From Scarcity to Capability: Empowering Fake News Detection in Low-Resource Languages with LLMs

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ABSTRACT

The spread of fake news is a pressing global issue, especially in low-resource languages like Bangla, which lack sufficient datasets and tools for effective detection. Manual fact-checking, though accurate, is time-consuming and allows misleading information to propagate widely. Building on previous efforts, we introduce BanFakeNews-2.0, an enhanced dataset that significantly advances fake news detection capabilities in Bangla. This new version includes 11,700 additional meticulously curated and manually annotated fake news articles, resulting in a more balanced and comprehensive collection of 47,000 authentic news and 13,000 fake news items across 13 categories. In addition, we develop an independent test dataset with 460 fake news and 540 authentic news for rigorous evaluation. To understand the data characteristics, we perform an exploratory analysis of BanFakeNews-2.0 and establish a benchmark system using cutting-edge Natural Language Processing (NLP) techniques. Our benchmark employs transformer-based models, including Bidirectional Encoder Representations from Transformers (BERT) and its Bangla and multilingual variants. Furthermore, we fine-tune the large language models (LLMs) with Quantized Low-Rank Approximation (QLORA), leveraging gradient accumulation and a paged Adam 8-bit optimizer for classification tasks. Our results show that LLMs and transformer-based approaches significantly outperform traditional linguistic feature-based and neural network-based methods in detecting fake news. BanFakeNews-2.0's expanded and balanced dataset offers substantial potential to drive further research and development in fake news detection for low-resource languages. We publicly release our dataset and model at github to foster research in this direction.

CCS CONCEPTS

• **Computing methodologies → Language resources**.

KEYWORDS

Fake News, Fact Check, Bengali, NLP, LLM, Low-Resource-Language, BERT, Bangla

ACM Reference Format:
Hrithik Majumdar Shibu, Shrestha Datta, Nasrullah Sami, MD. Sumon Miah, Mahruba Sharmin Chowdhury, and Md Saiful Islam. 2024. From Scarcity to Capability: Empowering Fake News Detection in Low-Resource Languages with LLMs. In *Woodstock '18: ACM Symposium on Neural Gaze Detection, June 03–05, 2018, Woodstock, NY*. ACM, New York, NY, USA, 5 pages. https://doi.org/XXXXXXX.XXXXXXX

1 INTRODUCTION

The proliferation of fake news, defined as the intentional dissemination of false information, has emerged as a pervasive concern in modern society. Such misleading narratives, propagating through diverse channels such as social media, online news platforms, and even traditional newspapers, serve not merely as innocent fallacies but as instruments to deceive, influence, and sometimes manipulate public perception. The consequences of such disinformation can range from shaping public opinion on critical matters to catalyzing large-scale societal disturbances. For example, in 2020, misinformation about the COVID-19 vaccine's adverse effects led to widespread vaccine hesitancy [16, 17]. A study from Bangladesh [23] highlighted the dangerous effects of misinformation online, outlining incidents from unfounded rumors about child kidnappings to unjust religious hate speech. An incident in 2012 involved baseless attacks on Buddhist temples in Bangladesh, incited by false accusations on a social media platform, showing the extent of chaos that fake news can cause [4]. Fake news can take many forms, including written articles, images, videos, and even memes.

Addressing fake news detection, particularly in low-resource languages like Bangla, presents several significant challenges. The scarcity of high-quality, annotated datasets limits model development as existing research focuses mainly on English. Manual fact-checking is accurate but time-consuming and not scalable for

ACM ISBN 978-1-4503-XXXX-X/18/06
https://doi.org/XXXXXXX.XXXXXXX

real-time misinformation. Previous efforts, such as the BanFakeNews dataset, included only 100 fake news instances supplemented with satirical news [11]. Meanwhile, Sharma et al. [22] constructed a dataset with 1480 satire news for satirical news detection. More recent datasets, like those by [2], expanded the corpus to 4,500 news in Bangla and English but still fell short in terms of comprehensiveness and balance. Traditional approaches have utilized linguistic features and neural network-based methods with some success [12, 24], but the incorporation of state-of-the-art transformer models and large language models (LLMs) remains underexplored.

Table 1: Overview of existing Bangla fake news datasets. Here #FN represents no of fakenews and #TN represents the no of authentic news dataset

Dataset source	#FN	#TN
Bangla Fake News Dataset [19]	4.5K	10K
Religious Misinformation Dataset[2]	2K	5k
BanFakeNews [11]	1.3K	48.6k
Social Media News Dataset [13]	1K	2.5K
BanFakeNews-2 (Proposed)	13K	47k

To address these challenges, we introduce BanFakeNews-2.0, an enhanced dataset designed to significantly advance fake news detection capabilities in Bangla. BanFakeNews-2.0, an significant incremental advance version of BanFakeNews [11], where we follow similar data collection, annotation, and validation approaches. However, collect more data from various categories and domains including medical, religious, political etc. This newer version includes 13,000 meticulously curated and manually annotated fake news articles, resulting in a balanced and comprehensive collection of 60,000 news articles consisting of 47,000 authentic news and 13,000 fake news items across 13 categories. Additionally, we develop an independent test dataset of 1000 news with 460 fake news and 540 authentic news for rigorous evaluation. We employ traditional linguistic features and neural network-based methods and cutting-edge NLP techniques, including transformer-based models like BERT and its variants, and fine-tune large language models (LLMs) using Quantized Low-Rank Approximation (QLORA). We reproduce the BanFakeNews models and thoroughly evaluate them on BanFakeNews-2.0 with internal test data (15% of BanFakeNews-2.0) and an independent test data. We got best performance of macro F1 of 86 with all traditional linguistic features and macro F1 of 87 for BERT-based model. Our best performance comes with a fine-tune LLM based model BLOOM with macro F1 of 89. We conduct an ablation study and observe a significant performance drop of models that are trained on existing datasets and tested with independent test data. The main contributions of this research are highlighted as follows:

- We present a BanFakeNews-2.0, an significant incremental advance version of BanFakeNews [11] as shown in the Table 1. While previous research [2, 11, 13, 19] are limited in size and highly imbalanced we annotated 60,000 Bangla news articles, including 13k fake news.
- We conducted extensive experiments using traditional linguistic features, transformer-based models like BERT and large language models (LLMs) to improve the performance of detecting fake news in Bangla.
- We develop an independent test dataset for regoroius testing and validation for all the existing dataset as well as the newly build model comparisons. In addition, we publicly release our dataset and model to foster research in this direction.

2 DEVELOPMENT OF BANFAKENEWS-2.0

We invest efforts in data preparation to preserve linguistic richness with the following objectives: 1) Fake news should be collected from various sources and domains, and 2) Samples should enhance the dataset's diversity and reduce redundancy. We are introducing a newly created and annotated Bangla fake news dataset consisting of nearly 13000 fake (labeled as 0) and 47000 authentic (labeled as 1) content collected from different online news portals and mainstream news media. To collect authentic news articles, we selected the top 30 news portals in Bangladesh, renowned for their credibility and widespread readership. We collect news from the most common 13 categories of these newspapers. Simultaneously, for fake news, we identified six predominant fact-checking platforms extensively employed for debunking misinformation in the Bangladeshi context. Recognizing the variegated web structures of these platforms, we designed and implemented an automated web crawler tailored for each fact-checker. This ensured comprehensive data extraction across diverse webpage layouts, which was subsequently consolidated into a singular database. To reduce repetitiveness and noise, we remove duplicates and exclude instances that have more than 50% or 300 words of similar tokens. We aim to expand vocabulary size and contextual variety by including a wide range of news items. While diverse vocabulary may be challenging to model, it ultimately contributes to the development of more robust classification systems with better generalization capabilities.

Table 2: Statistics of the dataset.

Category	Authentic	Fake
Politics	3141	3403
Miscellaneous	2218	1655
International	6990	1461
Lifestyle	901	308
Medical	112	448
Religious	118	359
Sports	6526	925
Educational	1115	808
Technology	843	725
National	18708	1167
Crime	1272	720
Entertainment	2636	1441
Finance	1259	573

We use three different annotators to label each instance as fake or not. For this task, we employed five undergraduate students and provided them with detailed annotation guidelines. Annotators scrutinized many potentially misleading websites by pointing to pages replete with counterfeit news, and excluding repetitive news. We use majority voting to assign the final class label and assign either *fake* or *authentic* label. An inter-annotator agreement [9] score of 0.93 indicates a strong agreement across the dataset.

In our dataset analysis, we observed a myriad of categories, attributable to the distinct classification methodologies adopted by various news publishers and distributors of misinformation. For standardization, we consolidated analogous types across different news sources into unified categories. Consequently, all news items have been grouped into 13 distinct categories. We aimed to accrue up to 500 fake news articles for each category to ensure a balanced dataset. However, attaining this count proved challenging for certain categories, notably lifestyle, medical, and religious, though we endeavored to include as many articles as feasible for these sections. In total, the dataset comprises 60,000 news articles. The distribution across each category is delineated in Table 2.

3 METHODOLOGIES

In this section, we will outline the methods we are exploring to create a benchmark model for detecting fake news in Bangla. Our methodologies include traditional linguistic attributes as well as neural networks and transformer-based models.

Traditional Approaches: We extracted lexical linguistic features using TF-IDF for character n-grams (n = 3,4,5) and word n-grams (n = 1,2,3) similarly as existing works [11, 14]. We applied a Linear Support Vector Machine (SVM) [10] to these features for classification. Recognizing the value of semantic information, we experimented with pre-trained word embeddings to represent articles. Specifically, we used Bangla 300-dimensional word vectors pre-trained with FastText on Common Crawl and Wikipedia [11, 18]. Finally, we combined all the features with SVM.

Transformer-based BERT models: Encoder-based pre-trained BERT [8] models are exceptional in downstream tasks due to their superior contextual understanding capabilities. We chose five pre-trained model bases: BanglaBERT [3] and Bangla-BERT by [20] (later on referred to as SagorBERT), which are monolingual, XLM-RoBERTa (late referred as XRoBERTa) [6], multilingual-BERT cased and uncased (later on referred to as m-BERT-c and m-BERT-unc, respectively) by [7] which are multilingual. We shuffled the training samples and enforced gradient clipping to fine-tune these models. We utilized the outputs from the last two layers of multi-head attention, subsequently employing a linear layer for classification. We fine-tuned the model using Adam optimizer [15].

Large Language Model: Large language models (LLM) have recently demonstrated remarkable proficiency in the realm of linguistic analysis and reasoning. BLOOM [21] is a decoder-based LLM, a product of the most extensive single project collaboration of AI researchers. For finetuning BLOOM and Phi3, we loaded the models in 4-bit precision using QLoRA, setting their rank and alpha to 8 and 32, respectively, for trainable adapters. For computing, models were set to half-precision floating-point format and their quantization to normalized float 4-bit. The last token was used to do classification. We used gradient accumulation from each step and a paged Adam 8-bit optimizer for fine-tuning. In addition, we experimented with our dataset with the latest Large Language Model, Phi 3 Mini [1], a transformer decoder architecture[26] with a default context length 4K.

4 EXPERIMENTAL SETUP

Data Pre-Processing: English words and hyperlinks were removed from the dataset. Text normalization, punctuation, and stop-words removal were performed for traditional models. We have done some pre-processing, including removing NaN values, deleting duplicate rows of news, etc As punctuation is essential for capturing context in a sentence, there was no punctuation removal for our experimentation with BERT and BLOOM.

Model Validation and Dataset Split: We validated the models using the holdout method. For this purpose, we split the dataset into train, validation, and test sets containing 70%, 15%, and 15%, respectively, while keeping the same class ratio.

Baselines: In our experimental evaluation, we benchmark our results against two baseline approaches. Firstly, a majority baseline assigns the predominant class label (in this case, 'authentic news') to all articles. The second is a random baseline, which randomly classifies articles as authentic or fake. Table 3 presents the average precision, recall, and F1-score obtained from 10 random baseline experiments.

Experiments: For each experiment, we chose the hyperparameters based on the validation set and evaluated the model on the test set. For traditional models, we only trained on the content of the news. For BERTs and LLMs, we trained both on content and headlines while keeping a maximum limit of 512 input tokens. To differentiate the headline and content of each news sample, we added the string “ \\ “between these.

5 RESULT AND ANALYSIS

All the experiment results (in percentages) are shown in Table 3. In our approach, performances were validated using the holdout method, leading to a more unbiased performance measure than the previous similar works in Bangla. The Precision (P), Recall (R), and F1 (F1-Score) of the authentic class, and the P of the fake class are quite high, while the R of the authentic class is almost perfect. Among the word n-grams, we observe better performance with unigram (84) compared to bigram (83) and trigram (78). Combining them all improves the macro-F1, and we achieve an F1-score of (85). We observe similar classification performance with the character n-grams. Surprisingly, different combinations of the character n-grams do not show significantly higher gains.

In most cases, we achieve more than 90% Precision, Recall, and F1 for authentic class. However, the results of Precision, Recall, and F1-Score of fake class vary from experiment to experiment. While the experiment with linguistic features with SVM outperforms LLM and transformer-based models in classifying authentic news, LLM-based models outperform SVM models in classifying fake news with higher F1 scores. Transformer models (m-BERT-uncased (m-BERT-unc) and BLOOM) performed quite well in detecting fake with an F1 score of 81% compared to the fake class F1 score of 77% by C3-Gram. On the other hand, the transformer models, with the highest F1 score of 96, performed slightly worse than the traditional models, whose highest F1 score was 98. This can be credited to the significant increase in fake news in the dataset compared to all others. We see that LLM BLOOM and m-BERT-uncased performed the best in all aspects compared to other transformer models. SagorBERT, m-BERT-c (cased), m-BERT-unc (uncased), and BLOOM performed

Table 3: Precision (P), Recall (R), and F1 score for each categorical class (Authentic and Fake)

Model	Authentic			Fake			Macro
	P	R	F1	P	R	F1	F1
Baselines							
Majority	79	100	88	0	0	0	78
Random	79	50	61	21	51	30	63
Linguistic Features with SVM							
Unigram(U)	92	95	93	78	70	74	84
Bigram(B)	91	95	93	78	67	72	83
Trigram(T)	91	88	90	62	69	66	78
U+B+T	92	95	94	79	70	75	85
C3-Gram(C3)	96	97	98	80	74	77	86
C4-Gram(C4)	97	98	97	79	75	77	86
C5-Gram(C5)	96	97	96	81	74	77	86
C3+C4+C5	97	98	97	79	75	77	86
Embedding	89	98	93	90	57	70	82
All Features(All)	92	96	94	85	72	78	86
BERT models							
BanglaBERT	89	99	94	97	53	69	81
SagorBERT	92	99	95	95	68	79	87
m-BERT-c	92	98	95	93	69	79	87
m-BERT-unc	92	98	95	93	70	79	87
XRoBERTa	90	98	94	89	61	72	83
LLMs							
BLOOM	92	100	96	99	69	81	89
Phi 3 mini	90	98	94	92	58	71	83

similarly in all aspects except for P of the fake class. Conversely, BanglaBERT fell behind due to its low P and R for authentic and fake classes, respectively.

Among linguistic features, the C3-Gram model performed the best among character-based linguistic feature models and unigram+bigram+trigram (U+B+T) performed best among word-based feature models. Character-based linguistic features outperformed word-based features in fake news detection, scoring higher performance, where C3-Gram performed 1%, 4%, and 2% higher P, R, and F1, respectively, compared to U+B+T features. C3-gram also outperformed U+B+T in authentic news identification, indicating a higher performance of character-based linguistic features compared to word-based linguistic features in fake news detection.

To validate our model's performance and generalizability, we used a manually curated external test dataset of 1,000 samples. We evaluated our top-performing models: the traditional linguistic feature-based SVM and the LLM-based BLOOM. Both models were trained on the BanFakeNews dataset and tested on both an internal test set from BanFakeNews-2.0 and the external test set. As shown in Table 4, the models trained with BanFakeNews-2.0 consistently outperformed those trained with the existing BanFakeNews dataset. These results highlight the improved diversity and balance of the BanFakeNews-2.0 dataset, making it a more robust resource for fake news detection. This approach, similar to refining interview question sets to cover a broader range of scenarios, ensures that the models are well-prepared to handle diverse and complex data.

Table 4: Ablation experiments with different train-test combinations of existing BanFakeNews and proposed BanFakeNews-2.0

Model	Train dataset	Test dataset	Macro F1
SVM (All)	BanFakeNews	Test (internal)	74
SVM (All)	BanFakeNews-2.0	Test (internal)	86
SVM (All)	BanFakeNews	Test (external)	39
SVM (All)	BanFakeNews-2.0	Test (external)	91
BLOOM	BanFakeNews	Test (internal)	78
BLOOM	BanFakeNews-2.0	Test (internal)	89
BLOOM	BanFakeNews	Test (external)	29
BLOOM	BanFakeNews-2.0	Test (external)	67

6 CONCLUSION

In this study, we introduced BanFakeNews-2.0, the most comprehensive and robust Bangla fake news dataset to date, containing 13,000 manually annotated fake news articles. This dataset covers 13 vital news categories, enhancing its real-world relevance and research applicability. Our evaluations included traditional linguistic feature-based models, BERT-based models, and LLM-based models. We fine-tuned phi-3 mini and BLOOM with QLORA, employing gradient accumulation and leveraging a paged Adam 8-bit optimizer for Bangla fake news detection. Our results showed that BLOOM and the BERT variant model, m-BERT-unc outperformed their counterparts, highlighting the importance of diverse datasets in achieving superior performance. Interestingly, while previous evaluations on the BanFakeNews dataset favored traditional models, our diverse BanFakeNews-2.0 dataset saw transformer models gaining an edge. This underscores the significance of context and diversity, which overshadow character-based linguistic features. We also noted the prevalence of punctuation marks, escape characters, and HTML tags within our fake news dataset—challenges adeptly addressed by our chosen models. The persistent spread of fake news mandates ongoing surveillance and mitigation, emphasizing the need for balanced and diverse datasets. Future directions include refining dataset features, enhancing model capabilities, and developing real-time monitoring mechanisms. Additionally, exploring zero-shot classification using emerging LLMs like LLAMA 2 and LLAMA 3 [25] and GPT 3,4,4o [5] could provide further insights into their efficacy in fake news detection. We remain optimistic that our contributions will bolster future research endeavors in the domain of Bangla fake news detection and mitigation.

REFERENCES

[1] Marah Abdin, Sam Ade Jacobs, Ammar Ahmad Awan, Jyoti Aneja, Ahmed Awadallah, Hany Awadalla, Nguyen Bach, Amit Bahree, Arash Bakhtiari, Jianmin Bao, Harkirat Behl, Alon Benhaim, Misha Bilenko, Johan Bjorck, Sébastien Bubeck, Qin Cai, Martin Cai, Caio César Teodoro Mendes, Weizhu Chen, Vishrav Chaudhary, Dong Chen, Dongdong Chen, Yen-Chun Chen, Yi-Ling Chen, Parul Chopra, Xiyang Dai, Allie Del Giorno, Gustavo de Rosa, Matthew Dixon, Ronen Eldan, Victor Fragoso, Dan Iter, Mei Gao, Min Gao, Jianfeng Gao, Amit Garg, Abhishek Goswami, Suriya Gunasekar, Emman Haider, Junheng Hao, Russell J. Hewett, Jamie Huynh, Mojan Javaheripi, Xin Jin, Piero Kauffmann, Nikos Karampatziakis, Dongwoo Kim, Mahoud Khademi, Lev Kurilenko, James R. Lee, Yin Tat Lee, Yuanzhi Li, Yunsheng Li, Chen Liang, Lars Liden, Ce Liu, Mengchen Liu, Weishung Liu, Eric Lin, Zeqi Lin, Chong Luo, Piyush Madan, Matt Mazzola, Arindam Mitra, Hardik Modi, Anh Nguyen, Brandon Norick, Barun Patra, Daniel Perez-Becker, Thomas Portet, Reid Pryzant, Heyang Qin, Marko Radmilac,

Corby Rosset, Sambudha Roy, Olatunji Ruwase, Olli Saarikivi, Amin Saied, Adil Salim, Michael Santacroce, Shital Shah, Ning Shang, Hiteshi Sharma, Swadheen Shukla, Xia Song, Masahiro Tanaka, Andrea Tupini, Xin Wang, Lijuan Wang, Chunyu Wang, Yu Wang, Rachel Ward, Guanhua Wang, Philipp Witte, Haiping Wu, Michael Wyatt, Bin Xiao, Can Xu, Jiahang Xu, Weijian Xu, Sonali Yadav, Fan Yang, Jianwei Yang, Ziyi Yang, Yifan Yang, Donghan Yu, Lu Yuan, Chengruidong Zhang, Cyril Zhang, Jianwen Zhang, Li Lyna Zhang, Yi Zhang, Yue Zhang, Yunan Zhang, and Xiren Zhou. 2024. Phi-3 Technical Report: A Highly Capable Language Model Locally on Your Phone. arXiv:2404.14219 [cs.CL]

[2] Md. Sayeed Al-Zaman and Mridha Md. Shiblee Noman. 2023. A dataset on social media users' engagement with religious misinformation. *Data in Brief* 49 (2023), 109439. https://doi.org/10.1016/j.dib.2023.109439

[3] Abhik Bhattacharjee, Tahmid Hasan, Wasi Ahmad, Kazi Samin Mubasshir, Md Saiful Islam, Anindya Iqbal, M. Sohel Rahman, and Rifat Shahriyar. 2022. BanglaBERT: Language Model Pretraining and Benchmarks for Low-Resource Language Understanding Evaluation in Bangla. In *Findings of the Association for Computational Linguistics: NAACL 2022*. Association for Computational Linguistics, Seattle, United States, 1318–1327. https://aclanthology.org/2022.findings-naacl.98

[4] Pragyananda Bhikkhu. 2014. *Who will be tried for Ramu destruction?* https://en.prothomalo.com/opinion/Who-will-be-tried-for-Ramu-destruction Published: 30 Sep 2014, 16: 58.

[5] Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. *arXiv preprint arXiv:2005.14165* (2020).

[6] Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Unsupervised Cross-lingual Representation Learning at Scale. *CoRR* abs/1911.02116 (2019). arXiv:1911.02116 http://arxiv.org/abs/1911.02116

[7] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. *CoRR* abs/1810.04805 (2018). arXiv:1810.04805 http://arxiv.org/abs/1810.04805

[8] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805* (2018).

[9] Joseph L Fleiss. 1971. Measuring nominal scale agreement among many raters. *Psychological bulletin* 76, 5 (1971), 378.

[10] Marti A. Hearst, Susan T Dumais, Edgar Osuna, John Platt, and Bernhard Scholkopf. 1998. Support vector machines. *IEEE Intelligent Systems and their applications* 13, 4 (1998), 18–28.

[11] Md Zobaer Hossain, Md Ashraful Rahman, Md Saiful Islam, and Sudipta Kar. 2020. BanFakeNews: A Dataset for Detecting Fake News in Bangla. In *Proceedings of the Twelfth Language Resources and Evaluation Conference*. European Language Resources Association, Marseille, France, 2862–2871. https://aclanthology.org/2020.lrec-1.349

[12] Md Gulzar Hussain, Md Rashidul Hasan, Mahmuda Rahman, Joy Protim, and Sakib Al Hasan. 2020. Detection of bangla fake news using mnb and svm classifier. In *2020 International Conference on Computing, Electronics & Communications Engineering (iCCECE)*. IEEE, 81–85.

[13] Md Gulzar Hussain, Md Rashidul Hasan, Mahmuda Rahman, Joy Protim, and Sakib Al Hasan. 2020. Detection of Bangla Fake News using MNB and SVM Classifier. In *2020 International Conference on Computing, Electronics & Communications Engineering (iCCECE)*. 81–85. https://doi.org/10.1109/iCCECE49321.2020.9231167

[14] Khondoker Ittehadul Islam, Tanvir Yuvraz, Md Saiful Islam, and Enamul Hassan. 2022. EmoNoBa: A Dataset for Analyzing Fine-Grained Emotions on Noisy Bangla Texts. In *Proceedings of the 2nd Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 12th International Joint Conference on Natural Language Processing (Volume 2: Short Papers)*, Yulan He, Heng Ji, Sujian Li, Yang Liu, and Chua-Hui Chang (Eds.). Association for Computational Linguistics, Online only, 128–134. https://aclanthology.org/2022.aacl-short.17

[15] Diederik P Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980* (2014).

[16] Sun Kyong Lee, Juhyung Sun, Seulki Jang, and Shane Connelly. 2022. Misinformation of COVID-19 vaccines and vaccine hesitancy. , 13681 pages.

[17] Cathal O'Connor and Michelle Murphy. 2020. Going viral: doctors must tackle fake news in the covid-19 pandemic. *Bmj* 369, 10.1136 (2020).

[18] Nauros Romim, Mosahed Ahmed, Md Saiful Islam, Arnab Sen Sharma, Hriteshwar Talukder, and Mohammad Ruhul Amin. 2022. BD-SHS: A Benchmark Dataset for Learning to Detect Online Bangla Hate Speech in Different Social Contexts. In *Proceedings of the Thirteenth Language Resources and Evaluation Conference*, Nicoletta Calzolari, Frédéric Béchet, Philippe Blache, Khalid Choukri, Christopher Cieri, Thierry Declerck, Sara Goggi, Hitoshi Isahara, Bente Maegaard, Joseph Mariani, Hélène Mazo, Jan Odijk, and Stelios Piperidis (Eds.). European Language Resources Association, Marseille, France, 5153–5162. https://aclanthology.org/2022.lrec-1.552

[19] SadikAlJarif. 2022. bangla fake news dataset. https://www.kaggle.com/datasets/sadikaljarif/bangla-fake-news-detection-dataset?select=final_bn_data.csv.

[20] Sagor Sarker. 2020. BanglaBERT: Bengali Mask Language Model for Bengali Language Understanding. https://github.com/sagorbrur/bangla-bert

[21] Teven Le Scao, Angela Fan, Christopher Akiki, Ellie Pavlick, Suzana Ilić, Daniel Hesslow, Roman Castagné, Alexandra Sasha Luccioni, François Yvon, Matthias Gallé, et al. 2022. Bloom: A 176b-parameter open-access multilingual language model. *arXiv preprint arXiv:2211.05100* (2022).

[22] Arnab Sen Sharma, Maruf Ahmed Mridul, and Md Saiful Islam. 2019. Automatic detection of satire in bangla documents: A cnn approach based on hybrid feature extraction model. In *2019 International Conference on Bangla Speech and Language Processing (ICBSLP)*. IEEE, 1–5.

[23] Sharifa Umma Shirina and Md. Tabiur Rahman Prodhan. 2020. Spreading Fake News in the Virtual Realm in Bangladesh: Assessment of Impact. *Global Journal of Human-Social Science* 20, A17 (Jul. 2020), 11–25. https://doi.org/10.34257/GJHSSAVOL20IS17PG11

[24] Tasnuba Sraboni, Md Rifat Uddin, Fahim Shahriar, Ruhit Ahmed Rizon, and Shakib Ibna Shameem Polock. 2021. *FakeDetect: Bangla fake news detection model based on different machine learning classifiers*. Ph. D. Dissertation. Brac University.

[25] Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. 2023. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288* (2023).

[26] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2023. Attention Is All You Need. arXiv:1706.03762 [cs.CL]