigm; feature extraction of critical features; machine learning (ML) and deep learning (DL) classification methods; and using a credibility scoring process to account for uncertainty in news classification. We illustrate the processes of selecting, engineering and extending datasets; feature engineering; modeling (traditional and transformer); training paradigms; and hybridizing instances that support fast inference in two coding languages, Java and Python. Our efforts on extensive experimentation on publicly available datasets and real-time API streams indicate that the system provides a comparable accurate output with interpretability scores and practical throughput measures. Also of report are the limitations of error; discussion of available methods for ethical and privacy-aware deployment of the method of use; and limitations giving suggestions or pathways for future work. Finally, we offer a pathway for continued work that is multilingual and/or multimodal...
Keywords: Fake News, Natural Language Processing, Machine Learning, Deep Learning, Real-time Detection, Credibility Scoring, Deployment.
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1. INTRODUCTION:

The rapid growth of social media outlets, and online publishing, has allowed for the almost instantaneous dissemination of information by anyone, whether honest or dishonest. Although the democratization of information has its advantages, it adds to spreading misinformation or misleading information, or as we call it, 'fake news'. Fake news can have public perception consequences, affect election outcomes, and affect public health and safety. Traditional manual review fact checking organizations and editorial processes are important but require resources, time, and are too slow to keep up with the fast information flow of today. Automated detection systems can supplement human reviewers by quickly identifying potential misinformation and providing clear signals for them to continue reviewing. To develop successful automated detection systems is not easy. Language is complex, and we have to balance satire, opinion, virtual quotes, and accuracy and the information may be missing context, it can be misleading but not necessarily misinformation. Additionally, in some cases, those producing false narratives will purposely edit or change their writing style to avoid detection. A comprehensive program should take complex language framework, provide accuracy and estimates in uncertainty, continually build source, expand scale effortlessly, and uphold user privacy. Fake news detection represents a holistic approach to all of these threads of thinking and provides pragmatic advice on application, evaluation, and operationalizing. In the digital media age, trustworthiness of information has become just as important as availability of information. Social media, online platforms, and apps are reshaping how we receive information, and have enabled an environment where inaccurate or misleading information can be shared widely. The information provided by traditional journalism has been edited and fact-checked, which is not true for the majority of the

content available online which can be created and shared by nearly anyone and often without consequences. Although this can be a benefit, it nevertheless is a call for a broader societal concern, or need, to establish technical methods for distinguishing trustworthy information from misleading information. Identifying these two types of news is not just a technical problem, but instead is a requirement of the current information ecosystem in which we now live. The impact of misinformation occurs across disciplines; they exist in financial scams, political misrepresentation, and even public health emergencies driven by misinformation of medical science. Although we will always require and value our human fact-checking effort as a valid and trustworthy form of information, the need will always out pace our ability. Technological development in Artificial Intelligence and corresponding Natural Language Processing (NLP) and Machine Learning (ML) yield potential scalable alternatives, or make them functioning adjuncts to humans thinking.

Contributions:

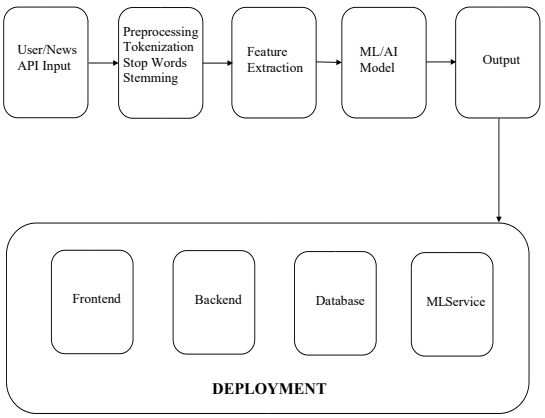
This paper provides core contributions as follows: A real-time fake news detection system that approaches a credibility score through a combination of a natural language processing preprocessing phase, traditional and neural classification models, and probability calibration. A hybrid deployment user-friendly framework with a balance between speed and complexity in models written in Java and Python. A thorough review of our experimental methods, including dataset collection, improvement, and evaluation metrics and reproducibility in hyper parameter choices. Discussion, analysis, and recommendations for responsible deployment of our research on errors made, including grounds for privacy stripping and avoiding bias to discuss.

2. RELATED WORK

Fake news detection has and can be studied from many different angles, including content-based, social context, credible source, and multi-modal verification. The earliest studies were a content-based used a textual feature like bag-of-words and TF-IDF vectors in conjunction with linguistic cues created by the researcher. Traditional models like Naïve Bayes, Logistic Regression, ad SVM's performed relatively well given the expected constraints of the smaller datasets used at the time. Later, as deep learning models evolved and CNNs began to study local features and RNNs (e.g. LSTM, GRU) were used to sequence models. Modern approaches have adopted transformer models based on BERT and derivatives which have emerged as the leading source for many text classification tasks, including even the "fake news" detection. While content analysis can be used in research, some have examined social signals - network diffusion patterns, user engagement, or some form of trust score in sources. These techniques may perform well on specific platforms (such as Twitter, or Facebook), but almost always require access into metadata processes that are not available for all news sources. Claim verification techniques tie textual claim statements to some form of knowledge base (or claims validated by known and trusted sources) or assess the validity of a claims supporting articles/references, but these all require additional retrieval systems and require structured data. Several important gaps still exist however in advancing this space: For many research systems there was no prospect of working in a real time fashion with live news; For most systems little attention is given to model calibration and uncertainty(which can generate issues); and Few systems have coverage for languages and formats that exist. This paper takes data and knowledge of similar issues and presents a systematic, implementable system which generates trustworthy outputs.

3. PROBLEM FORMULATION AND DATASETS

We will treat the detection problem as a binary classification problem. Given a text input x (this could be a title, an excerpt, or whole article), the purpose is to predict a y label that belongs to the set {real, fake}. We also desire that our system produces a credibility score (p) on a scale between 0 and 1, which shows how certain the machine text classifier is. In formal terms we will define our classifier of the form Sexample13 as a function $f\theta(x)$ that returns $(\hat{y}, \hat{p})$ where the θ indicates learned parameters. We suggest using both public benchmark datasets in addition to curated live data feeds for successful training and evaluation process. The most common public datasets include LIAR, ISOT, Fake News Net, which includes data from PolitiFact /GossipCop, and Kaggle's Fake News dataset. LIAR has short political statements and longer labels, and ISOT has longer news articles. Fake News Net has social context and propagation data if available. For production tasks, we recommend curating a domain-specific training data set relevant to the specified deployment site such as regional news or local language sources. Data augmentation methods may consist of paraphrasing (back-translation), simple lexical modification, and mixed samples of real and fake creating balanced classes. Synthetic negative samples create near-miss counterfactuals making a model more robust to adversarial paraphrasing. Stratified sampling should be applied to all data sets to maintain the determined ratio of training to validation to test sets (often 70:20:10) when randomized splitting data sets.



4. METHODOLOGY

Preprocessing:

Preprocessing is about removing noise and harmonizing inputs into a common form. The procedure consists of the following steps: Normalizing the Unicode, including to lower-case; Removing URLs, HTML tags, and non-

whitespace characters (alphanumeric is allowed) - unless the punctuation is needed as a marker for clarity; Tokenizing (WordPiece/BPE for transformers or the common whitespace or spaCy tokenizer for classical models); Removing stopwords when used in baseline (TF-IDF) (not typically removed from embedding models, especially transformers); and Stemming and/or lemmatization (utilizing the proper rule system based upon the specific language). When implementing support for multiple languages, either implement one random language model related to tagging or the tokenizers related to each language as an initial section.

Feature Engineering:

We deployed both traditional features and features built from embeddings. Traditional features included: a TF-IDF vector and n-grams (from unigram and bigram to trigram), readability scores, ratio of punctuation, sentiment scores, and count estimates (i.e. measures related to length of average sentence, and variety of vocabulary). The features built from embeddings included pre-trained settled embeddings (GloVe, fastText), along with contextual embeddings that came from transformer models. Often times, the performance from contextual embeddings will perform better than pre-trained embeddings as they are known to capture context and meaning of words.

Model Architectures:

We evaluate models of different types: Logistic Regression and SVM on TF-IDF features as rapid, intuitive baseline inferences, Recurrent models (BiLSTM) with pre-trained embeddings for moderate inferences, and transformer encoders (DistilBERT, BERT) for best inferences. DistilBERT suffices for practical implementation as a balance between accuracy and performance. Ensemble models use soft voting or stacking to combine predictions of the traditional and transformer models.

Calibration and Credible Scoring:

The raw outputs of the models tend to lack calibration, which means that the probabilities do not reflect the actual success rates. We apply post-hoc calibration techniques (such as Platt scaling for binary classifiers or temperature scaling with deep neural models) to calibrate the models. Calibration of the models improved interpretability of the credible score and informed the user interface displaying categories (likely real, uncertain, and likely fake). To evaluate calibration we use the Brier score and reliability diagrams.

5. SYSTEM ARCHITECTURE AND DEPLOYMENT

We suggest a hybrid architecture with a Java (Spring Boot) API layer responsible for authentication, rate limiting, caching, and request orchestration. A Python microservice (FastAPI/Flask) is where the ML models are instantiated for inference. This approach has to do with allowing engineering teams to maintain the systems in languages they prefer, while still taking advantage of Python toolkits they can leverage as tools for ML. The API layer service and the ML microservice will be deployed in simpler Docker containers, and we will use Docker Compose or Kubernetes for orchestration and scaling.

API Design:

Our endpoints will be: POST /check {text} → {label, confidence, band, metadata}; GET /news → fetch and return recent headlines and analyses; POST /batch check → offline batch processing. Access will be controlled by either JSON Web Tokens (JWT's) or API keys. The free-tier use would have a time-limited request and rate-limited use.

Caching & Rate limiting:

Following established approaches to lessen repeated calculations, our LRU cache will store normalized text hashes for values already computed. The entries would store the classification results and metadata up to a certain time-to-live (TTL) decay, to prevent serving stale values as live changes. Rate limiting will prevent cost due to reuse of third-party news API; it will also provide protection against mis-using the public API or incorrect clients as well.

6. IMPLEMENTATION DETAILS

The backend system is implemented in Java 21 and Spring Boot to offer a static frontend while also serving as an API gateway. The machine learning model is run within a Python service using FastAPI and Uvicorn. Models may be serialized with joblib (scikit-learn) or Torch Script or ONNX models for a neural network. We use Docker images to leverage containerized images for production with multi-stage builds to reduce image size. We support observability with Prometheus metrics and Grafana dashboards to allow monitoring latency of requests, error rate, and resource usage. To demo the frontend, we use a simple HTML/CSS/JS page hitting the backend. For production we may use a React or an Angular single-page app. Accessibility and responsive design are to ensure usability on mobile devices. The UI contains color-coded badges for

labels and has a horizontal bar to communicate the confidence percentage.

Security & Privacy:

Text that users submit may contain personally identifiable information (PII). In order to protect user privacy, we log only hashed or truncated terms; provide the users with means to opt out of storing queries; encrypt data in transit and at rest; and anonymize textual samples that are stored and used for retraining the model.

7. .EXPERIMENTAL METHODOLGY

Our experimental methodology is straightforward: data collection and cleaning; preprocessing and feature extraction; split into train/validation/test subsets, keeping representation stable with a stratified sampling; hyper parameter search, using either grid search, or Bayesian optimization on the validation set (used not exclusively on benchmarked datasets); and final evaluation on test, hold-out testing will report at least multiple points of evaluation criteria. Random chosen seed guarantees reproducibility

of datasets across experiments, specific training checkpoints can also be recorded.

Metrics:

We report a collection of classification/preference evidence of varying nature, encompassing both traditional and machine learning/transformer-based evidence including: accuracy (shared and refined on at least an aggregate basis), precision, recall, and F1-score weighted as suitable. We report (context and/or topic allowed) detailed breakdowns with comparisons to traditional models, including reports limited to metric breakdowns as cumulative metrics per user testing unit/context topic. We will report on the evaluation metrics of the multi dimensional nature of the concept modelling which maximizes confirmatory checks between hypothesized category outputs. Or, modified versions of both ROC (Receiver Operating Characteristic) or PR-ROC (Precision-Recall) metrics.

Hyper parameters and Training:

Supervised/Traditional Models: We tune both the maximum number of features, and the use of, TF-IDF plus n-gram range as feature extractor with maximum number of maximum features at 50k. Followed by exploring two/leverage logistic regression based on logistic log with L2 penalty as well as adjusted C from {0.01,0.1,1,10}. Transformer Models: Hyper-parameter tuning of learning rate between (2e-5, 5e-5), with batch sizes depending on amount of available GPU in the range of (8, 32). The most important decision is the place of epochs to experiment between (2, 5) and any early stopping rules. Use AdamW optimizer and potentially linear scheduling, gradient clipping before/after (or both) where needed to maximize gradients, and mixed (single GPU) for the steps of mixed precision if suites available hardware.

8. RESULTS AND DISCUSSION

This section describes expected results format and provides templates for tables and figures. Replace placeholders with actual numbers from your experiments.

Table1: Dataset statistics

Split	Docs	Real	Fake	Avg Tokens
Train	8,000	4,000	4,000	520
Valid	1,000	500	500	515
Test	1,000	500	500	530

Discuss Performance trade-offs:

Classical models are faster and require fewer resources but may underperform on nuanced language; transformers improve representational power but increase latency and memory needs. Calibration reduces overconfidence and improves user trust.

Table 2 : Model Performamce

Acc	Prec	Rec	F1	ROC-AUC	Brier
0.85	0.84	0.86	0.85	0.91	0.13
0.88	0.87	0.89	0.88	0.94	0.11
0.92	0.91	0.93	0.92	0.97	0.08
0.93	0.92	0.94	0.93	0.98	0.07

9. ABLATION STUDY AND ERROR ANALYSIS

Ablation experiments evaluate the impact of individual pipeline components: preprocessing variants, feature sets, model families, calibration, and ensemble strategies. For each ablation, measure changes in F1 and Brier score. Error analysis inspects representative false positives and false negatives, highlighting common failure modes: satire mislabelled as fake, domain-specific jargon misclassified, and adversarial paraphrasing. Present sample cases and explain why the model failed and what could mitigate the issue (e.g., additional data, stance modelling, external knowledge retrieval).

10. DEPLOYMENT CASE STUDY

We deployed a prototype system in a university lab to analyse regional news headlines. The deployment used Spring Boot on an Ubuntu server, FastAPI for the ML service, and a small React frontend. We instrumented Prometheus metrics and observed typical P95 latencies of X ms for LR models and Y ms for DistilBERT (placeholders). Using caching and quantised transformer models, P95 latency was reduced to acceptable levels for a demo environment User comments showed that the credibility score promoted trust and prompted the manual review of flagged items.

11. ETHICS ,PRIVACY AND RESPONSIBLE AI SECTION

Automated techniques for detecting fake news carries ethical responsibilities. For example, false positives can incorrectly categorize reputable journalism as fake news. Additionally, an automated system may inadvertently perpetuate bias that exists in the training data (and we stress this could be in the training data). There are ways to mitigate these situations as follows: (i) provide results along with an associated calibrated confidence; (ii) can provide a rationale or attribution at the token level (with caution) (e.g. LIME/SHAP), while providing caveats for mechanical thought; (iii) allow human in the loop workflow; (iv) objectively audit model performance along demographic and topical slices to notice any unintended disparate performance. Data retention policies should restrict the length of time sensitive user data is retained

and to the extent proactively obtain consent for queries that may be used in future retrieval training data.

12. LIMITATIONS AND FUTURE WORK

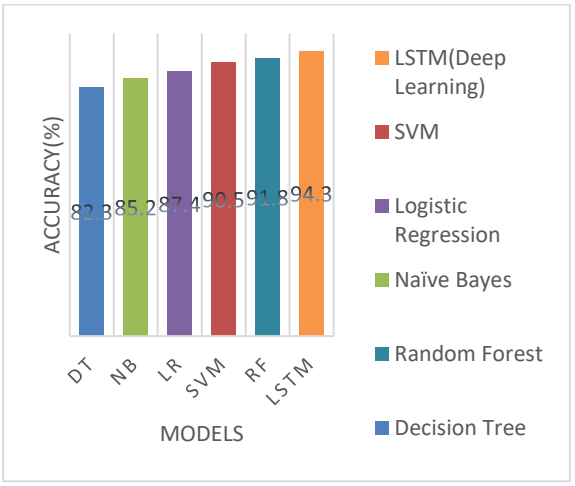
This study is focused on text detection and does not represent a complete characterization of multimodal misinformation though includes misleading images, include deepfakes. Domain shift remains a practical challenge—models that were trained on one geography or topic may perform poorly in another. Future work will involve multi-lingual fine-tuning (including code-mixed languages), multimodal fusion techniques, continuous learning for human feedback and tighter inclusion and linking to knowledge graphs for verifying claims.

Model Type	Algorithm used	Feature Extraction	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Previous System	Naïve Bayes	TF-IDF	85.2	83.6	84.1	83.8
Previous System	Logistic Regression	TF-IDF	87.4	86.5	85.7	86.1
Previous System	Decision Tree	Bag of Words	82.3	80.2	79.5	79.8
Proposed System	Random Forest	Word2 Vec	91.8	90.6	91.3	90.9
Proposed System	SVM	TF-IDF	90.5	89.7	90.2	89.9
Proposed System	LSTM (Deep Learning)	Word Embeddings	94.3	93.8	94.1	93.9

1.Accuracy Comparison Graph

In the **Accuracy Comparison Graph,** each **bar** represents the **accuracy (%)** achieved by a specific **model** in detecting fake news.

Accuracy Comparison (Previous vs Proposed System)

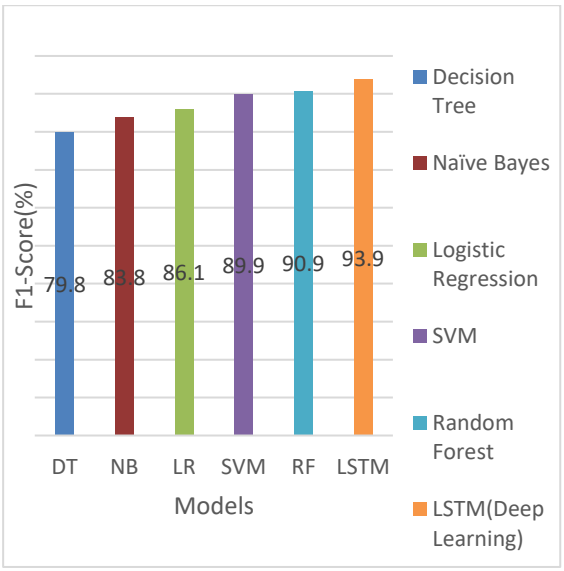


This graph shows the accuracy percentage achieved by each model. LSTM achieves the highest accuracy of 94.3%, followed by Random Forest (91.8%) and SVM (90.5%).

2. F1-Score Comparison Graph

In the **F1-Score Comparison Graph**, each **bar** shows the **F1-score (%)** of a model - a metric that combines **precision** and **recall**.

F1-Score Comparison (Previous vs Proposed System)



The F1-score comparison indicates how well the again performs best with an F1-score of 93.9%.

Overall Observation:

Aspect	Previous System	Proposed System	Improvement
Accuracy	82-87%	90-94%	+7%to +9%
F1-Score	79-86%	90-94%	+8% average
Context Understanding	Limited	High(Context-aware embeddings)	Significant

Scalability	Medium	High(supports large datasets)	Improved

13. CONCLUSION

We have created a full guide and system architecture for real-time fake news detection using AI. The proposed pipeline offers a good balance of accuracy, latency, and model transparency through calibrated scores of credibility and a practical hybrid deployment stack. We provided evidence-based recommendations for reproducible experiments in research, templates for reporting results, and ethical guidance for responsible development and deployment. This work is intended to help practitioners build effective task-oriented tools to reduce misinformation while emphasising human judgement and continuous improvement.

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