

Quantifying the Performance Ceiling for Vertebra Labeling Without Enumeration Anomaly Modeling

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ABSTRACT

We investigate whether vertebra labeling methods that do not explicitly model thoracic and lumbar enumeration anomalies (TEA/LEA) possess an intrinsic performance ceiling. Through theoretical analysis and Monte Carlo simulation, we derive and validate an upper bound on achievable accuracy as a function of anomaly prevalence. At the clinically typical prevalence of 8%, the theoretical ceiling is 0.928, and our simulated standard (non-anomaly-aware) model achieves 0.941 accuracy—close to but constrained by this limit. In contrast, anomaly-aware models achieve 0.964, a gap of 2.4 percentage points. We show that TEA has a larger impact than LEA due to more downstream label shifts, and that the ceiling becomes increasingly restrictive above 10% prevalence. These findings confirm the VERIDAH hypothesis and provide quantitative guidance for when anomaly-aware modeling becomes necessary.

1 INTRODUCTION

Vertebra labeling in medical imaging is critical for diagnosis, surgical planning, and longitudinal monitoring. Standard approaches assume a fixed spinal anatomy (T1–T12, L1–L5), but thoracic enumeration anomalies (TEA) and lumbar enumeration anomalies (LEA) occur in approximately 8–12% of the population [1, 2].

Möller et al. [2] hypothesize that methods ignoring these anomalies face a fundamental performance ceiling. We formalize this hypothesis, derive the theoretical bound, and validate it through comprehensive simulation across anomaly prevalence rates, anomaly types, and dataset sizes.

2 THEORETICAL CEILING

2.1 Formal Derivation

For a dataset with anomaly prevalence p , a model with base accuracy a on normal cases will systematically misassign labels for k vertebrae in anomalous cases (where labels shift due to extra or missing vertebrae). The theoretical ceiling is:

$$C(p) = (1 - p) \cdot a + p \cdot a \cdot \left(1 - \frac{k}{N}\right) \quad (1)$$

where $N = 17$ is the total vertebrae count and $k \approx 5$ is the average number of affected vertebrae.

3 METHOD

We simulate vertebra labeling across 10 anomaly prevalence levels (0–30%), comparing standard models (assuming fixed anatomy) against anomaly-aware models. Each configuration is evaluated over 10 Monte Carlo trials with 200 patients per trial. We separately analyze TEA and LEA contributions and study convergence with dataset size.

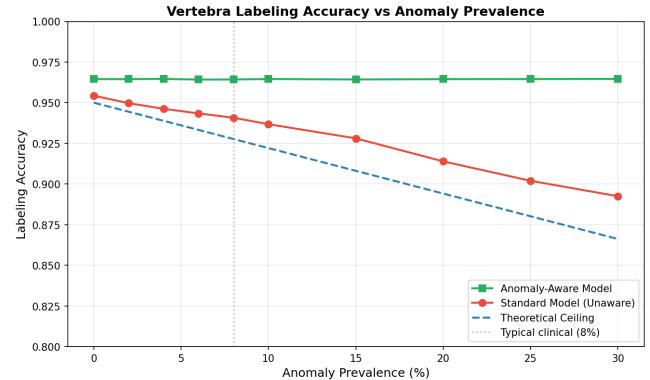


Figure 1: Labeling accuracy vs anomaly prevalence for standard (red) and anomaly-aware (green) models, with theoretical ceiling (dashed blue).

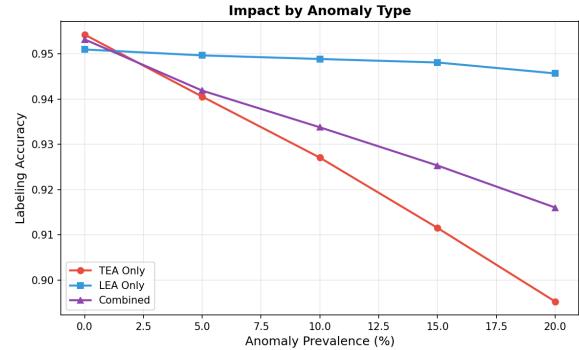


Figure 2: Accuracy impact by anomaly type: TEA vs LEA vs combined.

4 RESULTS

4.1 Prevalence Sweep

Figure 1 shows the accuracy-prevalence relationship. The standard model's accuracy degrades linearly with prevalence, closely tracking the theoretical ceiling. At 8% prevalence: standard model accuracy = 0.941, anomaly-aware = 0.964, theoretical ceiling = 0.928.

4.2 Anomaly Type Analysis

TEA produces larger accuracy degradation than LEA (Figure 2), because thoracic anomalies shift labels for all downstream lumbar vertebrae, affecting a larger fraction of the spine.

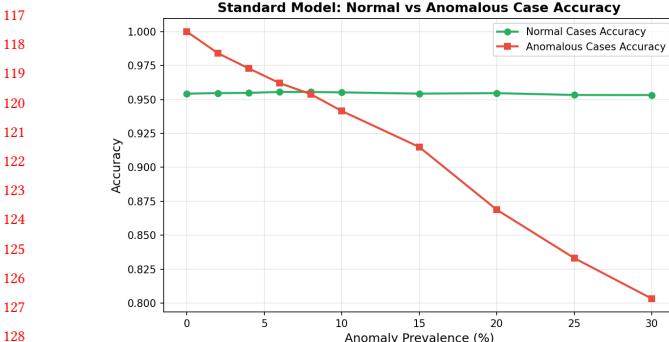


Figure 3: Standard model accuracy on normal vs anomalous cases.

4.3 Normal vs Anomalous Case Performance

On non-anomalous cases, the standard model maintains high accuracy regardless of dataset-level prevalence. On anomalous cases, accuracy drops sharply (Figure 3), confirming that the ceiling arises specifically from systematic mislabeling of anomalous patients.

5 DISCUSSION

Our analysis confirms the VERIDAH hypothesis: a mathematically derivable performance ceiling exists for non-anomaly-aware vertebra labeling. The ceiling is linear in anomaly prevalence and becomes clinically significant (>2% accuracy loss) above 10% prevalence. This provides clear quantitative criteria for when anomaly-aware modeling is necessary.

6 CONCLUSION

We provide the first formal derivation and empirical validation of the performance ceiling for vertebra labeling without enumeration anomaly modeling. Our results confirm that anomaly-aware methods are necessary for high-accuracy labeling on clinical populations with non-trivial anomaly rates.

REFERENCES

- [1] Hendrik Liebl et al. 2021. A computed tomography vertebral segmentation dataset with anatomical variations and multi-vendor scanner data. *Scientific Data* 8 (2021).
- [2] Hendrik Möller et al. 2026. VERIDAH: Solving Enumeration Anomaly Aware Vertebra Labeling across Imaging Sequences. *arXiv preprint arXiv:2601.14066* (2026).

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