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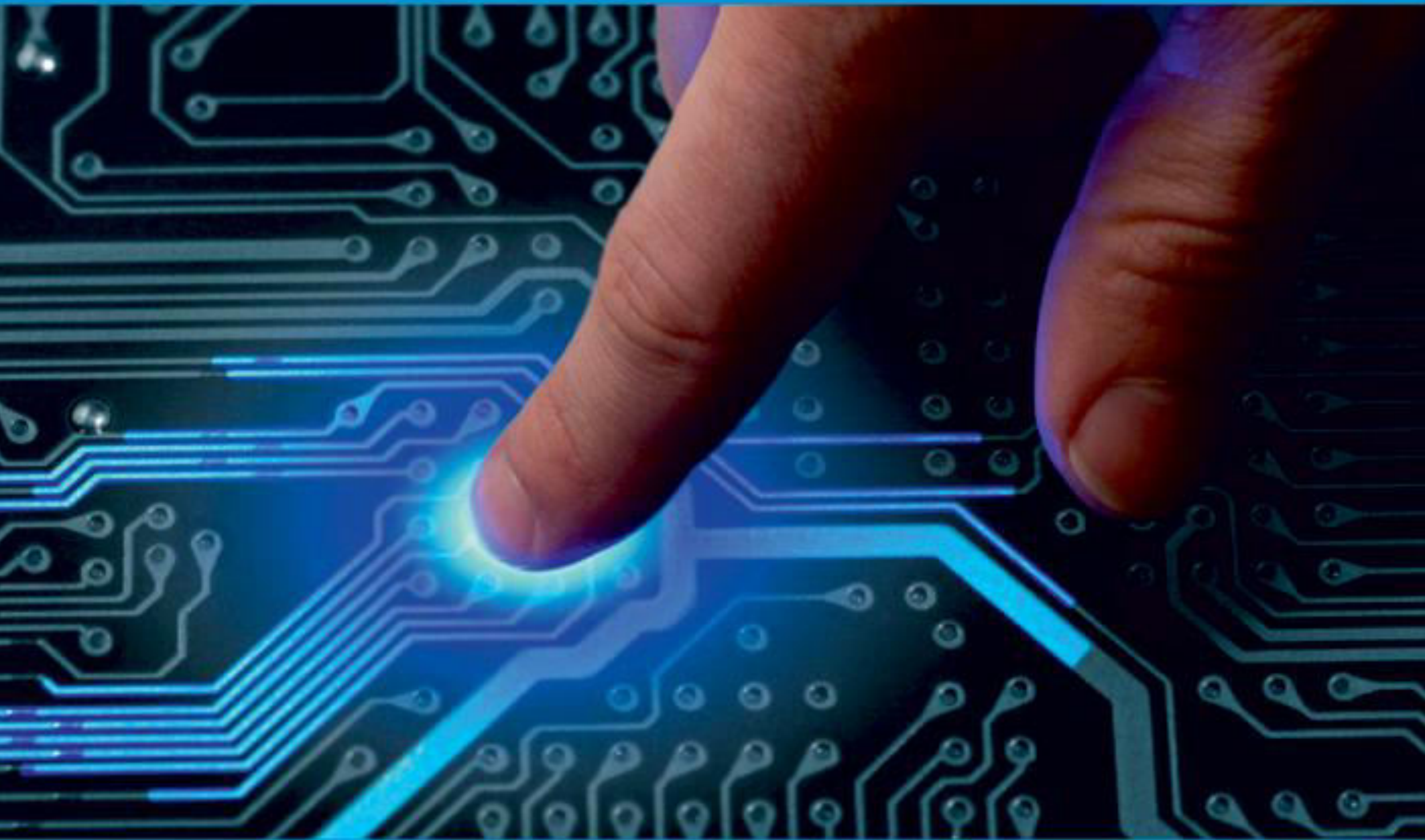

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Fake News Detection using Deep Learning

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ABSTRACT: The expansion of the Internet and information technologies has led to a general increase in access to information that is consumed and raises fake news concerns. This can have wide-ranging repercussions, from government destabilization including instances of the US Election Campaigns to even anything in between. The problem has been attempted to be solved in many ways some of the more recent researches into this problem have focused on using deep learning techniques for fake news detection.. Fake news detection through textual analysis has been tried out by various methods like BERT, RoBERTa and DistilBERT in an attempt to find how effective they can be. Moreover, it has shown promising results by leveraging RoBERTa for emotion classification of news titles via emotion profiles. For example, combination of these methods, such as using emotion probability vectors with a Binary Random Forest classifier resulted into 88% accuracy in distinguishing fake news. These are more advanced techniques than traditional machine learning models like KNN and Naive Bayes that no longer work well providing scalable solutions for automated fake news detection systems with high accuracy and reliability levels.

KEYWORDS: BERT, RoBERTa, DistilBERT ,fake news ,fine-tunning, Pre-trained model.

I. INTRODUCTION

The problem of spreading false information is a big concern in the modern world, as fake news usually aims at attracting attention by causing strong emotions using certain oriented keywords and phrases. Unlike fake news, which is more emotional than real news whose main purpose is to inform people with a neutral attitude. This can have wide-ranging repercussions, from government destabilization including instances of the US Election Campaignsto even anything in between. The problem has been attempted to be solved in many ways; some of the more recent researches into this problem have focused on using deep learning techniques for fake news detection. It classifies texts into one of seven emotions: joy, rage, repulsion, fear, grief, surprise and neutral respectively from top-six according to psychologist Paul Ekman's typology.

This model has been trained ontext annotated with emotions and further used for classification of emotion in titles of news. Eventually, the Fake/Real News Recognition was performed using Random Forest Binary Classifier based on emotion probability vectors.

New internet-based digital media has changed the consumption of news from conventional roots like newspaper and television to online platforms. In 2021, social media was the most preferred news source in Indonesia signifying the problem of identifying what is genuine and fake news on online platforms. Through ease of creating unauthenticated websites that spread false information, this can be a threat to individuals as well as entities. But identifying it is hard because many people cannot differentiate between fake and real information. However, even existing machine learning models like KNN and Naive Bayes cannot fully represent true context and meaning of words. Consequently, there have been suggestions for transformer-based models such as BERT, RoBERTa, DistilBERT which could enable better detection of fake news due to improved understanding of word semantics and context.These new technologies are transforming how we consume knowledge as they revolutionize traditional formats in favor of online platforms such as social media YouTube podcasts. This change has brought about an abundance of unconfirmed information that is frequently accepted by the general public as facts. Indeed, the 2016 US presidential election campaign demonstrated the extent to which fake news can influence choice making leading to major tech companies such as Twitter Facebook Google designing tools for detection purposes. Nonetheless, this would still remain a complex task The goal of this work is to develop deep neural network models for detecting and categorizing fake news, providing a trust indicator for information consumers to reduce bias and misinformation.

II. LITERATURE SURVEY

CB-Fake: A Multimodal Deep Learning Framework for Automatic Fake News Detection Using Capsule Neural Network and BERT by Balasubramanian Palani, Sivasankar Elango, and Vignesh Viswanathan K presents a model that

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analyzes both textual and visual content of news articles for early fake news detection. The model integrates BERT to extract semantic relationships in text and CapsNet to capture detailed visual features. It achieves classification accuracies of 93% and 92% on the Politifact and Gossipcop datasets, respectively. This approach enhances the progress of the SpotFake+ model to a huge extent; hence, this works better, setting up a new benchmark in fake news detection accuracy. (Balasubramanian, Sivasankar, & Vignesh, 2022)

A pre-trained transformer-based ensemble model for automated Indonesian fake news classification by Pauw Danny Andersen and Derwin Suhartono focuses on the Indonesian language news datasets. It harnesses features from BERT, RoBERTa, and DistilBERT; it ensembles using model-averaging prediction with an attained maximum accuracy of 0.887 and a maximum F1-score of 0.878. It suggests increasing the size of the datasets and the incorporation of more pre-trained models like IndoBERT and Multilingual BERT for potential improvements in results in future research work.. (Pauw Danny Andersen & Derwin Suhartono, A Pre-trained Transformer-based Ensemble Model for Automated Indonesian Fake News Classification, 2023)

AugFake-BERT: Handling Class Imbalance with Fake News Augmentation Using BERT for Improved Fake News Classification by Ashfia Jannat Keya, Md. Anwar Hussen Wadud, M. F. Mridha, Mohammed Alatiyyah, and Md. Abdul Hamid addresses the class imbalance of fake news datasets using text augmentation with BERT for generating synthetic fake data. The augmented dataset has enhanced performance in classification tasks to an accuracy of 92.45%, hence outperforming twelve state-of-the-art models. The paper has showcased the effectiveness of the AugFake-BERT model with respect to class imbalance handling and further improving fake news classification, which thus forms the basis of future studies oriented towards robust self-supervised language-model-based systems for fake news detection. (Ashfia Jannat Keya, Md. Anwar Hussen Wadud, M. F. Mridha, Mohammed Alatiyyah , & Md. Abdul Hamid, 2022)

Dhanaraj Jadhav and Jaibir Singh, in their work on Web Information Extraction and Fake News Detection in Twitter Using Optimized Hybrid Bi-gated Deep Learning Network, proposed EDLM-ODA as an optimized deep learning network for fake news detection in Twitter. Their proposed model extracts the features through TF-IADF, n-gram, character level, and hashing vectorizers and classifies real and fake news through a dual attention-based convolutional bi-gated reptile optimal network. It yields high accuracy on the PHEME, Liar, and FakeNews Net data sets 99%, 99.12%, and 99.2%, respectively. The model further Patil et al. suggests improvements with multi-modal DL strategies and application on other social media platforms to get better scalability and accuracy. (Dhanaraj Jadhav & Jaibir Singh, 2023)

A Better Fake News Detector: BERT-Based Mental Model Jia Ding, Yongjun Hu, and Huiyou Chang: This paper proposes a BERT-based mental model to improve the performance in fake news detection by capturing mental features. They fine-tuned BERT with incorporated patterned text, outperforming state-of-the-art models on the LIAR dataset by 16.71%. This survey depicts major improvements in performance with the integration of mental features into BERT and points to the application of mental features in other classification tasks. (Jia Ding, Yongjun Hu, & Huiyou Chang, 2020)

III. METHODOLOGY

The research uses three-step methodologies which include initiation, model building and evaluation of the model. In phase one we collected datasets from previous studies. Among these datasets contain 228 instances known as false news whereas 372 are real news instances. For labeling purpose on fake news articles taking a value of 1 while genuine ones take a value of Augmentation and pre-processing of datasets are done before feature extraction is initiated, which puts the data in a format that can be easily used by deep learning models. Finally, the performance of a model is evaluated using different metrics.

3.1. Preprocessing

In the present study, the authors focus on the Indonesian Hoax News Detection Dataset, consisting of 600 news articles from which 288 were fake and 372 were real. This data set is manually harvested from several online media sources; each article was tagged with respect to being fake or genuine by three arbitrators. The final label for each article comes from a voting procedure between the referees.Data augmentation technique is employed to address data scarcity issue and lack of diversity. The augmented dataset has 450 fake news articles and 450 genuine ones. Thereafter, the dataset is divided into training, validation and testing sets with respective distributions of 70%,15%and 15%.There are several steps involved in preprocessing stage aimed at maximizing the efficiency of feature extraction. Some of these include:

1. DATA AUGMENTATION (DA): By creating variants of the original data without actually collecting new data, it artificially augments the size of training data. Easy Data Augmentation techniques are employed in which randomly the words in the sentences are selected and replaced with their synonyms or words are swapped in pairs

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of two. This way, it ensures that class categories are preserved to enhance the performance in the classification task. In more detail, the datasets are augmented and preprocessed before starting to extract features to make them accessible for deep learning models. Various metrics then score the performance of these models.Noise Removal: Here, numbers, symbols and punctuation marks that may affect text analysis are removed from the text.

2. Tokenization: The process involves splitting up the text into small small units called as tokens
3. Stop Words Removal: Some words which have no significant meaning in the text are deleted so as to make the dataset simpler.
4. Lowercasing: To ensure uniformity and reduce variability, all texts are made lowercase.
5. Lemmatization: The root forms of words are found through part-of-speech tagging for better accuracy in lemmatizing words.

3.2 Modelling Architecture

This is the suggested modelling architecture, which uses several language models pre-trained in BERT, RoBERTa, and DistilBERT that best fit the Indonesian dataset.

• BERT: This is a bidirectional transformer pre-trained on huge corpora, such as the Toronto Book Corpus and Wikipedia, for masked language modeling and next sentence prediction.

• RoBERTa: A Robustly Optimized BERT Pretraining Approach is also a variant of BERT, published by researchers from the University of Washington, with a very large dataset and more training iterates. This text is tokenized using a byte version of Byte-Pair Encoding with a vocabulary size of 50,257. There are also tokens for marking the beginning of each document.

• DistilBERT: A smaller, faster, and cheaper version of BERT, DistilBERT keeps over 95% performance yet employs only 40% parameters from BERT while executing at a speed that is 60% faster than it. The language appears in lower case letters and gets tokenized into WordPiece tokens with about 30,000 tokens in its vocabulary. In this case the input format resembles that of BERT with [CLS] Sentence A [SEP] Sentence B [SEP].

The feature extraction process comprises several stages. Initially, [CLS] and [SEP] tokens are prepended to every sentence respectively. Next all words within the sentence are converted into tokens thereby resulting into sequence-like word tokens. Afterward this tokenized text undergoes segment embedding as well as positional embedding for contextual purposesAhy: Each model has a maximum sequence length of 512 tokens but gets truncated for longer sequences.

• RoBERTa: This is an improved variant of BERT with a much larger dataset of 30 billion words and was developed by researchers at the University of Washington. This text is tokenized using a byte version of Byte-Pair Encoding (BPE) with a vocabulary size of 50,257. There are also tokens for marking the beginning of each document.

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• Accuracy: It is the proportion of correct predictions against total predictions made.

• Precision: Generally, it is defined as the ratio of true positives to both true and false positive classifications. It measures how well the model predicts the positive cases.

• Recall: This measures the amount of true positive predictions over real positives. It really is an important measure as it considers whether the model has been able to pick up real cases where positive is the situation.

• F1 Score : It is the score that serves in combining the precision and recall into a single value, especially when the distribution of classes is imbalanced.

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3.3. Parameter Tuning

To optimize model performance, parameter tuning must be done. Batch size and learning rate were adjusted in this study. shows results from several experimental scenarios with batch sizes as 8, 16, and 32; learning rates as 1.00E-5, 3.00E-5, and 5.00E-5 were considered too.The learning rate was dynamically adjusted using a learning rate scheduler during training.A comprehensive approach to detecting fake news leveraging multiple pre-trained language models and extensive preprocessing and data augmentation techniques aims at achieving high accuracy in classifying news articles as fake or genuine based on a deep-learning framework.This paper provides details about evaluation metrics and process of parameter tuning

IV. RESULT AND DISCUSSION

In previous studies BERT model performance which was high in Politifact and Gossipcop datasets with an accuracy of 0.9 and 0.91 respectively [Palani, Elango, & Vignesh V K]. The precision, recall and F1-scores for these datasets were also impressive demonstrating consistency in their findings with precision values of 0.89 and 0.92, recall values of 0.95 and 0.97; as well as F1-scores of 0.92 and 0.94.It was noted that the BERT model did not perform very well on the System Baseline dataset [Andersen & Suhartono] It had an accuracy of 0.803, a precision of 0.772, a recall of 0.785 and F1-Score 0.778 compared to RoBERTa which registered slightly lower results with an accuracy of 0.739, a precision rate if 0.726, However, DistilBERT performed better in System Baseline dataset with an accuracy level equal to those obtained by RoBERTa (87%), a higher level compare to BERT (65%); moreover, DistilBERT had higher precision (90%) but lower recall (86%). The research carried out by Raveen Narendra Babu et al.,(2023) showed the performance of various models on the LIAR dataset among which BERT exhibited itself as having achieved an accuracy score worth only about two thirds being equal to approximately 68 percent while its precision equated 63 percent as regards ROBERTA whose overall rates were almost identical albeit slightly higher when it came down recalling things related to figures from memory during this period, recall of 0.65, and F1-score of 0.65, while DistilBERT also had an accuracy of 0.69, precision of 0.62, recall of 0.65, and F1-score of 0.63. On the FNC-1 dataset BERT, RoBERTa, and DistilBERT had accuracies of 0.98, 0.99, and 0.98 respectively as well as precision, recall and F1-scores all around 0.97 to 0.98 mark.The Balanced Dataset for Fake News Analysis recorded a very high performance by BERT with an accuracy of 0.97, precision of 0.96, recall of 0.96 and F1-score at the same time while RoBERTa scored perfectly on it with all the accuracy, precision, recall and F1-score at one values.DistilBERT also performed well on this dataset with an accuracy of 0.96; hence its precision; recall; and f1 scores are at 0.96. Fake_news_elections_labelled_data_BERT model results were reported by MSVP.J Satvik et al (2023), which include accuracy 0.78, precision 0.81 recall=0.84 f1score 0.83. DistilBERT showed better results in the same dataset having an accuracy 0.83 (precision is 0.83,recall is 0.84,f1 score is 0.84).Shaina Raza et al (2024) reported BERT performances on several datasets: Gossipcop with an accuracy equal to 0.85 where the corresponding values for Precision ,recall ,and F1_score are 0.76,0.89,0.82 respectively Politifact with an overall result of 0.91accuracy together with related measures like Precision is 0.93 Recall is 0.91 & F1 score is 0.92 and CoAID with high metrics—accuracy of 0.99, precision of 0.97, recall of 0.99, and F1-score of 0.98.In my studies[2024] I have seen different result on different models for different datasets. for Fake_News_Detection, the BERT model returned an accuracy of 0.76, with high precision of 0.91 but a relatively lower recall of 0.83, and an F1 score of 0.82. RoBERTa performed very poorly on Fake_News_Detection its accuracy was 0.4 Fake_News_Detection dataset: accuracy 0.96, precision 0.99, recall 0.98, and an F1-score equal to 0.98. On Marathi_Fake_News, BERT returned an accuracy of 0.64, a precision of 0.64, a recall of 1, and an F1-score of 0.78. This was considerably lower on the same dataset, with accuracy at 0.64 and precision and recall both at 0, for an F1 score of 0. DistilBERT's performance on Marathi_Fake_News was also pretty low, with accuracy at 0.64 and precision and recall both at 0.

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Table 1: Performance Comparison of NLP Models Across Multiple Datasets and Studies

Author	Model	Dataset	Accuracy	Precision	Recall	F1-Score
B Palani, S Elango, Vignesh V K [2021]	BERT	Politifact	0.9	0.89	0.95	0.92
	BERT	Gossipcop	0.91	0.92	0.97	0.94
Pauw Danny Andersen, Derwin Suhartono [2023]	BERT	System Baseline	0.803	0.772	0.785	0.778
	RoBERTa		0.739	0.726	0.766	0.766
	DistilBERT		0.887	0.902	0.857	0.878
Raveen Narendra Babu, Chung-Horng Lung, Marzia Zaman [2023]	BERT	LIAR	0.68	0.63	0.64	0.63
	RoBERTa		0.69	0.64	0.65	0.65
	DistilBERT		0.69	0.62	0.65	0.63
	BERT	FNC-1	0.98	0.97	0.98	0.98
	RoBERTa		0.99	0.98	0.98	0.98
	DistilBERT		0.98	0.98	0.97	0.97
	BERT	Balanced Dataset for Fake News Analysis	0.97	0.96	0.96	0.97
	RoBERTa		1	1	1	1
	DistilBERT		0.96	0.96	0.96	0.96
MSVP.J SATVIK,Mukesh K M,Sibasankar P(2023)	BERT	Fake_news_elections_labelled_data	0.78	0.81	0.84	0.83
	DistilBERT		0.8	0.83	0.84	0.84
Shaina Raza ,Tahniat Khan ,Veronica C(2024)	BERT	Gossipcop	0.85	0.76	0.89	0.82
	BERT	Politifact	0.91	0.93	0.91	0.92
	BERT	CoAID	0.99	0.97	0.99	0.98
Sandip Jadhav [2024]	BERT	Fake_News_Detection_dataset	0.76	0.91	0.83	0.82
	RoBERTa	Fake_News_Detection_dataset	0.4	0	0	0.52
	DistilBERT	Fake_News_Detection_dataset	0.96	0.99	0.98	0.98
	BERT	Marathi_Fake_News	0.64	0.64	1	0.78
	DistilBERT	Marathi_Fake_News	0.64	0	0	0

Table 2:Comparing result of all three models on fake news detection dataset :

	Fales/true	Precision	Recall	F1 Score	Accuracy
BERT	0	0.76	0.91	0.83	0.82
	1	0.90	0.74	0.81	
RoBERTa	0	0.40	00	0	0.52
	1	0.52	1.00	0.69	
DistilBERT	0	0.96	0.99	0.98	0.98
	1	0.99	0.97	0.98	

V. CONCLUSION

This research provides an extensive comparison of different strategies to construct a fake news classification system using fake news detection dataset. Experimental results indicate that deep learning approach based on pre-trained language models such as BERT, RoBERTa and DistilBERT and proposed ensemble model by employing model averaging method significantly outperformed other approaches in terms of mean accuracy and F1 scores. Among these models tested, DistilBERT portrayed the best performance with an accuracy level of 0.98 and F1 score at 0.98. Also

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proposed ensemble model showed strong results but had a bit lower performance then DistilBERT because it has high variability performance among its Results show that the ensemble model is promising but is most effective when combined with models having comparable performance levels. The result of such variances in individual model outcomes is therefore that the performance of ensemble model did not improve as expected. Nevertheless, both the ensemble and DistilBERT models performed better than previous work on similar data sets suggesting improvement in fake news detection.

This made hyperparameter tuning, which consisted of 5-fold cross-validation, crucial for optimizing the performance of our models. Taking a batch size of 32 and a learning rate scheduler that varied between 5.00E-5 and 0.0 was found to be appropriate, giving a stable learning process to guide optimization efforts on our best performing models. This careful tuning accounted significantly for how well the models worked. Future exploration and expansion are pointed out in this research. This would, in future experiments, be conducted on a bigger and more diverse Indonesian dataset to strengthen generalizability and robustness for these models. This may be improved further with the incorporation of other pre-trained frameworks, such as IndoBERT or multilingual BERT, otherwise capable of improving the overall performance if translation were removed so that the original context and meaning of Indonesian are retained.

Growth in the prevalence of AI-generated content: This present paper places a premium on the development of robust systems for the effective detection and mitigating spread of fake news. The proposed models, especially DistilBERT, demonstrate that advanced transformer-based architectures can effectively address this challenge.

In the present context, the knowledge gained from this study proposes that deep learning models have a significant advantage for various kinds of stakeholders like individual users and Social media companies. The implementation of such models will greatly reduce misinformation propagation and elevate trustworthiness in public information accessibility.

The future calls for more refining of these models as well as increasing datasets used in their training. To maintain its relevance and accuracy, however, it is essential to use recent diverse data which can be collected through automated systems. Moreover, user-friendly applications and integrationssuch as browser extensions and mobile apps need to be developed so that they can enable these models to be deployed in real-life scenarios thus making them available to the public.

To sum up the study indicates how deeply learning model might help detect fake news with notable improvements over past approaches. Expanding datasets further and improving models strengthens these systems making them an influential weapon against disinformation. This research gives a stepping stone towards more sophisticated lies detection, which has promising implications on enhancing fake news detection integrity

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