From Text to Code: Predicting Abbreviated Injury Scale 2015 from Clinical Narratives

Chien-Ming Lee*, Pei-Ling Lee†, Chia-Yeuan Han*,
Joffrey Hsu†, Chuan-Yu Hu†
*Department of Medical Information,
Kaohsiung Medical University Hospital, Kaohsiung Medical University,
Kaohsiung, Taiwan
e-mail: {nomoney.lee | hoganhan2}@gmail.com
†Division of Trauma and Surgical Critical Care, Department of Surgery,
Kaohsiung Medical University Hospital, Kaohsiung Medical University,
Kaohsiung, Taiwan
e-mail: peiling@trauma.tw, {joffrey.hsu | chuanchuan19}@gmail.com

***Abstract*—Accurate coding of traumatic injuries using the Abbreviated Injury Scale (AIS) is very important for trauma registrants. However, manual AIS coding requires trained personnel and is very time-consuming. This study explores the feasibility of using a pre-trained Natural Language Processing (NLP) model to automatically predict complete AIS codes from unstructured diagnostic text entered by emergency physicians. Without additional training or fine-tuning, a publicly available transformer-based model was applied to emergency department narrative data. This preliminary result shows that such models can find clinically relevant information from these free-typing texts and then map to the correct AIS codes. This work highlights the potential of leveraging existing NLP models to assist in injury classification and AIS coding, especially without labeled datasets for training.**

Keywords-abbreviated injury scale; natural language processing.

I. Introduction

The Abbreviated Injury Scale (AIS) 2015 revision [1] is a globally recognized system for classifying and coding trauma injuries. Accurate and consistent AIS coding is essential for trauma registry maintenance and trauma severity scoring. In particular, the AIS 2015 revision provides detailed seven-digit codes that represent body region, type of anatomical structure, specific nature of injury, level, and severity scoring.

In general, AIS coding is performed manually by trained registrants based on structured clinical data or narrative documentation, including free-text diagnoses from emergency physicians. However, this process is time-consuming, and prone to human error, especially in a busy emergency department setting, the typed narrative diagnoses often vary widely.

Recent advances in Natural Language Processing (NLP), such as the transformer-based language models for biomedical use [2], make it possible to automatically understand complex clinical text narratives. In this study, we demonstrate the feasibility of using a publicly available pre-trained model to automatically predict complete AIS 2015 codes from unstructured diagnostic narratives written by emergency physicians. We focus on zero-shot methods, without labeled data, to evaluate whether such publicly available NLP models can be applied to real-world clinical data.

The remainder of the paper is organized as follows: Section II describes the steps of code mapping procedures. Section III presents preliminary evaluation results. Section IV discusses the findings and limitations. Finally, Section V concludes the paper and future directions.

II. Related work | Methods

A. Overview

To predict complete AIS 2015 codes from unstructured emergency department diagnosis narratives, we establish a multi-step matching pipeline that leverages anatomical keyword recognition and NLP models. The approach does not involve model training or fine-tuning. Instead, it uses domain knowledge and semantic similarity scoring to map free-text diagnoses to relevant AIS 2015 codes.

B. Step 1: Extraction of Body Region Keywords

We first find the anatomical keywords mentioned in the AIS coding description. These keywords, such as “skull,” “thorax,” or “femur,” represent anatomical parts involved in trauma and serve as primary factors for matching. The resulting list is manually reviewed to remove ambiguous terms.

C. Step 2: Mapping Body Regions to AIS Codes

For each identified anatomical keyword, we recognize all AIS codes whose descriptions contained that keyword. This generates a mapping table in which each keyword is associated with one or more possible AIS codes. These many-to-many mappings can effectively narrow the comparison range during prediction.

D. Step 3: Body Region Detection in Diagnostic Texts

When processing diagnostic narratives, we scan the entire narrative for the anatomical keywords found in step 1. Depending on the clinical note, zero or more body regions may be detected. These found keywords are used to select candidate AIS codes.

 ISBN: 978-1-68558-312-5

E. Step 4: Semantic Similarity Based Code Selection

For each candidate code retrieved via anatomical keyword mapping, we compute the semantic similarity between the diagnostic text and the code description using a pretrained biomedical language model. Sentence-level embeddings are generated using a transformer-based model trained on clinical and biomedical corpora. Specifically, we use the BioBERT model pre-trained on a large amount of literature in the biomedical domain and is particularly optimized for NLP tasks in the biomedical fields, which is public available on Hugging Face [3]. The AIS code with the highest cosine similarity to the diagnostic text is selected as the predicted result.

III. Results

Table I shows the prediction accuracy of AIS 2015 codes categorized by body region, based on a total of 54 cases. Extremity injuries demonstrates the best performance, with Top-1 accuracy of 70% and Top-5 accuracy of 90%. The Thorax region has the lowest accuracy, without correct Top-1 predictions and only 20% Top-5 accuracy.

Head injuries have no Top-1 hits but reached 50% in Top-5 accuracy. Face/Neck injuries show the moderate accuracy, with 43% Top-1 accuracy and 71% Top-5 accuracy. Abdomen and Spine regions both have relatively low accuracies, around 25-40%. External injuries have better performance, with 60% accuracy for both Top-1 and Top-5. The Other category has a Top-1 accuracy of 25% and a Top-5 accuracy of 63%.

TABLE I. Prediction Accuracy by Body Region

Region	Count	Top-1 Acc.	Top-5 Acc.
Extremity	10	70% (7)	90% (9)
Thorax	5	0% (0)	20% (1)
Head	6	0% (0)	50% (3)
Face/Neck	7	43% (3)	71% (5)
Abdomen	5	40% (2)	40% (2)
Spine	8	25% (2)	25% (2)
External	5	60% (3)	60% (3)
Other	8	25% (2)	63% (5)
All	54	35.2% (19)	55.6% (30)

Overall, the result shows a Top-1 accuracy of 35.2% and a Top-5 accuracy of 55.6% across all body regions, indicating a reasonable performance for predicting AIS codes from free-text emergency department narratives, especially the notable accuracy in extremity injuries.

IV. Discussion | Evaluation

The results indicate that the proposed semantic similarity based approach is feasible for AIS code prediction from free-text Emergency Department (ED) diagnoses, even without the labeled training data. Although the current Top-1 and Top-5 accuracy suggest there is room for improvement, the system still demonstrates potential as a decision support to assist trauma registry personnel in aiding the manual coding process and reducing workload.

Accuracy differs across body regions: better performance for extremity injuries where terminology is more consistent, and lower accuracy for thoracic cases where phrasing is more variable. Current keyword-mapping approach was designed to improve efficiency, but future work may compare against full-text searches with alternative similarity metrics. Preliminary observations indicate that comparison with all AIS code description may result in misclassification for identical injury descriptions and does not significantly improve accuracy; however, further evaluation is needed. In addition, a simple keyword-only baseline was not implemented due to time constraints, it still represents a useful direction for future work to clarify the benefit of semantic similarity.

Practical limitations remain: the approach predicts one AIS code per diagnosis and does not yet support multiple injuries in a single narrative. Small dataset (n = 54) and imbalance body regions also limit generalizability. The reliance on exact keyword matching in body region detection may miss relevant terms due to synonym variation or misspellings. Additionally, since the model is used without any fine-tuning, the results may vary due to different wording by emergency physicians, especially in complex injury scenarios.

V. Conclusion and Future Work

This study proposes a knowledge-driven approach for predicting complete AIS 2015 injury codes from unstructured emergency department diagnostic narratives. By integrating body region keyword detection with semantic similarity scoring using a pretrained biomedical NLP model, the system effectively maps free-text entries to structured AIS codes without relying on labeled training data.

Although the preliminary evaluation result for body region with terminology, especially extremity injuries, shows encouraging Top-1 and Top-5 accuracy, the overall accuracy still has room for improvement. Despite current limitations, such as sensitivity to variable phrasing and the lack of fine-tuning, the results represent the approach's feasibility as a supportive tool within trauma coding workflows.

Future work will focus on expanding the dataset, enhancing body region detection by improving synonym handling and contextual interpretation, and incorporating structured clinical information to improve the accuracy. In the long term, such systems may aid to improve the efficiency, accuracy, and consistency of trauma registry data collection in real-world clinical environment.

References

[1] Association for the Advancement of Automotive Medicine, “The Abbreviated Injury Scale 2015 Revision.” Chicaco, IL, USA: AAAM, 2025.

[2] J. Lee et al., “BioBERT: a pre-trained biomedical language representation model for biomedical text mining,” *Bioinformatics*, vol. 36, no. 4, pp. 1234–1240, Feb. 2020. DOI: https://doi.org/10.1093/bioinformatics/btz682

[3] P. Deka, BioBERT-mnli-snli-scinli-scitail-mednli-stsb, Hugging Face, 2021. [Online]. Available: https://huggingface.co/pritamdeka/BioBERT-mnli-snli-scinli-scitail-mednli-stsb. [retrieved: April, 2025.] Licensed under Creative Commons Attribution-NonCommercial 3.0 (CC BY-NC 3.0). See https://spdx.org/licenses/CC-BY-NC-3.0.