MSR59

Advancing Systematic Literature Reviews: The Integration of AI-Powered NLP Models in Data Collection Processes

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CONCLUSION

The NLP-driven strategy employed in automating SLR screening proved effective, with the BERT algorithm exhibiting the highest accuracy among all models studied. This automation reduces manual workload, enhancing efficiency and representing a significant improvement in optimizing the SLR process.

INTRODUCTION

- A systematic literature review (SLR) involves extensively evaluating the quality of previous research and presenting key findings on a topic. However, the process is time-consuming and sometimes results in outdated findings[1]
- Incorporating natural language processing (NLP) models[2-5] to automate SLRs signifies groundbreaking progress in research methodology
- These models harness the power of artificial intelligence (AI) to navigate through extensive content efficiently, streamlining the SLR process undertaken by human reviewers

OBJECTIVES

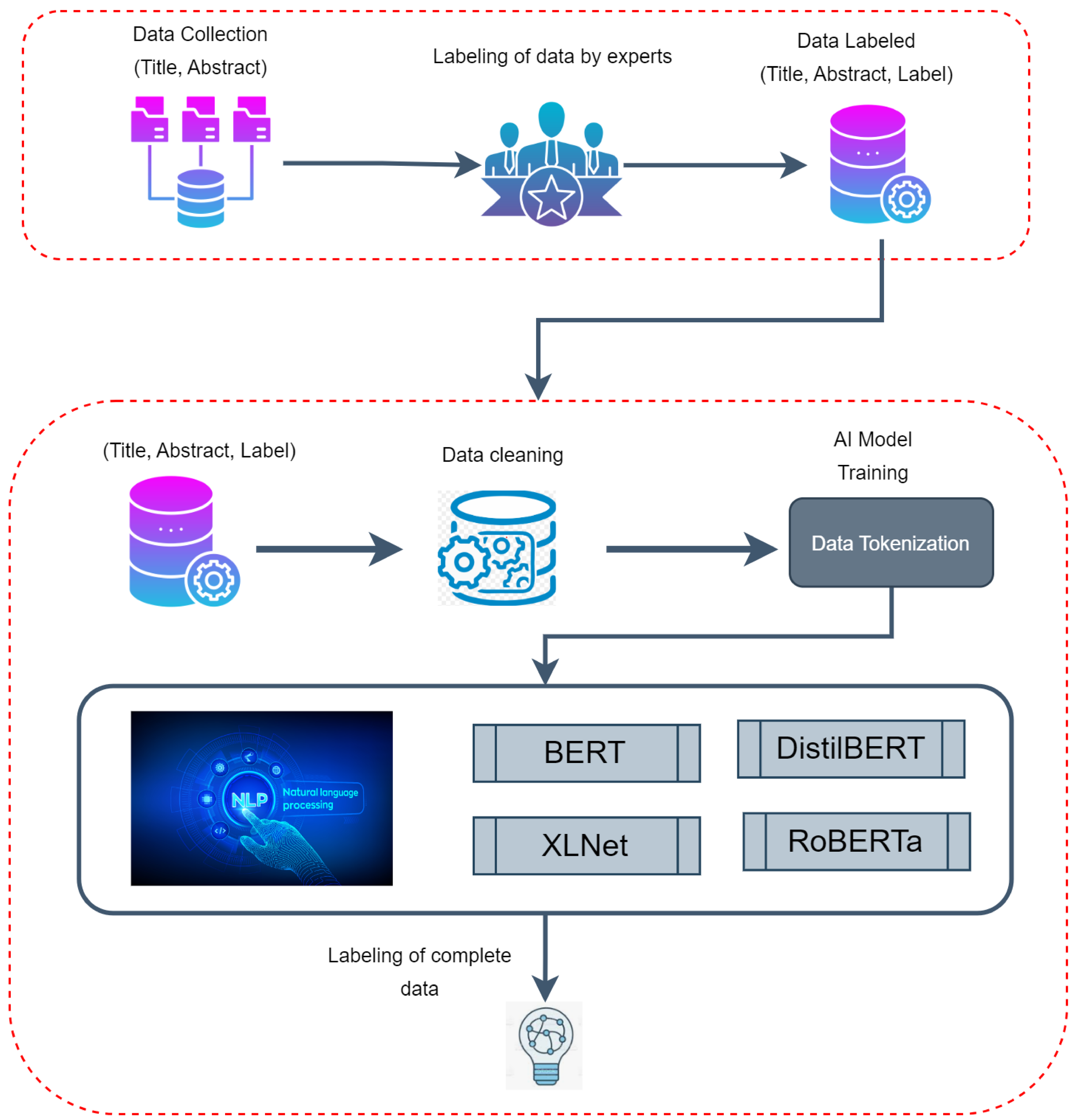
- This SLR aimed to assess the efficiency of different NLP models, including BERT, DistilBERT, RoBERTa, and XLNet, based on semantic analysis of titles and abstracts

METHODS

- Python-based NLP models (BERT, DistilBERT, RoBERTa, and XLNet) were developed to enhance the efficiency of screening literature for SLRs
- A domain expert with over a decade of experience manually screened the title and abstracts of the data sample for model training and improvement
- Subsequently, to effectively capture contextual relationships within the data, texts underwent tokenization using tokenizers specific to the models
- The models' performance was validated using the remaining data, which constituted previously unseen data
- To address the class imbalances, a random oversampling to ensure a balanced dataset was employed
- To ensure a thorough and accurate assessment of the models' capabilities, the training set was subdivided through K-Fold Cross-Validation (K=5), enhancing robustness in the evaluation; the model results were compared using the performance metrics
- **Figure 1** provides a comprehensive depiction of the entire process
- **Metrics:** Accuracy and Sensitivity are calculated using confusion matrix values (**Figure 2**), i.e., True Positive, False Positive, False Negative, and True Negative using the following formulas:

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \qquad \text{Sensitivity} = \frac{TP}{TP+FN}$$

Figure 1: First stage screening using NLP models



RESULTS

- Across the various NLP models considered for title and abstract-based screening, BERT showcased better performance in the validation phase, with an accuracy of 90.05% and a sensitivity of 84.16%, surpassing other models (**Figure 3**)
- DistilBERT closely followed with competitive results, achieving an accuracy and sensitivity of 88.90% and 75.25%, respectively (**Figure 3**)
- XLNet performed well, securing an accuracy of 87.24% and a sensitivity of 81.19% (**Figure 3**)
- Nevertheless, RoBERTa demonstrated a marginally lower accuracy of 78.34%, coupled with a sensitivity of 82.10%, suggesting a relative performance dip (Figure 3)

Figure 2: Confusion matrix of different models

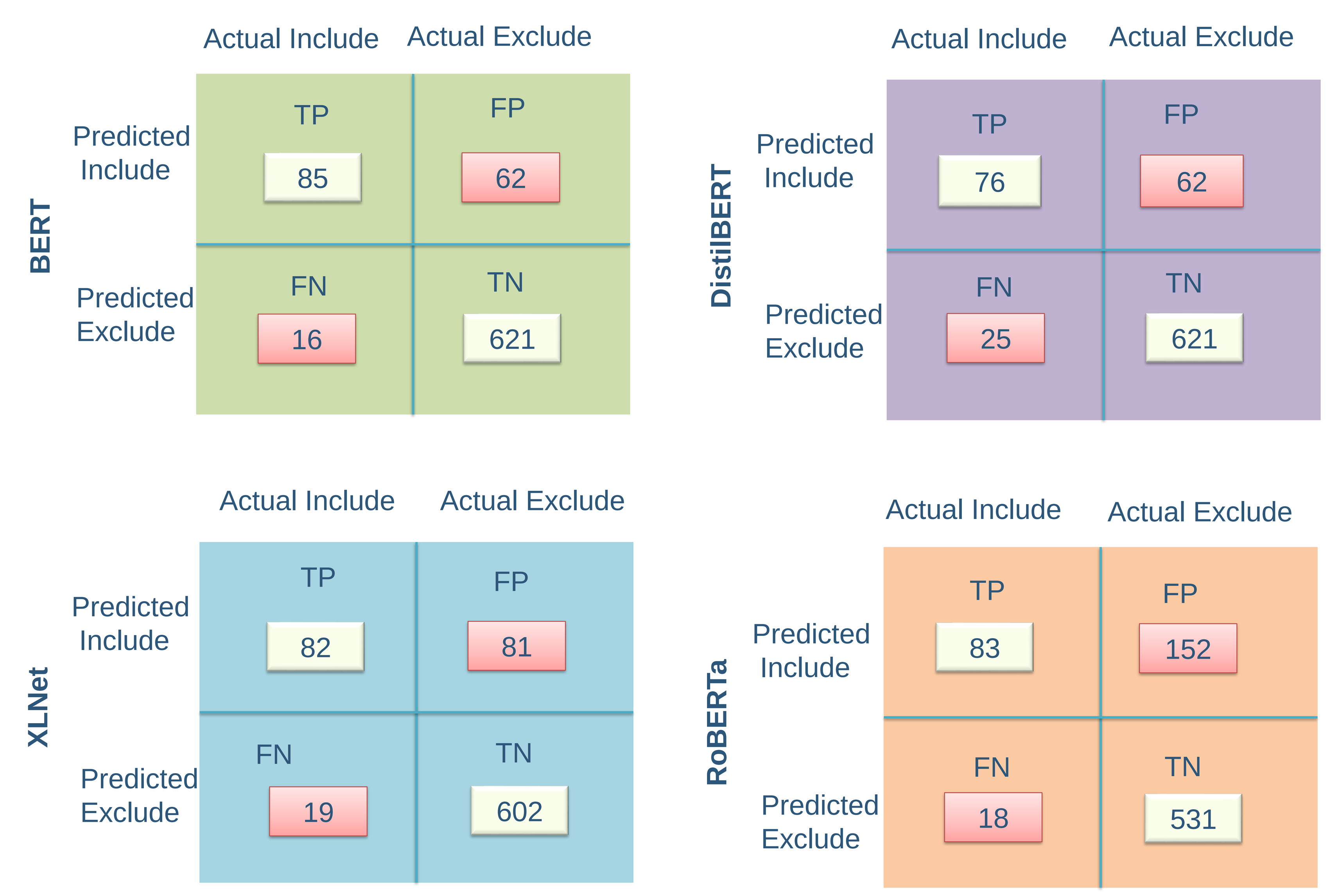
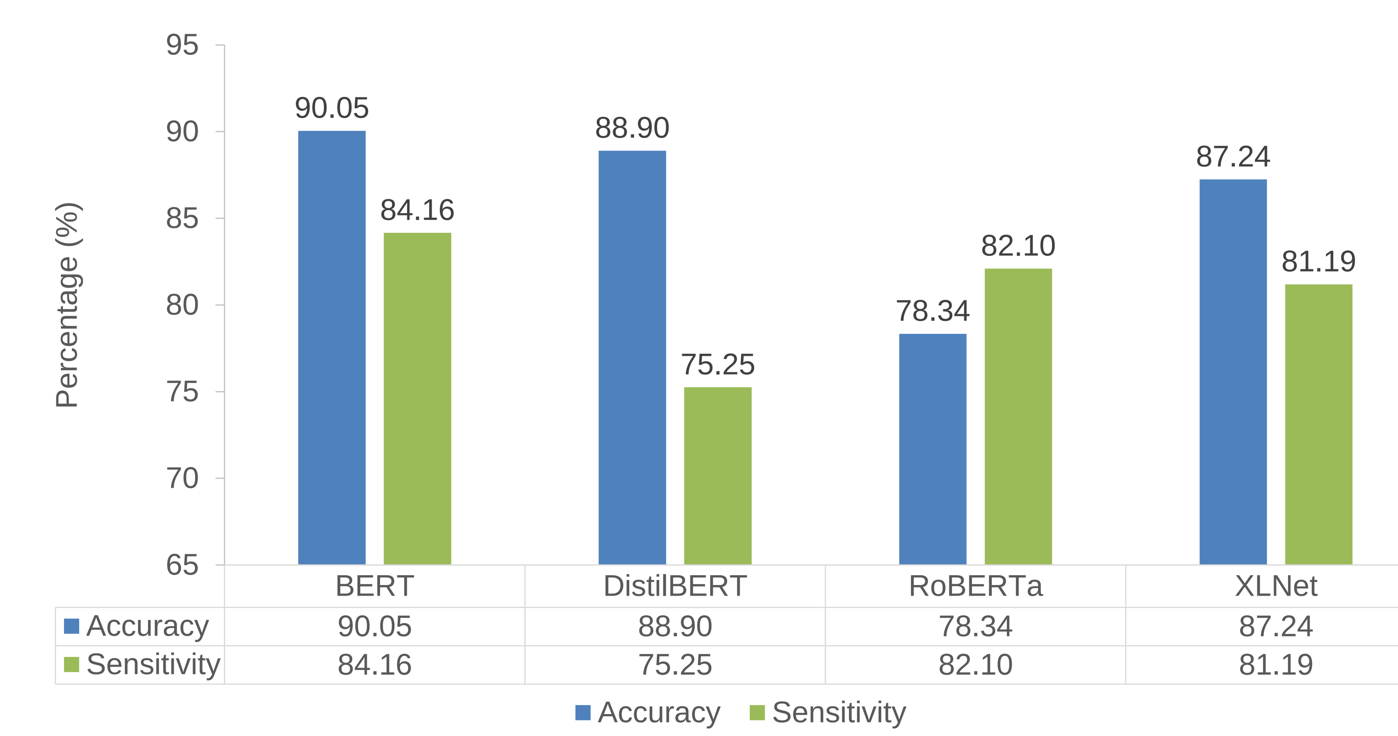


Figure 3: Comparison of performance of different NLP models



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Disclosure

PR, RK, SP, SA, GK, and BS, the authors, declare that they have no conflict of interest

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