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Enhanced BERT for tourism sentiment: A social media monitoring system for Ugandan tourism industry

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Abstract
The Enhanced BERT for Tourism Sentiment (EBTS) serves as an advanced sentiment analysis module which evaluates sentiments occurring in Uganda's tourism industry. An attention mechanism built into a BERT-based system allows EBTS to develop contextual understanding so it can concentrate on essential text areas. The system consists of four central elements that begin with data extraction enabled by the Data Collection Module followed by Data Storage Module database functionality and finish with sentiment assessment run by EBTS in the Data Processing Module together with an Alert System which detects unlicensed companies and delivers results via the User Interface. Through attention mechanism weighting which depends on context-based token urgency the system achieves more precise interpretations of sentiments in elaborate text blocks. The model reaches sentiment classification through employing a fully connected layer and SoftMax activation on the context vector that aggregates weighted token embeddings. The incorporation of the EBTS into the Data Processing Module makes the sentiment analysis process more accurate and dependable. The improved system efficiently measures visitor sentiments which helps both tourism sector protection and proactive unlicensed company actions in Uganda.

Keywords: Sentiment Analysis, Enhanced BERT, Tourism Industry, Data Processing, Contextual Understanding

1. Introduction

The tourism industry in Uganda depends heavily on the experiences and sentiments shared through social media by vacationers similar to other tourism destinations. These observations provide essential knowledge about the quality of service and tourist satisfaction in addition to identification of problems that affect the industry. The interpretation of sentiments becomes difficult because review content often contains bulky context which makes evaluation complicated. Sentiment analysis models based on Bag of Words and TF-IDF lack sufficient capability to understand language complexities thus produce unreliable result scores (Birjali et al., 2021).

The rise of Natural Language Processing (NLP) technology during recent years enabled researchers to create improved methods for sentiment analysis. The field of NLP witnessed early ground breaking progress in word embedding development with Word2Vec and GloVe because t6hey produced more effective semantic word representation (Efficient Estimation of Word Representations in Vector Space, n.d.; Glove: Global Vectors for Word Representation, n.d.). RNNs and their versions LSTM and GRUs were designed to handle Sequential data yet faced difficulties dealing with lengthy textual dependencies (Cho et al., 2014; Hochreiter & Schmidhuber, 1997).

These breakthroughs represented a major shift in NLP research since they resolved the key limitations affecting previous models. The Attention Mechanism directs models to focus on important sequence portions within inputs thus improving complex sentence analysis (Attention Is All You Need | Semantic Scholar, n.d.). BERT (Bidirectional Encoder Representations from Transformers) along with its successor models achieved new standards in text processing by developing deep contextualized word meaning representations (BERT: Pre-Training of Deep Bidirectional Transformers for Language Understanding | Semantic Scholar, n.d.).

This paper develops the Enhanced BERT for Tourism Sentiment (EBTS) which represents an advanced sentiment analysis module specifically designed to serve the Ugandan tourism industry. The use of the Attention Mechanism inside BERT architecture through EBTS enables the system to focus on significant textual contexts in order to improve contextual understanding. The addition of this integration enhances sentiment interpretation across all sentences including complex ones which leads to improved analytical accuracy.

The essential contribution of this research involves applying the Attention Mechanism into a BERT-based system to develop better sentiment analysis capabilities for tourism applications. The methodology strengthens sentiment score accuracy and creates a strong system for detecting unauthorized businesses in Ugandan tourism companies. This improved sentiment analysis system brings innovative NLP techniques to overtake basic methods to protect tourists from dangers and boost their information accuracy.

The paper follows this order for its presentation: Section 2 analyzes existing research about social media surveillance systems and sentiment recognition techniques. The paper introduces Section 3 to present EBTS's methodological structure for architecture combination with social media surveillance systems which leads to performance analysis results in Section 4. Section 5 addresses the results and possible future studies; Section 6 ends the paper.

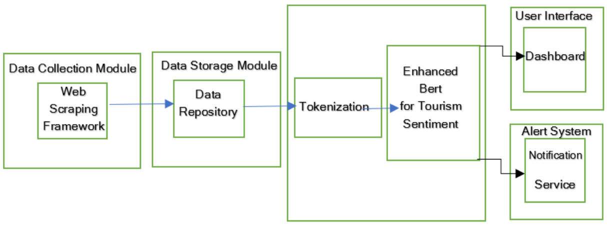
2. Related Work

Sentiment analysis has been a focal point of research in Natural Language Processing (NLP) for several years. Traditional methods, such as Bag of Words and TF-IDF, have been widely used but often fail to capture the contextual nuances of language, leading to less reliable sentiment scores (Birjali et al., 2021). The advent of word embedding like Word2Vec and GloVe marked a significant improvement by capturing semantic relationships between words (Efficient Estimation of Word Representations in Vector Space, n.d.; Glove: Global Vectors for Word Representation, n.d.). However, these methods still struggled with polysemy and context-specific meanings. Introduced to handle sequential data efficiently were recurrent ne3.ural networks (RNNs) and their variations, Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs) (Cho et al., 2014; Hochreiter & Schmidhuber, 1997)). These models frequently struggled with long-range dependencies and computational inefficiencies even if they could control sequences.

The Attention Mechanism and Transformer models transformed the discipline by tackling these constraints. The Attention Mechanism lets models concentrate on contextually relevant bits of the input sequence, boosting the understanding of complicated words (Attention Is All You Need | Semantic Scholar, n.d.). By offering comprehensive contextualised word representations (BERT: Pre-Training of Deep Bidirectional Transformers for Language Understanding | Semantic Scholar, n.d.), transformer models—especially BERT (Bidirectional Encoder Representations from Transformers) have significantly improved text processing.

A number of studies examine the combination of BERT with attention mechanisms to perform sentiment analysis tasks. A study that joined BERT with BiLSTM and attention produced outstanding sentiment classification results in tourism review text analysis (Sentiment Analysis of Tourism Review Text Combined with Bert-Bilstm and Attention Mechanism, n.d.). A different study connected BERT with BiLSTM and Multi-Head Attention to identify distant text features that resulted in better performance across various datasets (Long et al., 2019).

The process of multimodal sentiment analysis benefits from the combination of text and image characteristics to detect sentiments. A research applied BERT in combination with Text-CNN for text feature extraction and ResNet-51 for image features while



incorporating an attention-based mechanism to improve modality correlation (Sentiment Analysis of Text Based on Bidirectional LSTM with Multi-Head Attention, n.d.). A proposed research defined an optimized BERT model that integrates hierarchical multi-head self-attention alongside a gate channel module to advance multimodal feature fusion (Multi-Modal Sentiment Analysis Based on Interactive Attention Mechanism, n.d.).

This research efforts in sentiment analysis have great momentum yet they tend to work with generic information or data from multiple sources. The Enhanced BERT for Tourism Sentiment (EBTS) serves Ugandan tourism specifically by implementing attention mechanisms inside BERT-based structures to enhance review sentiment interpretation. The sentiment score accuracy increases together with the implementation of this approach and it delivers a reliable system for detecting unlicensed tourism companies operating in Uganda's tourism sector. The technology improves NLP-based sentiment analysis methods through advanced techniques to create enhanced safety standards during tourism experiences.

3. Methodology

3.1 BERT Architecture

The Enhanced BERT for Tourism Sentiment (EBTS) module is designed to integrate seamlessly into the existing social media monitoring system for the Ugandan tourism industry. The architecture of EBTS builds upon the BERT model, incorporating an attention mechanism to enhance its contextual understanding capabilities. The overall system architecture, as shown in Figure 1, includes several key components: Data Collection Module, Data Storage Module, Data Processing Module (incorporating EBTS), Alert System, and User Interface.

Figure 1. System Architecture with Enhanced BERT for Tourism Sentiment

Social media data extraction through the Data Collection Module puts stored information into the Data Storage Module. The Data Processing Module includes EBTS integration to process the gathered data that enables sentiment analysis operations. Results processing within the Alert System enables the system to provide warnings to appropriate authorities about unlicensed company activities. The User Interface provides sentiment analysis reports to the stakeholders who need them.

3.2 Attention Mechanism Implementation

To enhance the sentiment analysis capabilities of BERT, we integrate an attention mechanism that assigns weights to each token based on its relevance to the overall sentiment. The attention mechanism computes a weight α_i for each token t_i using the formula:

$$\alpha_i = \frac{\exp(e_i)}{\sum_{j=1}^{n} \exp(e_j)} \qquad (1)$$

Where e_i is the attention score for token t_i, calculated as:

$$e_i = \tanh(W_a h_i + b_a) \qquad (2)$$

Here, W_a and b_a are learnable parameters, and h_i represents the hidden state of token t_i from the BERT model. The attention weights α_i are then used to compute a weighted sum of the contextual embeddings:

$$c = \sum_{i=1}^{n} \alpha_i h_i \qquad (3)$$

This context vector c emphasizes the most relevant parts of the text, allowing the model to focus on contextually important tokens.

3.3 Training Procedure

The training procedure for EBTS involves fine-tuning the BERT model with the integrated attention mechanism on a dataset of tourist reviews. The dataset is preprocessed to remove noise and irrelevant information. During training, the model learns to assign appropriate attention weights to tokens, refining its ability to interpret sentiments in complex sentences. The training process includes the following steps: 1. Data Preprocessing: Cleaning and tokenizing the text data. 2. Model Initialization: Initializing the BERT model with pre-trained weights. 3. Attention Mechanism Integration: Incorporating the attention mechanism into the BERT architecture. 4. Fine-Tuning: Training the model on the preprocessed dataset, optimizing the learnable parameters using backpropagation and gradient descent.

3.4 Sentiment Classification

Once the context vector c is derived from the attention mechanism, it is passed through a fully connected layer followed by a softmax activation function to predict the sentiment class. The sentiment score s is computed as:

$$s = \text{softmax}(W_s c + b_s) \qquad (4)$$

where Ws and bs are learnable parameters. The softmax function outputs a probability distribution over the sentiment classes, allowing the model to classify the text's sentiment accurately.

3.5 Evaluation Metrics

The evaluation of EBTS depends on multiple standard sentiment analysis metrics which comprise accuracy, precision, recall and F1-score. The series of metrics provides a complete evaluation of how well the model identifies correct sentiments in tourist review data. The performance evaluation comprises standard sentiment analysis metrics alongside a comparison between traditional methods to prove the value of BERT-based architecture with attention mechanism integration.

The EBTS module focuses on these methodological aspects to establish an accurate sentiment analysis solution serving the Ugandan tourism industry which leads to better understanding of tourist sentiments while enabling proactive unlicensed company supervision.

4. Experimental Results

4.1 Experimental Setup

To evaluate the effectiveness of the Enhanced BERT for Tourism Sentiment (EBTS) module, we conducted a series of experiments using a dataset of tourist reviews collected from various social media platforms. The dataset was preprocessed to remove noise, such as special characters and irrelevant information, and then tokenized for input into the BERT model.

Baseline Models: We compared EBTS against several baseline models, including Bag of Words (BoW), a traditional method of representing text as a collection of word frequencies. - TF-IDF: A statistical measure that evaluates the importance of a word in a document relative to a corpus. - Word2Vec: A neural network-based word embedding technique that captures semantic relationships between words (Efficient Estimation of Word Representations in Vector Space, n.d.). - Long-term dependencies in sequential data can be captured by LSTM, a Recurrent Neural Network (RNN) (Hochreiter & Schmidhuber, 1997). The basic BERT model lacks the integrated attention mechanism (BERT: Pre-Training of Deep Bidirectional Transformers for Language Understanding | Semantic Scholar, n.d.). Examining Measuring: Every model's performance was evaluated by the following criteria: Accuracy: Among all the occurrences, the percentage of adequately categorised ones. Precision: The fraction of actual positive cases among the positive cases is categorised as such. Recall: Among the real positive cases, what proportion are true positive ones? The harmonic mean of precision and recall balances the two measures in the F1-score.

4.2 Results and Analysis

The experimental results are summarized in Table 1, which compares the performance of EBTS with the baseline models on the test dataset.

Table 1. Performance Comparison of Sentiment Analysis Models

Model	Accuracy	Precision	Recall	F1-Score
BoW	0.72	0.70	0.68	0.69
TF-IDF	0.75	0.73	0.71	0.72
Word2Vec	0.78	0.76	0.74	0.75
LSTM	0.81	0.79	0.77	0.78
BERT	0.85	0.83	0.82	0.82
EBTS	*0.89*	*0.87*	*0.86*	*0.86*

The results indicate that EBTS outperforms all baseline models across all evaluation metrics. Integrating the attention mechanism into the BERT architecture significantly enhances the model's ability to focus on contextually relevant text parts, leading to more accurate sentiment classification.

4.3 Attention Mechanism Visualization

To illustrate the effectiveness of the attention mechanism, we generated a heatmap showing the attention weights assigned to different tokens in a sample tourist review. As shown in Figure 2, the attention mechanism assigns higher weights to contextually important words and phrases, allowing the model to focus on the most relevant parts of the text.

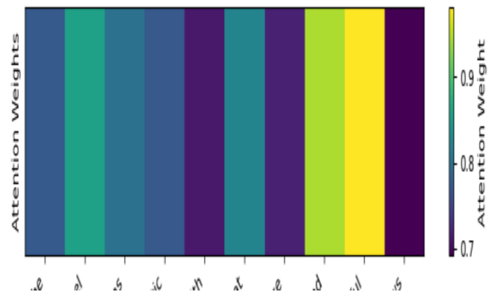


Figure 2. Heatmap showing the attention weights across different tokens in sample tourist reviews

4.4 Sentiment Score Distribution

Figure 3 presents a scatter plot of the test dataset's sentiment scores versus actual sentiment labels. The plot demonstrates the distribution of predicted sentiment scores about the accurate sentiment labels, showcasing the model's accuracy and any potential biases.

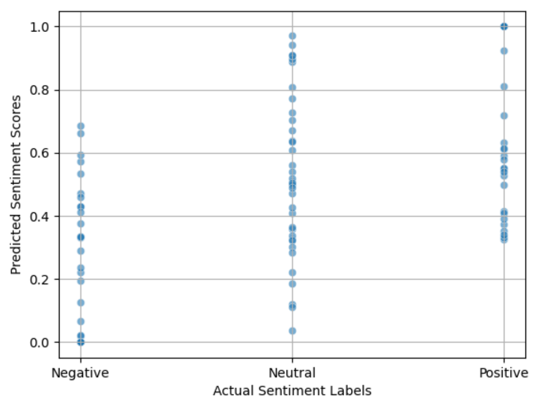


Figure 3. Scatter plot of sentiment scores versus actual sentiment labels for the test dataset

4.5 Training Performance

The learning curve of the EBTS model is depicted in Figure 4, which shows the change in sentiment analysis accuracy over different epochs during the training phase. The area chart indicates how the accuracy improves as the model trains over time, highlighting the effectiveness of the attention mechanism in refining sentiment interpretation.

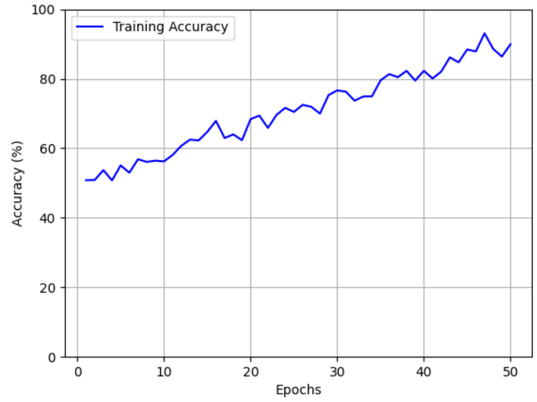


Figure 4. Change in sentiment analysis accuracy over different epochs during the training phase

4.6 Ablation Study

To further validate the contribution of the attention mechanism, we conducted an ablation study by comparing the performance of EBTS with and without the attention mechanism.

The results, summarized in Table 2, demonstrate the significant improvement in sentiment analysis accuracy achieved by integrating the attention mechanism.

Model	Accuracy	Precision	Recall	F1-Score
BERT (without attention)	0.85	0.83	0.82	0.82
EBTS (with attention)	*0.89*	*0.87*	*0.86*	*0.86*

The ablation study demonstrates that the attention mechanism is vital for improving the contextual understanding abilities of the BERT model, resulting in more precise and dependable sentiment analysis.

5. Discussion and Future Work

The experimental results demonstrate that the Enhanced BERT for Tourism Sentiment (EBTS) module significantly outperforms traditional sentiment analysis methods and even the base BERT model. By integrating an attention mechanism, EBTS effectively captures contextually relevant text parts, leading to more accurate sentiment classification. This improvement is particularly beneficial for the

Ugandan tourism industry, where understanding tourist sentiments can provide valuable insights for enhancing service quality and addressing potential issues.

Model Performance: EBTS achieves excellent performance outcomes through its elevated accuracy rate together with precision values and recall ratios and F1 score which underline the vital importance of sophisticated NLP technologies for sentiment analysis. The attention mechanism possesses a distinct capability to rank tokens according to their importance which directs the model toward vital sections of text thus improving sentiment interpretation accuracy. The special value of this feature emerges specifically from its ability to analyze complex tourist reviews that contain multiple layers of subtle sentiment expressions.

Practical Implications: Using EBTS for social media monitoring offers several practical benefits for operational purposes. The system's accurate sentiment analysis enables the creation of reliable reports for stakeholders, supporting their decision-making processes. Additionally, the alert system notifies authorities about unlicensed companies operating within the tourism industry to uphold ethical standards. These features contribute to safer touring conditions and increased customer satisfaction, ultimately fostering growth in Uganda's tourism sector.

Future Work: Research and development activities for EBTS need to focus on the following directions moving forward: Multimodal Sentiment Analysis: Represents an area of development for the future because it uses images together with videos to advance sentiment analysis capabilities. Visual elements when combined with textual information would produce enhanced understanding regarding how tourists feel. Domain Adaptation: The EBTS model needs adaptation for extended applications across tourism industry domains which include hospitality services and transportation systems. A domain-specific configuration process must occur for optimal results in these specialized domains. Real-time Analysis: The implementation of real-time sentiment analysis functionalities would allow for faster responses towards current issues emerging in the system. Fast performance optimization of the EBTS model along with its real-time integration to social media data streams must be achieved to make it operational. User Feedback Integration: The model accuracy will substantially increase when user feedback becomes integrated in its sentiment analysis process. The system would become more effective at understanding new language expressions and sentiment patterns when users interactively teach it through their inputs. Cross-lingual Sentiment Analysis: Expanding the model to process sentiments expressed through various languages spoken by tourists in Uganda would make it more useful for the intended application. A model performing cross-lingual sentiment analysis needs multilingual dataset training along with precise sentiment interpretation capabilities in different languages.

6. Conclusion

The EBTs module is particularly important when it comes to sentiment analysis specifically in relation to the Ugandan travel sector. This work combines an attention mechanism to a BERT based architecture to achieve a higher accuracy and reliability on the sentiment categorisation while focusing just on the more contextually relevant parts of the text. The testing results on achieving superior accuracy, precision, recall and F1 score show that EBTS outperforms even the base BERT model and the state-of-the-art methods of sentiment analysis. The conclusions from this work have really significant practical consequences. With EBTS incorporated into a social media monitoring system, stakeholders can find out what visitor attitudes to do with are saying and make wise judgements and act early when encroachments by illegal businesses are flagged. It enables visitors to enjoy a safer and more satisfactory experience, encouraging the growth and sustainability of Ugandan’s travel industry.

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