## Original Paper

# ConBERT: A concatenation of bidirectional transformers for the standardization of operative reports from electronic medical records

## Abstract

**Background:** An operative report is a document containing the details of the surgery. The standardization of the medical terminology appearing in the operative report that is written in free text is important for medical research and the establishment of insurance systems by allowing the accurate sharing of information on treatment. However, the standardization of operative reports is a labor-intensive task with a risk of induced errors.

**Objective:** We propose a concatenated bidirectional encoder representation from transformers (ConBERT) model for predicting the International Classification of Disease (ICD)-9 code from operative reports and diagnoses recorded in free-text to automatically standardize the operative report.

**Methods:** We compared the pre-trained BERT and Character BERT models and created a new model by concatenating the combinations of each model.

**Results:** Our proposed ConBERT showed a micro F1 score of 0.7610, a precision of 0.8164, and a recall of 0.7125. We also developed a publicly accessible web-based application to demonstrate the performance and provide the functions of our model.

**Conclusions:**

**Keywords:** Operative Report Standardization; Medical Code Prediction; ConBERT; ICD-9 Code

## Introduction

Remarkable and steady development in medical research and tools had led to the continuous improvement of surgical treatments such that different kinds of surgery are now performed in various fields. In general surgery, for example, an identical procedure can be performed using an open approach or minimally invasive tools such as laparoscopy and robotic systems [1]. Additionally, different types of operative reports for rectal cancer, including low or ultra-low anterior resections, can be produced for individuals according to the distance from the anus to rectal cancer [2]. The exact documentation of operation records, therefore, is essential to provide appropriate information.

The operative report, which denotes a representative procedure such as “appendectomy” or “cholecystectomy,” is an important component of the surgical record as it contains key surgical information. The operative report is dictated immediately after an operation and included in the patient's electronic health record. This report contains important information such as the type of surgery and method of approach. Operative records are primarily created by surgeons; however, their documentation varies substantially. Surgeons generally record operative reports in free-text and use unofficial abbreviations (e.g., appendectomy, laparoscopic appendectomy, lap. appendectomy, lapa. appe, appendectomy, laparoscopic, etc.). The use of non-standard terminology in operative reports may significantly affect the data quality and confuse physicians. Therefore, the standardization of operative reports is an important topic for analysis as it plays a critical role in clinical research and quality assurance in healthcare. The International Classification of Diseases (ICD) is a database of clinical terminologies managed by the World Health Organization (WHO) that is widely accepted as a guide for standardized medical terminology [3]. The standardization of operative reports implies matching unstructured data from operative reports written in free text to structured data such as ICD codes. However, such standardization requires a manual chart review, which is time- and effort-consuming.

Recently, active research [4-8] has aimed to automate ICD-9 codes. Most studies use clinical notes and discharge summaries, which are information-heavy data sources. To our knowledge, no study has yet attempted to standardize ICD-9 codes using data sources that contain less information, such as operative reports and diagnoses. We propose a Bidirectional Encoder Representations from Transformers (BERT)-based model to predict the ICD-9 code using the operative report and diagnosis. BERT [9] has shown remarkable performance in various natural language processing fields. However, BERT trained on the general domain corpora has shown a relatively low performance on medical data. Therefore, BERT trained in biomedical corpora are provided separately. Additionally, given the nature of clinical data, typographical errors, new words, and abbreviations occur frequently; hence, the existing word-level BERT is not suitable. Therefore, a Character BERT, also known as character-level BERT, has been proposed [10]. Although Character BERT showed strength in small amounts of data, it showed weakness in large amounts of data. We propose a concatenation model that utilizes both word- and character-level BERT for ICD-9 code automation. This proposed model showed an F1 score of 0.7610, precision of 0.8164, and recall of 0.7125 for ICD-9 code automation. We provide this service as a publicly available web-based application at http://opti.ziovision.ai/.

## Methods

### Clinical Data

From the electronic medical records (EMRs) of two independent tertiary referral hospitals (Korea University Anam Hospital and Korea University Guro Hospital), we collected all surgical records of patients who underwent surgeries in the Departments of Surgery between January 2009 and December 2020. The surgical records contained data on patient ID, date, division, surgeon, preoperative diagnosis, postoperative diagnosis, operative report, operative findings, and others (blood loss, complications during surgery, anesthesia, etc.). From all surgical records, date, division, postoperative diagnosis, and operative report were extracted to establish a dataset (Table 1). The division included eight sub-departments in the Department of Surgery: Breast and Endocrine Surgery, Gastroesophageal Surgery, Hepatobiliary Surgery, Colorectal Surgery, Pediatric Surgery, Transplantation and Vascular Surgery, General Surgery, and Acute Care Surgery. The postoperative diagnosis was a record written in free text. The operative report comprised three records of an original text and an ICD-9-matched code and name. Distinct datasets from two institutions were gathered and merged. The sample sizes of the two independent datasets were 45,211 and 35,862 patients for Korea University Anam Hospital and Korea University Guro Hospital, respectively. Ethical clearances were obtained from the respective Institutional Review Boards of Korea University Anam Hospital and Korea University Guro Hospital (2021AN0210, 2020GR0511).

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| ID | Date | Division | Postoperative diagnosis | Operative report (original) | Operative report (ICD-9) | Code  (ICD-9) |
| 1 | 2019-08-06 | Hepatobiliary | GB stone | lap.cholecystectomy | Cholecystectomy; laparoscopic | 51.23 |
| 2 | 2012-05-21 | Colorectal | rectal ca.(AV 4cm) | ULAR | Resection; rectum, other anterior | 48.63 |
| 3 | 2020-01-29 | Colorectal | r/o appendiceal cancer | Lap.RHC | Hemicolectomy; right | 45.73 |
| Laparoscopy | 54.21 |
| 4 | 2018-06-22 | Endocrine and Breast | Rt.PTC | THYROIDECTOMY, TOTAL | Thyroidectomy; complete | 06.4 |
| central LN dissection | Dissection; neck, not otherwise specified, radical | 40.40 |
| 5 | 2020-08-19 | Transplantation and Vascular | HBV LC with HCC | LDLT | Transplant; liver, other | 50.59 |
| … | … |  | … | … | … | … |

Table . Surgical records in the dataset

### Preprocessing

Four types of preprocessing were performed to learn data effectively (Figure 1). First, for data-cleansing, data with missing values and special characters such as +, --->, >, <, 《, 》—that is, content-wise insignificant information—were removed. Additionally, specific numbering symbols such as [1] and ①, which are used only in specific institutions, were removed. Second, we removed stop words—grammatically appropriate but contextually meaningless words—using the Natural Language Toolkit [11] (NLTK), which is a text-processing library available in Python. Third, we created an input by combining the operative report and diagnosis. Finally, duplicate data among the same final input data and ICD-9 codes were removed. After preprocessing, the number of data was 45,853.

There was a unique case where there is only one data with a specific label (ICD-9 code such as 45.72, 48.63, 54.21). These data cannot be divided into train and test sets, making it difficult to accurately measure performance. Therefore, we used data after removing a small number of such labels. Additionally, the proposed model used multi-label data, which refers to one or multiple labels coexisting in a single data. The D2SBERT [12] study addressed this problem by using only the top-50 labels. In this study, we identified the removal rate that could be equally split between the train and test sets through empirical experiments. Consequently, data were removed for ICD-9 codes that appeared ≤11 times. The removed data accounted for 3% of the total data and were removed because they were uncommon terms. After removal, 44,341 data and 353 ICD-9 codes remained. Data were used in the multi-label classification library to ensure that the multi-label ICD-9 codes were balanced between the train and test sets. The multi-label classification library was used in scikit-learn [13], an open-source machine learning available in Python. The train and test datasets were divided in an 8:2 ratio.

Graphical user interface, text, application, email

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Figure 1. Preprocessing Workflow

### Computational methods

This section discusses the ConBERT model, which is an ensemble model that achieved higher performance for ICD-9 code prediction.

#### Embedding

Embedding is a natural language processing technique that expresses words as numerical vectors. The generated vector contains semantic and grammatical information so to allow various operations, such as calculating the similarity between words and sentences. In the case of ICD-9 code automation, the indication of the operative report and diagnosis differs even with the same ICD-9 code. In this case, the similarity of expressions can be compared through embedding. Representative embedding models include Word2Vec [16], Glove [17], Fasttext [18], ELMo [19], and BERT. As BERT has shown outstanding performance on various tasks among other models, we utilized BERT-based embedding. The pre-trained models and corresponding corpuses used for pre-training are shown in Table 2. Detailed descriptions of each model are provided in the following sections.

Table 2. Pre-training models and learned corpuses

|  |  |
| --- | --- |
| Model | Corpus |
| MedicalBERT[10] | MIMIC-III Clinical note, PMC OA biomedical paper abstract |
| UmlsBERT[14] | Intensive Care III (MIMIC-III), MedNLi, i2b2 2006, i2b2 2010, i2b2 2012, i2b2 2014 |
| BioBERT[15] | English Wikipedia, BooksCorpus, PubMed Abstracts, PMC Full-text articles |
| MedicalCharacterBERT[10] | MIMIC-III Clinical note, PMC OA biomedical paper abstract |

#### BERTs

BERT, proposed by Google in 2018, is a model to output an embedding vector of a word according to a given context. Existing embedding models such as Word2Vec, Glove andFasttext ignore the bidirectionality of the context, which limits contextual understanding; in contrast, BERT considers bidirectionality and can better understand more complicated contexts. Additionally, through fine-tuning, BERT has achieved state-of-the-art in various downstream tasks; however, it is difficult to estimate its performance on datasets containing biomedical texts. Moreover, the word distributions of general and biomedical corpora are quite different [15]. Therefore, we utilized a pre-trained BERT for biomedical corpora.

#### Character BERT

Whereas BERT only outputs a word-level embedding vector, Character BERT outputs a character-level embedding vector. BERT shows performance degradation on noisy datasets because it treats words with typographical errors as new words. In practice, operative reports and diagnoses have frequent typographical errors, various forms of abbreviations, and novel jargon. To address this problem, we used not only BERT but also Character BERT, which uses character-level embedding and shows robustness in noisy datasets and novel words. The pre-trained models and corpuses used for pre-training are shown in Table 2.

#### Model Aggregation

We propose a ConBERT, which is a concatenation BERT that combines word- and character-level BERTs to improve performance. The vectors generated through these two BERTs are concatenated. The concatenated embedding vector is then converted into a probability through the fully connected and sigmoid layers. The final output is an ICD-9 code with a probability value above the threshold. The model architecture is shown in Figure 2.

Graphical user interface, website

Description automatically generated

Figure 2. ConBERT Model Architecture

#### Training Details

We performed the training using Pytorch Framework 1.7.1, Python 3.8.12, and NVIDIA RTX 2080Ti. The batch size was 16, the optimizer was AdamW [20], the initial learning rate was 2e-5, and learning rate scheduler and warmup [21] and earlystopping, were used. The max sequence length of BERT was 256 and the max token length of Charter BERT was 256.

#### Evaluation

We evaluated the models based on the F1 score, precision, recall, and area under the curve (AUC) used in previous studies [22, 23]. Each metric is defined as follows,

in which the AUC is the area below the receiver operating characteristic (ROC) curve. In the graph of the ROC curve, the x-axis is the false positive rate (FPR), while the y-axis is the true positive rate (TPR). FPR and TPR are defined as follows:

## Results

### Input Comparison

Table 3 shows the results of comparisons of data combining the operative report and diagnosis and each feature. Consequently, the data combining the operative report and diagnosis showed improvement in all performance indicators.

Table 3. Comparisons of operative reports and diagnosis data

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Proposed model | Precision | | Recall | | F1 | | AUC | |
| Micro | Macro | Micro | Macro | Micro | Macro | Micro | Macro |
| Diagnosis | 0.6065 | 0.2421 | 0.3822 | 0.1425 | 0.4689 | 0.1660 | 0.9735 | 0.9365 |
| Operative report | 0.8065 | 0.4801 | 0.6678 | 0.3708 | 0.7306 | 0.4021 | 0.9889 | 0.9696 |
| Operative report+Diagnosis | **0.8164** | **0.5081** | **0.7125** | **0.4103** | **0.7610** | **0.4376** | 0.9817 | **0.9698** |

### Comparison of Pre-trained Models

The prediction performances of the five pre-trained BERT models are shown in Table 4. The model with the highest performance was the Umls BERT model, with a precision of 0.8081, a recall of 0.7032, an F1 score of 0.7520, and an AUC of 0.9815 based on the micro average setting. Unlike the other models, the base BERT model was trained using the general rather than medical corpus. Therefore, as explained above, it showed a lower performance. Additionally, the overall performance of the Medical Character BERT model was lower than those of the other word-level BERTs (Table 5). However, its performance on the minority data was higher than that of other word-level BERTs.

### Comparison of Aggregated Models

The results of combinations of three word-level BERTs (Umls, Medical, and Bio) and the Medical Character BERT are shown in the Model Aggregation in Table 4. An aggregated model showed better macro performance compared to a single model, without degradation of micro performance. Therefore, we propose a combination of Medical BERT and Medical Character BERT, which showed the best macro F1 performance., as a mode with a high macro indicator is good for minority data.

Table 4. Comparisons of models

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Model | | Precision | | Recall | | F1 | | AUC | |
| Micro | macro | micro | macro | micro | macro | micro | macro |
| Single Model | aBase | 0.8133 | 0.4702 | 0.6953 | 0.3632 | 0.7497 | 0.3931 | 0.9812 | 0.9646 |
| Umls | 0.8081 | 0.4809 | 0.7032 | 0.3855 | 0.7520 | 0.4123 | 0.9815 | 0.9647 |
| Medical | 0.8053 | 0.4736 | 0.6977 | 0.3740 | 0.7477 | 0.4022 | 0.9796 | 0.9643 |
| Bio | 0.8095 | 0.4868 | 0.7010 | 0.3854 | 0.7513 | 0.4130 | 0.9648 | 0.9810 |
| bMC | 0.8121 | 0.4524 | 0.6900 | 0.3459 | 0.7461 | 0.3762 | 0.9820 | 0.9656 |
| Aggregated Model | Medical+ bMC | 0.8164 | **0.5081** | **0.7125** | **0.4103** | **0.7610** | **0.4376** | 0.9817 | **0.9698** |
| Umls+ bMC | 0.8251 | 0.5025 | 0.7026 | 0.3952 | 0.7590 | 0.4271 | 0.9819 | 0.9680 |
| Bio+ bMC | **0.8238** | 0.5067 | 0.7030 | 0.3930 | 0.7586 | 0.4247 | **0.9822** | 0.9685 |

a(Base) Base BERT: Pre-trained with general corpuses

b(MC): Medical Character BERT

Comparison of Umls BERT to the Character BERT based on micro F1 score revealed that Umls BERT showed better performance for majority data, while the Character BERT showed better performance for minority data.

Table 5. Comparisons of F1 scores by labels

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | ICD-9 code | F1 | | # of Data  in the test set |
| Umls | Character |
| Majority labels | 51.23 | **0.9221** | 0.9156 | 628 |
| 6.4 | **0.9756** | 0.9698 | 266 |
| 50.12 | **0.4142** | 0.3684 | 109 |
| Minority labels | 46.43 | 0.8 | **0.8235** | 27 |
| 38.03 | 0.7407 | **0.8235** | 23 |
| 39.43 | 0.2857 | **0.3571** | 16 |
| 85.86 | 0.2857 | **0.4444** | 5 |

### Web-based Application

We developed a web application based on the developed model. The front-end is implemented through Vue.js and the model server is implemented through TorchServe. The model used for the web application was trained using the entire dataset. The web application can perform both single and multi-predictions. On the single prediction page (Figure 3), by entering the name of the surgery and diagnosis, the corresponding ICD-9 code and probability can be obtained. Figure 4, which shows the multi-prediction page, demonstrates how ICD-9 codes and probabilities for multiple operative reports and diagnoses can be obtained by uploading a csv file.

Graphical user interface

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Figure 3. Single Prediction Page

Timeline

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Figure 4. Multi-prediction Page

## Discussion

In the present study, we developed the ConBERT model, which utilized both word- and character-level BERT to automate the standardization of operative reports written in free text in EMRs with an acceptable prediction ability. Most previous studies used the MIMIC-III dataset to predict the ICD-9 code, as well as detailed descriptions of diseases such as discharge summaries [24]. Our proposed model achieved an F1 score of 0.7610 by predicting the ICD-9 code based only on the operative report and diagnosis. Accordingly, by matching various operative reports to ICD-9 codes, surgeons can provide accurate and standardized data automatically without modifying their current methods of recording operative reports in free text. Moreover, manual standardization depends on the quality of mapping tables or skills, which can differ depending on individuals or institutions. Our model can replace inefficient labor and provide more consistent and accurate standardization of operative reports.

The proposed model utilizes the advantages of word- and character-level BERTs to solve problems such as non-standardized operative reports, typographical errors, and abbreviations that exist due to the data characteristics of surgical records. The performance was 18–19% and 32–34% higher compared to that in previous studies, based on the micro and macro F1 scores (Table 6).

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | F1 | | AUC | |
| Micro | macro | micro | macro |
| RAC[18] | 0.586 | 0.127 | 0.991 | 0.948 |
| JointLAAT[19] | 0.575 | 0.107 | 0.988 | 0.921 |
| Proposed model | **0.7610** | **0.4376** | 0.9817 | **0.9698** |

Table 6 Comparisons to Existing Papers

The common data model (CDM) is based on common standard terms and was previously proposed as a healthcare data model based on a standardized machine learning framework [25-26]. An international network of researchers and data partners, the Observational Health Data Science and Informatics (OHDSI), maintains an analytics solution, the Observational Medical Outcome Partnership (OMOP) CDM, to transform diverse and heterogeneous databases worldwide into a common format [27-28]. The OMOP CDM enables participating researchers to investigate standardized content with high consistency and extensibility. The operative report, which contains patient treatment-related information, can be utilized for medical research and serve as an indicator to evaluate the appropriateness of treatments and establish the insurance policy. Therefore, CDMs should include accurate operative reports, and standardization of operative reports written in free text into ICD is essential to build CDMs. Our BERT-based model can serve as an excellent tool to standardize operative reports. Although various tools have been developed to help researchers automatically transform data into standard terminologies [29-30], to our knowledge, no model exists to standardize operative reports. Our model may facilitate the more efficient mapping of operation data to a CDM.

However, our study has several limitations. First, approximately 3% of the total data was removed. Although these data were unlikely to be used in actual hospitals, this may be a hindrance to accurate automation. Therefore, subsequent studies should collect more data and secure data with a single label to solve this problem. Second, the data in this study were limited to the Department of Surgery. For better performance and predictivity, data from multiple institutions and other departments such as orthopedic and neurosurgery should be integrated to expand the scope of our model. Third, as the ICD codes have been recently revised, studies on converting ICD-9 to ICD-10 codes are needed. Despite these limitations, our suggested model showed excellent efficiency in automating the standardizing process of operative reports and an extensional property that can be utilized in CDM mapping.

## Conclusion

We developed the ConBERT model using pre-trained and Character BERTs to standardize operative reports to ICD-9 codes. Our model showed acceptable performance, with a micro F1 score of 0.7610, a precision of 0.8164, and a recall of 0.7125. Our model allows automation of the manual standardizing process, as well as reduced potential for data errors. Additionally, our model can be further developed to integrate data from multiple institutions and other departments and may be utilized in mapping operation data to CDM.

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### Conflicts of Interest

### Abbreviations

JMIR: Journal of Medical Internet Research

RCT: randomized controlled trial

AUC: area under the ROC curve

BERT: bidirectional encoder representations from transformers

CDM: common data model

conBERT: concatenation BERT

EMRs: electronic medical records

FPR: false positive rate

ICD: International Classification of Disease

NLTK: Natural Language Toolkit

OHDSI: Observational Health Data Science and Informatics

OMOP: Observational Medical Outcome Partnership

ROC: receiver operating characteristic

TPR: true positive rate

WHO: World Health Organization

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