Exploring The Performance of XLNet and BiLSTM Models For Clickbait Detection In Online News Headlines: A Comparative Study

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***Abstract*— The use of clickbait headlines in the digital era is becoming more prevalent and can lead to the spread of misinformation. Detecting clickbait headlines is crucial for ensuring accurate and trustworthy information, also to prevent spread of misinformation. Deep learning models, such as Bidirectional Long Short-Term Memory(BiLSTM) and XLNet, have become popular for clickbait detection due to their good performance and ability to handle large amounts of data. This paper presents a comparative analysis of the training and testing results obtained from two different models, BiLSTM and XLNet for detecting clickbait using Online News Dataset, which was retrieved from Kaggle. Considering five parameters for the evaluation such as, accuracy, recall, precision, F1-score, lastly time duration of training and testing. Using Adam optimizer, the result shows XLNet model outperformed the BiLSTM model in terms of accuracy, recall, precision, and F1-score. However, the BiLSTM model still showed great performance with slightly lower scores than XLNet. In Addition, the BiLSTM model took a shorter training and testing time compared to the XLNet model.**

Keywords—Clickbait, XLNet, BiLSTM, Deep Learning, News Headlines

I. Introduction

Clickbait is an online content that is intended to get as many clicks as possible. This kind of content frequently employs deceptive or inflated headlines to persuade users to click on a link. In social media, online news articles, and blog postings, clickbait is frequently employed[1]. Although clickbait may increase the number of clicks and views, it can also undermine the authority of online material and deceive readers.

In recent years, deep learning models have become popular for clickbait detection due to their very good performance and ability to handle large amounts of data[2][3]. The most popular deep learning models are Bidirectional Long Short-Term Memory(BiLSTM), XLNet, Convolutional Neural Networks(CNNs), and Gated Recurrent Units(GRUs)[2][3]. But we will only be focusing on BiLSTM and XLNet models.

In this digital era, the use of clickbait headlines is becoming more prevalent and common[4]. Clickbait headlines, which often use sensationalism and exaggeration to lure readers and generate clicks, can lead to the spread of misinformation for the readers[5]. A theory proposed by Lowenstein states that knowledge gaps created by one's curiosity is one of the reasons why many people fall into clicking a clickbait headlines[6]. Detecting clickbait headlines is very important to ensure the information is accurate and trustworthy

In this paper, our goal is to find out which model will give us the best result for detecting clickbait headlines. We will compare the performance of two deep learning models for clickbait detection, BiLSTM and XLNet, based on accuracy, precision, recall, and F1 score. To find out which one is the best at detecting clickbait headlines. In this paper, our goal is to find out which model will give us the best result for detecting clickbait headlines. We will compare the performance of two deep learning models for clickbait detection, BiLSTM and XLNet, based on accuracy, precision, recall, F1-score, and time duration of the training and testing. To find out which one is the best at detecting clickbait headlines.

II. Literature Review

In this chapter, we review the existing literature on clickbait detection, including the approaches and techniques used in the field.

A. Clickbait Detection

Clickbait is a type of content that uses sensational headlines or images to attract users' attention and encourage them to click through to a website. Clickbait has become a common practice on social media and other online platforms, leading to concerns about its impact on user engagement and the spread of misinformation[7]. Clickbait detection has become an important task in natural language processing and information retrieval, with several approaches and techniques proposed in the literature. Clickbait headlines have become a major problem in the online media industry, leading to the spread of misinformation and fake news.

To address this issue, researchers have explored various approaches to detecting clickbait, ranging from using machine learning techniques to leveraging human semantic knowledge and knowledge graphs[7].

B. Deep Learning Models for Clickbait Detection

Deep learning models have been shown to be effective in clickbait detection due to their ability to extract meaningful features from large amounts of text data[8]. Bi-directional Long Short-Term Memory (BiLSTM) is a type of recurrent neural network (RNN) that has been widely used in clickbait detection. BiLSTM can capture the contextual information of the text by processing the input sequence in both forward and backward directions[9][10][16]. However, BiLSTM has limitations in handling long sequences of text and may suffer from vanishing gradient problems[9][10][16].

To overcome the limitations of BiLSTM, XLNet, a transformer-based language model, has emerged as a promising alternative for clickbait detection. XLNet is a state-of-the-art model that has shown superior performance in a variety of NLP tasks due to its ability to capture long-term dependencies and bidirectional context[8]. Unlike traditional masked language models like BERT, XLNet uses permutation language modeling to prevent the pre-training-fine-tuning discrepancy and improve the generalization of the model[8].

C. Related Works

Clickbait has become a major issues in recent years, as it is used to attract viewers with misleading content. So, clickbait detection has become an important research topic where several approaches or research have been proposed to identify clickbait using traditional machine learning models to advanced pre-trained language models.

One common theme among many approaches or research is the use of deep learning models, such as BERT, transformers, and recurrent neural networks, to detect clickbait. "Clickbait Detection in Indonesian News Title with Gray Unbalanced Class Based on BERT," "Automatic Detection of Clickbait Headlines Using Semantic Analysis and Machine Learning Techniques," and "Flagging clickbait in Indonesian online news websites using finetuned transformers" all demonstrate the effectiveness of these models in detecting clickbait[11][12][13]. "BerConvoNet: A deep learning framework for fake news classification" use BerConvoNet to classify the given news text into fake or real with minimal error, achieving 96.85% accuracy [14]. "A deep model based on Lure and Similarity for Adaptive Clickbait Detection" use deep model based on lure and similarity for adaptive clickbait detection on two dataset, achieving 0,88 accuracy for clickbait challenge datasets and 0,935 accuracy for Chinese clickbait datasets [15]. "Deep neural approach to Fake-News identification" use FNN and LSTM model with and without mined features to improve the detection of Fake-News, achieving 83,3% without mined features and 84,3% with mined features in FNN model and achieving 83,7% without mined features and 91,3% with mined features in LSTM model [16]. "Fake News Detection using Bi-directional LSTM-Recurrent Neural Network" use Bi-directional LSTM-RNN to predict fake news article, achieving 0,9875 accuracy and achieving the highest accuracy compared to other models[10].

Several studies have proposed the use of pre-trained language models such as BERT, XLNet, and RoBERTa to detect clickbait in Indonesian news titles. The paper "Clickbait Detection in Indonesian News Title with Gray Unbalanced Class Based on BERT" achieved an accuracy of 88.5% using BERT[11]. Similarly, "BERT, XLNet or RoBERTa: The Best Transfer Learning Model to Detect Clickbaits" compared the performance of these three models and concluded that RoBERTa achieved the best results with 90.2% accuracy[8]. The paper "A benchmark study of machine learning models for online fake news detection" compare traditional machine learning models, deep learning models, and advanced pre-trained language models performances to find the best models for fake news detection [17].

Some research papers focus on leveraging human semantic knowledge, attention-based neural networks, knowledge graphs, and GCNs for detecting clickbait. "An Attention-based Neural Network Using Human Semantic Knowledge and Its Application to Clickbait Detection" proposes a novel attention-based neural network that incorporates human semantic knowledge for detecting clickbait[18]. Similarly, "Leverage knowledge graph and GCN for fine-grained level clickbait detection" proposes a novel approach that leverages knowledge graphs and graph convolutional networks (GCN) to detect clickbait at a fine-grained level[19]. The paper "Automatic Detection of Clickbait Headlines Using Semantic Analysis and Machine Learning Techniques" proposed an attention-based neural network using human semantic knowledge and achieved an accuracy of 84.75%[12]. Additionally, "An Attention-based Neural Network Using Human Semantic Knowledge and Its Application to Clickbait Detection" used a similar approach and achieved an accuracy of 91.5%[18].

Other studies explored the use of hybrid models to detect clickbait. "Detecting clickbaits using two-phase hybrid CNN-LSTM biterm model" use CNN + LSTM to show the effectiveness of CNN-LSTM model which helps to identify the various categories of clickbait headlines that are spread on social media platforms and The proposed approach outperforms when compared to the existing clickbait systems [20]. "Fake news detection: A hybrid CNN-RNN based deep learning approach" use CNN-RNN model and achieving 0,60 accuracy on FA-KES dataset and 0,99 accuracy on ISOT dataset, shows that hybrid CNN-RNN work well on a specific dataset but don't generalize well [21].

Finally, Several studies have explored the effectiveness of using other types of models, methods, and features for clickbait detection. "A temporal ensembling based semi-supervised ConvNet for the detection of fake news articles" propose an innovative Convolutional Neural Network semi-supervised framework built on the self-ensembling concept to take leverage of the linguistic and stylometric information of annotated news articles, achieving 97.45% accuracy and achieving the highest accuracy using 50% labelled articles on Fake News Data Kaggle dataset [22]. "Rapid detection of fake news based on machine learning methods" develop a new model to quickly discover fake news and obtain good results after the initial analysis of the news titles [23]. "Leveraging relevant summarized information and multi-layer classification to generalize the detection of misleading headlines" contributes to the fight against the spread of misleading information by presenting a generic and flexible multi-level hierarchical classification and concluded that the best result were obtained with extractive summarization approaches (TextRank and BERT) [24].

In conclusion, the spread of clickbait headlines has become a major challenge in the online media industry. These papers highlight the importance of developing effective and accurate clickbait detection models to combat the spread of misinformation and fake news. The use of machine learning and deep learning models, such as BERT and transformers, has demonstrated high accuracy in detecting clickbait[25]. However, researchers should also explore other approaches, such as leveraging human semantic knowledge and knowledge graphs, to improve the accuracy of clickbait detection. Ultimately, effective clickbait detection models can help ensure the integrity of news headlines and promote the dissemination of accurate information in the online media industry.

Based on this literature review, we decided to compare the performance of Bidirectional Long Short – Term Memory (BiLSTM) model and XLNet model to find out which is the best for clickbait detection out of our curiosity. We chose XLNet model instead of BERT model, because XLNet uses permutation language modeling to prevent the pre-training-fine-tuning discrepancy and improve the generalization of the model. We chose BiLSTM model instead of CNN model, because BiLSTM model tends to be a more suitable choice where sequential and semantic understanding is crucial.

III. METHODOLOGY

A. Data Collection

We collected a dataset of news headlines from Kaggle. The dataset contains two columns for each data, first one contains the headlines title and second one contains numerical labels of clickbait in which 1 represents that it is clickbait and 0 represents that it is not the clickbait headlines. The dataset contains a total of 32000 rows of which 50% are clickbait and the other are non-clickbait[29].

B. Data Preprocessing

For BiLSTM model we performed data preprocessing by normalizing the text in the first columns or the headlines title. Firstly, we tokenized the text, where each sentence was separated into words. Then, we performed lemmatization, which transformed words into their base or lemma form. After that, we removed punctuation and lowercase the data. Next, we removed empty tokens in the text. Finally, we removed stop words or words that are considered significant.

For XLNet model we performed data preprocessing by using the built-in XLNet tokenizer.

C. Model Architecture

We used two different architectures for clickbait detection: BiLSTM and XLNet. Both models were implemented using the TensorFlow framework.

1. BiLSTM Model

Bidirectional Long Short-Term Memory (BiLSTM) is a recurrent neural network used primarily for natural language processing. Unlike standard LSTM, the input flows in both directions, and it's capable of utilizing information from both sides. It's also a powerful tool for modeling the sequential dependencies between words and phrases in both directions of the sequence[26].

We created a basic architecture using Bidirectional LSTM. We used text vectorization and an embedding layer before the LSTM layer and added max pooling and dropout. We chose Bidirectional LSTM because the model can understand context more easily by using information from both directions, easy to implement, and sufficient for clickbait detection[26].

Table 1
BiLSTM Model Summary

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 1)]	0
text_vectorization (TextVectorization)	(None, 500)	0
embedding (Embedding)	(None, 500, 32)	160032
bidirectional (Bidirectional)	(None, 500, 64)	16640
global_max_pooling1d (GlobalMaxPooling1D)	(None, 64)	0
dropout (Dropout)	(None, 64)	0
dense (Dense)	(None, 1)	65

Total params : 176,737
Trainable params : 176,737
Non-Trainable params : 0

2. XLNet Model

XLNet is an auto-regressive language model that provides the joint probability of token sequences based on the transformer architecture with recurrence. The probability of a word token conditioned on all word token permutations in a sentence, as opposed to just those to the left or right of the target token, is XLNet training objective[27].

We chose XLNet model as the pretrained model because it is more advanced general NLP model compared to BERT. The reasons are XLNet does not use masking which eliminates the pretraining-fine-tuning discrepancy and XLNet also generally provides better results compared to BERT[28].

Table 2
XLNet Model Summary

Layer (type)	Output Shape	Param #
word_inputs (InputLayer)	[(None, 128)]	0
tfxl_net_model (TFXLNetModel)	TFXLNetModelOutput(last_hidden_state = (None, 128, 768), mems = ((128, None, 768), (128, None, 768), (128, None, 768), (128, None, 768), (128, None, 768), (128, None, 768), (128, None, 768), (128, None, 768), (128, None, 768), (128, None, 768), (128, None, 768), (128, None, 768)), hidden_states = None, attentions = None)	116718336
tf.__operators__.getitem (SplicingOpLambda)	(None, 1, 768)	160032
tf.compat.v1.squeeze (TFOpLambda)	(None, 768)	0

dropout_38 (Dropout)	(None, 768)	0
outputs (Dense)	(None, 1)	769

Total params : 116,719,105
Trainable params : 116,719,105
Non-Trainable params : 0

IV. RESULT AND EVALUATION

A. *Model Training and Evaluation Parameters*

We split the dataset into training, validation, and testing sets. We used 80% of the data for training, 10% for validation, and 10% for testing. We trained the models using the Adam optimizer. We used early stopping to prevent overfitting and selected the best models based on their performance on the validation set. To evaluate the models, we used several metrics, including accuracy, precision, recall, F1-score, and time duration for training and testing.

B. *Training Results*

For BiLSTM model we used 10 epochs and 512 for batch size for training the model.

Table 3
BiLSTM Training Result

Epoch	Result
1	25s 280ms/step - loss: 0.6490 - accuracy: 0.7902 - val_loss: 0.4905 - val_accuracy: 0.9075
2	8s 157ms/step - loss: 0.2502 - accuracy: 0.9358 - val_loss: 0.1719 - val_accuracy: 0.9538
3	6s 119ms/step - loss: 0.1519 - accuracy: 0.9598 - val_loss: 0.1514 - val_accuracy: 0.9569
4	5s 104ms/step - loss: 0.1126 - accuracy: 0.9700 - val_loss: 0.1423 - val_accuracy: 0.9581
5	4s 88ms/step - loss: 0.0922 - accuracy: 0.9747 - val_loss: 0.1336 - val_accuracy: 0.9581
6	4s 80ms/step - loss: 0.0775 - accuracy: 0.9772 - val_loss: 0.1373 - val_accuracy: 0.9553
7	4s 71ms/step - loss: 0.0674 - accuracy: 0.9786 - val_loss: 0.1251 - val_accuracy: 0.9584
8	4s 72ms/step - loss: 0.0647 - accuracy: 0.9809 - val_loss: 0.1271 - val_accuracy: 0.9591
9	4s 72ms/step - loss: 0.0647 - accuracy: 0.9809 - val_loss: 0.1271 - val_accuracy: 0.9591
10	4s 71ms/step - loss: 0.0434 - accuracy: 0.9870 - val_loss: 0.1339 - val_accuracy: 0.9597

For XLNet model we used 5 epochs and 64 for batch size for training the model.

Table 4
XLNet Training Result

Epoch	Result
1	904s 2s/step - loss: 0.0741 - accuracy: 0.9730 - val_loss: 0.0185 - val_accuracy: 0.9944
2	862s 2s/step - loss: 0.0222 - accuracy: 0.9926 - val_loss: 0.0094 - val_accuracy: 0.9969
3	859s 2s/step - loss: 0.0100 - accuracy: 0.9969 - val_loss: 0.0158 - val_accuracy: 0.9956
4	855s 2s/step - loss: 0.0064 - accuracy: 0.9978 - val_loss: 0.0067 - val_accuracy: 0.9975
5	858s 2s/step - loss: 0.0043 - accuracy: 0.9985 - val_loss: 0.0095 - val_accuracy: 0.9978

Table 3 presents the training results obtained from the BiLSTM model. The model achieved an initial accuracy of 79.02% and steadily improved over subsequent epochs. The accuracy increased to 98.70% by the tenth epoch. The validation accuracy also showed consistent improvement, reaching 95.97% by the final epoch. The loss decreased significantly from 0.6490 in the first epoch to 0.0434 in the tenth epoch.

Table 4 showcases the training results obtained from the XLNet model. The initial accuracy achieved was 97.30%, and it exhibited steady improvement with each epoch. The model achieved a remarkable accuracy of 99.85% by the fifth epoch. The validation accuracy consistently improved as well, reaching 99.78% by the end of training. The loss decreased substantially from 0.0741 in the first epoch to 0.0043 in the fifth epoch.

The training duration of the XLNet model required more time in training compared to BiLSTM model. The XLNet model completed its training in 1 hour and 13 minutes, meanwhile the BiLSTM model completed its training in a much shorter time of 1 minute and 25 seconds.

To enhance readability, we have included a line chart showcasing the train and validation loss plot for both BiLSTM and XLNet model.

Fig 1 : BiLSTM Train and Validation Loss Graph

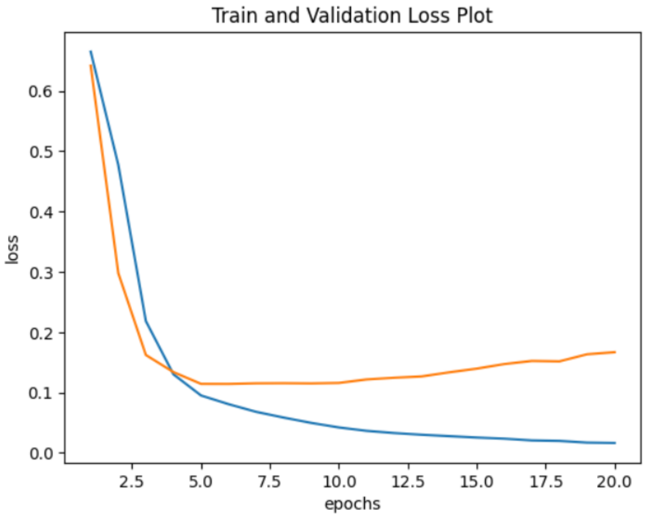
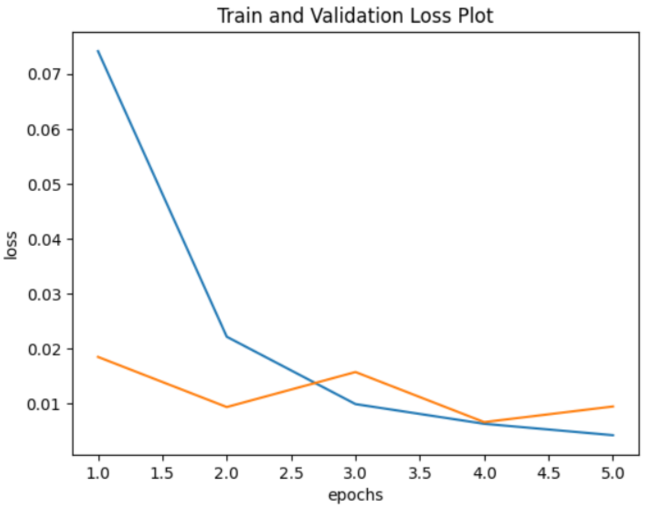


Fig 2 : XLNet Train and Validation Loss Graph



C. *Testing Results*

Table 5

BiLSTM Testing Result

1s 14ms/step - loss: 0.2085 - accuracy: 0.9509 The model test accuracy is 0.9509375095367432. The model test F1-score is 0.9509373802182134
Predicted Class: [1 0 1 ... 1 1 0] Ground Truth: [1 0 1 ... 0 1 0]
Confusion Matrix: [[1524 76] [81 1519]]

Classification Report:

	Precision	Recall	F1-score	support
0	0.95	0.95	0.95	1600
1	0.95	0.95	0.95	1600
accuracy			0.95	3200
micro avg	0.95	0.95	0.95	3200
weighted avg	0.95	0.95	0.95	3200

Table 6

XLNet Testing Result

39s 357ms/step - loss: 0.0262 - accuracy: 0.9966 The model test accuracy is 0.9965624809265137. The model test F1 Score is 0.9965624916076455
Predicted Class: [1 0 1 ... 0 1 0] Ground Truth: [1 0 1 ... 0 1 0]
Confusion Matrix: [[1524 3] [8 1519]]

Classification Report:

	Precision	Recall	F1-Score	support
0	1.00	1.00	1.00	1600
1	1.00	0.99	1.00	1600
accuracy			1.00	3200
micro avg	1.00	1.00	1.00	3200
weighted avg	1.00	1.00	1.00	3200

The testing result for the BiLSTM model is presented in table 5. The BiLSTM model achieved a testing accuracy of 0.9509, indicating its ability to correctly detect clickbait with a high level of accuracy. The F1-score, which combines precision and recall, also reached 0.9509, highlighting the model's balanced performance. The confusion matrix demonstrates the distribution of predicted classes compared to the ground truth labels. In this case, the model correctly predicted 1524 instances of class 0 and 1519 instances of class 1, with a small number of misclassifications (76 false positive and 81 false negative).

The testing result for the XLNet model is presented in table 6. The XLNet model achieved an impressive testing accuracy of 0.9966, showcasing its ability to accurately detect clickbait with exceptional precision. The F1-score further confirmed the model's outstanding performance, reaching 0.9966. The confusion matrix revealed that the model correctly predicted 1524 instances of class 0 and 1519 instances of class 1, with only a few misclassifications (only 3 false positive and 8 false negative).

The XLNet model showed slightly higher accuracy and F1-score compared to the BiLSTM model. The

XLNet model almost achieved near-perfect accuracy and F1-Score. However, the BiLSTM model also showed great result(only slightly lower than XLNET), but the time duration is slightly faster. Overall, these results highlight the effectiveness of both models in clickbait detection tasks.

V. Conclusion And Future Research

In conclusion, both the BiLSTM and XLNet models exhibited strong performance in clickbait detection tasks. The BiLSTM model achieved a testing accuracy of 0.9509 and an F1-score of 0.9509, indicating its ability to accurately detect clickbait with a high level of precision and recall. Similarly, the XLNet model achieved impressive results with a testing accuracy of 0.9966 and an F1-score of 0.9966, showcasing its exceptional precision in clickbait detection.

While the XLNet model outperformed the BiLSTM model in terms of accuracy, recall, precision, and F1-score. However, the BiLSTM model still showed great performance with slightly lower scores.. In addition, the BiLSTM model took a shorter training time compared to the XLNet model. Therefore, the choice of model for clickbait detection tasks may depend on a balance between accuracy requirements and computational resources available.

In the future, researchers can further advance clickbait detection techniques, accuracy, and efficiency. By addressing some areas, for example using larger and diverse datasets can provide insights into both model robustness and generalization capabilities. Researchers can also increase both model performance by fine-tunning the model, adjusting the parameters and exploring different architectures may improve their performance.

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