An Enhanced Machine Learning Framework for Fake News Identification

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***Abstract*—This paper proposes a collaborative approach for detecting fake news on Twitter by leveraging a multi-Trends sentiment classification framework. With the proliferation of online consumer reviews, our method automatically identifies significant aspects of topics to enhance sentiment analysis. We address the challenge of limited labeled data by decomposing sentiment classifiers into global and Trends-specific components. While models tailored to individual trends capture distinct sentiment expressions within each trend, the global model collects broad sentiment knowledge shared across datasets. By extracting Trends-specific sentiment knowledge from labeled and unlabeled samples, we improve fake news detection accuracy, particularly on datasets like Credbank and Pheme. Additionally, we integrate dataset similarities as regularization terms to encourage sentiment information sharing between similar datasets. This collaborative approach utilizing stochastic gradient descent (SGD) algorithm for optimization, not only enhances the accuracy of fake news detection on Twitter but also facilitates early trend categorization for more effective sentiment analysis.**

***Keywords*— Twitter, fake news, collaborative multi- Trends sentiment classification, accuracy, early trend categorization.**

I. INTRODUCTION

In an era dominated by the rapid dissemination of information through digital platforms, the prevalence of fake news poses a significant challenge to the integrity of public discourse and decision-making. A Fake News Detector stands as a beacon of truth in this landscape, leveraging advanced technologies and methodologies to sift through the vast sea of information, distinguishing fact from fiction. With its vigilant algorithms and robust fact-checking mechanisms, it empowers users to navigatethe a culture of critical thinking and accountability. As misinformation continues to proliferate, the Fake News Detector emerges as a vital ally in the ongoing battle for truth and transparency, safeguarding the integrity of our shared knowledge and democratic principles.

II. RELATED WORK

1. Unsupervised fake news detection in multipleplatforms and languages

In the discussed paper, a method is proposed for detecting fake news across multiple languages and platforms using text features independent of source platform and language. Experiments on datasets in Germanic, Latin, and Slavic languages yielded competitive results compared to benchmarks. Notably, Support Vector Machines and Random Forest classifiers outperformed other algorithms, with bag-of-words features showing the best overall performance. Findings suggest that features such as text length, Word2Vec representation, lexical size, and sentiment polarity are particularly useful in fake news detection. These results contribute to the ongoing debate on fake news detection and provide insights for future research across diverse linguistic and platform contexts

2. Polarization and fake news: early warning ofpotential misinformation targets

This paper introduces a framework to identify polarizing content on social media, aiding in the prediction of future fake news topics with 77% accuracy. Additionally, the framework contributes to a fake news classifier achieving 91% accuracy. By analyzing user behavior and polarization, this approach aims to mitigate misinformation phenomena, crucial in today's digital landscape. This novel methodology marks a significant step towards early detection of potential fake news topics, despite challenges posed by the complexity of misinformation online.

3. Fake news detection model on social media byleveraging sentiment analysis of news content and emotion analysis of users' comments

This paper presents a method to detect fake news on social media by analyzing sentiment and emotion in news articles and user comments. Utilizing a bidirectional long short-term memory (Bi-LSTM) model, the proposed system achieved a high accuracy of 96.77% on the Faked it dataset. Emotion-based features significantly contributed to the model's performance, highlighting the importance of considering user attitudes in fake news detection. While challenges with imbalanced datasets were encountered, future research may explore techniques such as GANs to address this issue and further improve detection accuracy using transformer-based models.

4. Supervised learning for fake news detection this paper presents a comprehensive examination ofexisting

features and supervised learning classifiers for fake news detection on social media platforms. Results demonstrate the effectiveness of proposed features incombination with classifiers, offering promisingdiscriminative power for fake news detection. The studysuggests utilizing automatic detection as an auxiliary toolfor fact-checkers, with explanations supporting algorithmoutputs. Additionally, it advocates for continual datalabeling and active learning approaches.

5. Exploring deep neural networks for rumor detection

This This paper presents a Deep Learning-based BiLSTM-CNN model for rumor detection on microblogging platforms like Twitter. The model considers contextual information in both forward and backward directions, achieving an accuracy of 86.12% on a benchmark Twitter dataset. Experimental results demonstrate the effectiveness of the proposed method in outperforming baseline approaches and improving classification performance.

III. PROPOSED SYSTEM

The proposed system is a collaborative multi-Trends sentiment classification framework that aims to enhance the accuracy and robustness of sentiment classifiers acrossdiverse datasets, specifically CREDBANK, PHEME, andBuzz feed News Fact-Checking. The system begins by loading labeled sentiment data from CREDBANK and PHEME, along with fact-checked news articles from Buzz feed. Through dataset alignment, features and labels are standardized across datasets. The model employs a decomposition of sentiment classifiers, incorporating a global component for general sentiment knowledge sharedacross datasets and a Trends-specific component to capture unique sentiment expressions in each Trend. Additionally, the system leverages both labeled and unlabeled samples to extract Trends-specific sentiment knowledge, further improving classification performance.A key predictive task involves distinguishing between fake and real news articles within the Buzz feed dataset, providing valuable insights into the prevalence of misinformation. This collaborative approach facilitateseffective sentiment analysis and fact-checking across multiple Trends, promoting more accurate and reliable classification outcomes, especially in scenarios where labeled data is limited.

A. Data Collection

Data collection is the process of gathering and measuring information from countless different sources.Collecting data allows you to capture a record of past events so that we can use data analysis to find recurring patterns. We have collected the dataset from Kaggle and GitHub repositories. Therefore the dataset includes CREDBANKand PHEME datasets

B. Data Loading

Firstly, data from the CREDBANK and PHEME datasets,containing labeled sentiment examples and sentiment information related to rumors or events, respectively, is loaded. Additionally, the Buzz feed News Fact-Checkingdataset, comprising news articles with fact-checking labels, is loaded.

C. Data Alignment

The datasets (CREDBANK, PHEME, and Buzzfeed) are aligned to ensure consistency and compatibility in terms of features, sentiment labels, and any other relevant characteristics. By addressing these issues, data alignment enhances the reliability and accuracy of the sentiment analysis framework across multiple datasets, facilitating more robust and meaningful insights into sentiment trendsand patterns.

D. Architecture Diagram

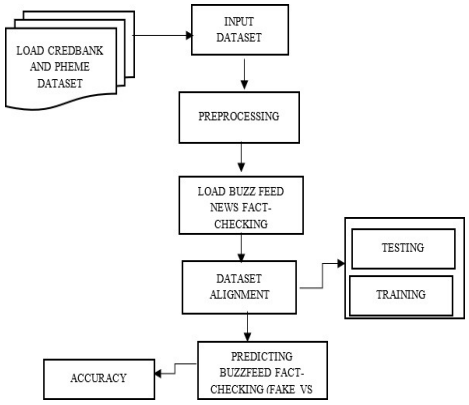

Fig 1. Architecture Diagram

IV. RESULT AND DICUSSION

The sentiment analysis system presents key insights derived from analyzing the CREDBANK and PHEME datasets, showing the sentiment polarity of different topics or events. It also predicts the authenticity of news articlesin the Buzzfeed dataset, indicating the count of articles classified as real or fake. Visualizations like bar charts or pie charts may be used to show sentiment distribution across topics or the prevalence of misinformation. Overall, the output provides actionable insights into sentiment trends and news credibility, helping decision- making in various fields.

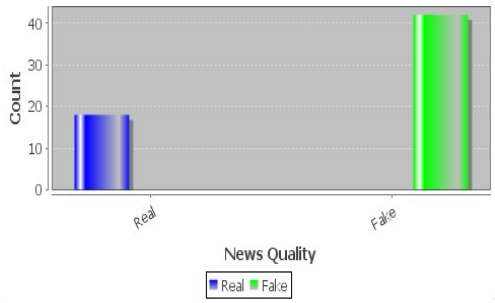

Fig 2. Comparison graph of fake and real news

Automatically Fake News Detection Results

Correctly Classified Instances	941	98.8445 %
Incorrectly Classified Instances	11	1.1555 %
Kappa statistic	0.9769	
Mean absolute error	0.0116	
Root mean squared error	0.1075	
Relative absolute error	2.3112 %	
Root relative squared error	21.4997 %	
Coverage of cases (0.95 level)	98.8445 %	
Mean rel. region size (0.95 level)	50 %	
Total Number of Instances	952	

Fig 3. Model Evaluation

The results of the fake news detection system show that itcorrectly classified 98.84% of instances, which is quite accurate. Only 1.16% of instances were classified incorrectly. The system's performance is consistent, with a strong agreement between predicted and actual classifications. Errors in prediction are minimal, with lowmean absolute and root mean squared errors. The system'spredictions are close to the actual values, with only small variations. At a 95% confidence level, the system's predictions cover almost all cases, indicating its reliability. The predictions are evenly distributed across the dataset. Overall, these results highlight the system's effectiveness in detecting fake news, offering a promising solution to combat misinformation.

V. CONCLUSION AND FUTURE WORK

The outlined approach establishes a systematic pipeline for sentiment analysis and fact-checking across diverse datasets, including CREDBANK, PHEME, and BuzzfeedNews. By aligning these datasets, it provides a unified framework for analyzing sentiments and verifying news authenticity. Through predictive modeling, it effectively distinguishes between real and fake news articles, contributing to the accuracy and reliability of sentiment analysis while combating misinformation in online content. Moving forward, integrating advanced techniques such as transfer learning and continual learning could further improve the model's performance across different domains and over time. And incorporating user feedback mechanisms could enhance the timeliness and relevance of sentiment analysis.

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