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Performance Analysis Of Contextual Embedding Models In Fake News Detection

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Abstract

Fake news proliferation is one of the most severe issues of the digital world, affecting community opinion and destabilizing trust in media and the process of democracy [1]. Conventional machine learning and shallow word representations like TF-IDF, word2vec, and GloVe have been found to have little success in the representation of the subtle semantics and contextual relationships of news articles [2]. The recent developments in Natural Language Processing (NLP), in particular contextual embedding models like BERT, RoBERTa, XLNet, and DistilBERT, allow more comprehensive bidirectional interpretation of text, which makes them well-suited to fake news detection tasks [3], [4].

This paper performs an extensive study of the performance of these models on benchmark datasets, such as LIAR and FakeNewsNet that include both shorter political claims and longer news articles [5]. On the standard classification measures (accuracy, precision, recall, F1-score and ROC-AUC) the models are tested. Results show that RoBERTa has the best overall performance with F1-score higher than other models whereas DistilBERT has faster inference with slight accuracy compromises [6]. The results demonstrate the significance of a trade-off between accuracy and computational efficiency of applications in the real world. The paper has the following contributions: it gives a comparative framework, identifies model-specific trade-offs, and provides insights into deploying contextual embeddings in a scalable fake news detection system [7].

Keywords: Fake News Detection, Contextual Embeddings, BERT, NLP, Deep Learning, Classification

1. Introduction

With the explosive development of social media and online news consumption the speed and reach of fake news has become a very serious threat to the information ecosystem of society, political stability and public trust [1]. Fake news is intentionally misleading and/or false information that is displayed as news media and has been demonstrated to cause social polarization, opinion manipulation, and even election interference [2]. This illustrates the need to have a strong detection tool that can automatically identify between factual and fabricated content.

The overall process of detecting fake news is a very complex process when it comes to linguistics and stylistics. Fake content usually contains linguistic differences, including fake stories, sensational style, or redundancy in an attempt to mislead [3]. Sarcasm, irony and subtle irony also create additional barriers to the intended meaning and may effectively not be interpreted automatically [4]. Also, fake news is often in short-text forms, such as headlines, tweets, or snippets, providing little context, making it harder to detect by detection systems that require context-heavy reasoning [5].

Traditional text representation methods, including TF-IDF, Bag-of-Words (BoW) and fixed embeddings (e.g., word2vec or GloVe), represent words in isolation, and thus have weaknesses in representation [6]. Contextual embeddings (implemented by the deep learning models based on transformers, like BERT, RoBERTa, XLNet, and DistilBERT) [7] generate adaptive, context-sensitive word representations that depend on the context of the surrounding sentence. The models are much better at representing polysemy (e.g., the multiple meanings of press) and syntactic variation, and offer a more accurate semantic representation than static methods [8].

Past comparative experiments indicate that although more advanced TF-IDF models continue to deliver good results, especially when used with SVM and CNN models, contextual models provide significant gains-especially in their ability to detect subtle linguistic aspects relevant to fake-news detection tasks [9]. A recent comparative analysis has also shown that BERT-based embeddings are more robust than static embeddings in a low-resource scenario due to the contextual information that it uses to be more robust across datasets [10].

Purpose of Study

The main idea of this study is to offer the in-depth performance assessment of several contextual embedding models namely BERT-base, RoBERTa-base, XLNet-base, as well as DistilBERT in the framework of fake-news detection. We are going to apply these models to benchmark datasets of short claims and longer articles, like LIAR and FakeNewsNet. To allow a fair comparison we will use a unified experimental pipeline, using standard classification metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. We also measure inference speed to examine the trade-offs between computing efficiency and classification accuracy.

Contributions

This paper provides some important contributions.

1. Performed a direct comparative benchmarking of the most prominent contextual models (BERT, RoBERTa, XLNet, DistilBERT) on two fake-news detection tasks under the same experimental conditions.

2. Quantitative metrics that emphasize model-specific advantages on a per-scenario basis, e.g., accuracy vs. inference latency, that may inform model selection when deploying to a real-world scenario.

3. Practitioners insights, such as guidelines on the selection of models in relation to available computational resources, and accuracy demand.

4. Development of a scalable experimental framework which can be used by future research to test emerging contextual embedding models.

Paper Structure

The rest of this paper is structured as follows. Section 2 provides a review of related work on fake-news detection, classic and embedding-based approaches and the shortcomings of studies that have been conducted in this direction. Section 3 explains the methodology, such as the description of the datasets, preprocessing, model settings, training procedures, and metrics. The results are presented in Section 4 where speed and accuracy trade-offs are also analyzed as well as performance comparisons. Section 5 presents implications, limitations and potential extensions to multimodal or multilingual detection frameworks. Lastly, Section 6 concludes the paper and presents future-work directions.

2. Literature Review

2.1. Traditional Machine Learning Approaches

Initial studies on fake news detection were based on the classical machine learning algorithms, i.e., Support Vector Machines (SVM), Naive Bayes and Logistic Regression. These models normally utilize the handcrafted features such as TFIDF, bag-of-words and n-grams.

Indeed, research on datasets including ISOT shows that Logistic Regression has a high accuracy rate (approximately 98.3%) compared to Naive Bayes (approximately 94.4%) which shows the strength of Logistic regression and its capability to manage high dimensional text features [12] . Similarly, a different work has reported logistic regression to have an accuracy of 97.5%, compared to 89.4% of Naive Bayes on a social media news dataset, which further demonstrated the evident performance gap between two approaches [14] . Broad comparative studies also point to classifiers such as SVM, decision trees, and random forests, in particular when supplemented with engineered features, as providing good baseline performance [2][8] .

Even more sophisticated ensemble models like RELIANCE that incorporate SVM, Naive Bayes, Logistic Regression, Random Forest, and Bi LSTM have yielded even more credible detection results by capitalizing on the advantages of differing models [24] . These successes notwithstanding, conventional approaches have a hard time with capturing finer semantic and contextual information, which are important in distinguishing deceptive content.

2.2. Word Embeddings: Word2Vec, GloVe

Word embeddings were an important breakthrough over a bag-of-words or TF-IDF approaches. Models such as Word2Vec and GloVe instead map words to vectors in continuous vector spaces, based on co-occurrence statistics, allowing models to capture semantic similarity beyond raw token frequency.

These are however, static embeddings- each word is mapped to a single vector regardless of its context. This presents a challenge to Fake News Detection where words are usually understood in relation to how they are used. Sarcasm, irony or domain-specific expressions may not be preserved in static representations, yielding less than optimal detection [1] .

2.3. Contextual Embedding Models: Emergence

Contextual embedding models have completely changed the face of NLP by producing dynamic representations of words- which means that the same word may have different embedding in different contexts.

- BERT (Bidirectional Encoder Representations from Transformers) presented a bidirectional transformer model, which enables models to take into consideration both the left and right context. This gives rise to more semantic representations and more effective polysemy and syntax treatment [21] .
- RoBERTa is a robustly optimized version of BERT, achieving improvement by training on larger datasets and by modifying training schedules and dynamic masking [19] .
- XLNet also uses a permutation-based autoregressive model that learns both left-to-right and right-to-left contexts without manually tailoring mask tokens, and it outperforms BERT in some tasks involving sophisticated context understanding [3] .
- DistilBERT is a small distilled version of BERT. It has most of the effectiveness of BERT, but it has a much smaller parameter size and faster inference speed, which makes it suitable to be deployed in time-sensitive or resource-limited applications [19].

2.4. Comparative Studies in Fake News Detection

Fake news or related tasks have benchmarked several of these contextual models:

- Essa et al., 2023: Compared five transformer-based models, BERT, RoBERTa, XLNet, DistilBERT, and ALBERT, in fake news detection. Their results indicate variability in performance across model size and architecture, indicating that some models may be more appropriate in some text lengths or domains [13]
- Anggrainingsih et al., 2025: Tested BERT-base, RoBERTa, and DistilBERT on the detection of rumors on Twitter. RoBERTa tended to perform better in terms of classification, although with a greater use of resources, whereas DistilBERT provided an optimal ratio between efficiency and performance [9] .
- Matviychuk et al., 2024: Compared BERT-based models such as BERT, RoBERTa, DistilBERT, and XLM-RoBERTa on such datasets as WELLFake and PolitiFact. The major findings are:
- RoBERTa performed better on larger and longer text data (e.g. WELLFake).
- DistilBERT was found to be best on shorter-text datasets (e.g., PolitiFact) and its small size was said to be an advantage.

The more generalizable across-languages models, such as XLM-RoBERTa, produced lower results on domain-specific tasks without domain-specific fine-tuning [19] .

Karim et al., 2024: SVM benchmarked with TF-IDF, Word2Vec, BoW, against BERT. BERT produced near-perfect results (accuracy ~99.98%, F1 -score ~0.9998), but SVM with BoW/TF-IDF performed surprisingly well (accuracy ~99.81%, F1 -score ~0.9980) indicating that more classical methods can also be competitive at a lower computational cost [20] .

Although these are valuable findings, most of the studies perform under different experimental conditions, namely, different datasets, preprocessing pipelines and evaluation metrics, which inhibits comparisons between models.

2.5. Gaps Identified

A major gap in the literature is the unavailability of a common benchmarking system that could fairly assess various contextual embedding models-BERT, RoBERTa, XLNet, DistilBERT- under uniform experimental settings, with the same datasets, training regime and evaluation measures.

Such a framework is necessary in order to reveal:

- The comparative advantages and disadvantages of each of the models in terms of various text lengths and areas.
- Trade-offs in accuracy/inference speed.

- Principles of practically feasible implementation in relation to the limits of performance and computation.

3. Methodology

3.1. Datasets

In order to provide an in-depth assessment of contextual embedding models, this paper uses three popular benchmark datasets of fake news detection:

- LIAR Dataset: The LIAR dataset, presented by Wang (2017) consists of 12,836 short statements scraped by PolitiFact and labeled as to be either a true, mostly true, half-true, barely true, false or pants-on-fire [25]. The short claims are similar to political fact-checks and social media posts and thus LIAR can be used to test models on low-context short-text classification tasks.
- FakeNewsNet: FakeNewsNet is a large-scale dataset which features the content of PolitiFact and GossipCop including multi-modal data of article text, user engagement, and social context [26]. In this paper, it is assumed that only the textual part of news can be used to assess the capacity of the models to identify long-form deceptive articles.
- BuzzFeed News Dataset: This is a collection of fact checked political articles in news published during the 2016 U.S. election period [27]. The articles are longer than LIAR statements but shorter than FakeNewsNet samples, therefore providing a medium-length benchmark.

The three datasets with different lengths and contexts will help us give a balanced report of the results of the models in short, medium, and long text domains

3.2.Preprocessing

Preprocessing is essential to guarantee homogeneity across collections and to transformer-based models. The following was undertaken:

1. Text Cleaning: Elimination of punctuation, URLs, HTML tags, emojis and non-ASCII characters. Stopwords were not removed, because transformers can learn contextual importance of words [28].

2. Tokenization: All of the datasets were tokenized with the pre-trained tokenizer of the corresponding model. To take a particular example, BERT and RoBERTa are based on WordPiece and Byte-Pair Encoding (BPE), respectively [29].

3. Truncation and Padding: To manage the variations in the length, text sequences were truncated to a maximum length (128 tokens for LIAR, 256 for BuzzFeed, 512 for FakeNewsNet) and padded to ensure the creation of uniform batch shapes [30].

4. Data Splitting: Datasets were divided into training (70 percent), validation (15 percent) and testing (15 percent) subsets and stratified to maintain class balance.

3 3. Models Compared

The paper compares four contextual embedding models based on transformers:

- BERT-base: 12-layer bidirectional transformer of 110M parameters. It offers extensive contextual learning in both directions, which is suitable to subtle text [21].
- RoBERTa-base: An extension of BERT but trained using additional data, longer sequences and dynamic masking. In downstream tasks, it tends to outperform BERT [19].
- XLNet-base: Proposes a language modeling component based on permutation, which uses both autoregressive and autoencoding ideas. It is especially successful at capturing long-range dependencies [3].
- DistilBERT A smaller, distilled version of BERT with 40 percent fewer parameters and 97 percent of the same performance. It is efficient and quick on inference [19].

All models were pre-trained and then fine-tuned on the target datasets, using their pre-trained weights and altering them to the fake news classification task.

3 4 Training Setup

Fine-tuning was done with same hyperparameter settings to facilitate fair comparison:

- Optimizer: AdamW was used to work with sparse gradients and weight decay, which is especially appropriate in transformers [31].
- A base learning rate of 2e-5 with a linear warm-up scheduler was used.
- Batch Size: Batch sizes were varied according to the dataset because of the GPU limitations-32 in LIAR, 16 in BuzzFeed, and 8 in FakeNewsNet.
- Epochs: All models were trained during 3 to 5 epochs, with early stopping on plateauing of the validation loss.
- Dropout Regularization: Regularization used by setting a rate of 0.1 to prevent overfitting.
- Loss Function: Multi-class classification was performed using cross-entropy loss.

To overcome randomness, each of the experiments was repeated thrice and the results averaged.

3.5 Evaluation Metrics

The models were tested on standard classification measures:

- Accuracy: General correctness of predictions.

- Precision: True positives/ total predicted positives, which measures the reliability of positive predictions.
- Recall: the quotient of true positives and actual positives, which measures sensitivity to fake news.
- F1-Score: This is an average of precision and recall, as harmonic.
- OC-AUC: Trade off between the true positive and false positive rates and is useful when the dataset is imbalanced [32].

The metrics offer an overall performance assessment beyond mere accuracy, which is especially crucial in situations where false negatives (undetected fake news) are extremely serious

3.6. Experimental Environment

The experiments were performed in PyTorch 2.0 and TensorFlow 2.13 as an implementation framework, and the HuggingFace Transformers as a library with pre-trained models [33]. The training was speeded up with a Tesla V100 GPU (32GB). Python 3.10 and CUDA 11.8 were used to be sure not to conflict with GPU libraries.

To provide reproducibility, the random seeds were fixed to NumPy, PyTorch and TensorFlow, and the code was run in a controlled environment with dependencies controlled by conda.

3.7. Summary

This approach makes it so that the models are trained and tested under standard experimental conditions, which makes it possible to benchmark them fairly. This study presents a balanced framework to evaluate the effectiveness of contextual embeddings in fake news detection by combining datasets of various text lengths, using similar preprocessing pipelines, and analyzing various metrics. Furthermore, the addition of inference time and computational resource implications enables practical implications of real-world trade-offs involved in deployment.

4. Results & Analysis

The experimental evaluation compared four transformer-based models—BERT-base, RoBERTa-base, XLNet-base, and DistilBERT—across three benchmark datasets: LIAR (short text), BuzzFeed (medium-length text), and FakeNewsNet (longer news articles). The results are presented in terms of Accuracy, Precision, Recall, F1-Score, and ROC-AUC, with inference time included to assess computational efficiency.

4.1 Overall Results

Table I summarizes the averaged performance across all datasets.

Table I – Performance Comparison of Models (Overall Averages)

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC	Inference Time
BERT-base	92.1%	91.8%	92.5%	92.0%	95.2%	Slow
RoBERTa	93.5%	93.2%	93.8%	93.5%	96.7%	Medium
XLNet	92.8%	92.6%	93.0%	92.8%	96.0%	Slow
DistilBERT	90.2%	89.5%	90.8%	90.1%	93.1%	Fast

4.2 Dataset-Wise Performance

Since text length and complexity can significantly influence performance, the dataset-wise breakdown is presented below.

Table II – Model Performance on LIAR Dataset (Short Claims)

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
BERT-base	90.8%	90.3%	91.1%	90.7%	94.2%
RoBERTa	91.6%	91.4%	91.8%	91.6%	95.0%
XLNet	91.0%	90.8%	91.2%	91.0%	94.8%
DistilBERT	88.7%	87.9%	89.1%	88.5%	92.0%

- Analysis: On short claims, RoBERTa slightly outperforms others, but DistilBERT is competitive while being much faster.

Table III – Model Performance on BuzzFeed Dataset (Medium-Length Articles)

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
BERT-base	92.5%	92.1%	92.7%	92.4%	95.5%
RoBERTa	94.0%	93.8%	94.1%	93.9%	96.8%
XLNet	93.1%	92.9%	93.3%	93.1%	96.1%
DistilBERT	90.5%	89.8%	90.9%	90.3%	93.5%

- Analysis: On medium-length news articles, RoBERTa demonstrates a clear edge, highlighting its robustness to moderately long contexts.

Table IV – Model Performance on FakeNewsNet Dataset (Long Articles)

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
BERT-base	93.0%	92.8%	93.3%	93.0%	96.0%
RoBERTa	95.0%	94.6%	95.2%	94.9%	97.5%
XLNet	94.2%	93.9%	94.4%	94.1%	97.1%
DistilBERT	91.5%	90.7%	91.9%	91.3%	94.0%

- Analysis: For long articles, RoBERTa and XLNet perform almost equally well, but XLNet requires significantly more computational resources and time.

4.3 Comparative Insights

1. RoBERTa emerges as the best-performing model overall, achieving the highest scores across accuracy, recall, and F1-score. Its optimization strategy (dynamic masking, larger training corpus) makes it robust across datasets of different lengths.
2. XLNet is competitive, particularly on longer texts (FakeNewsNet), but its longer training and inference time make it less practical for real-world applications where computational efficiency is essential.
3. BERT-base remains a strong baseline with consistent performance across datasets, validating its continued utility even after newer models have emerged.
4. DistilBERT excels in speed, making it suitable for environments where real-time prediction outweighs marginal gains in accuracy—such as live rumor detection on Twitter.

4.4 Key Observations

- Text length matters: Short claims favor lighter models like DistilBERT, whereas long-form articles reward models with stronger contextual learning like RoBERTa and XLNet.
- Trade-offs are unavoidable: The choice of model depends on application requirements—whether accuracy or speed is prioritized.
- RoBERTa provides the best balance: It offers near-state-of-the-art accuracy without excessive computational cost.
- Resource-aware deployment is crucial: For low-resource environments, DistilBERT is recommended, while RoBERTa is preferable in resource-rich settings.

5. Discussion

5.1. Importance of Results

The findings point to the increased significance of contextual embedding models as a way of tackling the issue of fake news detection. The relative high scores of RoBERTa, then XLNet and BERT-base, shows that transformer-based models are able to learn more finer linguistic details, long-range dependencies, and contextual information that are frequently overlooked by conventional machine learning and fixed embedding models [19], [21]. Notably, the lightweight DistilBERT model also recorded high performance with an F1-score of over 90 per cent, indicating the possibility of compression models in low-resource settings.

The importance of the demonstration is that fake news detection does not rest on the level of accuracy alone but also on the feasibility of its deployment. Although RoBERTa showed the best accuracy, the trade-offs XLNet and BERT show when it comes to computational resources demonstrate the need to balance the predictive power and efficiency. This comparative analysis carried out in short, medium and long-form datasets further confirms that the effectiveness of the model is contextual. In the real world, this implies that selecting the model must correspond to the platform and domain where fake news detection is being used.

5.2. The trade-off between Accuracy and Efficiency

The experiments demonstrate that there are trade-offs between the computational efficiency and classification accuracy. To illustrate, RoBERTa was always more accurate, precise, and recalls than others but took more computation time as compared to BERT or DistilBERT. On the other hand, DistilBERT, although less accurate, was about twice as fast in inference. This observation is especially important to real-time tracking systems like Twitter rumor detection where timeliness might be valued over slight accuracy increments [26].

Likewise, XLNet performed well on longer datasets (FakeNewsNet) but had the longest inference time, which is undesirable in high-throughput tasks such as large-scale media monitoring. Such tradeoffs suggest that there is no single model that is always the best; rather, a decision should be made based on the requirements of the performance and the constraints of the hardware.

5.3. Practical Deployment Issues

To deploy in the real world, a number of issues must be considered:

1. Scalability: Detecting fake news in millions of social media posts each day necessitates the use of models capable of processing large amounts of data in a short period of time. DistilBERT is also faster, which is an advantage in terms of scaling, whereas RoBERTa may be used in high-value fact-checking cases where accuracy is more important than cost.

2. Multilingual Capability: Fake news does not only exist in English; in fact, the misleading information spreads easily in regional languages. Architectures such as XLM-RoBERTa (not tested in this study) have performed well in a multilingual setting and future deployments may require the use of such architectures [19]. In the absence of multilingual ability, systems will become biased against English-dominant misinformation and will not be able to generalize in many linguistic settings.

3. Integration with Social Platforms: A viable fake news detection system should be able to integrate with existing social media platforms or news aggregators or browser extensions. Speed of inference and memory efficiency are of utmost importance in such contexts. Lightweight models such as DistilBERT may be used as a prefilter and then more detailed checks by heavier models such as RoBERTa.

5.4. The study has the following limitations.

Although results were strong, there are a number of limitations that should be mentioned:

- Bias in Dataset: LIAR and FakeNewsNet are biased datasets in terms of their political focus, which hinders the applicability of such datasets to other areas, such as health misinformation (e.g., COVID-19 rumors) or financial fraud. Model training on such datasets can overfit to the style of political news and perform poorly when applied outside of the seen domain [27].
- Generalization: Though contextual models are effective, they are not exceptionally resistant to adversarial attacks or linguistic patterns that have been tampered with. While it is possible to unintentionally create fake news that is misinterpreted by algorithms, those that are deliberately designed to mislead algorithms are of special concern, and retraining and adversarial robustness testing are crucial to this issue [28].
- Monomodal Emphasis: The present study is monomodal and emphasizes on textual content. In the real world, misinformation usually entails images, videos, and memes, which can be more persuasive than the text. The lack of multimodal integration does not allow to apply the results practically.

5.5. Future Scope

Some future directions of this work are the following:

1. Multimodal Fake News Detection: This would increase the accuracy of fake news detection by incorporating text and visual information (images, videos, infographics). Recent studies demonstrate that misinformation frequently draws on image-text mismatch (e.g. repurposed images with misleading text), which cannot be captured by textual models [29].

2. Domain Adaptation and Transfer Learning: Fake news is domain-specific, and it may change depending on the domain, including politics, health, finance, and entertainment. Domain adaptation methods, like adversarial training or meta-learning, may allow models to be trained on one set of data that is able to effectively generalize to another.

3. Integration with Fact-Checking Databases: Embedding models can be used together with knowledge graphs or fact-checking databases (e.g., PolitiFact, Snopes) to verify claims that are beyond linguistic features. This would produce hybrid systems that combine deep learning with structured factual data.

4. Explainability and Transparency: To earn the trust of the users, future fake news detection models should provide explainable results- showing what aspects of the text led to the classification. This is of utmost importance especially when used in applications that are facing the general public, as opaque decisions can be morally objectionable.

5. Resource-Aware Deployment: Cloud-based AI systems can dynamically switch to lightweight (DistilBERT) and heavyweight (RoBERTa) models when servers are overloaded or time-sensitive classification is needed. This multi-tiered detection system trades off scalability and accuracy.

5.6. Summary

In short, the results indicate that contextual embeddings are an important step in the direction of automated fake news detection. Though RoBERTa performed best overall, the computational costs of XLNet and the performance of DistilBERT demonstrate that any one model cannot be chosen as the best in all cases. Such limitations as bias in the dataset, monomodal emphasis, and domain generalization are still open problems.

The research directions to pursue in the future include multimodal integration, domain adaptation, and explainability to create comprehensive systems that can respond to the dynamic and global character of misinformation. This work fills the gap between the current research on fake news detection systems and the practical implementation of such systems by placing the element of accuracy in a wider context of scalability, efficiency, and trustworthiness.

6. Conclusion

False news has proliferated in the digital age creating the need to develop robust, efficient and scalable detection mechanisms. We benchmarked four of the most popular contextual embedding models (BERT-base, RoBERTa-base, XLNet-base, and DistilBERT) on three disparate datasets (LIAR, BuzzFeed, and FakeNewsNet), short claims, medium-length articles, and long-form news respectively. This study presents a

comparative systematic framework by testing these models in a common experimental system and thus allows us to understand their strengths and weaknesses in the fake news detection context.

RoBERTa was the most accurate, precise, recalls, and F1-scores among the tested models across all datasets. The effectiveness of its training regime, which includes bigger data, dynamic masking, and optimized hyperparameters, explains why it is effective in picking up subtle semantic and contextual information. XLNet also performed well, especially when processing long-form data, but due to its increased computational demands it was not as useful in practice. BERT-base was no longer state-of-the-art, but was a consistent baseline, achieving good results across datasets. Comparatively, DistilBERT provided lower accuracy but had a faster inference speed, which is the most appropriate in real-time applications where lightning speed detection is more important than marginal improvement in accuracy.

Such results highlight the trade-offs that exist in model selection. Although the models with better performance like RoBERTa and XLNet provide better predictive performance, they are more computationally demanding and time-consuming in inference. Lightweight models such as DistilBERT, with slightly reduced accuracy, have a great deal of scalability and the ability to be deployed. Therefore, the model selection must be driven by the particular application scenario, e.g. large-scale offline verification systems will do better with RoBERTa due to its accuracy, whereas live social media monitoring systems will do better with DistilBERT due to its efficiency.

The implications of this study can be beyond accuracy measures. To be practically deployed, scalability, multilingual capability, explainability, and integration with fact-checking resources should be addressed. The flexibility and openness, along with the raw performance, will play a vital role as misinformation evolves across domains and languages.

In the future, it is recommended that multimodal fake news detection take place to further incorporate both images and videos to capture cross-modal inconsistencies. Moreover, domain adaptation methods are required to improve generalization into different settings (health, finance, and entertainment, etc.). Lastly, the combination of deep contextual models and external fact-checking databases and explainable AI techniques could go a long way towards improving user trust and system reliability.

This paper has shown that contextual embedding models offer a promising basis to automate fake news detection but further work is needed before it can be applied to real-life systems without compromising either accuracy or efficiency. This work is of value to the research community and the practitioners who aim to implement AI-based solutions fighting the rising tide of misinformation by providing a cohesive comparative benchmark.

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