NLI-24 at the NTCIR-18 RadNLP

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Introduction

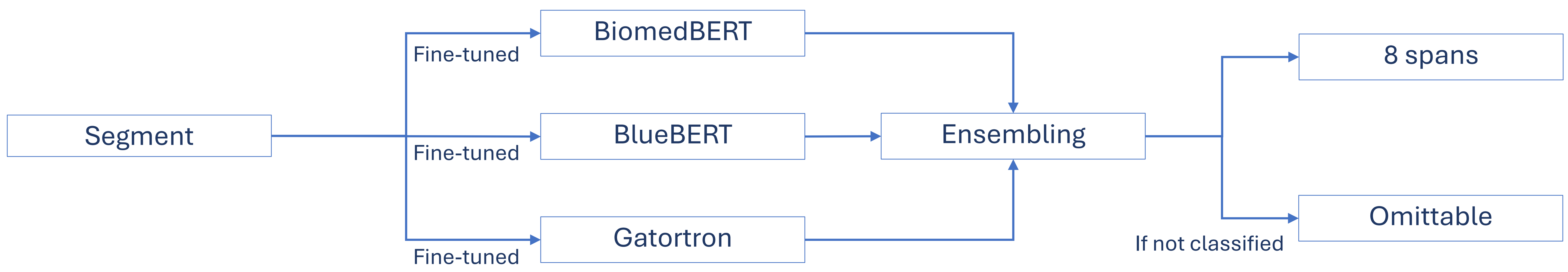
- Lung cancer poses a significant global health challenge with low survival rates (less than 21% five-year survival).
- Accurate TNM staging is crucial for effective treatment planning.
- Radiology reports derived from CT/MRI, while informative, often lack explicit TNM staging, requiring manual extraction.
- Manual extraction leads to delays in tumor registries, impeding timely treatment and access to clinical trials.
- **Our Solution:** We present an automated NLP solution for TNM staging from radiology reports.
    - Document segmentation to identify key information classes.
    - Automated TNM staging using transformer-based models.
    - Aims to expedite staging, improve diagnosis, and enhance treatment planning.

Tasks

- RadNLP at NTCIR-18: A shared task focused on NLP for radiology.
- **Subtask:** Document Segmentation: Classifying sections of radiology reports.
- **Main Task:** TNM Staging: Automated lung cancer staging from radiology reports.

Methodology

Subtask

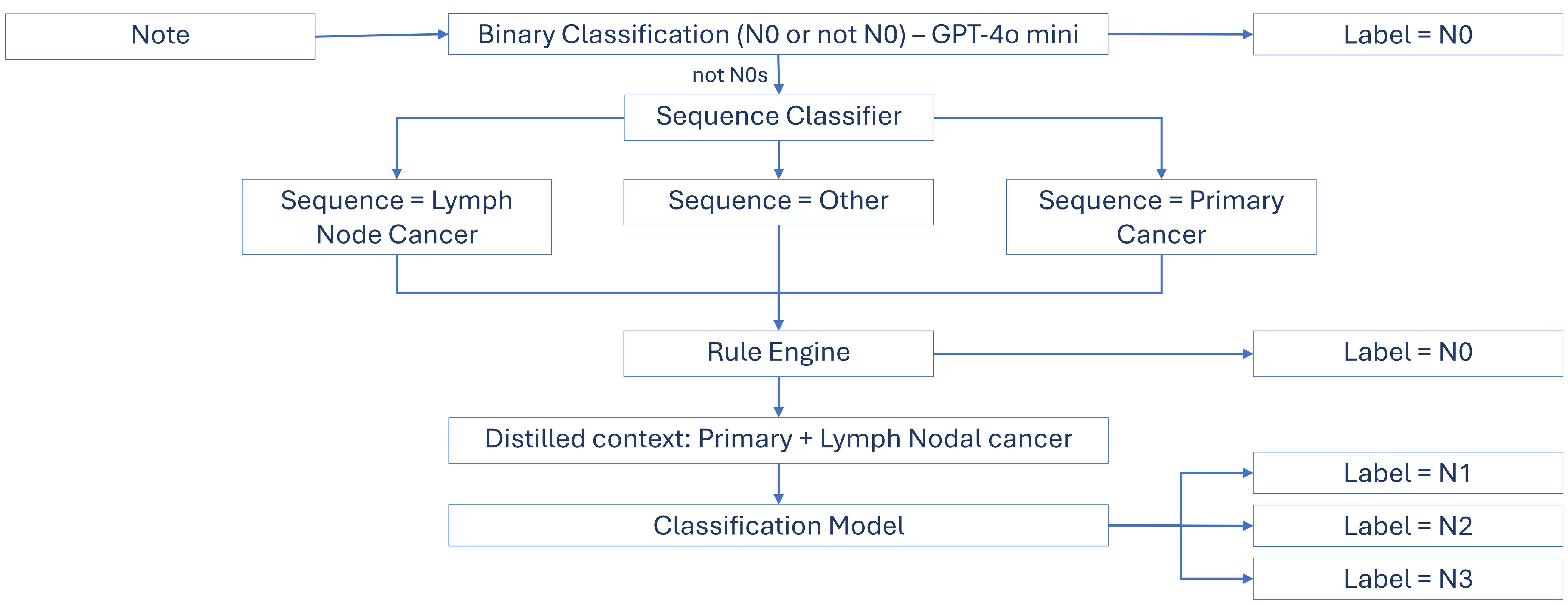


Main task

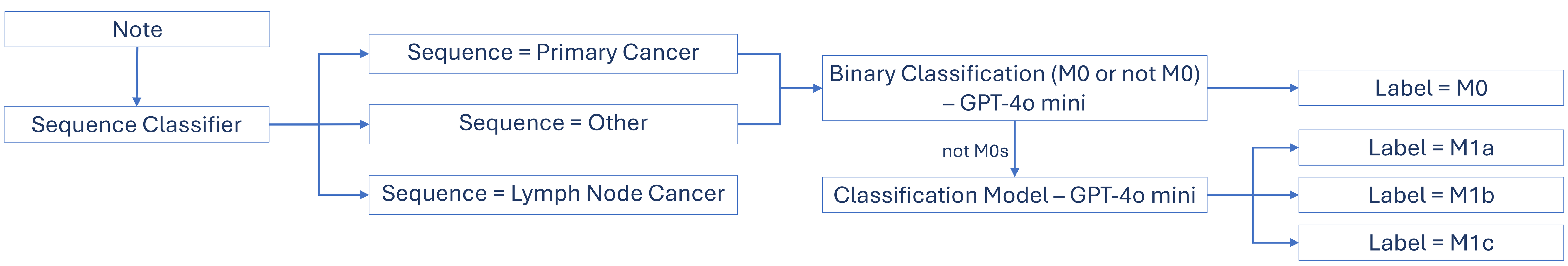
T Classification

- A two-step rule-based approach using GPT 4o-mini was implemented: first classifying overarching T categories (T0-T4), then separately classifying T1/T2 subclasses.

N Classification



M Classification



Results

Subtask

Rank	ID	Overall	Inclusion	Measure	Extension	Atelectasis	Satellite	Lymp.	Pleural	Distant
1	NLI24	0.9433	0.9719	0.8440	0.7512	0.8407	0.8631	0.9886	0.9615	0.9122
2	TMUNLPG3	0.9336	0.9297	0.8207	0.7522	0.8696	0.7831	0.9770	0.9615	0.8306
3	tsukurad	0.9180	0.9551	0.7111	0.7466	0.9211	0.7831	0.9653	0.9615	0.8746
4	Dhananjaya	0.9180	0.9647	0.8351	0.7692	0.7143	0.6928	0.9770	0.9223	0.8103
5	TMUNLPG3	0.9155	0.9508	0.7940	0.7273	0.8407	0.6845	0.9808	0.9615	0.8276

Main task

rank	id	Joint (fine)	T (fine)	N (fine)	M (fine)	Joint (coarse)	T (coarse)	N (coarse)	M (coarse)
1	TMUNLPG3	0.6543	0.7037	0.9136	0.8889	0.6914	0.7407	0.9136	0.9136
2	TMUNLPG3	0.6296	0.7284	0.9383	0.8395	0.6667	0.7407	0.9383	0.8889
3	CYUT	0.6049	0.6914	0.9383	0.9259	0.6296	0.7037	0.9383	0.9383
4	NLI24	0.5679	0.6914	0.9506	0.8395	0.7160	0.8272	0.9506	0.8519
5	tsukurad	0.5556	0.6049	0.9506	0.8765	0.6914	0.7160	0.9506	0.9136

Conclusion

- **Multi-Step Approach:** Novel method improves TNM classification & report segmentation using anatomical boundaries.
- **Improved Efficacy:** Decomposing tasks highlights anatomical boundaries, amplifying the efficacy of transformer models & LLMs.
- **NER Potential:** Named Entity Recognition (NER) can further enhance the multi-step framework.
- **RadNLP2024 Performance:** Achieved top rankings in the RadNLP2024 evaluation.
    - **Subtask:** Rank 1
    - **Main Task:** Rank 4
- **Future Directions:** Refine T-staging classification and address data limitations to improve clinical decision support.

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