

Department of Computer Science and Engineering  
Bangladesh University of Business and Technology (BUBT)

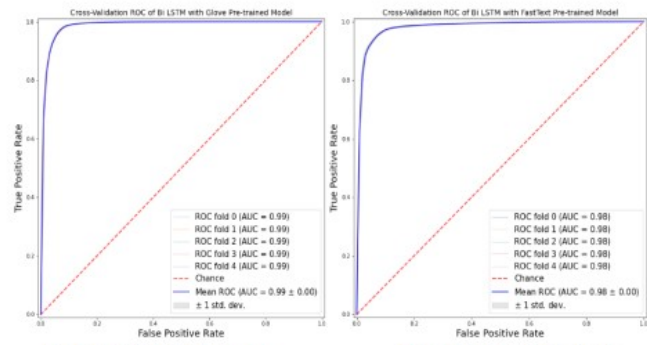


**CSE 478: Literature Review Records**

<b>Student's Id and Name</b>	<b>Name:</b> Akash Kumar Nondi and <b>ID:</b> 19202103325
<b>Project Title</b>	Bangla Fake news detection using machine learning
<b>Course Teacher's Name &amp; Designation</b>	<b>Name:</b> Khan Md. Hasib & <b>Designation:</b> Assistant Professor, Department of CSE, BUBT

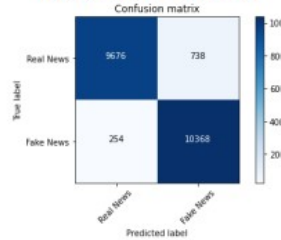
Aspects	Paper # 1 (Title)																																																																																																																													
<b>Title / Question</b> (What is problem statement?)	A Study towards Bangla Fake News Detection Using Machine Learning and Deep Learning																																																																																																																													
<b>Objectives / Goal</b> (What is looking for?)	The objective of the study mentioned in the provided sources is to identify and detect fake news articles written in the Bangla language using machine learning and deep learning techniques. The study aims to address the challenge of verifying Bangla fake news, especially with the abundance of updates from various sources such as social media and online news portals. The researchers trained their corpus with 57,000 Bangla news items related to trustworthiness and counterfeit. They applied K-fold cross-validation on top of Bi-LSTM with Glove and FastText models.																																																																																																																													
<b>Methodology/Theory</b> (How to find the solution?)	<p>Datasets was collected from - UCI repository.</p> <p><b>Fig. 1.</b> Architecture diagram of the proposed research.</p>																																																																																																																													
<b>Software Tools</b> (What program/software is used for design, coding and simulation?)	Implementation work was carried out at Intel(R) Core (TM) i3 CPU M60 @ 2.80 GHz in Python.																																																																																																																													
<b>Test / Experiment</b> (How to test and characterize the design/prototype?)	<p><b>Table 3.</b> Classification report for Word2Vec approach.</p> <table><tr><th rowspan="2">Algorithm</th><th rowspan="2">P</th><th colspan="3">Authentic</th><th colspan="3">Fake</th></tr><tr><th>P</th><th>R</th><th>F1</th><th>P</th><th>R</th><th>F1</th></tr><tr><td>DTC</td><td>0.81</td><td>0.80</td><td>0.81</td><td>0.80</td><td>0.82</td><td>0.81</td></tr><tr><td>RF</td><td>0.84</td><td>0.80</td><td>0.83</td><td>0.82</td><td>0.84</td><td>0.83</td></tr><tr><td>KNN</td><td>0.84</td><td>0.75</td><td>0.79</td><td>0.77</td><td>0.86</td><td>0.81</td></tr><tr><td>NB</td><td>0.56</td><td>0.52</td><td>0.54</td><td>0.54</td><td>0.59</td><td>0.56</td></tr><tr><td>GB</td><td>0.61</td><td>0.63</td><td>0.62</td><td>0.61</td><td>0.59</td><td>0.60</td></tr><tr><td>SVM</td><td>0.57</td><td>0.34</td><td>0.43</td><td>0.53</td><td>0.74</td><td>0.62</td></tr><tr><td>LR</td><td>0.56</td><td>0.53</td><td>0.54</td><td>0.55</td><td>0.57</td><td>0.56</td></tr></table> <p><b>Table 4.</b> Classificati Classification report of Deep Learning algorithms (based on the features extraction approach)</p> <table><tr><th rowspan="2">Algorithm's</th><th rowspan="2">Feature Extraction</th><th colspan="3">Authentic</th><th colspan="3">Fake</th></tr><tr><th>P</th><th>R</th><th>F1</th><th>P</th><th>R</th><th>F1</th></tr><tr><td>LSTM</td><td>One hot encoding</td><td>0.93</td><td>0.99</td><td>0.96</td><td>0.99</td><td>0.93</td><td>0.96</td></tr><tr><td>Bi-LSTM</td><td>One hot encoding</td><td>0.93</td><td>0.99</td><td>0.96</td><td>0.99</td><td>0.93</td><td>0.96</td></tr><tr><td>CNN</td><td>One hot encoding</td><td>0.93</td><td>0.99</td><td>0.96</td><td>0.98</td><td>0.93</td><td>0.95</td></tr><tr><td>GRU</td><td>One hot encoding</td><td>0.76</td><td>0.82</td><td>0.79</td><td>0.80</td><td>0.74</td><td>0.77</td></tr><tr><td>Bi-LSTM with Glove</td><td>Glove</td><td>0.93</td><td>0.98</td><td>0.95</td><td>0.97</td><td>0.93</td><td>0.95</td></tr><tr><td>Bi-LSTM with Fasttext</td><td>FastText</td><td>0.93</td><td>0.96</td><td>0.94</td><td>0.96</td><td>0.92</td><td>0.94</td></tr></table>	Algorithm	P	Authentic			Fake			P	R	F1	P	R	F1	DTC	0.81	0.80	0.81	0.80	0.82	0.81	RF	0.84	0.80	0.83	0.82	0.84	0.83	KNN	0.84	0.75	0.79	0.77	0.86	0.81	NB	0.56	0.52	0.54	0.54	0.59	0.56	GB	0.61	0.63	0.62	0.61	0.59	0.60	SVM	0.57	0.34	0.43	0.53	0.74	0.62	LR	0.56	0.53	0.54	0.55	0.57	0.56	Algorithm's	Feature Extraction	Authentic			Fake			P	R	F1	P	R	F1	LSTM	One hot encoding	0.93	0.99	0.96	0.99	0.93	0.96	Bi-LSTM	One hot encoding	0.93	0.99	0.96	0.99	0.93	0.96	CNN	One hot encoding	0.93	0.99	0.96	0.98	0.93	0.95	GRU	One hot encoding	0.76	0.82	0.79	0.80	0.74	0.77	Bi-LSTM with Glove	Glove	0.93	0.98	0.95	0.97	0.93	0.95	Bi-LSTM with Fasttext	FastText	0.93	0.96	0.94	0.96	0.92	0.94
Algorithm	P			Authentic			Fake																																																																																																																							
		P	R	F1	P	R	F1																																																																																																																							
DTC	0.81	0.80	0.81	0.80	0.82	0.81																																																																																																																								
RF	0.84	0.80	0.83	0.82	0.84	0.83																																																																																																																								
KNN	0.84	0.75	0.79	0.77	0.86	0.81																																																																																																																								
NB	0.56	0.52	0.54	0.54	0.59	0.56																																																																																																																								
GB	0.61	0.63	0.62	0.61	0.59	0.60																																																																																																																								
SVM	0.57	0.34	0.43	0.53	0.74	0.62																																																																																																																								
LR	0.56	0.53	0.54	0.55	0.57	0.56																																																																																																																								
Algorithm's	Feature Extraction	Authentic			Fake																																																																																																																									
		P	R	F1	P	R	F1																																																																																																																							
LSTM	One hot encoding	0.93	0.99	0.96	0.99	0.93	0.96																																																																																																																							
Bi-LSTM	One hot encoding	0.93	0.99	0.96	0.99	0.93	0.96																																																																																																																							
CNN	One hot encoding	0.93	0.99	0.96	0.98	0.93	0.95																																																																																																																							
GRU	One hot encoding	0.76	0.82	0.79	0.80	0.74	0.77																																																																																																																							
Bi-LSTM with Glove	Glove	0.93	0.98	0.95	0.97	0.93	0.95																																																																																																																							
Bi-LSTM with Fasttext	FastText	0.93	0.96	0.94	0.96	0.92	0.94																																																																																																																							

**Simulation/Test Data** (What parameters are determined?)

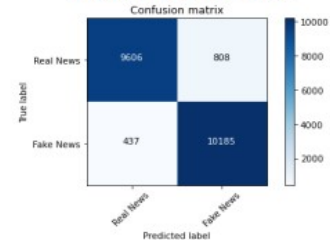


**Fig. 2.** Roc curve for Bi-LSTM.

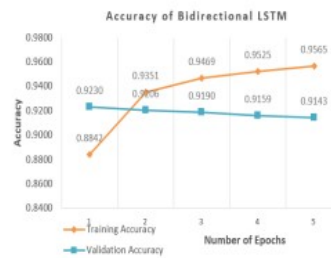
**Fig.3.** Roc curve for Bi-LSTM.



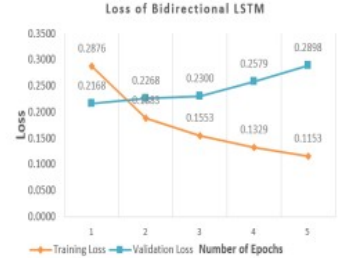
**Fig. 4.** Confusion matrix of Bi-LSTM with Glove.



**Fig. 5.** Confusion matrix of Bi-LSTM with fastText.



**Fig. 6.** Accuracy Mesurment of Bi-LSTM.



**Fig. 7.** Loss Mesurment of Bi-LSTM.

**Result / Conclusion** (What was the final result?)

**Table 5.** Comparasion Table.

Paper's	Algorithm	Feature Extraction	Accuracy	Match with proposed accuracy (Yes/No/Equal)
[4]	MNB	Count Vectorizer, TF-IDF	82.44%	No
[5]	GRU	TF-IDF	70.10%	No
[6]	CNN	Word2Vec, TF-IDF.	96%	Equal
[8]	SVM	Word2Vec	91%	No
Our proposed model.	Bi-LSTM	One Hot Encoding	96%	

**Terminology** (List the common basic words frequently used in this research field)

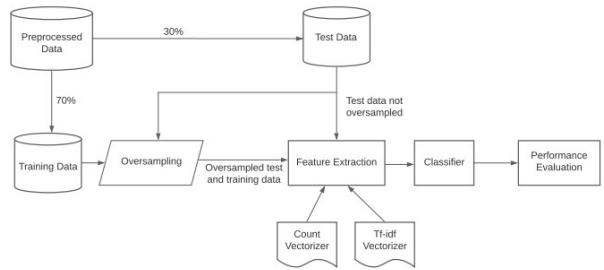
Bangla Fake News, Text Classification, Machine Learning, Random Forest, LSTM, Bi-LSTM, CNN, Glove, Fasttext, Gated Recurrent Unit (GRU)

**Review Judgment** (Briefly compare the objectives and results of all the articles you reviewed)

The reviewed articles aim to detect Bangla fake news using various machine learning and deep learning techniques. The results show high accuracy rates, ranging from 77 percent to 96 percent, depending on the models and algorithms used.

**Review Outcome** (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)

The articles highlight the effectiveness of Bi-LSTM models with Glove and FastText embeddings, achieving accuracy rates of 95 percent and 94 percent respectively. The LSTM experiment also achieved an accuracy of 96 percent.

Aspects	Paper # 2 (Title)																																																																														
<b>Title / Question</b> (What is problem statement?)	Approaches for Improving the Performance of Fake News Detection in Bangla: Imbalance Handling and Model Stacking																																																																														
<b>Objectives / Goal</b> (What is looking for?)	The objective of the research paper is to improve the performance of fake news detection in Bangla by addressing the issue of imbalanced datasets. The researchers propose several strategies for resolving the imbalance issue, including data manipulation techniques such as SMOTE and Stacked Generalization. By implementing these strategies, the researchers were able to achieve a significant improvement in performance, with an F1-score of 93.1 percent using data manipulation techniques and 79.1 percent without data manipulation. The paper aims to pave the way for fake news detection in Bangla by removing the obstacles of imbalanced datasets and improving performance.																																																																														
<b>Methodology/Theory</b> (How to find the solution?)	<div></div> <p><b>Fig. 1.</b> Illustration of Oversampling Technique</p>																																																																														
<b>Software Tools</b> (What program/software is used for design, coding and simulation?)	Implementation work was carried out at Intel(R) Core (TM) i3 CPU M60 @ 2.80 GHz in Python.																																																																														
<b>Test / Experiment</b> (How to test and characterize the design/prototype?)	<p><b>Table 2.</b> Oversampled Data</p> <table><tr><th></th><th>Before Oversampling</th><th>After Oversampling</th></tr><tr><td>Train Data (Authentic)</td><td>34,075</td><td>34,075</td></tr><tr><td>Train Data (Fake)</td><td>909</td><td>34,075</td></tr><tr><td>Test Data (Authentic)</td><td>14,603</td><td>14,603</td></tr><tr><td>Test Data (Fake)</td><td>390</td><td>14,603</td></tr></table>		Before Oversampling	After Oversampling	Train Data (Authentic)	34,075	34,075	Train Data (Fake)	909	34,075	Test Data (Authentic)	14,603	14,603	Test Data (Fake)	390	14,603																																																															
	Before Oversampling	After Oversampling																																																																													
Train Data (Authentic)	34,075	34,075																																																																													
Train Data (Fake)	909	34,075																																																																													
Test Data (Authentic)	14,603	14,603																																																																													
Test Data (Fake)	390	14,603																																																																													
<b>Simulation/Test Data</b> (What parameters are determined?)	<p><b>Table 3.</b> Overall Performance of All Methods</p> <table><tr><th>Method</th><th>Feature Extraction</th><th>Classifier</th><th>F1-Score</th></tr><tr><td rowspan="2">Baseline</td><td>Count</td><td>LR</td><td>0.604</td></tr><tr><td>TF-IDF</td><td>LR</td><td>0.676</td></tr><tr><td rowspan="2">Random Oversampling (N)</td><td>Count</td><td>LR</td><td>0.452</td></tr><tr><td>TF-IDF</td><td>LR</td><td>0.703</td></tr><tr><td rowspan="2">Random Oversampling</td><td>Count</td><td>MNB</td><td>0.845</td></tr><tr><td>TF-IDF</td><td>LR</td><td>0.826</td></tr><tr><td rowspan="2">SMOTE (N)</td><td>Count</td><td>MNB</td><td>0.476</td></tr><tr><td>TF-IDF</td><td>LR</td><td>0.696</td></tr><tr><td rowspan="2">SMOTE</td><td>Count</td><td>LR</td><td><b>0.931</b></td></tr><tr><td>TF-IDF</td><td>LR</td><td>0.863</td></tr><tr><td rowspan="2">ADASYN (N)</td><td>Count</td><td>MNB</td><td>0.460</td></tr><tr><td>TF-IDF</td><td>LR</td><td>0.695</td></tr><tr><td rowspan="2">ADASYN</td><td>Count</td><td>BNB</td><td>0.914</td></tr><tr><td>TF-IDF</td><td>LR</td><td>0.866</td></tr><tr><td rowspan="2">Random Undersampling</td><td>Count</td><td>BNB, RFC</td><td>0.893</td></tr><tr><td>TF-IDF</td><td>MNB</td><td>0.911</td></tr><tr><td rowspan="2">Near-Miss</td><td>Count</td><td>RFC</td><td><b>0.943</b></td></tr><tr><td>TF-IDF</td><td>SVM</td><td>0.935</td></tr><tr><td rowspan="2">Modifying Class-Weight</td><td>Count</td><td>LR</td><td>0.493</td></tr><tr><td>TF-IDF</td><td>LR</td><td>0.757</td></tr><tr><td>Model Stacking</td><td>TF-IDF</td><td>RFC</td><td>0.791</td></tr></table>	Method	Feature Extraction	Classifier	F1-Score	Baseline	Count	LR	0.604	TF-IDF	LR	0.676	Random Oversampling (N)	Count	LR	0.452	TF-IDF	LR	0.703	Random Oversampling	Count	MNB	0.845	TF-IDF	LR	0.826	SMOTE (N)	Count	MNB	0.476	TF-IDF	LR	0.696	SMOTE	Count	LR	<b>0.931</b>	TF-IDF	LR	0.863	ADASYN (N)	Count	MNB	0.460	TF-IDF	LR	0.695	ADASYN	Count	BNB	0.914	TF-IDF	LR	0.866	Random Undersampling	Count	BNB, RFC	0.893	TF-IDF	MNB	0.911	Near-Miss	Count	RFC	<b>0.943</b>	TF-IDF	SVM	0.935	Modifying Class-Weight	Count	LR	0.493	TF-IDF	LR	0.757	Model Stacking	TF-IDF	RFC	0.791
Method	Feature Extraction	Classifier	F1-Score																																																																												
Baseline	Count	LR	0.604																																																																												
	TF-IDF	LR	0.676																																																																												
Random Oversampling (N)	Count	LR	0.452																																																																												
	TF-IDF	LR	0.703																																																																												
Random Oversampling	Count	MNB	0.845																																																																												
	TF-IDF	LR	0.826																																																																												
SMOTE (N)	Count	MNB	0.476																																																																												
	TF-IDF	LR	0.696																																																																												
SMOTE	Count	LR	<b>0.931</b>																																																																												
	TF-IDF	LR	0.863																																																																												
ADASYN (N)	Count	MNB	0.460																																																																												
	TF-IDF	LR	0.695																																																																												
ADASYN	Count	BNB	0.914																																																																												
	TF-IDF	LR	0.866																																																																												
Random Undersampling	Count	BNB, RFC	0.893																																																																												
	TF-IDF	MNB	0.911																																																																												
Near-Miss	Count	RFC	<b>0.943</b>																																																																												
	TF-IDF	SVM	0.935																																																																												
Modifying Class-Weight	Count	LR	0.493																																																																												
	TF-IDF	LR	0.757																																																																												
Model Stacking	TF-IDF	RFC	0.791																																																																												

<b>Result / Conclusion</b> (What was the final result?)	<div>Table 4. Performance of Model Stacking</div> <table><tr><td></td><td colspan="4">TF-IDF Vectorizer</td></tr><tr><td></td><td>Accuracy</td><td>Precision</td><td>Recall</td><td>F1-Score</td></tr><tr><td>LR</td><td>0.988</td><td>0.844</td><td>0.690</td><td>0.759</td></tr><tr><td>SVM</td><td>0.989</td><td>0.839</td><td>0.706</td><td>0.767</td></tr><tr><td>MNB</td><td>0.981</td><td>0.602</td><td>0.669</td><td>0.675</td></tr><tr><td>BNB</td><td>0.978</td><td>0.923</td><td>0.142</td><td>0.247</td></tr><tr><td>RFC</td><td>0.990</td><td>0.846</td><td>0.742</td><td>0.791</td></tr><tr><td>DTC</td><td>0.987</td><td>0.776</td><td>0.718</td><td>0.746</td></tr></table>		TF-IDF Vectorizer					Accuracy	Precision	Recall	F1-Score	LR	0.988	0.844	0.690	0.759	SVM	0.989	0.839	0.706	0.767	MNB	0.981	0.602	0.669	0.675	BNB	0.978	0.923	0.142	0.247	RFC	0.990	0.846	0.742	0.791	DTC	0.987	0.776	0.718	0.746
	TF-IDF Vectorizer																																								
	Accuracy	Precision	Recall	F1-Score																																					
LR	0.988	0.844	0.690	0.759																																					
SVM	0.989	0.839	0.706	0.767																																					
MNB	0.981	0.602	0.669	0.675																																					
BNB	0.978	0.923	0.142	0.247																																					
RFC	0.990	0.846	0.742	0.791																																					
DTC	0.987	0.776	0.718	0.746																																					
<b>Terminology</b> (List the common basic words frequently used in this research field)	text classification ,imbalanced data, stacked generalization																																								
<b>Review Judgment</b> (Briefly compare the objectives and results of all the articles you reviewed)	The objective of the research paper in is to improve the performance of fake news detection in Bangla by addressing the issue of imbalanced datasets. The researchers propose strategies such as data manipulation techniques and model stacking to achieve better results. They obtained a 93.1 percent F1-score using data manipulation techniques and a 79.1 percent F1-score without data manipulation.																																								
<b>Review Outcome</b> (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)	The provided sources offer insights and strategies for improving the performance of fake news detection in Bangla by addressing the issue of imbalanced datasets. These can serve as a starting point for designing a new methodology for a research project in this domain.																																								

Aspects	Paper # 3 (Title)
<b>Title / Question</b> (What is problem statement?)	Bangla Fake News Detection using Machine Learning, Deep Learning and Transformer Models
<b>Objectives / Goal</b> (What is looking for?)	The objective of the study was to build a Bangla Fake news dataset and experiment with different machine learning, deep learning, and transformer models to detect fake news in the Bangla language. The researchers aimed to address the lack of resources and language processing tools for low-resource languages like Bangla. They collected new fake news data and combined it with available secondary datasets to create a dataset with 4678 distinct news data. The researchers then experimented with multiple models, including Machine Learning (LR, SVM, KNN, MNB, Adaboost, and DT), Deep Neural Networks (LSTM, BiLSTM, CNN, LSTM-CNN, BiLSTM-CNN), and Transformer (Bangla-BERT, m-BERT). The best performing models were CNN, CNN-LSTM, and BiLSTM, with accuracies of 95.9 percent, 95.5 percent, and 95.3 percent respectively. The models also showed a significant increase in recall of fake news data compared to prior studies.

**Methodology/Theory** (How to find the solution?)

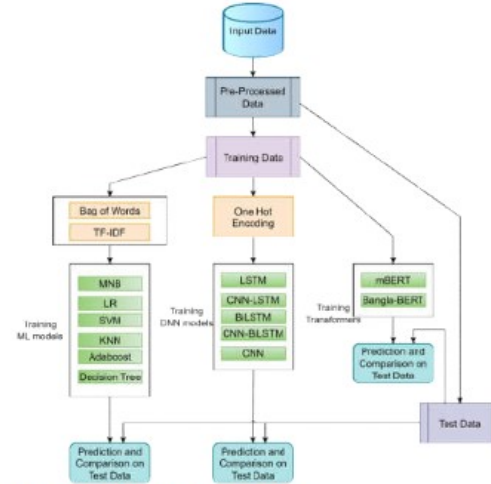


Fig. 1. Architecture of the proposed models

**Software Tools** (What program/software is used for design, coding and simulation?)

Implementation work was carried out at Intel(R) Core (TM) i3 CPU M60 @ 2.80 GHz in Python.

**Test / Experiment** (How to test and characterize the design/prototype?)

TABLE II. CLASSIFICATION RESULTS OF ALL MODELS

Method	Classifier	Precision	Recall	F1	Accuracy
Machine Learning	SVM	95.2	95.2	95.2	95.2
	LR	94.1	94.1	94.1	94.1
	MNB	91.6	91.5	91.1	91.5
	KNN	88.9	88.5	88.5	88.5
	DT	85	85	85	85
	AdaBoost	84.9	84.9	84.9	84.9
Deep Neural Network	CNN	<b>95.9</b>	<b>95.9</b>	<b>95.9</b>	<b>95.9</b>
	LSTM	94.5	94.5	94.4	94.4
	BiLSTM	95.3	95.3	95.3	95.3
	CNN+LSTM	95.5	95.5	95.5	95.5
	CNN+BiLSTM	94.9	94.9	94.9	94.9
Transformer model	Bangla-Bert-Base	94.1	94.1	94.1	93.3
	mBERT	93.9	93.9	93.9	93.8

**Simulation/Test Data** (What parameters are determined?)

TABLE III. MODELS PERFORMANCE ON SEPERATE DATASETS

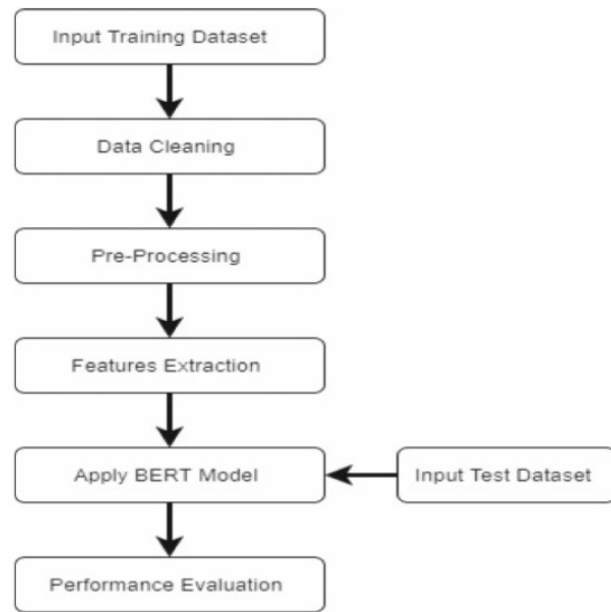
Dataset	Criterion	Machine Learning						Deep Neural Network				
		MNB	LR	KNN	SVM	DT	AdaBoost	CNN	LSTM	BiLSTM	CNN+LSTM	CNN+BiLSTM
BanFakeNews [20] 55k real, 2k fake data (duplicate data exist)	Recall (Fake News classification)	46.6	47.8	35.9	87.6	93	92.5	94	91.5	99.4	90.3	92.9
	Average Accuracy	95.8	97.8	97	99.4	98.9	99	99.8	99.4	92.5	99.4	99.6
Bangla_Fake-Real_News Small_Dataset [6] 1.5k real, 1k fake data (duplicate data exist)	Recall (Fake News classification)	77.1	88.4	88.4	91.6	97	96.4	92.5	98.8	96.8	95.6	99.6
	Average Accuracy	91	95.4	95.3	96.8	98.1	97.5	96.2	97.5	97.5	97.6	88.5
Our Dataset 2.3k real, 2.3k fake (no duplicate data)	Recall (Fake News classification)	88.2	94.1	83.3	96	86	85.6	96.3	93.8	94.2	93.5	94.9
	Average Accuracy	94.1	88.5	95.2	85	84.9	94.4	95.9	95.3	95.9	94.9	93.3



<b>Result / Conclusion</b> (What was the final result?)	<table><tr><th>Dataset</th><th></th><th>Classifier</th><th>Accuracy %</th></tr><tr><td rowspan="2">BanFakeNews [20] 55k real, 2k fake data (duplicate data exist)</td><td>Previous work best performance</td><td>BiLSTM</td><td>96</td></tr><tr><td>Our model performance</td><td>LSTM</td><td>99.8</td></tr><tr><td rowspan="2">Bangla_Fake-Real_News Small_Dataset [6] 1.5k real, 1k fake data (duplicate data exist)</td><td>Previous work best performance</td><td>SVM</td><td>96.7</td></tr><tr><td>Our model performance</td><td>AdaBoost</td><td>98.1</td></tr></table>	Dataset		Classifier	Accuracy %	BanFakeNews [20] 55k real, 2k fake data (duplicate data exist)	Previous work best performance	BiLSTM	96	Our model performance	LSTM	99.8	Bangla_Fake-Real_News Small_Dataset [6] 1.5k real, 1k fake data (duplicate data exist)	Previous work best performance	SVM	96.7	Our model performance	AdaBoost	98.1
Dataset		Classifier	Accuracy %																
BanFakeNews [20] 55k real, 2k fake data (duplicate data exist)	Previous work best performance	BiLSTM	96																
	Our model performance	LSTM	99.8																
Bangla_Fake-Real_News Small_Dataset [6] 1.5k real, 1k fake data (duplicate data exist)	Previous work best performance	SVM	96.7																
	Our model performance	AdaBoost	98.1																
<b>Terminology</b> (List the common basic words frequently used in this research field)	Bangla Fake News, Bangla Fake News classification, Bangla Text Classification, Bangla Natural Language Processing, Machine Learning, Deep Learning, Transformer.																		
<b>Review Judgment</b> (Briefly compare the objectives and results of all the articles you reviewed)	The objective of the article was to build a Bangla Fake news dataset and experiment with different models to detect fake news in the Bangla language. The researchers collected new fake news data and combined it with available secondary datasets to create a dataset with 4678 distinct news data. They experimented with multiple models and found that CNN, CNN-LSTM, and BiLSTM performed the best with accuracies of 95.9 percent, 95.5 percent, and 95.3 percent respectively. The models also showed a significant increase in recall of fake news data compared to prior studies.																		
<b>Review Outcome</b> (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)	Experiment with various machine learning, deep learning, and transformer models to detect fake news. Consider models like CNN, CNN-LSTM, and BiLSTM, which showed promising results in the Bangla language . Also, explore the use of LSTM, CNN, and SVM models for improved accuracy.																		

Aspects	Paper # 4 (Title)
<b>Title / Question</b> (What is problem statement?)	Bengali Fake News Detection: Transfer Learning Based Technique with Masked LM Process by BERT
<b>Objectives / Goal</b> (What is looking for?)	The objective of the research paper is to detect fake news in the Bengali language using a transfer learning-based technique with a Masked LM process by BERT. The researchers aim to address the increasing spread of false information on social media and its negative impact on various industries. They compare the performance of their proposed BERT model with other models such as LSTM with regularization, SVM, NB, and CNN, using different evaluation matrices. The results show that the suggested BERT model outperforms the other models with a precision rate of 95 percent. The researchers also utilize the BERT model for encoding and decoding text data, using masked LM where words are replaced by a mask before sending to BERT. The model is trained using specific parameters and tested using dataset2. The BERT model is chosen due to its exceptional performance in natural language processing tasks and its ability to detect fake news effectively, especially with a short dataset.

**Methodology/Theory** (How to find the solution?)



**Fig. 1.** Workflow diagram

**Software Tools** (What program/software is used for design, coding and simulation?)

Implementation work was carried out at Intel(R) Core (TM) i3 CPU M60 @ 2.80 GHz in Python.

**Test / Experiment** (How to test and characterize the design/prototype?)

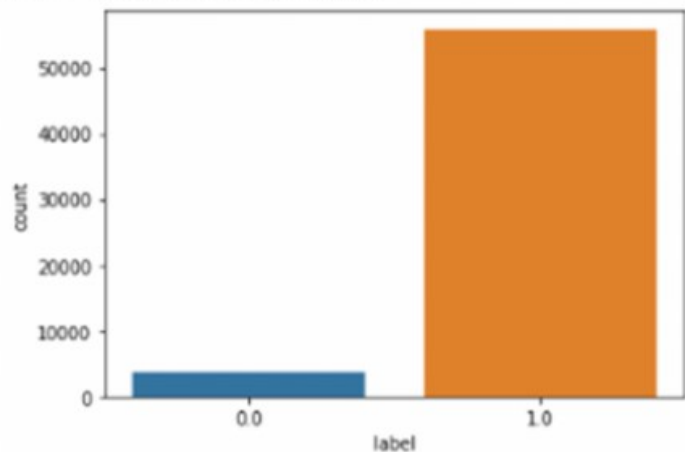
**Table 3.** The dataset's description

Dataset	Real	Fake
Dataset1	48678	1299
Dataset2	1548	993

```

0.0    3591
1.0    55880
Name: label, dtype: int64

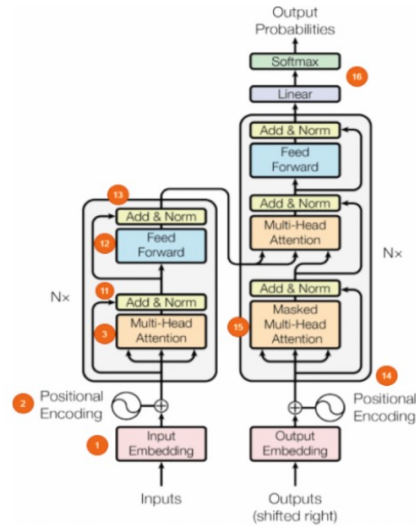
```



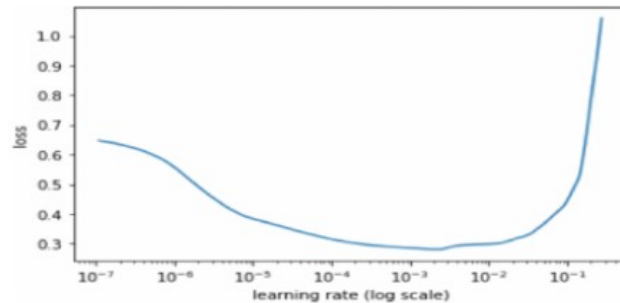
**Fig. 2.** Visualization of datasets



**Simulation/Test Data** (What parameters are determined?)



**Fig. 3.** Architecture of transformer



**Fig. 5.** Learning rate

**Result / Conclusion** (What was the final result?)

**Table 5.** Comparison of overall performance among models

Evaluation matrices	Fake news detection models				
	Transformer (BERT)	LSTM with regularization	CNN	SVM	NB
AUC	0.95	0.88	0.92	0.61	0.55
Precision	0.95	0.82	0.95	0.44	0.44
Recall	0.94	0.90	0.84	0.60	0.61
F1 score	0.94	0.85	0.89	0.50	0.51

**Table 6.** Comparison of performance among models for fake news detection

Evaluation matrices	Fake news detection models				
	Transformer (BERT)	LSTM with regularization	CNN	SVM	NB
Precision	95%	82%	95%	44%	44%
Recall	93%	90%	84%	60%	61%
F1 score	94%	85%	89%	50%	51%

**Terminology** (List the common basic words frequently used in this research field)

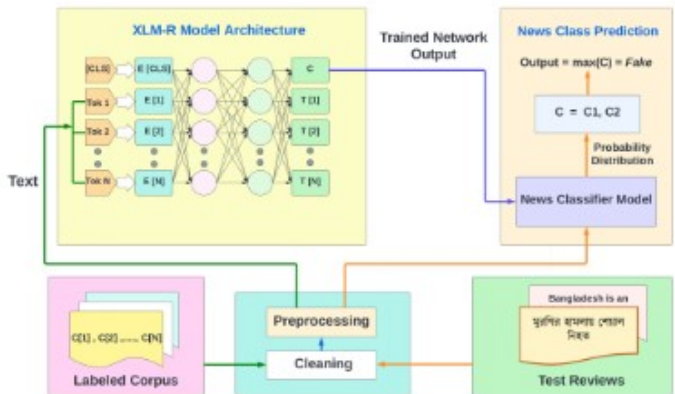
BERT ,Transformer ,Tokenizer ,Fake ,Bangla

**Review Judgment** (Briefly compare the objectives and results of all the articles you reviewed)

Overall, the reviewed articles aim to detect fake news using various techniques such as transfer learning with BERT, LSTM, Nave Bayes, and SVM. They highlight the importance of accurate results and the challenges of limited data in fake news detection.

**Review Outcome** (Make a decision how to use/refer the obtained knowledge to prepare a separate and new methodology for your own research project)

Based on the provided sources, there is no specific information related to the subject of the input question. Therefore, it is not possible to generate an answer using the provided sources.

Aspects	Paper # 5 (Title)																																																		
<b>Title / Question</b> (What is problem statement?)	FaND-X: Fake News Detection using Transformer-based Multilingual Masked Language Model																																																		
<b>Objectives / Goal</b> (What is looking for?)	The objective of the research paper is to develop a framework called FaND-X for detecting fake news in Bengali using transformer-based and neural network-based approaches. The researchers also aim to create a dataset called BFNC consisting of 5K fake news data. The paper evaluates the performance of various machine learning techniques, deep neural networks, and transformer-based approaches for fake news classification. The results show that the XLM-R model achieves the highest f1-score of 98 percent on the test data, outperforming other techniques.																																																		
<b>Methodology/Theory</b> (How to find the solution?)	<div></div> <p>Figure 1. Overall architecture of the FaND-X model for fake news detection</p>																																																		
<b>Software Tools</b> (What program/software is used for design, coding and simulation?)	Implementation work was carried out at Intel(R) Core (TM) i3 CPU M60 @ 2.80 GHz in Python.																																																		
<b>Test / Experiment</b> (How to test and characterize the design/prototype?)	<div><p>Table IV OPTIMIZED HYPERPARAMETERS FOR DEEP LEARNING MODELS</p><table><tr><th>Hyperparameters</th><th>Hyperparameter Space</th><th>CNN</th><th>BiLSTM</th><th>CNN+BiLSTM</th></tr><tr><td>Filter Size</td><td>3,5,7,9</td><td>3</td><td>-</td><td>7</td></tr><tr><td>Pooling Type</td><td>'max', 'average'</td><td>'max'</td><td>-</td><td>'max'</td></tr><tr><td>Embedding Dimension</td><td>30, 35, 50, 70, 90, 100, 150, 200,250, 300</td><td>300</td><td>300</td><td>300</td></tr><tr><td>Number of Units</td><td>16, 32, 64, 128, 256</td><td>128</td><td>128</td><td>128</td></tr><tr><td>Neurons in Dense Layer</td><td>16, 32, 64, 128, 256</td><td>-</td><td>16</td><td>-</td></tr><tr><td>Batch Size</td><td>16, 32, 64, 128, 256</td><td>32</td><td>32</td><td>32</td></tr><tr><td>Activation Function</td><td>'relu', 'tanh', 'softplus', 'sigmoid'</td><td>'relu'</td><td>'relu'</td><td>'relu'</td></tr><tr><td>Optimizer</td><td>'RMSprop', 'Adam', 'SGD', 'Adamax'</td><td>'Adam'</td><td>'Adam'</td><td>'Adam'</td></tr><tr><td>Learning Rate</td><td>0.5, 0.1, 0.05, 0.01, 0.005, 0.001, 0.0005, 0.0001</td><td>0.001</td><td>0.001</td><td>0.001</td></tr></table></div>	Hyperparameters	Hyperparameter Space	CNN	BiLSTM	CNN+BiLSTM	Filter Size	3,5,7,9	3	-	7	Pooling Type	'max', 'average'	'max'	-	'max'	Embedding Dimension	30, 35, 50, 70, 90, 100, 150, 200,250, 300	300	300	300	Number of Units	16, 32, 64, 128, 256	128	128	128	Neurons in Dense Layer	16, 32, 64, 128, 256	-	16	-	Batch Size	16, 32, 64, 128, 256	32	32	32	Activation Function	'relu', 'tanh', 'softplus', 'sigmoid'	'relu'	'relu'	'relu'	Optimizer	'RMSprop', 'Adam', 'SGD', 'Adamax'	'Adam'	'Adam'	'Adam'	Learning Rate	0.5, 0.1, 0.05, 0.01, 0.005, 0.001, 0.0005, 0.0001	0.001	0.001	0.001
Hyperparameters	Hyperparameter Space	CNN	BiLSTM	CNN+BiLSTM																																															
Filter Size	3,5,7,9	3	-	7																																															
Pooling Type	'max', 'average'	'max'	-	'max'																																															
Embedding Dimension	30, 35, 50, 70, 90, 100, 150, 200,250, 300	300	300	300																																															
Number of Units	16, 32, 64, 128, 256	128	128	128																																															
Neurons in Dense Layer	16, 32, 64, 128, 256	-	16	-																																															
Batch Size	16, 32, 64, 128, 256	32	32	32																																															
Activation Function	'relu', 'tanh', 'softplus', 'sigmoid'	'relu'	'relu'	'relu'																																															
Optimizer	'RMSprop', 'Adam', 'SGD', 'Adamax'	'Adam'	'Adam'	'Adam'																																															
Learning Rate	0.5, 0.1, 0.05, 0.01, 0.005, 0.001, 0.0005, 0.0001	0.001	0.001	0.001																																															

<b>Simulation/Test Data</b> (What parameters are determined?)	<div>Table VII</div> <div>CLASS-WISE PERFORMANCE OF BEST ML, DNN AND PROPOSED MODELS ON THE TEST SET</div> <table><tr><th>Approach</th><th>Class</th><th>Precision</th><th>Recall</th><th><math>f_1</math>-score</th></tr><tr><td rowspan="2">Monolingual LR</td><td>Authentic</td><td>0.89</td><td>0.94</td><td>0.91</td></tr><tr><td>Fake</td><td>0.89</td><td>0.82</td><td>0.85</td></tr><tr><td>Monolingual</td><td>Authentic</td><td>0.90</td><td>0.95</td><td>0.93</td></tr><tr><td>CNN+BiLSTM (GloVe)</td><td>Fake</td><td>0.92</td><td>0.83</td><td>0.88</td></tr><tr><td rowspan="2">Multilingual XLM-R(Proposed)</td><td>Authentic</td><td>0.97</td><td>0.98</td><td>0.97</td></tr><tr><td>Fake</td><td>0.99</td><td>0.98</td><td>0.98</td></tr></table>	Approach	Class	Precision	Recall	$f_1$ -score	Monolingual LR	Authentic	0.89	0.94	0.91	Fake	0.89	0.82	0.85	Monolingual	Authentic	0.90	0.95	0.93	CNN+BiLSTM (GloVe)	Fake	0.92	0.83	0.88	Multilingual XLM-R(Proposed)	Authentic	0.97	0.98	0.97	Fake	0.99	0.98	0.98																																																																												
Approach	Class	Precision	Recall	$f_1$ -score																																																																																																										
Monolingual LR	Authentic	0.89	0.94	0.91																																																																																																										
	Fake	0.89	0.82	0.85																																																																																																										
Monolingual	Authentic	0.90	0.95	0.93																																																																																																										
CNN+BiLSTM (GloVe)	Fake	0.92	0.83	0.88																																																																																																										
Multilingual XLM-R(Proposed)	Authentic	0.97	0.98	0.97																																																																																																										
	Fake	0.99	0.98	0.98																																																																																																										
<b>Result / Conclusion</b> (What was the final result?)	<div>Table VI</div> <div>COMPARISON OF VARIOUS APPROACHES ON TEST SET</div> <table><tr><th>Method</th><th>Classifier</th><th>Accuracy</th><th>Precision</th><th>Recall</th><th><math>f_1</math>-score</th></tr><tr><td rowspan="5">ML models</td><td>LR+TF-IDF</td><td>0.89</td><td>0.89</td><td>0.89</td><td>0.89</td></tr><tr><td>RF+TF-IDF</td><td>0.87</td><td>0.87</td><td>0.87</td><td>0.86</td></tr><tr><td>MNB+TF-IDF</td><td>0.87</td><td>0.87</td><td>0.87</td><td>0.86</td></tr><tr><td>SVM+TF-IDF</td><td>0.87</td><td>0.87</td><td>0.87</td><td>0.86</td></tr><tr><td>DT+TF-IDF</td><td>0.87</td><td>0.87</td><td>0.87</td><td>0.86</td></tr><tr><td rowspan="12">DNN models</td><td>CNN(One Hot Encoding)</td><td>0.87</td><td>0.86</td><td>0.86</td><td>0.86</td></tr><tr><td>CNN(Word2Vec)</td><td>0.78</td><td>0.77</td><td>0.76</td><td>0.76</td></tr><tr><td>CNN(FastText)</td><td>0.83</td><td>0.83</td><td>0.83</td><td>0.83</td></tr><tr><td>CNN(GloVe)</td><td>0.90</td><td>0.90</td><td>0.90</td><td>0.90</td></tr><tr><td>BiLSTM(One Hot Encoding)</td><td>0.90</td><td>0.90</td><td>0.90</td><td>0.90</td></tr><tr><td>BiLSTM(Word2Vec)</td><td>0.80</td><td>0.82</td><td>0.79</td><td>0.79</td></tr><tr><td>BiLSTM(FastText)</td><td>0.86</td><td>0.85</td><td>0.86</td><td>0.85</td></tr><tr><td>BiLSTM(GloVe)</td><td>0.89</td><td>0.89</td><td>0.89</td><td>0.89</td></tr><tr><td>CNN + BiLSTM(One Hot Encoding)</td><td>0.90</td><td>0.89</td><td>0.90</td><td>0.89</td></tr><tr><td>CNN + BiLSTM(Word2Vec)</td><td>0.81</td><td>0.80</td><td>0.81</td><td>0.80</td></tr><tr><td>CNN + BiLSTM(FastText)</td><td>0.84</td><td>0.84</td><td>0.84</td><td>0.84</td></tr><tr><td>CNN + BiLSTM(GloVe)</td><td>0.91</td><td>0.91</td><td>0.91</td><td>0.91</td></tr><tr><td rowspan="3">Transformers</td><td>Bangla-BERT</td><td>0.88</td><td>0.88</td><td>0.88</td><td>0.88</td></tr><tr><td>m-BERT</td><td>0.84</td><td>0.84</td><td>0.84</td><td>0.84</td></tr><tr><td>XLM-R(Proposed)</td><td>0.98</td><td>0.98</td><td>0.98</td><td>0.98</td></tr></table>	Method	Classifier	Accuracy	Precision	Recall	$f_1$ -score	ML models	LR+TF-IDF	0.89	0.89	0.89	0.89	RF+TF-IDF	0.87	0.87	0.87	0.86	MNB+TF-IDF	0.87	0.87	0.87	0.86	SVM+TF-IDF	0.87	0.87	0.87	0.86	DT+TF-IDF	0.87	0.87	0.87	0.86	DNN models	CNN(One Hot Encoding)	0.87	0.86	0.86	0.86	CNN(Word2Vec)	0.78	0.77	0.76	0.76	CNN(FastText)	0.83	0.83	0.83	0.83	CNN(GloVe)	0.90	0.90	0.90	0.90	BiLSTM(One Hot Encoding)	0.90	0.90	0.90	0.90	BiLSTM(Word2Vec)	0.80	0.82	0.79	0.79	BiLSTM(FastText)	0.86	0.85	0.86	0.85	BiLSTM(GloVe)	0.89	0.89	0.89	0.89	CNN + BiLSTM(One Hot Encoding)	0.90	0.89	0.90	0.89	CNN + BiLSTM(Word2Vec)	0.81	0.80	0.81	0.80	CNN + BiLSTM(FastText)	0.84	0.84	0.84	0.84	CNN + BiLSTM(GloVe)	0.91	0.91	0.91	0.91	Transformers	Bangla-BERT	0.88	0.88	0.88	0.88	m-BERT	0.84	0.84	0.84	0.84	XLM-R(Proposed)	0.98	0.98	0.98	0.98
Method	Classifier	Accuracy	Precision	Recall	$f_1$ -score																																																																																																									
ML models	LR+TF-IDF	0.89	0.89	0.89	0.89																																																																																																									
	RF+TF-IDF	0.87	0.87	0.87	0.86																																																																																																									
	MNB+TF-IDF	0.87	0.87	0.87	0.86																																																																																																									
	SVM+TF-IDF	0.87	0.87	0.87	0.86																																																																																																									
	DT+TF-IDF	0.87	0.87	0.87	0.86																																																																																																									
DNN models	CNN(One Hot Encoding)	0.87	0.86	0.86	0.86																																																																																																									
	CNN(Word2Vec)	0.78	0.77	0.76	0.76																																																																																																									
	CNN(FastText)	0.83	0.83	0.83	0.83																																																																																																									
	CNN(GloVe)	0.90	0.90	0.90	0.90																																																																																																									
	BiLSTM(One Hot Encoding)	0.90	0.90	0.90	0.90																																																																																																									
	BiLSTM(Word2Vec)	0.80	0.82	0.79	0.79																																																																																																									
	BiLSTM(FastText)	0.86	0.85	0.86	0.85																																																																																																									
	BiLSTM(GloVe)	0.89	0.89	0.89	0.89																																																																																																									
	CNN + BiLSTM(One Hot Encoding)	0.90	0.89	0.90	0.89																																																																																																									
	CNN + BiLSTM(Word2Vec)	0.81	0.80	0.81	0.80																																																																																																									
	CNN + BiLSTM(FastText)	0.84	0.84	0.84	0.84																																																																																																									
	CNN + BiLSTM(GloVe)	0.91	0.91	0.91	0.91																																																																																																									
Transformers	Bangla-BERT	0.88	0.88	0.88	0.88																																																																																																									
	m-BERT	0.84	0.84	0.84	0.84																																																																																																									
	XLM-R(Proposed)	0.98	0.98	0.98	0.98																																																																																																									
<b>Terminology</b> (List the common basic words frequently used in this research field)	Natural language processing, Text pro-cessing, Fake news, Deep learning, Corpus																																																																																																													
<b>Review Judgment</b> (Briefly compare the objectives and results of all the articles you reviewed)	The objective of the research paper 'FaND-X: Fake News Detection using Transformer-based Multilingual Masked Language Model' is to develop a framework for detecting fake news in Bengali using transformer-based and neural network-based approaches. The paper also aims to create a dataset of fake news data and evaluate the performance of various machine learning and deep learning techniques. The results show that the XLM-R model achieves the high-est f1-score of 98 percent on the test data.																																																																																																													
<b>Review Outcome</b> (Make a deci- sion how to use/refer the obtained knowledge to prepare a separate and new methodology for your own re- search project)	The articles highlight the effectiveness ,consider the tech- niques and models used in the reviewed paper, such as transformer-based approaches like XLM-R, and neural network-based approaches like CNN and BiLSTM. These can serve as a starting point for own methodology.																																																																																																													