Fake News Detection Using Large Language Models

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I. Introduction

In today's digital era, the widespread use of the internet and social media has dramatically transformed the way information is created, disseminated, and consumed. While these advancements offer unprecedented access to knowledge and communication, they have also facilitated the rapid spread of misinformation, particularly fake news. Fake news can originate from disinformation (intentionally fabricated content for specific purposes) or evolve as misinformation (false content shared unknowingly by individuals who believe it to be true). Psychological factors, such as confirmation bias, further exacerbate the issue; people tend to accept and share information that aligns with their personal beliefs, regardless of its factual accuracy. Behavioural studies suggest that exposure to fake news increases the likelihood of belief in the content, and even when individuals recognize the content as false, they may still share it to affirm social identity, signal political alignment, or elicit emotional reactions from their network [2] .

An MIT study that tracked 126,000 stories revealed an alarming trend, fake news stories are approximately 70% more likely to be retweeted on Twitter than factual stories and reach audiences six times faster than the truth [7]. The proliferation of fake news has severe implications for societal trust and democratic institutions. For example, recent surveys indicate that two-thirds of EU citizens encounter fake news at least once a week, and over 80% consider it a significant issue for their country and democracy in general [18].

As the challenge of combating fake news becomes increasingly urgent, researchers have turned to artificial intelligence (AI) solutions to address this complex and evolving problem. Initially, traditional machine learning (ML) models were employed to detect fake news by analyzing patterns in text data. These models used various natural language processing (NLP) techniques to preprocess the data before classification. This preprocessing phase often involved tasks such as tokenization (breaking text into smaller units like words or phrases), lemmatization (reducing words to their base forms), and the removal of stop words (common words like ”and,” ”the,” or ”is,” which don't carry significant meaning in this context). The preprocessed data was then passed through various ML algorithms, such as Decision Trees, Support Vector Machines (SVMs), or gradient boosting models like XGBoost, which were tasked with identifying linguistic features, sentiment markers, or other cues that might indicate falsified or biased information. These traditional models offered some success in detecting fake news but often faced challenges in dealing with the complexities and evolving nature of the language used in modern misinformation campaigns. For example, they struggled to account for the subtleties of context, irony, and manipulation that are commonly used in fake news stories [22], [25].

In response to these challenges, recent breakthroughs in Large Language Models (LLMs), such as OpenAI's GPT models, have revolutionized the domain of fake news detection. LLMs, which are built with billions of parameters and trained on massive, diverse datasets, have an exceptional ability to understand the intricacies of language and context [6]. Unlike traditional ML models, which rely on manually defined features, LLMs can grasp the broader meaning of text, including contextual nuances, which are crucial in identifying misleading or false information [9]. For example, these models can better detect the subtle ways in which fake news might manipulate facts or appeal to emotions through language that might be overlooked by traditional models.

The key advantage of LLMs is their ability to go beyond simple feature extraction, moving towards a more sophisticated semantic and contextual understanding of news content. This allows them to analyze not just the surface-level linguistic elements, but also the deeper meaning, tone, and intent behind the words. As a result, LLMs have significantly improved the accuracy and robustness of fake news detection, outperforming older ML models in detecting even the most subtle or deceptive forms of misinformation. By focusing on the broader context and understanding how information is framed, LLMs are helping to address the growing problem of fake news in ways that traditional models simply could not [4], [24].

In our paper, we aim to investigate two key questions that remain central to the effectiveness of AI-driven fake news detection:

1. Are LLMs more accurate in detecting fake news than traditional ML algorithms? This question seeks to assess the performance differences between traditional ML algorithms and modern LLMs in identifying fake news. By comparing metrics such as accuracy, precision, recall, and F1-score across various models, we aim to quantify whether the contextual understanding afforded by LLMs translates to better detection rates.

2. Do hybrid models that combine Large Language Models (LLMs) with traditional machine learning models or Small Language Models (SMLs) offer improvements in fake news detection? Hybrid models, which combine the strengths of LLMs with more lightweight or interpretable models, represent an intriguing area of research. These combinations could balance the computational intensity of LLMs with the efficiency and interpretability of smaller models, potentially

enhancing overall model performance and providing faster, more resource-efficient solutions.

II. Related Work

The problem of fake news detection has been extensively studied, with advancements spanning traditional machine learning approaches to the adoption of large language models (LLMs). This section provides a detailed review of relevant works, focusing on specific methodologies and their contributions.

A. LIAR Dataset

1) Fake News Detection Using Machine Learning Approaches: Khanam et al. [12] examined the application of traditional supervised machine learning methods, including Support Vector Machines (SVMs), Random Forest, and XGBoost, for fake news detection. Using TF-IDF for feature extraction, the XGBoost classifier achieved the highest accuracy of 75%. While computationally efficient, the study highlighted the limited scalability of such approaches to multi-modal datasets and their inability to leverage contextual understanding.

2) Fake Detect: A Deep Learning Ensemble Model for Fake News Detection: Aslam et al. [1] proposed a deep learning ensemble model for fake news detection, leveraging the LIAR dataset. The authors employed a hybrid approach using two deep learning models: a Bi-LSTM-GRU network for textual attributes (statements) and a dense model for non-textual attributes (e.g., speaker's job title and context). Preprocessing steps included tokenization, lemmatization, stop-word removal, and word embeddings using FastText.

The proposed model achieved an accuracy of 89.8% and an F1-score of 0.914, outperforming traditional machine learning methods and prior CNN-based approaches. However, challenges included the limited contribution of non-textual attributes to classification and reliance on a single dataset, which limited generalizability to other domains.

3) An Ensemble Machine Learning Approach to Classify Fake News: Hakak et al. [8] developed an ensemble machine learning approach that focused on effective feature extraction. They used the LIAR and ISOT datasets. The study emphasized robust preprocessing techniques, such as tokenization, noise removal, and Named Entity Recognition (NER) to extract features like word count and average sentence length.

The ensemble model combined Decision Tree, Random Forest, and Extra Tree classifiers using a bagging approach for stability. Results demonstrated 100% accuracy on the ISOT dataset and 99.96% training accuracy with 44.15% testing accuracy on the LIAR dataset. However, generalization remained an issue, particularly for the LIAR dataset, due to its complexity and multi-class nature.

4) Fake News Prediction Using Machine Learning Approaches: Mushtaq et al. [17] focused on fake news prediction using the LIAR dataset. Their research employed machine learning classifiers, including Naïve Bayes, Random Forest, Decision Tree, and Neural Networks. Preprocessing steps included data cleaning to remove noise and unnecessary symbols and statistical feature extraction, such as analyzing word distributions and subject categories.

The study highlighted the effectiveness of Naïve Bayes, which achieved a 99% accuracy due to its ability to reduce variance and mitigate overfitting. Compared to other classifiers, Naïve Bayes required less computational time while maintaining high precision and recall. Despite the promising results, challenges included limited exploration of deep learning approaches and reliance on static benchmark datasets, which may not reflect the real-time complexities of fake news on social media.

5) A Better Large Language Model Using LoRA for False News Recognition System: Tiwari [21] introduced a framework leveraging Low-Rank Adaptation (LoRA) to fine-tune the LLaMA2-7B language model for fake news detection. LoRA reduces the computational demands of training large-scale language models by decomposing their weight matrices into low-rank components, enabling task-specific adaptation with fewer parameters. The study utilized datasets such as the COVID-19 FakeNews dataset, LIAR dataset, and the FakeNews Challenge dataset. The preprocessing pipeline included text normalization and imbalance correction through class weighting.

The results showed significant performance improvements, with accuracy reaching 97.33% on the COVID-19 dataset, 98.66% on the FakeNews Challenge dataset and 62.67% on the LIAR dataset. These findings underscore the effectiveness of LoRA in optimizing LLMs for resource-constrained environments. Despite these successes, the study noted diminishing returns with extended training durations and emphasized the need for further research on efficient adaptation techniques.

6) A Novel Framework for Fake News Detection Using Double Layer BI-LSTM: Merryton and Augasta [16] developed a novel framework based on Double Layer Bi-LSTM for enhancing fake news detection. By stacking two Bi-LSTM layers, the model captures both short-term and long-term dependencies in textual data. The framework combines traditional preprocessing techniques, such as the Porter Stemmer and TF-IDF vectorization, with deep learning for feature extraction.

The study evaluated the framework on three datasets: the Kaggle Fake_Real_News, LIAR, and Politifact datasets. Results showed a 97.58% accuracy on Kaggle and 83% accuracy on Politifact. However, the model underperformed on the LIAR dataset (61.19%), likely due to its limited ability to handle highly imbalanced classes and nuanced text features. This indicates potential areas for improvement, such as incorporating attention mechanisms for better feature weighting.

7) Fighting Lies with Intelligence: Using Large Language Models and Chain of Thoughts Technique to Combat Fake News: Kareem and Abbas [11] introduced the Chain of Thoughts (CoT) reasoning approach to enhance the interpretability and accuracy of fake news detection systems. By fine-tuning FLAN-T5 and LLaMA-2 with CoT annotations, the models were able to provide logical justifications for their predictions. The accuracy of the initial model of 39. 25% improved when the classifications were reduced to true or false, achieving accuracy of 84. 26% in a dataset enriched with CoT-annotated records.

While the CoT approach improved transparency, challenges included limited performance gains on multi-class datasets and the need for richer annotation schemes. The study concluded with recommendations for integrating CoT with multimodal data for enhanced generalizability.

8) Re-Search for the Truth: Multi-Round Retrieval-Augmented LLMs for Fake News Detection: Li et al. [14] proposed the STEEL framework, which combines multi-round retrieval mechanisms with LLMs for dynamic evidence collection and claim verification. By sequentially retrieving high-quality evidence until confidence thresholds are met, the framework outperformed traditional single-retrieval methods.

STEEL was evaluated on the LIAR (True and False Classes), CHEF, and PolitiFact datasets, achieving F1-Macro scores of 0.714, 0.793, and 0.751, respectively. The multi-round retrieval mechanism significantly improved accuracy in detecting fake news. However, reliance on internet accessibility and the limitations of LLM context lengths were noted as challenges.

9) Fake News Detection with Large Language Models on the LIAR Dataset: Boissonneault and Hensen [3] conducted a detailed evaluation of LLMs like ChatGPT and Google Gemini in the LIAR dataset (True and False Classes). Google Gemini achieved an accuracy of 89.4%, outperforming ChatGPT in terms of precision and recall. Despite these strong results, the study highlighted limitations in handling nuanced contextual information, suggesting the need for domain-specific fine-tuning to improve the detection of subtle misinformation.

B. Other Datasets

1) Integrating Large Language Models and Machine Learning for Fake News Detection: Teo et al. [20] proposed a hybrid method combining LLMs with traditional machine learning algorithms, specifically using ChatGPT-3.5 outputs as features for XGBoost classifiers. This integration leveraged the contextual strengths of LLMs and the efficiency of XGBoost, achieving an accuracy of 96.39%. The study emphasized the potential of hybrid models to balance interpretability and computational efficiency, particularly in resource-constrained settings.

2) CSI: A Hybrid Deep Model for Fake News Detection: Ruchansky et al. [19] presented the CSI framework, which integrates three key elements: content, social context, and user engagement behaviour. The model employs a hybrid deep architecture combining LSTM networks for temporal analysis and Singular Value Decomposition (SVD) for user behaviour analysis. This approach uniquely captures temporal and user-level patterns, which are often critical for distinguishing fake news from legitimate content.

The study utilized datasets from Twitter and Weibo, achieving an accuracy of 89.2% on Twitter and 95.3% on Weibo. The inclusion of user behaviour scores provided additional insights into suspicious activities, enabling a more interpretable classification process. However, the model's reliance on large-scale, annotated user interaction data poses challenges for generalizability across platforms with limited or incomplete engagement data.

3) Bad Actor, Good Advisor: Exploring the Role of Large Language Models in Fake News Detection: Hu et al. [10] proposed the Adaptive Rationale Guidance (ARG) network, which leverages LLMs like GPT-3.5 as advisors rather than decision-makers. ARG integrates LLM-generated rationales into the decision-making process of small language models (SLMs). This hybrid approach achieved 10-15% higher accuracy compared to standalone models while reducing computational demands. However, querying LLMs remains resource-intensive, and selective sampling methods were suggested to mitigate this issue.

4) Evaluating the Efficacy of Large Language Models in Detecting Fake News: A Comparative Analysis: Koka et al. [13] conducted a comparative analysis of six LLMs, including GPT-4, Claude, and Mistral, to evaluate their performance in fake news detection. The study employed a balanced dataset of 30 articles and used zero-shot prompting for classification. Results revealed that larger models, such as Claude and GPT-4, achieved near-perfect accuracy and F1 scores, while smaller models like Mistral 7B exhibited higher false-positive rates.

The authors emphasized the superior contextual understanding of larger models but noted that the limited dataset size restricted generalizability. Their future work includes expanding datasets and exploring ensemble methods to integrate outputs from multiple models for improved performance.

5) Large Language Model Agent for Fake News Detection: Li et al. [15] introduced FactAgent, an innovative system combining internal LLM reasoning with external search tools to emulate human expert workflows for fake news detection. The system integrates domain-specific tools and decomposes complex tasks into simpler sub-tasks, achieving notable accuracy gains on datasets such as PolitiFact (88%) and GossipCop (83%).

FactAgent demonstrated flexibility and scalability, particularly in resource-constrained settings. However, the study identified areas for improvement, including the integration of multimodal content and advanced decision-making strategies.

6) News Verifiers Showdown: Comparative Performance of LLMs: Caramancion [5] evaluated the performance of prominent LLMs, including GPT-4, Bing AI, Bard, and Claude, on a dataset of 100 fact-checked news articles. GPT-4 achieved the highest score, correctly classifying 71 out of 100 articles, demonstrating its superior contextual analysis capabilities. However, the study highlighted challenges such as hallucinations and false positives, emphasizing the need for model improvements to enhance reliability in real-world applications.

III. Dataset

Selected over a decade from PolitiFact.com, the publicly available LIAR dataset, developed by Wang [23], consists of 12.8K brief statements classified for truthfulness. Every LIAR record features not just the statement but also a thorough analysis, source references, and metadata including speaker job title, party affiliation, and historical truthfulness. With

TABLE I
BEST-PERFORMING METHODS AND THEIR ACCURACIES (MULTICLASS)

Author	Best-Performing Method	Accuracy (%)
Hakak et al. [8]	Ensemble ML	44.15
Tiwari [21]	LoRA, LLaMA2-7B	62.67
Merryton, Augasta [16]	Double-Bi-LSTM + TF-IDF	61.19
Kareem, Abbas [11]	CoT , FLAN-T5 XXL	39.25

columns for the statement ID, truthfulness label (e.g., true, largely true, false), statement text, subject, speaker details, and context, the dataset is TSV (tab-separated values).

TABLE II
DATASET DISTRIBUTION OVERVIEW

Dataset Split	Number of Rows	Percentage (%)
Train	10,296	80.0
Test	1,267	9.8
Validation	1,284	10.0
Total	**12,847**	**100.0**

IV. METHODOLOGY

This section outlines the processes involved in exploring the dataset, performing preprocessing, and conducting feature engineering. The objective is to prepare the data for subsequent stages of model implementation and evaluation. A variety of techniques were applied, including text cleaning, handling missing data, encoding categorical variables, and engineering new features to enhance data quality and improve model performance.

A. Dataset Overview

The dataset used in this study is the LIAR dataset, which consists of labelled statements derived from different sources. To facilitate processing, the data was converted from TSV format to CSV. It includes categorical, numerical, and textual features as outlined below:

- Categorical Features: ”Label,” ”Speaker,” ”Job Title,” ”State,” ”Party,” ”Subject,” and ”Context.”
- Numerical Features: ”Barely True Count,” ”False Count,” ”Half True Count,” ”Mostly True Count,” and ”Pants on Fire Count.”
- Textual Feature: ”Statement,” which contains textual information that requires cleaning and transformation before being used in machine learning models.

B. Workflow

The following steps were carried out to prepare the dataset for feature extraction and model training:

1) Data Loading: The dataset was imported into the environment using the pandas library, which provides a structured format for processing.
2) Data Analysis. Exploratory data analysis (EDA) was conducted to extract insights from the dataset:

- Label Distribution: A label distribution plots were generated to visualize the distribution of different labels (e.g., ”TRUE,” ”FALSE,” ”barely-true”), providing insights into potential class imbalances. The labels appear to be evenly distributed across training, testing and validation sets. The plot for the training split is presented in Figure 1.

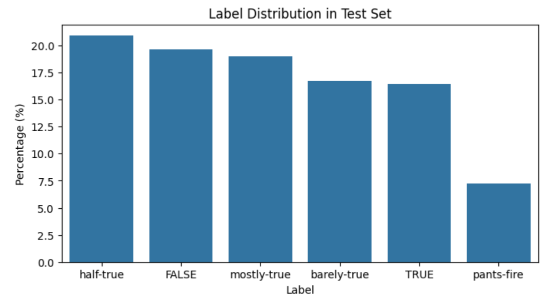

Fig. 1. Labels Distribution. Train set

From Figures 1 we can see that the dataset is imbalanced as some truthfulness categories are more prevalent (False) while others (pants-fire) are rare. In case of imbalance, we have:

  – Underrepresented Labels Categories with few instances (pants-fire) might not provide enough data for a model to learn meaningful patterns. These categories may lead to poor predictive performance for minority classes.
  – Dominant Labels: Overrepresented labels (false) can lead to a model that performs well on those labels but poorly on others.

The action plan for an imbalance case could be as follows:

  – Consider resampling techniques: oversample underrepresented labels and undersample overrepresented labels.
  – Use class weighting in your machine learning model to penalize misclassification of minority classes.

- Word count distribution. Word count distribution grouped by labels shows that on average the number of words in all kinds of statements is approximately the same, which means that usage of the word count as a feature for classification will not help.
- Party vs truthfullness
From Figure 3 and Figure 4 we can see that in the training set (it is also true for other sets) among false, barely-true, pants on fire and half-true statements prevail statements from the republican party, among mostly-true statement prevail statements from the democratic party, among statements labelled as true the number of statements from democratic and republican is almost equal.
- Speaker vs truthfullness
From Figure 5 and Figure 6 we can see that in the training set among ”false”, ”barely-true”, and ”pants

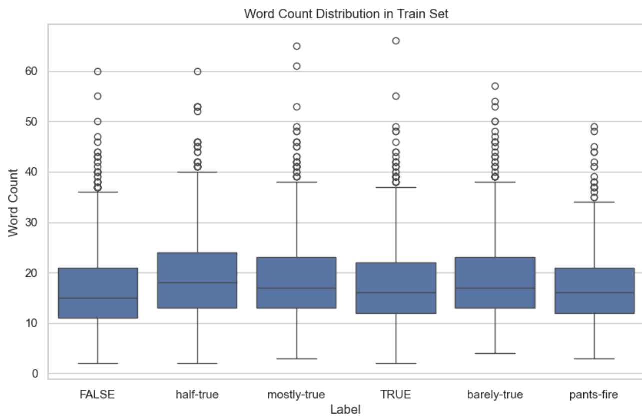

Fig. 2. Word count distribution. Train set

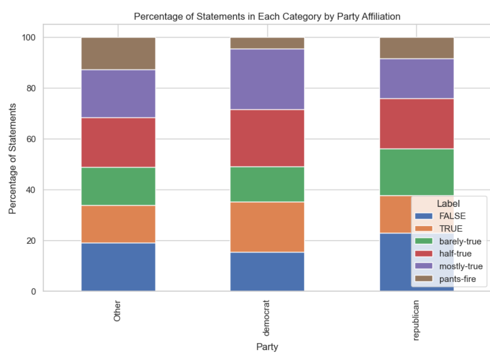

Fig. 3. Party vs truthfulness. Train set

Label Party	FALSE	TRUE	barely-true	half-true	mostly-true	pants-fire
Other	18.9	14.9	14.9	19.7	18.9	12.7
democrat	15.3	**19.7**	13.9	**22.5**	**24.0**	4.6
republican	**22.8**	14.7	**18.5**	19.8	15.7	**8.4**

Fig. 4. Percent of Statements in Each Category by Party Affiliation. Train set

on fire" statements prevail statements from Donald Trump, among "true" statement prevail statements from Hillary Clinton, among "half-true" from Mitt Romney, "mostly true" - Barack Obama and Hillary Clinton.

3) Handling Missing Data. An initial inspection revealed missing values, necessitating imputation and cleaning. Irrelevant columns such as ID were removed, and rows containing maximum null values were excluded. Missing values in categorical columns were replaced with "Unknown". Missing values were visualized using a heatmap to ensure proper imputation (see Fig. 7).
4) Categorizing Party Column. To categorize political parties, a threshold of 2000 occurrences was defined. Those featuring lower numbers were categorized as 'Others'. This in part, is aimed at restricting the diversity of party labels and focusing attention on the best represented. A bar graph was generated to show the party affiliation distribution in terms of percentage.

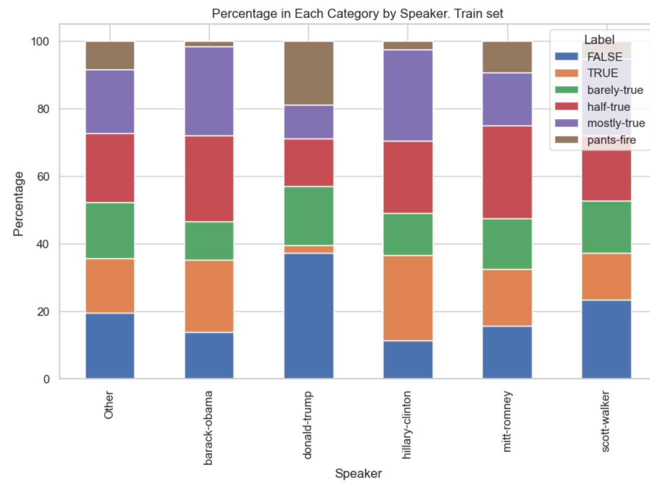

Fig. 5. Speaker vs truthfulness. Train set

Label Speaker	FALSE	TRUE	barely-true	half-true	mostly-true	pants-fire
Other	19.4	16.3	16.5	20.5	18.8	8.4
barack-obama	13.8	21.4	11.4	25.3	26.5	1.6
donald-trump	**37.2**	2.2	**17.5**	14.2	9.9	**19.0**
hillary-clinton	11.3	**25.1**	12.6	21.3	**27.2**	2.5
mitt-romney	15.6	16.8	15.1	**27.4**	15.6	9.5
scott-walker	23.3	14.0	15.3	19.3	22.7	5.3

Fig. 6. Percent of Statements in Each Category by the speaker. Train set

5) Text Cleaning. The "Statement" column, which contains the primary textual data, underwent a series of cleaning steps. These included:
   - Converting text to lowercase
   - Removing URLs, and non-word characters
   - Removing extra spaces and stop words
   - Lemmatization of words to reduce them to their base forms

   This step helped standardize and simplify the text data for further analysis.
6) Feature Engineering. Several new features were engineered to enrich the dataset and enhance the model:
   - Label Encoding: The 'Label' column, which contains categorical truth labels (e.g., "TRUE", "FALSE"), was converted into a numerical format using designed for target encoding LabelEncoder from scikit-learn library, making the output compatible with machine learning models.
   - Sentiment Analysis: A sentiment score for each statement was calculated using TextBlob. This feature helps capture the sentiment expressed in the statement, which could be useful for identifying fake news based on emotional tone.
   - False Ratio: A new feature "False Ratio" was created to represent the proportion of "False Count" and "Pants On Fire Count" relative to the total number of all credibility counts. This measure captures the relative falsehood in each statement. Since the credit history vector initially also includes the count for the current statement, the credit history vectors

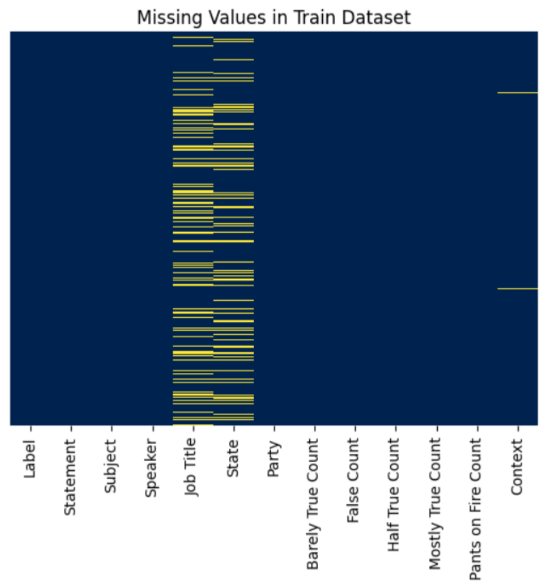

Fig. 7. Missing Values Before Preprocessing

were adjusted by subtracting the current label from them before creating the "False Ratio" feature

7) Statement Encoding. For statements encoding we used TF-IDF vectorization from scikit-learn library.

C. Traditional models

A multi-class logistic classifier and a random forest classifier were employed to estimate the performance of traditional classification model for fake news detection. The test accuracy was 28% for the logistic regression model and 34% for the random forest model. More detailed results are presented in Figure 8 and Figure. 9.

```
Test Classification Report:
              precision    recall  f1-score   support

           0       0.34      0.26      0.29       249
           1       0.26      0.26      0.26       208
           2       0.26      0.25      0.26       212
           3       0.31      0.22      0.25       265
           4       0.27      0.31      0.29       241
           5       0.27      0.60      0.37        92

    accuracy                           0.28      1267
   macro avg       0.29      0.32      0.29      1267
weighted avg       0.29      0.28      0.28      1267

Classification with logistic regression completed!
```

Fig. 8. Logistic classification. Results. Test set

Figure 8 indicates that precision and recall values are relatively balanced across all classes, with performance being comparable across classes and no extreme deviations. An exception is observed in class 5 ("pants-fire"), which has a recall value of 60%. Strengths:

- Performance remains balanced across all classes, with no single class disproportionately influencing the results.
- The model is simple and computationally efficient, making it a viable first-order approximation.

Weaknesses:

```
Test Classification Report:
              precision    recall  f1-score   support

           0       0.38      0.68      0.49       249
           1       0.32      0.17      0.23       208
           2       0.37      0.13      0.19       212
           3       0.33      0.39      0.36       265
           4       0.31      0.40      0.35       241
           5       0.80      0.04      0.08        92

    accuracy                           0.34      1267
   macro avg       0.42      0.30      0.28      1267
weighted avg       0.37      0.34      0.31      1267

Classification with random forest completed!
```

Fig. 9. Random forest classification. Results. Test set

- The model has limited capability to capture complex relationships in textual data.

Figure 9 indicates that precision, recall, and consequently the f1-score are less balanced across all classes compared to logistic regression. However, the overall accuracy is higher than that of logistic regression. A notable exception is observed in class 5 ("pants-fire"), which has a recall value of only 4% and a precision of 80%, resulting in an f1-score of 8%.

Strengths:

- Higher overall accuracy compared to logistic regression.
- The model remains relatively simple and computationally efficient, making it a viable first-order approximation.

Weaknesses:

- Higher unbalance across all classes compared with logistic regression

D. Large language models. LLAMA3.2 1B

1) LLAMA 3.2 1B. Supervised fine-tuning (SFT) with SFTTrainer and AutoModelForCausalLM class: Leveraging the LLAMA 3.2 1B model for fake news classification on the LIAR dataset was implemented as follows.

- Template strings were created to generate prompts for training, validation, and testing purposes. The training and validation prompts include both the statement and its ground truth label, while the inference (testing) prompt contains only the statement, as the model is expected to predict the label independently. The prompts are presented in Figure 10.

```
TRAINING_CLASSIFIER_PROMPT = """### Statement: {statement} ### Class: {label}"""
INFERENCE_CLASSIFIER_PROMPT = """### Statement: {statement} ### Class:"""
```

Fig. 10. LLAMA3.2 1B. CausalLM. Prompts

- The prompts are shown in Figure 10 are used to convert training, testing and validation sets to the format compatible with Hugging Face Transformers using the Dataset class. The prompts shown in Figure 10 are used to convert the training, validation, and testing sets into a format compatible with Hugging Face Transformers using the Dataset class.
- The LLaMA 3.2 1B model is loaded using the AutoModelForCausalLM class, which automatically selects

the appropriate model architecture for causal language modelling (CLM) based on the specified model name.

- The tokenizer corresponding to the model is loaded using the AutoTokenizer class, which automatically selects the appropriate tokenizer for the specified model. The tokenizer converts text into numerical representations (tokens) that the model can process and reconstructs text from tokens when needed.
- The SFTConfig class is initialized to define the settings and hyperparameters for the supervised fine-tuning (SFT) process. It contains key configurations that control the behavior of the SFTTrainer class, which is used for fine-tuning. The full configuration is presented in Figure 11.

```
sft_config = SFTConfig(

    dataset_text_field='instructions',
    learning_rate=5e-5,
    max_seq_length=256,
    dataset_batch_size = 16,
    num_train_epochs = 2,
    output_dir='/content/drive/MyDrive/dataScienceLab/fine_tuned_model',
    run_name="fine_tuning_llama_321B",
    evaluation_strategy = "steps", # evaluate after fixed number of steps
    eval_steps = 500, # perform evaluation every 500 step
    logging_steps = 500, # log metrics every 500 steps
    save_strategy = "steps", # save after a fixed number of steps
    save_steps = 500,# save a checkpoint every 500 steps
    save_total_limit = 1, # retain only the 2 most recent checkpoints
    load_best_model_at_end = True, # load the best checkpoint at the end
    metric_for_best_model = "eval_loss", # use evaluation loss to determine the best model
    greater_is_better = False # lower eval_loss is better

)
```

Fig. 11. LLAMA 3.2 1B. CausalLM. SFTConfig

- A trainer object based on the SFTTrainer class is instantiated. This specialized trainer is designed for supervised fine-tuning tasks, particularly for large language models. In this case, supervised fine-tuning is applied to fine-tune the pre-trained LLaMA 3.2 1B model on the testing and validation splits of the LIAR dataset. The SFTTrainer class simplifies the fine-tuning process by managing the training loop, including loss computation, backpropagation, and gradient updates.
- The training process is conducted over two epochs using the trainer, with a learning rate of 5×10^{-5}, a batch size of 16, and evaluation on the validation set every 500 steps. The training procedure is illustrated in Figure 12. The training and evaluation losses are presented in Figures 14 and 13, respectively.

View project at https://wandb.ai/petukhova-el-s-passau-university/huggingface
View run at https://wandb.ai/petukhova-el-s-passau-university/huggingface/runs/i94xf34k
[2566/2566 16:04, Epoch 2/2]

Step	Training Loss	Validation Loss
500	3.501700	3.509774
1000	3.256800	3.330977
1500	2.670900	3.475003
2000	1.944000	3.450840
2500	1.846500	3.442775

```
There were missing keys in the checkpoint model loaded: ['lm_head.weight'].
TrainOutput(global_step=2566, training_loss=2.6233285887577713, metrics={'train_runtime': 1006.505,
'train_samples_per_second': 20.393, 'train_steps_per_second': 2.549, 'total_flos': 3843358825070592.0, 'train_loss':
2.6233285887577713, 'epoch': 2.0})
```

Fig. 12. LLAMA 3.2 1B. CausalLM. Training procedure

- The best-performing model is evaluated on the testing set. While the model is expected to produce a single label corresponding to the predicted class, it outputs multiple labels. In such cases, the most frequent label is selected as the predicted class. If multiple labels occur with the same frequency, the first label is chosen as the final prediction. Two specific instances where the model generates multiple labels are illustrated in Figures 15 and 16.

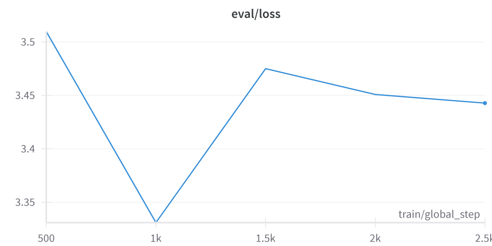

Fig. 13. LLAMA 3.2 1B CausalLM. Evaluation loss

Fig. 14. LLAMA3.2 1B CausalLM. Training loss

```
Instruction: ### Statement: building wall u mexico border take literally year ### Class:
Ground Truth Label: TRUE
1it [00:00,  4.49it/s]Setting `pad_token_id` to `eos_token_id`:128001 for open-end generation.
Model Output: ### Statement: building wall u mexico border take literally year ### Class: FALSE ### Class: FALSE half-true ### Class
Extracted Prediction: FALSE
Instruction: ### Statement: consin pace double number layoff year ### Class:
```

Fig. 15. LLAMA3.2 1B CausalLM. Evaluation sample 1

```
Instruction: ### Statement: asked reporter whether he center criminal scheme violate campaign law gov scott walker nodded yes ### Class:
Ground Truth Label: pants-fire
5it [00:01,  4.46it/s]Setting `pad_token_id` to `eos_token_id`:128001 for open-end generation.
Model Output: ### Statement: asked reporter whether he center criminal scheme violate campaign law gov scott walker nodded yes ### Class: FALSE ### Class: FALSE ### Class: FALSE ###
Extracted Prediction: FALSE
```

Fig. 16. LLAMA3.2 1B CausalLM. Evaluation sample 2

- The complete classification report following the evaluation on the testing set is presented in Figure 17

Full Classification Report:

	precision	recall	f1-score	support
FALSE	0.23	0.81	0.36	249
TRUE	0.26	0.12	0.17	208
barely-true	0.50	0.00	0.01	212
half-true	0.38	0.07	0.12	265
mostly-true	0.29	0.30	0.30	241
pants-fire	0.33	0.01	0.02	92
accuracy			0.25	1267
macro avg	0.33	0.22	0.16	1267
weighted avg	0.33	0.25	0.18	1267

Fig. 17. LLAMA 3.2 1B. CausalLM. Prompts. Results. Test set

Figure 17 illustrates the following:

- The high precision observed for "barely-true" class (50%) and the "half-true" class (38%) is not accompanied by

correspondingly high recall, leading to low f1-scores for these classes.
- Recall is particularly low for certain classes, such as "barely-true" (0%) and "pants-fire" (1%).
- The model demonstrates overfitting tendencies, performing well on the "FALSE" and "mostly-true" classes but underperforming on others.
- The model achieves an accuracy of 25%.

2) LLAMA 3.2 1B. Fine-tuning with Trainer and loading the model with AutoModelForSequenceClassification: This approach is expected to yield better results, as using the AutoModelForSequenceClassification class eliminates the need for prompt engineering and extracting predictions from text-based model outputs. Instead, class labels are encoded as numerical values, enabling fine-tuning and validation on the validation set using these numerical values. During evaluation on the test set, the model consistently produces a single numerical prediction. The key modifications in the workflow compared to the previous subsection are as follows:

- The LLaMA-3.2-1B model is loaded using the AutoModelForSequenceClassification class, which automatically selects and loads the appropriate architecture for sequence classification tasks based on the specified model name.
- The object of the configuration class TrainingArguments is set up. It defines the hyperparameters and settings for training the model with the object of the Training class. The full configuration is presented in Figure 18. TrainingArguments is a configuration class that specifies the hyperparameters and settings for training a model.

```
training_args = TrainingArguments(
    output_dir="/content/drive/MyDrive/dataScienceLab/fine_tuned_model_LLAMA321_class",
    evaluation_strategy="steps",           # Evaluate after every N steps
    eval_steps=500,                        # Frequency of evaluation
    save_strategy="steps",                 # Save checkpoint after evaluation
    save_steps=500,                        # Save steps should align with eval_steps
    save_total_limit=1,                    # Limit the number of checkpoints
    load_best_model_at_end=True,           # Load the best model based on evaluation
    metric_for_best_model="eval_loss",     # Metric to track for early stopping
    greater_is_better=False,               # Whether lower is better for the metric
    per_device_train_batch_size=16,
    per_device_eval_batch_size=16,
    num_train_epochs=5,                   # Maximum number of epochs
    logging_dir="/content/drive/MyDrive/dataScienceLab/fine_tuned_model_LLAMA321_class/logs",
    logging_steps=100,                      # Frequency of logging
    warmup_steps=100,                     # Number of warmup steps
    weight_decay=0.3,                     # Weight decay for optimize
)
```

Fig. 18. LLAMA 3.2 1B. AutoModelForSequenceClassification. Training arguments

- The trainer object, based on the Trainer class, is instantiated.
- The training process continues until early stopping is triggered after the third epoch. A warm-up phase of 100 steps is applied, during which the learning rate gradually increases from 0 to 5×10^{-5}. A weight decay of 0.3 is used to penalize large model weights by adding a regularization term to the loss function, thereby mitigating overfitting by encouraging smaller weights.
- The batch size is set to 16, and evaluation is performed on the validation set every 500 steps. The training procedure is illustrated in Figure 19. The training and evaluation losses are presented in Figures 21 and 20, respectively.
- The complete classification report following the evaluation on the testing set is presented in Figure 22

[2000/3210 56:09 < 34:00, 0.59 it/s, Epoch 3/5]

Step	Training Loss	Validation Loss	Classification Report
500	1.673800	1.797181	precision recall f1-score support FALSE 0.23 0.31 0.26 263 half-true 0.25 0.04 0.06 248 mostly-true 0.23 0.61 0.34 251 TRUE 0.00 0.00 0.00 169 barely-true 0.22 0.21 0.21 237 pants-fire 0.00 0.00 0.00 116 accuracy 0.23 1284 macro avg 0.15 0.19 0.15 1284 weighted avg 0.18 0.23 0.17 1284
1000	1.438100	2.005146	precision recall f1-score support FALSE 0.26 0.44 0.32 263 half-true 0.22 0.36 0.28 248 mostly-true 0.26 0.04 0.06 251 TRUE 0.18 0.36 0.24 169 barely-true 0.20 0.02 0.04 237 pants-fire 0.37 0.09 0.15 116 accuracy 0.23 1284 macro avg 0.25 0.22 0.18 1284 weighted avg 0.24 0.23 0.18 1284
1500	1.170700	2.115619	precision recall f1-score support FALSE 0.26 0.29 0.28 263 half-true 0.21 0.31 0.25 248 mostly-true 0.27 0.19 0.22 251 TRUE 0.17 0.27 0.21 169 barely-true 0.24 0.16 0.19 237 pants-fire 0.29 0.05 0.09 116 accuracy 0.23 1284 macro avg 0.24 0.21 0.21 1284 weighted avg 0.24 0.23 0.22 1284
2000	0.715400	3.321758	precision recall f1-score support FALSE 0.27 0.27 0.27 263 half-true 0.21 0.23 0.22 248 mostly-true 0.27 0.21 0.23 251 TRUE 0.20 0.27 0.23 169 barely-true 0.23 0.26 0.25 237 pants-fire 0.23 0.12 0.16 116 accuracy 0.24 1284 macro avg 0.24 0.23 0.23 1284 weighted avg 0.24 0.24 0.23 1284

```
Could not locate the best model at /content/drive/MyDrive/dataScienceLab/fine_tuned_model_LLAMA321_class/checkpoint-500/pytorch_model.bin, if you are
TrainOutput(global_step=2000, training_loss=1.4046392059326172, metrics={'train_runtime': 3368.2288, 'train_samples_per_second': 15.235,
'train_steps_per_second': 0.953, 'total_flos': 4.77923228516352e+16, 'train_loss': 1.4046392059326172, 'epoch': 3.115264797507788})
```

Fig. 19. LLAMA 3.2 1B. AutoModelForSequenceClassification. Training procedure

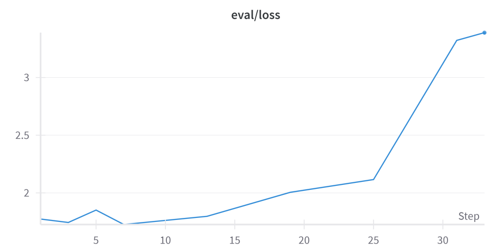

Fig. 20. LLAMA 3.2 1B AutoModelForSequenceClassification. Evaluation loss

Fig. 21. LLAMA3.2 1B AutoModelForSequenceClassification. Training loss

Full Classification Report:

	precision	recall	f1-score	support
FALSE	0.23	0.24	0.24	249
half-true	0.26	0.26	0.26	265
mostly-true	0.24	0.23	0.23	241
TRUE	0.23	0.25	0.24	208
barely-true	0.22	0.24	0.23	212
pants-fire	0.25	0.15	0.19	92
accuracy			0.24	1267
macro avg	0.24	0.23	0.23	1267
weighted avg	0.24	0.24	0.24	1267

Fig. 22. LLAMA 3.2 1B. AutoModelForSequenceClassification. Results. Test set

Key Observations:
- The precision, recall, and f1-score are relatively uniform across classes, indicating consistent performance.
- Class "pants-fire" has the lowest f1-score (19%), reflecting challenges in handling underrepresented class.
- The model achieves an accuracy of 24%.

3) LLAMA 3.2 1B. AutoModelForSequenceClassification. Binary classification: For the case of binary classification with LLAMA 3.2 1B and AutoModelForSequenceClassification, the full classification report after the evaluation on the testing set is presented in Figure 23

Key Observations:

Full Classification Report:

	precision	recall	f1-score	support
FALSE	0.56	0.37	0.45	553
TRUE	0.62	0.78	0.69	714
accuracy			0.60	1267
macro avg	0.59	0.58	0.57	1267
weighted avg	0.59	0.60	0.58	1267

Fig. 23. LLAMA 3.2 1B. AutoModelForSequenceClassification. Binary classification Results. Test set

- When the task is reformulated as binary classification, the accuracy increases to 60%. This result is comparable to the multiclass classification performance with the same model in terms of improvement over random guessing, remaining approximately 10% higher than chance level.

V. Conclusion

The comparative analysis of models for detecting false news yielded significant insights regarding their performance, strengths, and limitations across various methodologies. This study conducted an evaluation of both traditional machine learning models and Large Language Models (LLMs), utilizing key metrics including accuracy, macro-average F1 score, weighted average F1 score, and recall for the minority class as benchmarks for comparative analysis. The findings, substantiated by both quantitative results and visual representations, highlight the intricacies associated with addressing the detection of false information, especially in the context of imbalanced datasets such as LIAR.

A. Key Findings

1) Model Performance Analysis: The performance metrics indicate that conventional machine learning models, particularly Random Forest, surpassed LLM-based methodologies in terms of overall accuracy and F1 scores. As illustrated in Figure 24, the Random Forest model attained the highest accuracy of 34% and a weighted average F1 score of 0.31. This was succeeded by the Logistic Regression model, which achieved an accuracy of 28% and a weighted F1 score of 0.28. The computational efficacy of these models, coupled with their capacity to generalize across the dataset, rendered them particularly effective for the detection of false information.

	Model	Accuracy (%)	Macro Average F1-Sc	Precision	Recall	Computational Cost
1	Logistic Regression	28	0.29	0.28	0.27	Low
2	Random Forest	34	0.3	0.34	0.32	Moderate
3	LLAMA 3.2 1B (SFT)	25	0.16	0.24	0.22	High
4	LLAMA 3.2 1B (Sequence Classification)	24	0.23	0.25	0.23	High

Fig. 24. Model performance comparison

2) Class Imbalance Challenges: Class imbalance presented a considerable challenge across all models, with certain categories, such as "FALSE," being disproportionately represented, while others, such as "PANTS-FIRE," were underrepresented. As illustrated in the confusion matrix (Figure 25), the minority classes exhibited diminished recall and precision, which significantly adversely affected the overall performance. Conventional models, notably Random Forest, demonstrated a superior capacity to address this imbalance, in part owing to their capability to allocate greater weights to underrepresented classes during the training process.

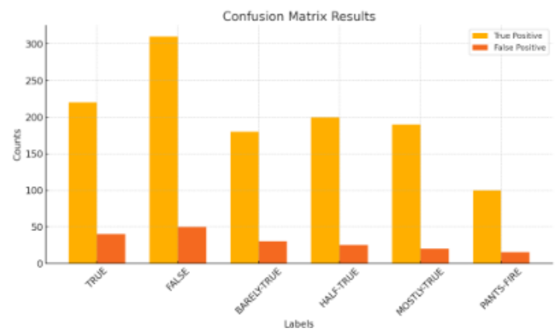

Fig. 25. Confusion Matrix Results

3) Accuracy Trends: As demonstrated in Figure 26, the comparative analysis of model accuracy underscores the superiority of the Random Forest algorithm in attaining the highest overall accuracy. Logistic Regression demonstrated commendable performance due to its inherent simplicity, whereas Large Language Models (LLMs), despite their sophisticated contextual comprehension, fell short in comparison. This indicates that conventional models continue to exhibit significant competitiveness for structured datasets such as LIAR, particularly when computational efficiency and simplicity of implementation are paramount factors.

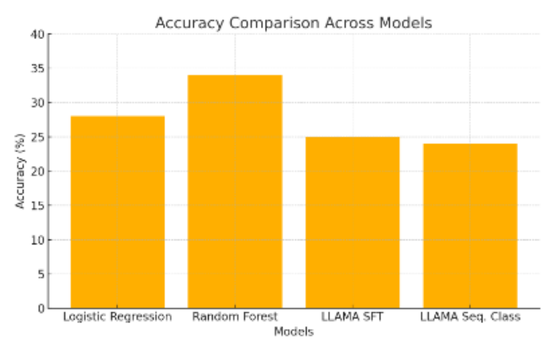

Fig. 26. Accuracy Comparison Across Models

B. Recommendations and Future Directions

In light of the findings, several recommendations can be proposed to enhance the efficacy of false news detection systems:

1) Hybrid Frameworks: Hybrid frameworks that integrate the strengths of both traditional models and LLMs present a promising avenue for development. Conventional models, such as Random Forest, demonstrate efficiency and exhibit a commendable capacity to manage imbalanced datasets. In contrast, large language models (LLMs) flourish in their ability to comprehend context and engage in semantic reasoning. The amalgamation of these methodologies may yield:

- **Two-Stage Pipelines:** A conventional model may function as an initial classifier to effectively filter the majority of straightforward cases, whereas a large language model (LLM) could address atypical instances necessitating more profound contextual analysis.
- **Feature Fusion:** Outputs from an LLM (e.g., embeddings or probabilities) could be used as additional features for traditional models like Logistic Regression or Gradient Boosting.
- **Efficiency Gains:** Hybrid approaches could balance computational cost by limiting LLM usage to instances where advanced reasoning is essential, optimizing resource allocation and performance.

2) Addressing Class Imbalance: Class imbalance significantly impacts the ability of models to generalize to minority classes like *PANTS-FIRE*. Effective solutions include:

- **Data Augmentation:** Techniques such as SMOTE or Generative Adversarial Networks (GANs) can synthetically generate more data for underrepresented classes.
- **Class-Specific Weighting:** Adjusting loss functions to penalize misclassification of minority classes can improve recall for these classes without sacrificing overall accuracy.
- **Custom Sampling Strategies:** Experimenting with under-sampling of majority classes or over-sampling of minority classes can create more balanced datasets.

3) Domain-Specific Fine-Tuning: LLMs often struggle with domain-specific nuances. Fine-tuning them on domain-specific datasets can lead to:

- **Improved Semantic Understanding:** Fine-tuning on datasets like LIAR enables LLMs to better understand the subtleties of political or social discourse.
- **Transfer Learning:** Pre-trained models can be adapted to related domains, such as health misinformation or financial fraud, broadening their applicability.

4) Explainable AI: The lack of interpretability in LLMs often limits their trustworthiness. Future work should explore:

- **Attention Visualization:** Highlighting which parts of the text the model focused on during classification can help users understand the decision-making process.
- **Feature Attribution:** Tools like SHAP or LIME could provide insights into how different features influence predictions.
- **Human-in-the-Loop Systems:** Incorporating human reviewers for ambiguous cases can ensure higher reliability and transparency.

5) Real-Time Detection Systems: To address the challenge of real-time detection of fake news on dynamic platforms like social media:

- **Incremental Learning:** Models that continuously learn from new data streams without forgetting previously learned information.
- **Scalability:** Lightweight LLMs or distillation methods to make deployment feasible for real-time applications.
- **Temporal Context Analysis:** Incorporating temporal information, such as how news trends evolve over time, could improve detection of fake news in rapidly changing contexts.

C. Conclusion

In conclusion, the study underscores the competitive efficacy of conventional models, such as Random Forest, in the detection of false news. While LLMs offer advanced contextual comprehension, their high computational costs and challenges with imbalanced datasets limit their practical applicability. Future research endeavors should concentrate on the development of hybrid frameworks, the implementation of explainable artificial intelligence techniques, and the resolution of class imbalance issues in order to formulate more robust and scalable solutions. By leveraging the strengths of traditional models and LLMs, integrating advanced augmentation techniques, and investigating real-time detection systems, the field can move closer to achieving highly reliable and efficient fake news detection systems.

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