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Evaluating the Performance of a Fake News Model on A Domain-Specific and Heterogeneous Dataset to Improve Detection

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Abstract

The rapid evolution of technology and the digital age has led to an increase in the spread of fake news, severely undermining the accuracy of information. This study aims to improve fake news detection methods in distinct domains through in-depth dataset analysis using a Convolutional Neural Network (CNN), the research-trained models using an optimized CNN model on publicly available datasets. The findings show that machine learning models trained on domain-specific datasets can accurately identify the nuances of fake news unique to those domains. Compared to models trained on broader datasets, the results demonstrate that models trained on domain-specific data achieved higher accuracy, precision, recall, and F1-score, increasing from 68% to 99% across all metrics when compared with a baseline CNN model. However, while domain-specific models perform exceptionally well in their respective contexts, models trained on a diverse range of datasets exhibit greater generalizability across domains. These findings suggest that dynamic and robust fake news detection systems should integrate both heterogeneous datasets and domain-specific features to enhance effectiveness.

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Keywords: Domain; Dataset; Detection; Fake-News.

1. Introduction

In today's information-rich world, distinguishing between real and fake news has become increasingly difficult. Due to the ease of creating and disseminating misinformation on digital platforms, trust in online content is diminishing. The rapid spread of fake news—often facilitated by social media, filter bubbles, and fast information-sharing mechanisms, poses a serious threat to society. Fake news, which benefits only its creators, can take many forms, including political propaganda and misleading health information. Recognizing the gravity of this issue, researchers have focused on developing machine learning models and algorithms that can accurately detect and flag misinformation. The impact of domain-specific data on model performance has been a subject of recent research [1]. This research investigates whether domain-specific embedding models are necessary for tasks such as fake news detection. Their findings suggest that domain-specific embeddings significantly enhance performance, particularly in areas where linguistic patterns and vocabulary usage differ from general-purpose datasets. The study emphasizes that models trained on specialized datasets outperform those trained on general datasets, reinforcing the need for customized data representations in fake news detection. Inspired by this, our research explores the role of domain-specific datasets in improving classification accuracy, precision, and recall F1-score. This study conducts a comprehensive examination of several datasets frequently used in fake news detection to train and test machine learning models. The objective of this study is to assess how dataset domains impact the overall performance of machine learning models. This was achieved by training various domain-specific datasets using a CNN model and evaluating the results. The research evaluates the models using accuracy, precision, recall, and F1-score. The gap in existing research lies in the limited exploration of how domain-specific dataset characteristics influence the performance and generalizability of fake news detection models. Developing more accurate and robust solutions for combating fake news will support ongoing efforts to improve the accuracy of detection methods, helping users, platforms, and organizations make informed decisions and mitigate the harm caused by misinformation.

2. Literature Review

The study by [2] provided fresh deep-learning algorithms for detecting fake news utilizing two datasets. The approaches proved suitable for this study because they had previously been shown to be effective in other investigations. The study's purpose was to identify the best-performing optimum models. The HyperOpt technique was employed for the neural network model. The performance of the improved models was compared to that of the models that were not optimized. The results revealed that for both datasets, CNN and LSTM performed much better when training the models with the optimal settings, with an average difference of 12.7% for Accuracy, 11.9% for Precision, 12.3% for Recall, and 15.4% for F1-Score. In the study by [3], SVM, Naïve Bayes, Random Forest, and Logistic Regression classifiers were compared for detecting false news across several datasets. The SVM model obtained the best accuracy (61%, 97%, and 96% for the Liar, Fake Job Posting, and Fake News datasets, respectively). SVM, Naïve Bayes, Random Forest, and Logistic Regression are implemented as fitness coefficients in

Nomenclature & Symbols			
CNN	Convolutional Neural Network	LSTM	Long Short-Term Memory
SVM	Support Vector Machine	LR	Logistic Regression
AVOA	African Vulture Optimization Algorithm	NLTK	Natural Language Toolkit

a new Genetic method-based fake news recognition method. With the suggested approach, the SVM and LR classifiers achieved 61% accuracy in the LIAR dataset. In comparison, SVM and RF earned the greatest accuracy of 97% on the fake job posting data set.

A study conducted by [4] applied the theory of uniformity to neural networks for enhanced processing of natural languages, thus increasing the detection of fake reports and deception. This study presents a hybrid HyproBert model for the automated identification of fake news. To begin, the adopted HyproBert framework relied on DistilBERT for tokenization and word embedding. The embedded data serve as input for the convolution section, which emphasizes and extracts spatial properties. The result is then sent into BiGRU, which extracts the contextual characteristics. CapsNet, together with the self-attention layer, proceeds to the BiGRU output to mimic the spatial feature hierarchy link. Lastly, a dense layer is utilized to group all of the information for classification. The recommended HyproBert model is tested with two fake news samples (ISOT and FA-KES). As an outcome, HyproBert outperformed other baselines and leading models. A similar study [5] aims to build a preliminary comprehensive fake news classification dataset for Pakistani content by merging several verified news APIs. The study also investigates the collected dataset employing a variety of cutting-edge artificial intelligence techniques. The following algorithms and approaches are utilized: Naïve Bayes, KNN, Logistic Regression, SVM, and Decision Trees. GloVe and BERT embeddings rely on two deep-learning techniques: CNN and LSTM. All models and embeddings are evaluated in terms of precision, F1-score, accuracy, and recall. The findings show that the LSTM initiated using GloVe Embeddings performed highest on the dataset, with an F1-score of around 0.94. The study also investigates the misclassified samples in comparison to human assessments.

A study by [6] presented a strategy for detecting fake news more efficiently in languages with limited resources, such as Hindi. This strategy utilizes an ensemble of developed transformer theories, with each one independently modified for fake news detection. The study demonstrated that using an additive collection made up of XLM-RoBERTa, mBERT, and ELECTRA may increase the accuracy of identifying false news in Hindi, which is superior to the constraints presented by separate transformer approaches. Another research [7] presented the findings of the Factify 2 collaborative objective, which offers a multifaceted information validation and fake news dataset, as a feature of the DeFactify 2 presentation during AAAI'23. The results point to a comparison-based strategy for the challenge, with social media claims matched with supporting materials in both text and picture and divided into five classifications using hybrid interactions. Over 60 people participated in the second phase of this study, and nine completed test sets were submitted. The best results were obtained with DeBERTa for textual and Swinv2 and CLIP for pictures. The maximum aggregate F1 score for all five categories was 81.82%. Another study by [8] described the Bio-inspired Artificial Intelligence with Natural Language Processing Deceptive Content Detection (BAINLP-DCD) approach for social networking. The proposed BAINLP-DCD approach was developed to identify the existence of fake or counterfeit material on social media. To achieve this, the BAINLP-DCD method carried out data preprocessing to transform the input dataset into a usable format. The BAINLP-DCD approach identifies false information by applying the Multi-Head Self-Attention Bi-directional Long Short-Term Memory (MHS-BiLSTM) model. The African Vulture Optimization Algorithm (AVOA) helped to determine the ideal hyperparameters for the MHS-BiLSTM model. Their approach was verified using simulation on two standard fake news datasets.

In their study, [9] examined the strengths and weaknesses of several algorithms for identifying fake news. Deep Learning Algorithms, LSTM and CNN, were compared to other popular machine learning models, such as Gaussian Naïve Bayes, Decision Tree Classifier, Random Forest Classifier, XGBoost, and LightGBM. The models that were evaluated using the accuracy metric suggest that deep learning models, notably LSTM and CNN, exceed machine learning approaches for detecting fake news. While CNN is effective at collecting basic data as well as local interactions, LSTM is particularly strong at recognizing long-term relationships and language patterns. The study highlighted the effectiveness of deep learning algorithms in identifying fake news and provided important insights that would help to develop more dependable detection systems. [10] in their study, they were able to categorize news collected from various online and print outlets as real or fraudulent. Using prominent automated language processing methods, data preprocessing, distinct deep neural networks, and predictive classification methods, their model recorded 81% accuracy for the small fake class and 99% accuracy in forecasting overall fake and real news.

3. Methodology

The methodology utilized in this study is outlined in Fig. 1. The procedures shown are further mentioned.

Fig. 1. Study methodology

3.1. Data collection

This study utilizes publicly available datasets collected from various online sources, each focusing on a specific domain. These datasets vary in size, language, and content, providing a diverse set of information for training and evaluating the fake news detection model. Table 1 summarizes the datasets, including their names, references, publication years, descriptions, and domains.

3.2. Data preprocessing

This is the process of cleaning and preparing data for training. Missing values, insignificant special characters, and links, among other things, can all impact data performance [2]. The following operations were performed:

- Punctuation Removal: Punctuation marks (e.g., ".", ",", "?", "!") do not carry semantic meaning in most NLP tasks and can add unnecessary noise. Removing punctuation ensures that words like "why" and "why?" are treated as the same word during text analysis, improving uniformity. The library used for this operation is re (Regular Expression Library).
- Removing stop words: Stop words (e.g., "a," "an," "the," and "and") frequently occur in the text but often contribute little to a sentence's meaning. Removing them reduces noise and focuses on meaningful words that help in analysis. The NLTK (Natural Language Toolkit) library was used to perform this procedure.
- Change to lowercase: Text is case-sensitive by default, so "Hello" and "hello" are treated as different words. Converting all text to lowercase ensures uniformity in analysis. This step was also carried out using the NLTK library.
- Lemmatization: Lemmatization reduces words to their base or root form (e.g., "running" → "run", "better" → "good"). It ensures that words with similar meanings are treated as the same, which improves model performance by reducing dimensionality. The WordNetLemmatizer() class under the NLTK library was used for this step.
- Elimination of links, special characters, multiple spaces, and single characters: This step is important because it reduces noise from the data and errors during tokenization. The re (Regular Expression Library) was used for this operation.

Table 1. Summary of datasets used in this study

ID	Dataset Name	Reference	Year	Description	Domain
1	Egyptian Football News Dataset	[11]	2023	Contains 20,000 real and fake football news articles collected from Twitter and Youm7.	Football
2	Syrian War Fake News Dataset	[12]	2019	Comprises 804 news articles labeled as real (1) or fake (0), compiled by scholars at the American University of Beirut.	War & Crime
3	Indian Fake News Dataset	[13]	2022	A dataset for fake news classification in Indian media, including politics, entertainment, and society.	Politics, Entertainment & Society
4	COVID-19 Fake News Dataset	[14]	2020	Consists of misinformation related to COVID-19 collected from Twitter, Facebook, and Instagram.	Health
5	Dezinfo SK Fake News Dataset	[15]	2023	A Slovak-language dataset containing real and fake news articles manually crawled and labeled.	Politics, Entertainment & Society
6	Russia-Ukraine War Fake News Dataset	[16]	2023	Includes 10,700 news headlines related to the Russian-Ukrainian war collected from Telegram.	War & Politics
7	French Fake News Detector Dataset	[17]	2020	A dataset built to classify fake and real news articles from French media sources.	Politics, Entertainment, Society, Science & Economy
8	Health Misinformation Dataset	[18]	2021	Contains 10,700 social media posts and articles related to health misinformation.	Health
9	Filipino Fake News Dataset	[19]	2020	This is a dataset of fake and real news in Filipino, labeled as 0 (fake) and 1 (real).	Politics, Entertainment, Society, Science & Economy
10	PHEME Dataset	[20]	2016	A multilingual dataset containing 4,842 tweets related to major news events, classified as true, false, or unverified.	Society & Politics
11	Chicago Hotel Reviews Dataset	[21], [22]	2011/2013	A dataset of true and misleading hotel reviews from 20 Chicago hotels was collected from multiple platforms.	Tourism
12	Spanish Fake News Corpus	[23], [24], [25]	2021	A Spanish-language dataset of 971 news articles labeled as real or fake.	Sports, Economy, Education, Entertainment, Politics, Health, Security & Society
13	US 2016 Presidential Election Fake News Dataset	[26]	2017	Contains 20,000 articles (11,941 fake and 8,074 real) collected from 240 sources, including the New York Times and Washington Post.	Politics & Elections

3.3. Model training

In [2], the authors employed Convolutional Neural Networks (CNN) and Long Short-Term Memory Networks (LSTM) to optimize models for fake news detection, leveraging the unique strengths of each architecture for text classification. Upon evaluation, the CNN model demonstrated superior performance over the LSTM model in terms of accuracy, training time, and generalization, likely due to its ability to effectively capture spatial patterns and n-gram features within textual data. Building on this finding, the CNN model proposed in [2] was adopted to train all the datasets used in this study, ensuring optimal performance in fake news detection tasks. The architecture of the adopted model is captured in Fig. 2.

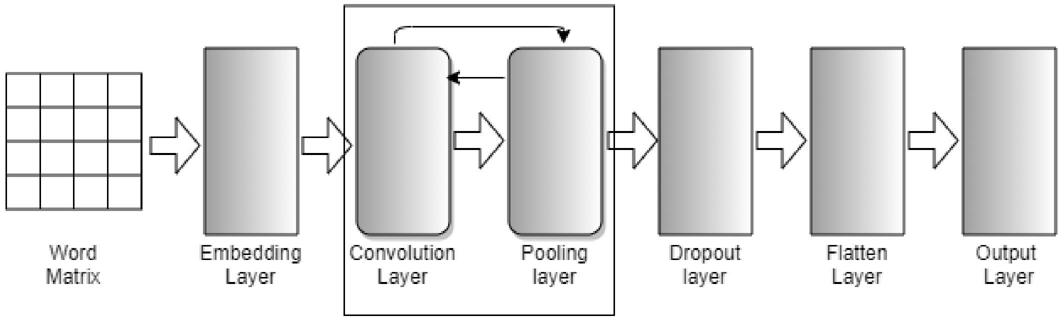

Fig. 2. Adopted CNN architecture from [2]

Table 2 presents the hyperparameter configurations used in training the CNN model. The settings were taken from the study by [2].

Table 2. Hyperparameter configuration for the CNN model used for tuning

Hyperparameter	Configuration Values	Description
Dropout:	0 – 1	Dropout to prevent overfitting
Activation:	Sigmoid, ReLu, TanH	Non-linearity to improve learning (Hidden Layers) Converts output to probability (Output Layer)
Epoch:	1-15	Number of training iterations
Batch Size:	30, 40, 50, 60	Number of samples per training batch
Kernel Size:	1-5	Window size for feature extraction
Filters:	35-75	Number of filters in the convolutional layer

For each of the layers, the layer specification includes:

- Input Layer: Word Embeddings (300D GloVe)
- Conv1D (Filters=200, Kernel=5, Activation=ReLU)
- GlobalMaxPool1D (Pool Size=2)
- Conv1D (Filters=256, Kernel=5, Activation=ReLU)
- GlobalMaxPool1D (Pool Size=2)
- Dropout (Rate=0.5)
- Flatten Layer
- Fully Connected (Dense, Units=64, Activation=ReLU)
- Dropout (Rate=0.5)
- Output Layer (Dense, Units=1, Activation=Sigmoid)

The implementation was carried out using Jupyter Notebook, an interactive Python environment running on Anaconda for streamlined dependency management. All experiments were conducted on an Apple MacBook equipped with 8GB of RAM and a 1.7GHz Core i5 processor, which provided sufficient computational power for training and evaluating the CNN model on the selected datasets. This setup highlights the practicality of using modest hardware configurations for effective model training and deployment in NLP tasks.

3.4. Model testing and evaluation

The dataset was divided into two parts to train and test the model effectively. Seventy percent of the data was used for training, allowing the model to learn patterns and features. In contrast, the remaining 30% was used for testing to evaluate how well the model performs on new, unseen data. To measure the model's performance, key metrics were used: Accuracy, to show how often the model made correct predictions overall; Precision, to check how many of the identified fake news instances were actually fake; Recall, to see how well the model captured all actual fake news instances; and F1-score, which provides a balance between Precision and Recall. Additionally, confusion matrices were created for each model, giving a clear picture of how many predictions were correct or incorrect. This matrix helped identify the number of true positives, true negatives, false positives, and false negatives, offering valuable insights into each model’s strengths and areas for improvement. Together, these evaluation methods provided a clear and comprehensive view of the models' performance.

3.5. Exploratory analysis

An exploratory analysis was carried out on all the datasets for better insight into the datasets using WordCloud. This section provides and discusses the results of the exploratory analysis of the various datasets. Fig. 3 shows the unique WordClouds derived from datasets 1 to 13.

The 13 Word Clouds on fake news from various datasets reveal complex patterns of themes and issues, with propaganda and disinformation emerging as the most common threads. These themes twirl through political, social media, and news organization datasets, indicating an overwhelming effort to influence the public's view through misleading or inaccurate data. Ukraine, Russia, Kyiv, Trump, and Clinton are prominent, especially in political and societal datasets, implying directed speech at specific personalities. In contrast, the presence of war, death, strike, and attack suggests a more subtle but still harmful form of fake news. This emphasizes the need for a multifaceted approach to combat fake news that incorporates verification of facts, media literacy, and critical thinking across various domains. Furthermore, the variation in themes across datasets demonstrates the adaptability and advancement of fake news strategies, highlighting the importance of a dynamic and responsive strategy to mitigate its negative effects on the community. The clouds collaboratively suggest that fake news is a complex, insidious, and ever-changing phenomenon that necessitates a long-term and comprehensive response to protect truth and accuracy in public discourse.

Fig. 3. Word cloud for datasets 1 to 13, respectively

4. Results and Discussion

This section discusses the results obtained by training and testing the CNN model with the 13 datasets from different domains. The results in Table 3 provide a comprehensive summary of the model's performance after it was trained and tested on various domain-specific datasets.

Table 3. The outcomes after training and testing

Dataset	Train Accuracy	Test Accuracy	Precision	Recall	F1-Score
1	0.9915	0.947	0.9471	0.947	0.947
2	0.9781	0.9185	0.9185	0.9185	0.9185
3	1.0000	0.9928	0.9928	0.9928	0.9928
4	1.0000	0.903	0.9032	0.903	0.903
5	0.9952	0.9111	0.9245	0.9111	0.9104
6	0.9981	0.9838	0.9829	0.9838	0.9829
7	1.0000	0.9684	0.9687	0.9684	0.9684
8	0.9999	0.9212	0.9218	0.9212	0.9211
9	1.0000	0.9397	0.9397	0.9397	0.9397
10	0.9389	0.8678	0.8632	0.8678	0.8648
11	0.9991	0.8271	0.8277	0.8271	0.8271
12	1.0000	0.6803	0.687	0.6803	0.679
13	0.9985	0.9561	0.9561	0.9561	0.956

The evaluation metrics used in this study, Train Accuracy, Test Accuracy, Precision, Recall, and F1-score, help provide a clear picture of how robust the model is, how well it generalizes to new data, and how effectively it adapts to different domains. The Train Accuracy values show that the model performs exceptionally well during training, with most datasets achieving nearly perfect scores (close to 1.0000). This indicates that the model learns effectively from the data it is exposed to. However, the Test Accuracy values reveal differences in how well the model performs on unseen data across various domains. For instance, Dataset 3 achieves the highest Test Accuracy (0.9928), showing strong generalization and alignment between training and testing, while Dataset 12 records the lowest Test Accuracy (0.6803), possibly due to overfitting or challenges like the dataset's complexity or lower quality. Metrics like Precision, Recall, and F1-score provide additional insights into the model's ability to identify fake news accurately. Dataset 3 stands out with exceptional performance across all metrics (0.9928), indicating a highly balanced and accurate detection process.

On the other hand, Dataset 12 struggles with the lowest scores, suggesting difficulties in distinguishing real news from fake news, likely due to inherent issues with the dataset, such as noise or limited data quality. Certain datasets, like Dataset 6 and Dataset 7, deliver consistently high performance across all metrics, showcasing the value of using domain-specific datasets for enhancing fake news detection. In contrast, moderate performance in datasets like Dataset 10 and Dataset 11 points to opportunities for further refinement, such as improved preprocessing or feature extraction techniques. Overall, the results highlight that while the model excels with some domain-specific datasets, its performance varies across domains. This variability emphasizes the importance of customizing models for specific datasets to improve their accuracy and adaptability in detecting fake news effectively.

Fig. 4 shows that using domain-specific datasets improves the performance of models in fake news detection far more than generic or combined datasets. The models that were trained on domain-specific data outperformed models trained on broader datasets in terms of accuracy, precision, recall, and F1-score, with increases ranging from 68% to 99%. This noted improvement shows that using domain-specific variables that reflect the distinct language and contextual nuances of different domains should be prioritized. Fig. 4 further demonstrates that, while domain-specific models perform excellently in their settings, models trained on a wider range of datasets provide higher generalizability, performing consistently across multiple domains. This implies that a balanced strategy, which incorporates both domain-specific and heterogeneous datasets, would be more beneficial for developing robust and flexible false news detection models. These findings highlight the importance of dataset specificity and diversity in improving the effectiveness of machine learning algorithms for detecting fake news.

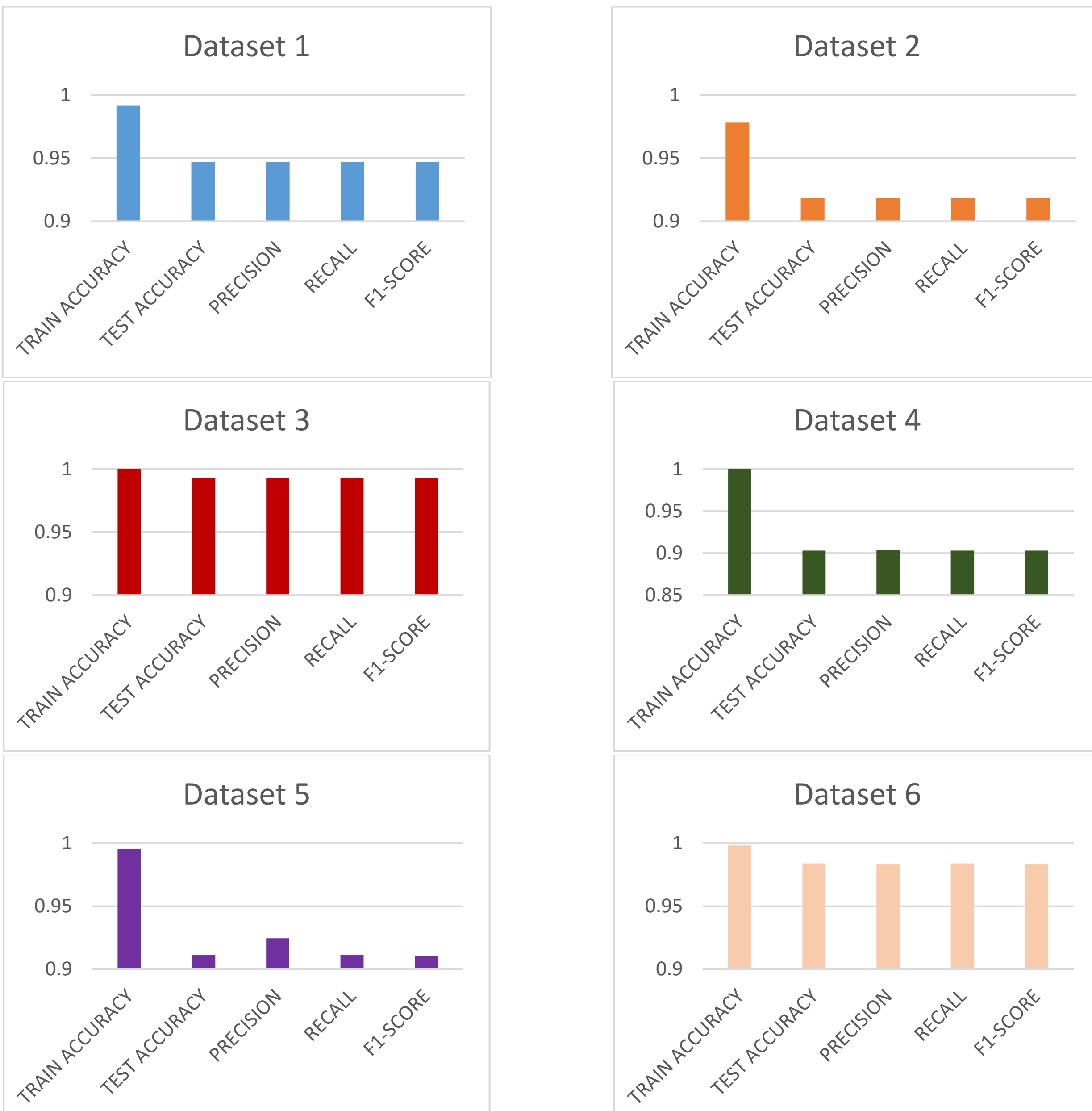

Fig. 4. Bar charts showing the results of training the models using distinct datasets

To evaluate the effectiveness of this research, the performance of our domain-specific dataset-based models was compared with those reported in prior studies.

Table 4 highlights the superiority of the proposed model in this research, achieving the highest accuracy (94.7%) and F1-score (0.947) compared to prior works. This improvement can be attributed to the use of domain-specific datasets, which provide more tailored data for training and testing, as opposed to general or mixed datasets that may introduce noise and reduce model performance. Among prior works, Ahmed et al.

(2021), who also used domain-specific datasets, achieved the closest results, validating the importance of dataset specificity. However, models like Naïve Bayes (Zhao et al., 2017) and SVM (Li et al., 2018) struggled significantly due to limitations in handling general datasets effectively, further emphasizing the relevance of dataset quality and optimization strategies. By including domain-specific datasets and optimizing model parameters, this research demonstrates the potential for significantly improving the accuracy and robustness of fake news detection systems.

Table 4. Performance comparison of domain-specific dataset-based models with prior studies

Study/Model	Dataset Type	Accuracy	Remarks
This research (proposed model)	Domain-Specific Dataset	>= 93%	Achieved superior performance through domain-specific dataset tuning.
(Alsaeedi and Al-Sarem, 2020)	Mixed Dataset	87.1%	General datasets limited the ability to capture domain-specific fake news characteristics.
(Girgis, et al, 2018)	General Dataset	27%	General datasets restricted the model's ability to distinguish between fake and real news effectively.
(Fernández-Reyes and Shinde, 2018)	Mixed Dataset	48.5%	Struggled with general datasets due to their noise and limited representation of fake news data.

5. Conclusion

In an age when disinformation and fake news spread rapidly via digital media, it is crucial to have systems that can effectively distinguish between real and fake news and flag them as such. This study sought to improve the reliability and effectiveness of false news detection models and systems by investigating how the properties of domain-specific datasets influence the performance of fake news detection models. The study discovered that the domain from which a dataset is drawn has a considerable impact on the performance of detection models within that specific domain. Different domains have distinct language and contextual characteristics that can influence the accuracy and generalizability of machine learning systems. This work identified the news domain as a critical parameter that contributes to the success of false news detection models after evaluating a range of datasets from diverse areas. The findings show that using domain-specific characteristics and carefully selecting balanced training data is critical for developing strong detection systems. Models trained on datasets that capture the different nuances and intricacies of specific domains are more capable of detecting false news properly within their domain. This method not only increases model performance but also makes detection strategies more adaptable to varied circumstances and forms of misinformation.

Furthermore, this work emphasizes the need to explore diversity and variety in datasets used when training and evaluating false news detection programs. By recognizing and harnessing the intricacies between domains, more accurate and resilient models can be designed. Further research should investigate the relationship between dataset qualities and model performance across a broader range of domains. This will assist in developing more dynamic, adaptable, and reliable false news detection systems, which will ultimately reduce the spread of fake news and help preserve the integrity of information in the digital era.

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