

## BACKGROUND

- Radiology reports contain critical information about tumor burden and treatment response. However, most reports remain unstructured narrative text, making automated extraction of clinical outcomes difficult.
- Structured oncology reports (SOR) provide standardized data that can be used to train natural language processing (NLP) models. Such models could enable automated tumor response classification, reducing manual workload and supporting large-scale oncology research.

## OBJECTIVE

To develop and evaluate a deep NLP model capable of classifying Tumor Response Categories (TRCs) from Free-Text Oncology Reports (FTOR) and compare its performance with:

Conventional NLP algorithms

Human annotators with varying radiology expertise

DATASET  
TOTAL REPORTS: 10,455  
FROM 3 INDEPENDENT  
RADIOLOGY DEPARTMENTS

Report Type	Number
Structured Oncology Reports (SOR)	9,653
Free-Text Oncology Reports (FTOR)	802

Tumor response labels were extracted from SOR using Response Evaluation Criteria in Solid Tumors (RECIST).

## METHODS

### NLP Models

#### Deep Learning Model

- BERT-based NLP model
- Fine-tuned on structured radiology findings

#### Conventional NLP Models

- Linear Support Vector Classifier (Linear-SVC)
- k-Nearest Neighbors (kNN)
- Multinomial Naïve Bayes
- Bag-of-Words feature representation

#### Evaluation Metrics

- F1 Score
- Accuracy
- Precision
- Recall

#### Human Comparison

Model performance was compared with:

- Radiologists
- Medical Students
- Radiology Technologist Students

Additional analyses evaluated:

- Lexical complexity
- Semantic ambiguity

## PERFORMANCE ON STRUCTURED REPORTS

Model	F1 Score
BERT	0.86

Structured data significantly improved classification performance.

## KEY FINDINGS

- Deep NLP models can automatically classify tumor response from radiology reports.
- BERT achieved near human-level performance.
- Structured reports improve model accuracy.
- Language ambiguity remains a key challenge.

## IMPACT OF LANGUAGE COMPLEXITY

Both human annotators and NLP models were affected by:

- **Lexical complexity**
- **Semantic ambiguity**

Maximum observed decrease in F1 score:

- Lexical complexity: **-0.19**
- Semantic ambiguity: **-0.17**

## CLINICAL IMPACT

Automated tumor response classification can enable:

- Scalable **oncology outcome extraction**
- **Clinical workflow optimization**
- Improved **longitudinal patient monitoring**
- Large-scale **radiology research datasets**

## RESULTS

The **BERT model outperformed conventional NLP methods** and approached the performance of human annotators.

Method	F1 Score
Radiologists	0.79
Medical Students	0.73
<b>BERT Model</b>	<b>0.70</b>
Technologist Students	0.65
Linear-SVC	0.63

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