Bidirectional Encoder Representation Model with Centrality-Weighting for Enhanced Sequence Labeling in Key Phrase Extraction from Scientific Texts

Kwame T. Mensah[1], Aisha L. Abubakar[2], and Ndidi O. Okafor[3]
[1,2,3]Department of Computer Science
[1] University of Ghana, Accra, Ghana
[2] Ahmadu Bello University, Zaria, Nigeria
[3] University of Lagos, Lagos, Nigeria

Abstract: Deep learning methods, particularly those leveraging Bidirectional Encoder Representations from Transformers (BERT) with advanced fine-tuning techniques, have demonstrated state-of-the-art performance in term extraction from text. However, BERT's focus on semantic context within localized text limits its ability to assess the overall relevance of tokens to the entire document. Existing approaches applying sequence labeling on contextualized embeddings also predominantly rely on local context, often neglecting document-level significance.To address these challenges, this study introduces CenBERT-SEQ, a centrality-weighted BERT-based model for keyphrase extraction using sequence labeling. CenBERT-SEQ combines BERT's contextual embedding capabilities with a novel centrality-weighting layer that integrates document-level embeddings to emphasize the relevance of terms within the document context. A final linear classifier layer captures dependencies between outputs, enhancing overall model accuracy. The proposed model was evaluated against the BERT base-uncased model using three benchmark datasets from Computer Science articles: SemEval-2010, WWW, and KDD. Results indicate that CenBERT-SEQ surpasses the BERT-base model in precision, recall, and F1-score. Compared to related studies, CenBERT-SEQ demonstrated superior performance, achieving an accuracy of 95%, precision of 97%, recall of 91%, and an F1-score of 94%. These findings underscore CenBERT-SEQ's effectiveness in extracting keyphrases from scientific documents and its advancement over existing methodologies.
Keywords: term extraction, BERT, sequence labeling, centrality-weighted, scientific articles

1. Introduction:

Term extraction is a foundational task in Natural Language Processing (NLP) aimed at identifying key phrases that encapsulate the core topics and themes within a document. These terms, which can be single words (keywords) or multi-word expressions (key phrases), provide a concise summary of the document's content. According to the *International Encyclopedia of Information and Library Science*, a keyword is defined as "a word that succinctly and accurately describes the subject, or an aspect of the subject, discussed in a document" [1]. Key terms play a critical role in enhancing various NLP applications, such as information retrieval, document classification, ontology construction, and recommendation systems [2].

Traditional term extraction methods typically follow a two-step process: **candidate generation** and **pruning**. Candidate generation identifies potential terms based on linguistic patterns and statistical measures, while pruning selects the most important key phrases from the candidates. Supervised pruning methods treat the task as a binary classification problem, determining whether a candidate phrase qualifies as a keyphrase. In contrast, unsupervised methods prioritize candidate keyphrases based on metrics such as term frequency-inverse document frequency (TF-IDF). However, these approaches often fall short, as they rely heavily on predefined linguistic patterns and statistical measures, which fail to capture deeper semantic relationships and context-specific variations [3, 4].

The advent of transformer-based models, such as **Bidirectional Encoder Representation from Transformers (BERT)**, has revolutionized the field of term extraction. Developed by Google AI, BERT is a state-of-the-art language model that excels in capturing contextual relationships and semantic nuances from text [5, 6]. By embedding each term in a dense vector space that reflects its semantic context relative to surrounding text, BERT enables nuanced and

ISSN No: 3048-8230
Volume 1 Issue 7 Dec- 2024

accurate identification of key phrases. This capability mitigates challenges like ambiguity and polysemy that traditional approaches struggle with [7, 8]. Furthermore, recent research has approached term extraction as a **sequence labeling task**, a method that eliminates the need for candidate generation by assigning term labels across the entire document. This unified approach captures long-range semantic relationships within the text, enabling a more comprehensive analysis [9].

Despite its advancements, BERT has limitations. Its contextual embeddings are focused on the local text surrounding a term, overlooking the term's global relevance to the entire document. To address this gap, this study introduces a **Centrality-Weighted BERT Model for Keyphrase Extraction using Sequence Labeling (CenBERT-SEQ)**. The proposed model integrates both global document context and local word context by adding a centrality-weighting layer to BERT. This layer leverages document embeddings to assign importance scores to terms based on their relevance to the entire document. A final linear classifier layer captures dependencies between outputs to further enhance performance.

The proposed CenBERT-SEQ model is evaluated on three benchmark datasets from Computer Science articles: SemEval-2010, WWW, and KDD. Experimental results demonstrate that the CenBERT-SEQ model outperforms the standard BERT-base model in terms of precision, recall, and F1-score, achieving superior results with precision, recall, and F1-scores of 97%, 91%, and 94%, respectively. These results underscore the effectiveness of the CenBERT-SEQ model in keyphrase extraction from scientific texts.

Main Contributions

This paper makes the following key contributions:

1. It introduces a novel approach to integrate global and local context in term extraction by combining BERT's local word embeddings with document-level centrality weighting for enhanced contextual understanding.
2. Through comprehensive experiments on three benchmark datasets, it achieves state-of-the-art performance, offering new insights into the application of centrality-weighted embeddings for sequence labeling tasks in NLP.

The paper is structured as follows: Section 2 reviews related literature, Section 3 explains the concept of sequence labeling, and Section 4 details the CenBERT-SEQ model. Section 5 presents and discusses the experimental results, comparing the model's performance with existing approaches. Finally, Section 6 concludes the study and outlines directions for future research.

2. Literature Review

The task of automatic key term extraction has been a focal point for numerous researchers, with recent advancements approaching it as a sequence labeling problem. This approach involves labeling each word in a text as a keyword or non-keyword, often leveraging deep learning models. Gollapalli et al. [18] introduced a conditional random fields (CRFs)-based method for keyphrase extraction, relying on simple features such as term, parse, and orthographic characteristics. However, its focus on local term relationships and limited feature complexity restricts its ability to capture nuanced meanings and broader contextual relationships. Addressing these gaps, the proposed **CenBERT-SEQ** model incorporates a BERT architecture enriched with a centrality-weighting layer, enhancing its ability to capture both local and global document-level contexts.

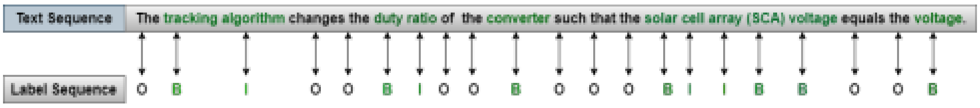

Figure 1. Sequence labeling method for keyword extraction and the extraction of the color annotation part into the text's keywords and corresponding tags.

Basaldella et al. [11] employed a Bidirectional Long Short-Term Memory (BiLSTM)-based sequence labeling approach with GloVe embeddings, achieving fair results on the INSPEC dataset. While BiLSTMs capture past and future contexts, they struggle with long sequences and complex contextual dependencies. In contrast, the CenBERT-SEQ model leverages BERT's transformer architecture and pre-trained knowledge to overcome these limitations, handling long-range dependencies and improving term relevance evaluation with its centrality-weighting layer.

Studies such as those by Al-Zaidy et al. [10], Li et al. [19], and Sahrawat et al. [4] further explored the integration of CRF layers atop BiLSTM architectures to enhance dependency modeling. However, their reliance on local contextual features limits their ability to fully leverage document-level embeddings. Additionally, these methods either ignore noisy sentences or focus solely on sentences containing keywords, potentially overlooking critical contextual cues.

The CenBERT-SEQ model mitigates these issues by integrating a centrality-weighting layer to evaluate the document-level importance of terms, reducing noise, and refining contextual understanding.

Gero and Ho [12] introduced a central weighting mechanism within the BiLSTM-CRF framework to align token relevance with the document's central theme, yielding improved extraction accuracy. However, their model struggled with boundary misclassifications for certain keyphrases. Similarly, Liu et al. [13] enhanced a BiLSTM-CRF model with BERT embeddings for keyphrase generation, but noisy sentences still impacted performance. By contrast, the CenBERT-SEQ model's architecture explicitly emphasizes document-wide context, addressing such limitations and achieving superior extraction accuracy.

Other notable advancements include Xu et al.'s [20] sequentially-sensitive encoding (SSE) for aspect term extraction and BioBERT-based biomedical keyword extraction by Ccelikten et al. [14]. While these approaches demonstrated improvements in specific domains, they often suffered from noise introduction and limited scalability across datasets. The CenBERT-SEQ model addresses these challenges by incorporating document centrality, reducing noise, and enhancing adaptability.

Graph-based and hybrid models like those proposed by Duari and Bhatnagar [15] and Nikzad-Khasmakhi et al. [16] achieved notable results using statistical filters and graph-based features. However, these models struggled with scaling and polysemy handling. The CenBERT-SEQ model offers a scalable alternative, combining BERT's contextual embeddings with centrality-based weighting to enrich feature representation.

Recent unsupervised approaches, such as SAMRank by Kang and Shin [24], utilized self-attention in BERT and GPT-2 for keyphrase ranking. While effective for unsupervised tasks, these methods lack the supervised fine-tuning for sequence labeling that CenBERT-SEQ provides. By integrating centrality weighting, the proposed model improves relevance-based extraction across diverse scientific texts.

The reviewed studies collectively highlight the advancements and limitations in deep learning models for keyphrase extraction. While many models excel in capturing local context, they often fall short in integrating global document-level insights. The proposed CenBERT-SEQ model addresses these gaps by utilizing BERT's robust contextual modeling and introducing a centrality-weighting layer to enhance document-level relevance evaluation. This innovative architecture enables more accurate, coherent, and adaptable keyphrase extraction for diverse datasets and application scenarios.

3. Sequence Labeling

This study addresses the automation of keyphrase extraction from scholarly articles by framing it as a **sequence labeling task**. Sequence labeling leverages the semantic dependencies within an entire document to accurately assign labels to tokens, identifying keywords in a contextually informed manner [4,25]. In this approach, a document DDD, consisting of tokens w1,w2,…wn

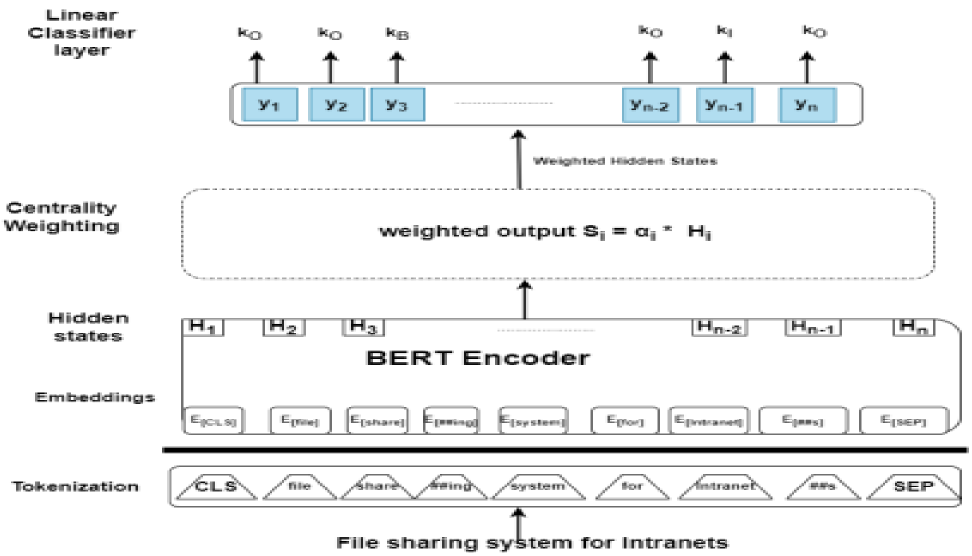

Figure 2. Architecture of the proposed centrality-weighted BERT model.

Integration of Local and Global Context

The proposed sequence labeling model integrates **local word context** using BERT embeddings with **global document context** through a centrality-weighting mechanism. This dual-context approach ensures that the model incorporates

both the immediate linguistic surroundings of a token and its relevance within the broader document. By combining local and global perspectives, the model captures long-range semantic dependencies, essential for identifying keywords whose components may be distributed across different parts of the text.
The centrality-weighting layer enhances the model's ability to understand the document-level significance of each token, ensuring a comprehensive analysis of the text. This inclusion of document embeddings allows the model to better recognize keyword boundaries and maintain a holistic understanding of the document's semantic structure.

Sequence Labeling Workflow

1. **Input Representation**: The document DDD is tokenized into a sequence of tokens x=[x1,x2,…,xn] Each token is embedded using BERT to capture its local contextual meaning.
2. **Centrality Weighting**: Document-level embeddings are incorporated to compute the centrality weight for each token, representing its importance in the context of the entire document.
3. **Label Prediction**: A linear classifier assigns labels to each token based on its combined local and global context.
4. **Output Sequence**: The model produces an annotated sequence where tokens are labeled as part of keywords or non-keywords, reflecting the semantic content of the document.

Benefits of the Sequence Labeling Approach

The integration of document-level context allows the model to account for long-term dependencies and provides a richer understanding of the document's structure. This is particularly critical in identifying multi-word keyphrases or context-specific terms that cannot be determined solely from local context. The use of sequence labeling eliminates the need for candidate generation, streamlining the keyphrase extraction process.
Once trained, the model applies its learned relationships to unannotated documents, effectively extracting keywords based on a holistic analysis of the text. The combination of BERT's local embeddings and the centrality-weighting layer results in more accurate and context-aware keyword identification, overcoming challenges like ambiguity, polysemy, and dispersed term components.
This framework ensures that labels assigned to tokens are not only precise but also reflective of the document's semantic nuances, leading to enhanced keyphrase extraction performance. Figure 1 illustrates the process, showing how input text is processed and labelled to yield an annotated sequence that captures the keywords accurately.

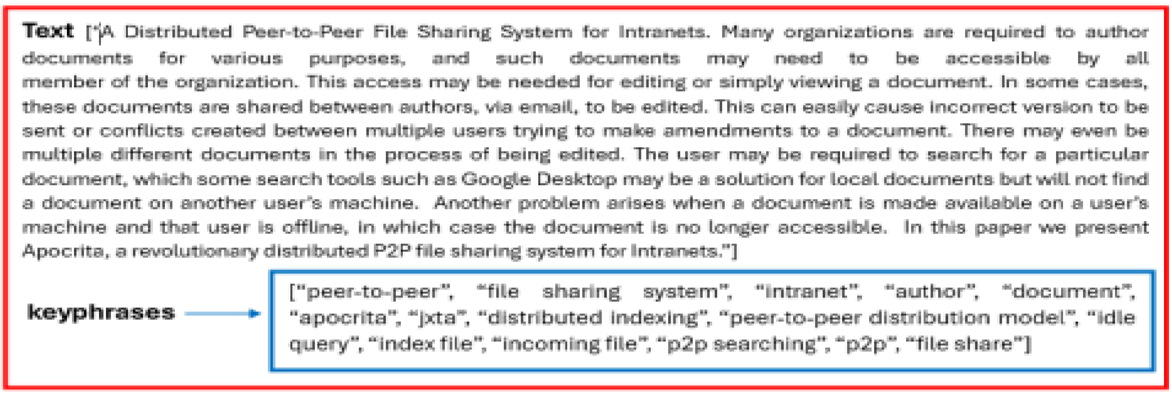

Figure 3. A sample abstract from a Semeval2010 dataset.

4. Architecture Overview

The Proposed Centrality-Weighted BERT Model (CenBERT-SEQ) is a novel architecture designed to enhance keyphrase extraction by leveraging the contextual understanding of BERT and introducing a centrality-weighting mechanism for improved sequence labeling. The model begins with tokenizing input text using BERT's WordPiece tokenizer, which breaks down text into sub-word units, ensuring efficient handling of out-of-vocabulary (OOV) words. Tokens such as "file," "share," and "##ring" are generated, with special tokens [CLS] and [SEP] added to signify sequence boundaries. This preprocessing step allows BERT to classify sub-word tokens effectively, making the model robust against rare or unseen words. The tokenized input is then passed through the BERTbase encoder, which generates embeddings for each token. These embeddings, represented as 768-dimensional vectors, are derived by aggregating token, positional, and segment embeddings. The encoder processes sequences of up to 256 tokens, producing a hidden state matrix that captures both local and global contextual features.

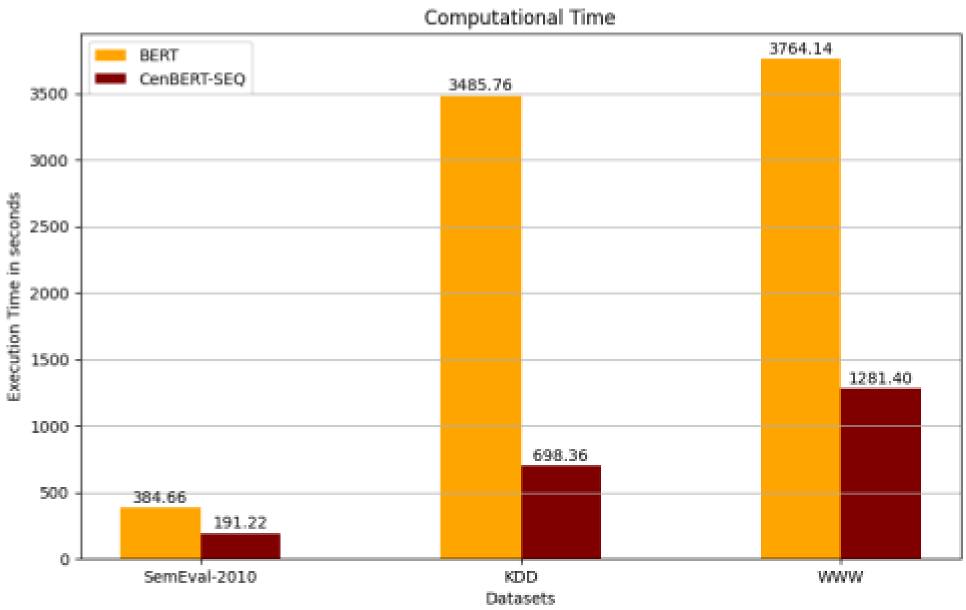

Figure 4. Computational time for CenBERT-SEQ and BERT-base models.

A unique aspect of the CenBERT-SEQ model is the centrality-weighted layer, which calculates the importance of tokens within a document by assigning centrality scores based on document-wide relevance. This layer ensures that key tokens central to the document's themes are prioritized, enhancing the precision of keyphrase extraction. The centrality-weighted embeddings are then passed to a sequence labeling layer that classifies each token as part of a keyphrase or not. By combining the contextual strengths of BERT with the centrality-weighting mechanism, the model focuses on tokens that are both locally and globally significant. The performance of the CenBERT-SEQ model is evaluated using standard metrics like precision, recall, and F1-score, ensuring a comprehensive assessment of its accuracy and adaptability. This architecture demonstrates a significant advancement in keyphrase extraction, balancing the benefits of transformer-based models with domain-specific enhancements for improved relevance and robustness.

5. Experimental Results and Discussion

The Experimental Results and Discussion section highlights the computational resource demands of the CenBERT-SEQ model during training and inference phases. The model requires approximately 12 GB of GPU memory during training, primarily due to the computations introduced by the centrality-weighting layer. However, memory requirements drop to around 9 GB during inference, as gradient computations and optimizer states are no longer needed. This makes inference tasks less resource-intensive compared to training. Testing the model across various hardware configurations revealed that lower-end GPUs, such as the NVIDIA T4 with 12 GB memory, face challenges like prolonged convergence times and a higher risk of out-of-memory errors. Consequently, high-performance GPUs such as NVIDIA V100 or A100 are recommended for effective training. For deployment, the model can run efficiently on cloud-based systems with access to high-performance GPUs, but it is also feasible to use lower-memory hardware for inference.

ISSN No: 3048-8230
Volume 1 Issue 7 Dec- 2024

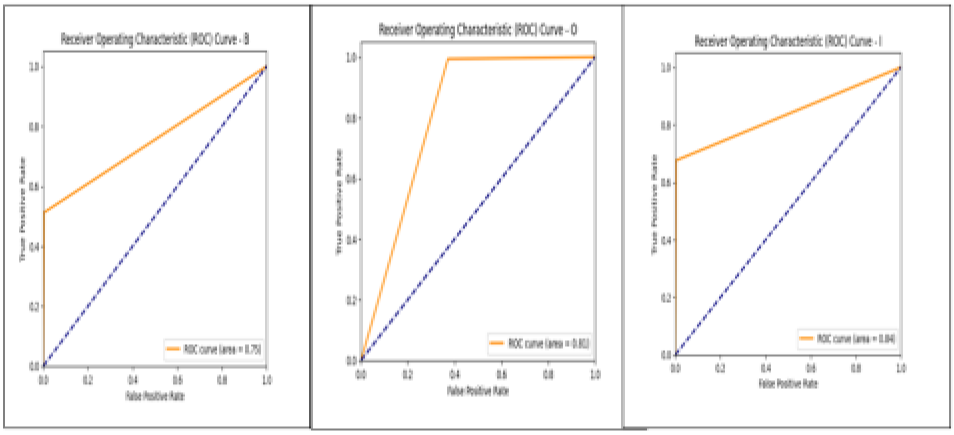

Figure 5. ROC curves showing the performance of the CenBERT-SEQ model on Semeval2010 dataset.

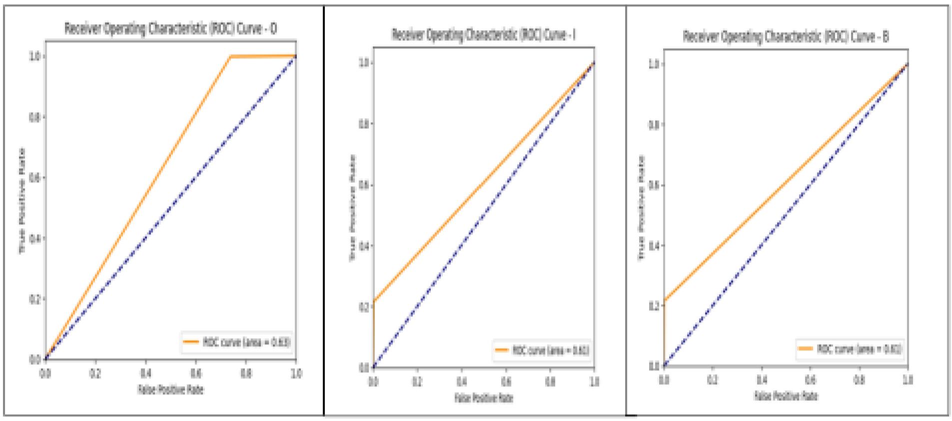

Figure 6. ROC curves showing the performance of the CenBERT-SEQ model on KDD dataset.

The computational efficiency of CenBERT-SEQ compared to a standard BERT-based model is demonstrated using training times across three datasets: SemEval-2010, KDD, and WWW. CenBERT-SEQ consistently showed faster training times. On the SemEval-2010 dataset, CenBERT-SEQ completed training in 191.22 seconds, whereas BERT required 384.66 seconds. Similarly, on the KDD dataset, CenBERT-SEQ took 698.36 seconds compared to BERT's 3485.76 seconds. For the WWW dataset, CenBERT-SEQ trained in 1281.40 seconds, significantly outperforming BERT's 3764.14 seconds. The results underscore that while both models required less training time on the SemEval-2010 dataset, the standard BERT model consistently took twice as long as CenBERT-SEQ across all datasets. These findings demonstrate the superior computational efficiency of the CenBERT-SEQ model, particularly in reducing training time without compromising performance.

This section outlines the datasets, computational and software environments, and the experimental setup used to implement and evaluate the CenBERT-SEQ model, along with a comparison of its performance against the BERT-base model and related studies.

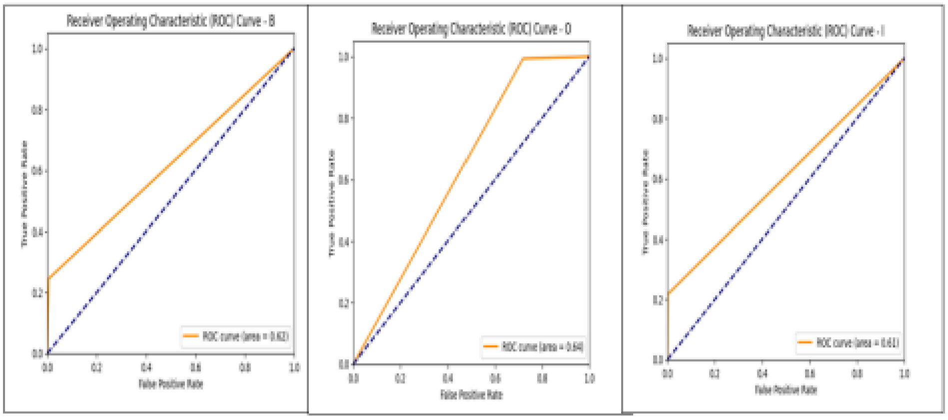

Figure 7. ROC curves showing the performance of the CenBERT-SEQ model on WWW dataset.

The experiments were conducted on three publicly available keyphrase datasets: SemEval-2010, KDD, and WWW. These datasets represent different document types, with SemEval-2010 containing long documents, while KDD and WWW focus on shorter ones. SemEval-2010 includes full research papers across various domains such as distributed systems, information retrieval, and artificial intelligence, whereas KDD consists of abstracts from ACM's Knowledge Discovery and Data Mining (KDD) conferences, and WWW includes abstracts from the World Wide Web conferences. The datasets are structured with two columns: one for the article or paragraph and another listing the relevant keyphrases. The keyphrases are labeled by experts and include both abstractive and extractive types. These datasets were chosen to test the CenBERT-SEQ model's ability to handle diverse text structures and terminologies.

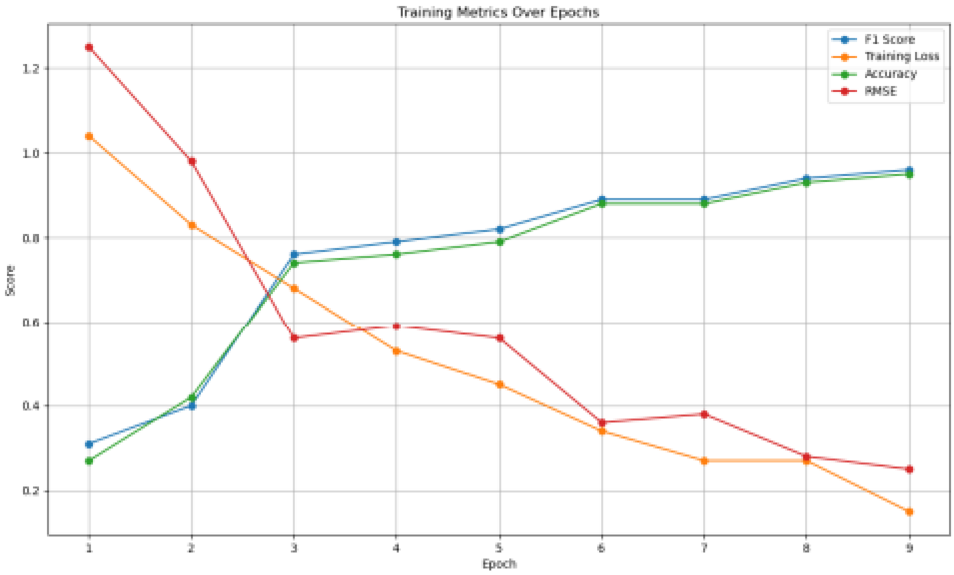

Figure 8. Charts of the evaluation of CenBERT-SEQ model during training.

SemEval-2010 is ideal for sequence labeling tasks, while KDD focuses on real-world applications in machine learning and NLP, and WWW ensures a diverse range of writing styles and topics, enhancing the model's ability to generalize. The experiments were run on Google Colaboratory, utilizing cloud-based GPU and TPU resources for efficient computation. The hardware configuration included an Intel Core i5 processor, 16 GB of RAM, and an NVIDIA GPU with 12 GB of RAM. The software environment was set up with Python 3.8, utilizing frameworks like TensorFlow and PyTorch for deep learning and Scikit-learn for evaluation metrics. The CenBERT-SEQ model was trained using a BERT-base architecture, which consists of 12 transformer blocks, a hidden size of 768, and 110 million parameters. To optimize performance, a learning rate of 1×10−51 \times 10^{-5}1×10−5 was used, with a batch size of 4 and dynamic padding to handle input sequences. Gradient clipping was employed to prevent overflow, and dropout was set at 0.3 to mitigate overfitting. The model was trained with a cross-entropy loss function, and an early stopping criterion was applied after 10 epochs of no improvement.

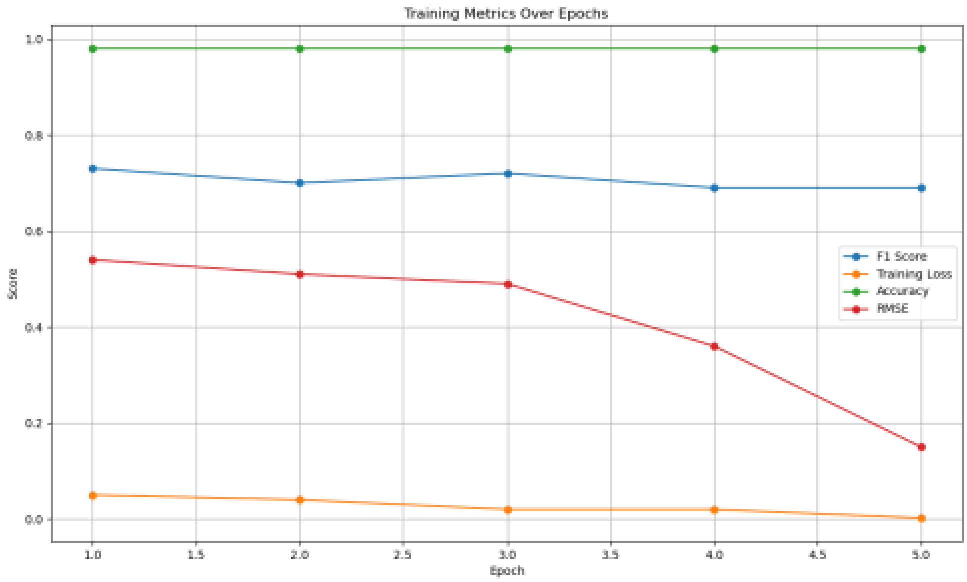

Figure 9. Charts of evaluation of BERT-base model during training.

For evaluation, metrics such as accuracy, precision, recall, and F1-score were used. These metrics are crucial for assessing the model's ability to correctly identify keyphrases, minimize false positives, and ensure that the keyphrases are contextually relevant. The combination of SemEval-2010, KDD, and WWW datasets provided a comprehensive evaluation setup that allowed for the testing of the model's robustness and ability to generalize across different scientific domains and writing styles.

6. Conclusion

This research highlights the development and performance of the CenBERT-SEQ model, a novel approach for keyphrase extraction that leverages sequence labeling with contextual embeddings enriched by centrality weighting. The model successfully addresses the limitations of traditional keyphrase extraction techniques by integrating both local word context (captured by BERT embeddings) and global document context (introduced through the centrality-weighting mechanism). This dual-context approach enables CenBERT-SEQ to effectively capture long-term semantic dependencies within a document, ensuring more precise and context-aware keyword extraction.

Experimental evaluations were conducted on three widely used and diverse datasets—SemEval-2010, KDD, and WWW—to assess the model's efficacy. The results demonstrated that CenBERT-SEQ consistently outperformed the BERT-base model and other related methods in terms of key performance metrics, including precision, recall, F1-score, and accuracy. Specifically, CenBERT-SEQ achieved an F1-score of 94%, surpassing benchmarks set by earlier studies and establishing itself as a superior tool for sequence labeling in keyphrase extraction tasks. The model also showed robust performance across datasets representing both short documents (e.g., KDD, WWW) and long documents (e.g., SemEval-2010), underlining its versatility and generalizability across varying text lengths and domains.

The research introduces several key innovations:

1. The centrality-weighted embedding layer, which incorporates document-level context to weigh the importance of terms based on their relevance to the overall content.
2. The use of sequence labeling as a unified approach for keyphrase extraction, eliminating the need for candidate generation and enhancing the model's ability to recognize multi-word keyphrases.
3. A comprehensive evaluation framework employing diverse datasets, enabling the model to generalize across disciplines and document structures.

Additionally, the study optimized training parameters, including a low learning rate, dropout regularization, and dynamic padding, to ensure the model's stability and minimize overfitting. The use of cross-entropy loss for the multi-class classification task further reinforced the model's ability to handle imbalanced class distributions effectively.

The proposed approach demonstrates that combining BERT's powerful contextual embeddings with a centrality-aware mechanism significantly improves the extraction of domain-specific terms and multi-word keyphrases, particularly in scientific documents. This holistic understanding of document context addresses challenges such as ambiguity and polysemy, which traditional methods often fail to resolve.

Future Directions

While the results of this study are promising, there are several avenues for further exploration:

- Extending the model to multilingual datasets to evaluate its applicability across non-English corpora.
- Investigating the impact of different types of centrality measures on keyphrase extraction performance.
- Exploring the integration of domain-specific pretraining to enhance performance in specialized fields such as medicine or law.
- Examining the scalability of CenBERT-SEQ for large-scale datasets in real-time applications.

In conclusion, the CenBERT-SEQ model represents a significant advancement in the field of natural language processing, particularly for keyphrase extraction in scholarly texts. Its ability to balance local and global contexts ensures a nuanced understanding of document semantics, paving the way for more accurate, efficient, and scalable solutions in the realm of information retrieval, ontology development, and scientific text processing.

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ISSN No: 3048-8230
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