TabText: A Flexible and Contextual Approach to Tabular Data Representation

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Abstract

Tabular data is an essential data format for applying machine learning tasks across various industries. However, traditional data processing methods do not fully utilize all the information available in the tables, ignoring important contextual information such as column header descriptions. In addition, pre-processing data into a tabular format can remain a labor-intensive bottleneck in model development. This work introduces TabText, a processing and feature extraction framework that extracts contextual information from tabular data structures. TabText addresses processing difficulties by converting the content into language and utilizing pre-trained large language models (LLMs). We evaluate our framework on ten healthcare prediction tasks—including patient discharge, ICU admission, and mortality—and validate its generalizability on an additional task from a different domain. We show that 1) applying our TabText framework enables the generation of high-performing and simple machine learning baseline models with minimal data preprocessing, and 2) augmenting pre-processed tabular data with TabText representations improves the average and worst-case AUC performance of standard machine learning models by as much as 5% additive points. All the code to reproduce the results can be found at `https://anonymous.4open.science/r/TabText-18F0`.

1 Introduction

Tabular data remains the most widely used and readily available data format across various fields ranging from education, healthcare, and technology, where it serves a vital role in capturing all domains of information. Pre-processing tabular data accurately and efficiently is essential for creating reliable downstream models in machine learning applications. Yet, two significant limitations exist for directly incorporating tabular data into generalizable modeling pipelines: they require labor-intensive, often manual, data processing to standardize information across heterogeneous tabular structures and data sources, and they ignore contextual information such as column headers and meta content descriptions.

In contrast to tabular approaches, language is a very flexible data modality that can easily represent information about different data points without imposing any structural similarity between them. Furthermore, recent developments on off-the-shelf large language models (LLMs) based on the Transformer architecture (Vaswani et al., 2017) offer state-of-the-art performances on a wide range of language tasks, including translation, sentence completion, and question answering. These pre-trained models are often developed with very large and diverse data sets, allowing them to exploit prior knowledge and make accurate predictions with very few new training samples. Some LLMs are trained to target specific domain knowledge and technical challenges, making them particularly useful in the corresponding applications. For example, LLMs fine-tuned on clinical notes and biomedical corpora such as ClinicalBERT (Alsentzer et al., 2019), BioBERT(Lee et al., 2019), and BioGPT(Luo et al., 2022) offer substantial advantages for medical learning tasks, and LLMs that specifically target long token sequences unveil opportunities for dealing with data that contains long texts (Beltagy et al., 2020; Li et al., 2022).

These successful language models offer a natural solution to represent and process contextual information from tabular structures. Standard machine learning models only utilize the explicit table contents, disre-

garding all accompanying context like column headers and table descriptions. Incorporating these metadata into the model via language could give meaning to the data values within the broader context. For example, a numerical value might be very relevant for disease prediction if it represents a person's age but not so much if it corresponds to the ward census. Moreover, LLMs could save significant manual labor for selecting, encoding, and imputing data (Sweeney, 2017; Geneviève et al., 2019; Nan et al., 2022). Missing data, in particular, is a challenging and frequent problem that requires attentive processing and expert knowledge. Current predictive models either exclude such attributes, potentially ignoring rare-occurring but valuable data or impute missing values with very few recorded instances. Additional processing challenges arise when units of measurement or data types are inconsistent across tabular data systems. By leveraging language, these difficulties could be addressed, for instance, by simply writing that particular values are missing and converting inconsistent values into text.

Previous works using LLMs have shown the potential of using natural language processing (NLP) models to systematically and efficiently process tabular data in the form of language (Herzig et al., 2020; Wang et al., 2023; Padhi et al., 2021; Somepalli et al., 2021). However, they have mainly relied on training fixed BERT-based models that are not flexible to changes in tabular structures. These works have mostly assumed that encoding data using LLMs leads to better performance than traditional data processing methods, but concrete evidence has not been provided. Other works augment tabular data with external unstructured data (Harari & Katz, 2022) but do not leverage contextual data from the original tabular source. In Wang et al. (2023), the authors do incorporate contextual data from the input tables, but this is generated via LLM prompting and is therefore exposed to hallucinations. In addition, language models are considered sensitive to their input representations (Miyajiwala et al., 2022), and most previous works do not thoroughly investigate how the choice of language affects their results. Hegselmann et al. (2023) do investigate different language variants, but in the context of zero-shot and few-shot classification as opposed to feature representation. Thus, guidance on the best way to construct the language data remains in need.

This paper builds and evaluates a new feature extraction methodology and addresses the aforementioned questions. We process tabular data by creating a text representation for each data sample. We then use this text as input for a pre-trained LLM to generate TabText embeddings of a fixed dimension. Finally, we augment the tabular features with these TabText embeddings to train any standard machine learning model for downstream prediction tasks.

The main contributions of this work are as follows:

1. We develop TabText, a systematic framework that leverages language to extract contextual information from tabular structures, resulting in more complete data representations.

2. We show the effectiveness of using TabText representations for general data pre-processing. Our experiments demonstrate that augmenting tabular data with our TabText representations can improve the AUC score by up to 5% across 11 classification tasks, with larger improvements observed for harder tasks.

3. We investigate the impact of several language syntactic parsing schemes on the performance of TabText representations and demonstrate the flexibility of our framework compared with traditional labor-consuming processing of unorganized data into a tabular feature space.

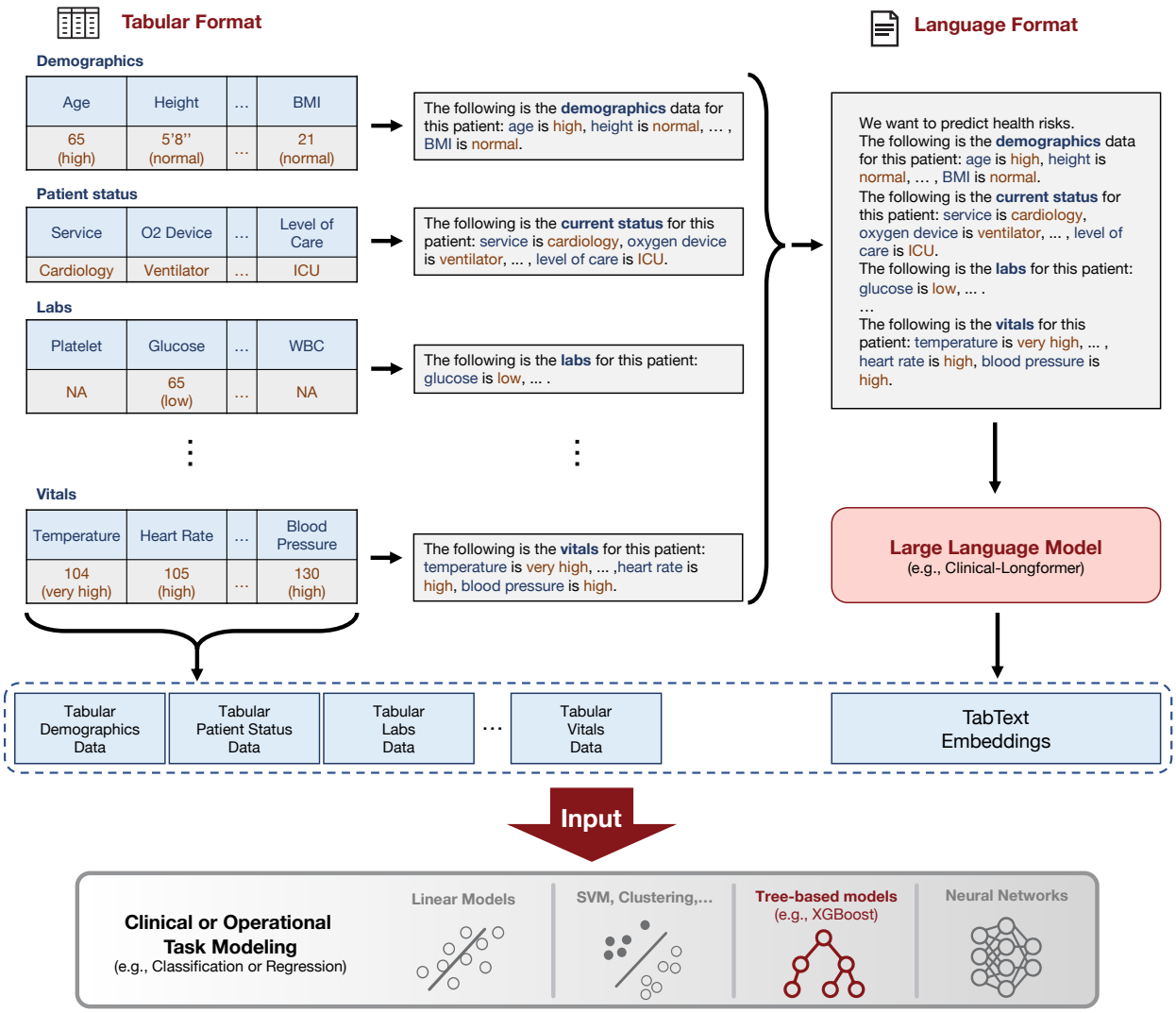


Figure 1: End-to-end TabText framework. The TabText framework integrates diverse tabular data sources cohesively into a language format that can be combined into a single patient description paragraph. This patient language representation is then fed to existing pre-trained LLMs to generate embeddings. An important advantage of this framework is the flexibility to replace this LLM as new models become available.

2 Methodology

Tabular data are often stored in various tabular formats. For example, in the context of healthcare, different tabular data sources may include demographics, vital signs, laboratory results, treatment status, etc. Effortless integration and utilization of these heterogeneous data for predictive modeling remains a significant challenge. The TabText framework addresses this by converting multiple structured data sources into a unified natural language representation. Specifically, it transforms each table into descriptive sentences that are then concatenated into a single summary paragraph for each data subject. This text contains the attributes of the columns with their corresponding values and potentially other available contextual information. This language-based representation is subsequently processed by a pre-trained LLM to generate TabText embeddings of fixed size that encode the textual data. Finally, we augment the tabular features with these TabText embeddings to train any standard machine learning model (e.g., decision trees, support

vector machines, gradient-boosted trees) for downstream prediction tasks. Figure 1 illustrates the overall TabText framework.

Given the design of our TabText framework, three main questions need to be addressed:

1. Which pre-trained LLM to use?
2. How to convert tabular data into language?
3. Should the LLM be fine-tuned with the specific language format chosen?

In this section we answer these in the context of healthcare. However, as we demonstrate in our experiment section, the overall pipeline can be applied to any other domain.

In developing our methodology, our goal is to address the above questions in a manner that generalizes across diverse tasks. Specifically, we aim to generate a single TabText embedding per data subject that performs well across multiple downstream prediction tasks, rather than tailoring embeddings to individual tasks. This approach not only promotes embeddings that capture all the relevant information in the input text, but also reduces computational overhead by eliminating the need to recompute embeddings for each new task.

To this end, we consider nine different binary classification tasks largely overlapping with Na et al. (2023), all related to inpatient flow predictions in a hospital. Two discharge-related outcomes are whether patients are discharged or not within the next 24 hours (resp. 48 hours). Four ICU-related outcomes include whether the patient will enter (resp. leave) the intensive care unit (ICU) for patients currently not in the ICU (resp. in the ICU) within the next 24 hours (resp. 48 hours). Two short-term expiration outcomes concern whether each patient will die in the next 24 hours (resp. 48 hours). One end-of-stay mortality outcome indicates whether patients die or not at the end of their stay.

Throughout this section we utilize a private real-world data set comprised of 63 columns corresponding to different laboratory results of inpatients in a teaching hospital. We use $60,000$ data samples for training and validation, and $10,000$ for testing, where each data point corresponds to a patient day. All results in Sections 2.1, 2.2, 2.3 utilize this data set and all nine prediction tasks mentioned above.

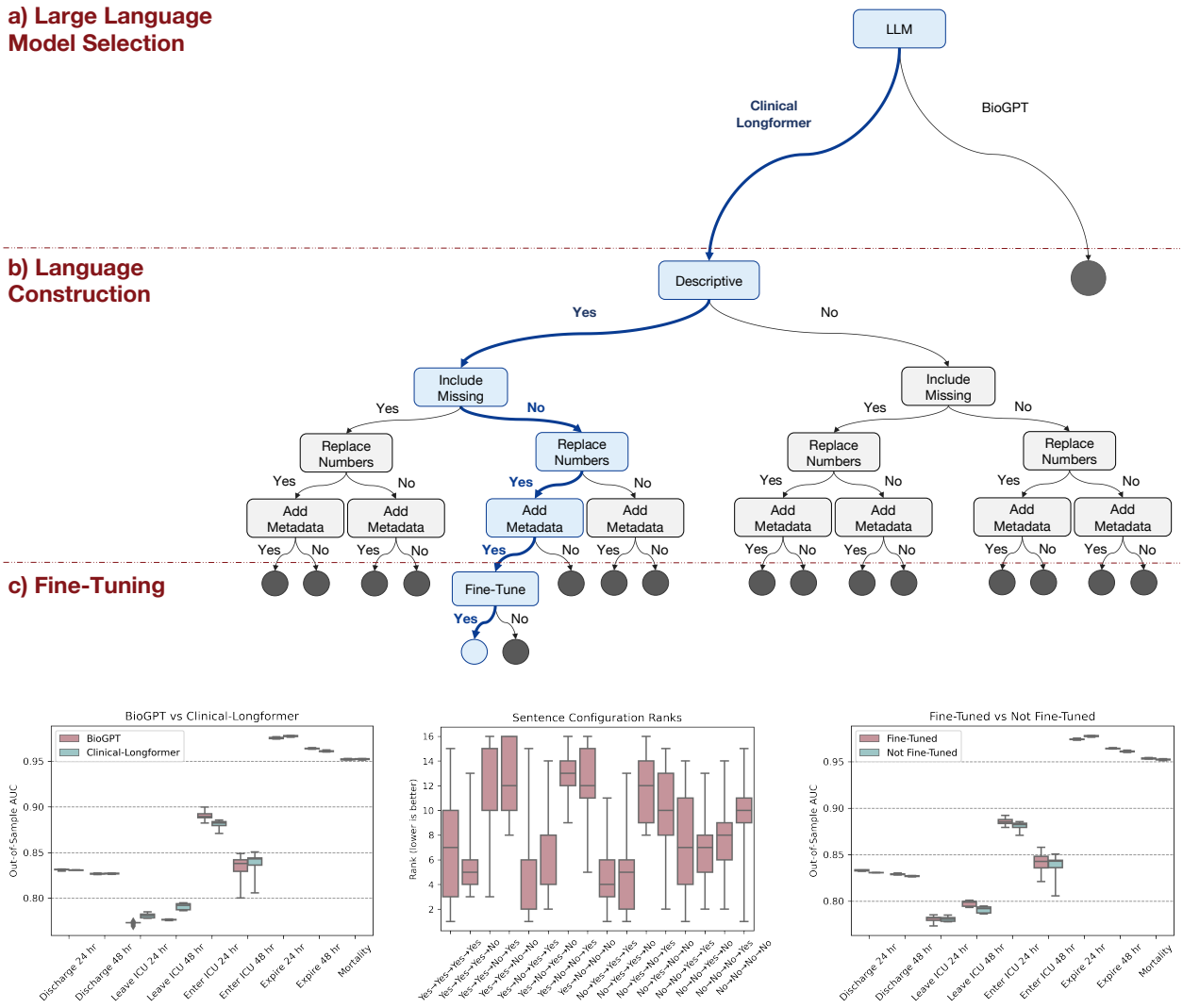
2.1 LLM Selection

We consider two different Transformer models, BioGPT and Clinical-Longformer (Li et al., 2022), both of which were pre-trained with MIMIC-III clinical notes (Johnson et al., 2016). Following the TabText framework, we convert the tabular data into simple text: for each row, the cell from column "attribute" with value X is transformed into "attribute: X" and the texts from all columns are concatenated into a single sentence with the comma character. We next create TabText embeddings and finally train gradient-boosted tree models for the nine tasks of interest. Figure 2a shows the boxplots for the out-of-sample AUC over 10 random 75%-25% train-validation splits for each task and each model. Both NLP models achieve similar performance across tasks, and we therefore choose the Clinical-Longformer model, as it allows for input text of larger size.

2.2 Language Construction

The versatility of language creates a challenge for consistency, as multiple textual expressions can convey the same information. Moreover, tabular data is often split across multiple tabular sources (e.g., vitals table, medications table), some of which include information only for a particular group of data subjects. This results in even more possibilities for textual representation.

The TabText framework creates a single paragraph for each data sample (e.g., for each patient day) as follows: we first create a sentence for each column in each table. Next, for each table, we concatenate contextual information and the sentences of its columns using the colon (":") and comma (",") characters, respectively. We then merge the text from all tables into a single paragraph using the period (".") character. While the exact punctuation doesn't significantly impact BERT-based transformers (Ek et al., 2020), the



(a) LLM Selection. (b) Language Construction. (c) Fine-Tuning.

Figure 2: Overview of our overall methodology. We start with the selection of an LLM. Figure (a) shows that BioGPT and Clinical Longformer achieve similar results, and we therefore choose Clinical Longformer, as it allows for input texts of larger sizes. Then, we look for the best language representations of the original patient data. In Figure (b) we observe the boxplots of the ranks for different sentence configurations, which were tested across different prediction tasks (lower rank is better). We select the configuration with the lowest median ranking; specifically, we use descriptive language, omit missing values, replace numerical values with text, and include metadata. Lastly, we fine-tune the LLM using this sentence configuration, as it leads to better performance as shown in Figure (c).

exact text chosen to build each sentence might have a larger impact on the final embedding. We therefore investigate different ways to construct sentences for each column attribute.

Descriptiveness: We consider whether or not to use descriptive language to construct text sentences. Specifically, consider a cell from column "attribute" that has value "X". If the column is non-binary, we consider the following options:

- Non-Descriptive Sentence: "attribute: X";
- Descriptive Sentence: "attribute is X".

For binary columns, we consider the verb associated with the specific attribute. For instance, if the column attribute is associated with the verb "to have" we consider

- Non-Descriptive Sentence: "has X: yes" or "has X: no";
- Descriptive Sentence: "has X" or "does not have X".

Missing Values: When the value for a column "attribute" is missing, we consider two options, to explicitly mention in the text that this information is not available ("attribute is missing"), or to simply skip this column when building the text representation.

Numerical Data: Transformer models often struggle to represent language with numerical data (Gorishniy et al., 2022). Therefore, we also consider whether or not to replace numerical values with text. For replacement, we compute the average (AVG) and standard deviation (SD) of the corresponding column with respect to the training data. We then replace a given cell value X as follows:

- "very low" if $X < \text{AVG} - 2\text{SD}$;
- "low" if $\text{AVG} - 2\text{SD} \leq X < \text{AVG} - \text{SD}$;
- "normal" if $\text{AVG} - \text{SD} \leq X < \text{AVG} + \text{SD}$;
- "high" if $\text{AVG} + \text{SD} \leq X < \text{AVG} + 2\text{SD}$;
- "very high" if $\text{AVG} + 2\text{SD} < X$.

Including Metadata: We investigate the added value of including metadata as part of the text representation. This corresponds to descriptions of table content (e.g., "This table contains information about the medications administered to this patient") or the prediction task of interest (e.g., "We want to predict mortality risk").

For each of the 16 possible sentence configurations, we use default values of the Clinical-Longformer model to obtain TabText embeddings that are given as input to a gradient-boosted tree model. In Figure 2b, the Language Construction results show the boxplot for the rank achieved with each configuration across tasks, where lower numbers correspond to better ranking. We choose the sentence configuration with the lowest median ranking; specifically, we use descriptive language, omit missing values from the text, replace numerical values with text, and include metadata.

2.3 Fine-Tuning

Although Clinical-Longformer was pre-trained with large language data sets, we can further improve its performance with a few more training iterations using our training data. Specifically, we convert our training data into language following the sentence configuration selected in Section 2.2, and we use it to fine-tune Clinical-Longformer following the original BERT training methodology, which includes self-supervised masked word prediction. We fine-tune for 3 epochs and with the default values for all hyperparameters. We then generate embeddings that are given as input to a gradient-boosted tree model. We show in Figure 2 the boxplots for the out-of-sample AUC over 10 random 75%-25% train-validation splits for each task. We see that fine-tuning the model with our local data slightly improves performance for eight out of the nine classification tasks of interest.

3 Results

This section presents extensive computational experiments evaluating the performance of our TabText framework. First, we show how our pipeline can quickly generate machine-learning models with competitive performance without any data cleaning by leveraging the flexibility of language. We then demonstrate with pre-processed data that augmenting standard tabular representations with our TabText embeddings can

increase out-of-sample AUC by up to 5% additive points, with the largest improvements observed for the most challenging predictions.

Text Encoder: We first convert the input training data from tabular to textual format as described previously in Section 2.2. We use the sentence configuration that led to the highest average AUCs (i.e., skipping sentences for missing values, replacing numbers with text, using descriptive language, and adding metadata). Then, we use the fine-tuned Clinical-Longformer model to extract language embeddings of size 768.

Training Methodology: For each prediction task, we compare two approaches: our TabText framework (see Figure 1) and the standard Tabular approach in which only the tabular data is given as input to the machine learning model. We use gradient-boosted tree models in all experiments performed. For all reported results, the average performance is computed over 10 random train-validation splits (identical 10 splits across all experiments) for a fair comparison. The optimal model is selected using a hyperparameter grid search (see details in the appendix) based on its performance on the validation set. We emphasize that, for the TabText framework, both the sentence construction and model fine-tuning are performed exclusively on the training set of each data split, ensuring that no information from the test set or validation set is used during training.

Implementation: All our code is written in Python 3.8.2. We trained all models using one Intel Xeon Platinum 8260 or Intel Xeon Gold 6248 CPU and GPU. We conducted all of our predictive experiments using the XGBoost (Chen & Guestrin, 2016) library from Python. The Clinical-Longformer model is directly accessed from HuggingFace.

3.1 Patient Flow Predictions

We here evaluate the TabText framework on the same nine patient flow predictive tasks described in Section 2, but this time using a much larger data set that contains medical records of all inpatients over a four-year period. Each data point represents a patient day. There are 160 columns of different patient attributes on demographics, patient status, vital signs, laboratory results, diagnoses, treatments, and other information. We emphasize that this data set was not used for the development of the TabText methodology in Section 2. The summary of the data set and data sizes utilized can be found in the appendix in Tables 2 and 3. Experiments are reported across 10 random 75%-25% train-validation splits with a fixed test set.

3.1.1 High Performance with Minimal Pre-Processing

We first leverage the TabText framework to replace the heavy lifting of data cleaning by simply creating a text representation for each data sample using the information as it appears in the raw data tables that we received from the hospital. In particular, columns that require data cleaning to be converted to appropriate data types can be simply transformed into text. For example, the sentence corresponding to a column for a sedation score with the value "-4 $\rightarrow$ deep sedation" can be considered as a categorical column and written as "sedation score is -4 $\rightarrow$ deep sedation", as opposed to parsing the original string into a numeric value of -4 as part of the traditional pre-processing steps. Therefore, TabText representations enable us to quickly build baseline machine learning models utilizing the tabular data in its raw form. Only minimal data pre-processing was required, including constructing the meta information of the tables and columns, which is estimated to have taken only a couple of hours of manual work. We then followed our TabText pipeline to train a gradient-boosted tree model for each classification task. The results are shown in Table 1. The baseline TabText models with minimally processed data already achieve high out-of-sample AUC performance, reaching practically implementable benchmarks in hospital systems. The average AUCs across 10 random 75%-25% train-validation splits are close or above 0.8 for all prediction tasks except for Enter ICU 48 hr, which is a notoriously difficult classification task (Na et al., 2023).

3.1.2 Enhanced Performance with Contextual Representation

Given the raw tabular data files, we perform several data processing steps following Na et al. (2023) to obtain a clean feature space. These steps include merging raw data tables, parsing string columns, encoding categorical variables, constructing features, and imputing missing data, as described in more detail below. In

Table 1: Out-of-sample average AUCs achieved by baseline TabText models with minimally processed data and across 10 random train-validation splits.

Prediction Task	**TabText Baseline AUC**
Discharge 24 hr	0.803
Discharge 48 hr	0.790
Enter ICU 24 hr	0.801
Leave ICU 24 hr	0.839
Enter ICU 48 hr	0.757
Leave ICU 48 hr	0.835
Expire 24 hr	0.943
Expire 48 hr	0.933
Mortality	0.895

Na et al. (2023), the authors reported approximately one year of effort jointly by machine learning researchers and hospital specialists on obtaining, cleaning, and processing the data.

String Parsing: Some columns in string format require string parsing to extract numerical features as continuous variables. For instance, the normal ranges of laboratory tests in forms such as "50–70" are replaced with two columns: one with a value of 50 for the lower bound and another with a value of 70 for the upper bound.

Categorical Encoding: Categorical columns (e.g., department, mobility level, the reason for visit) must be converted to ordered numerical levels (consecutive integers) using label-encoding or binary categories using one-hot encoding. Due to the large number of categories, we use label encoding for all categorical variables.

Feature Engineering: To better capture the clinical information, we compute various auxiliary variables:

1) Current conditions extracted from records (e.g., whether the patient is in ICU or IV)
2) Normal indicators (whether the clinical measurement is within the normal/critical range) instead of the ranges themselves.
3) Counts (e.g., number of days in ICU, number of attending physicians).
4) Pending procedures/results (time until surgery, whether MRI is pending, etc.).
5) Historical record linked to the patient (e.g., number of days since the previous admission and length of the previous stay).
6) Non-patient-specific operational variables (e.g., day of the week, ward census and utilization, hospital admission volume on the previous day).

Missing Data Imputation: Since the raw data comes from a hospital system, it contains many missing values. We impute most missing entries with 0, except for a few cases. From communications with the hospital, we impute certain variables with prior knowledge of the meaning of missingness (e.g., missing Do Not Resuscitate (DNR) means the patient did not sign a DNR form). For some auxiliary variables, we apply some rules, such as imputing counts with 0 if no record exists and imputing the number of days since previous admission with a large number (e.g., 9999) if no previous admission exists.

We next process the data and group all features into 6 tables (see a summary in Table 2), which we combine and feed into the TabText Framework from Figure 1. We perform experiments on the same data and classification tasks as in Section 3.1.1 but using the cleaned data this time. The results obtained using the standard Tabular approach and our TabText framework are shown in Figure 3. The average AUCs across 10 random 75%-25% train-validation splits for the Enter ICU 48 hr and Discharge 48 hr prediction task are improved by an additive increment of 1.2%–1.4%. We also see a substantial but smaller benefit for Mortality risk prediction. For the remaining tasks, Tabular and TabText achieve similar performance with

differences in average AUC smaller than 0.25%. We also notice in Figure 3 that the largest TabText benefits occur for the classification tasks with the lowest Tabular performance (high variability and low AUCs), while practically no effect was observed for the tasks with stable Tabular results (low variability and high AUCs).

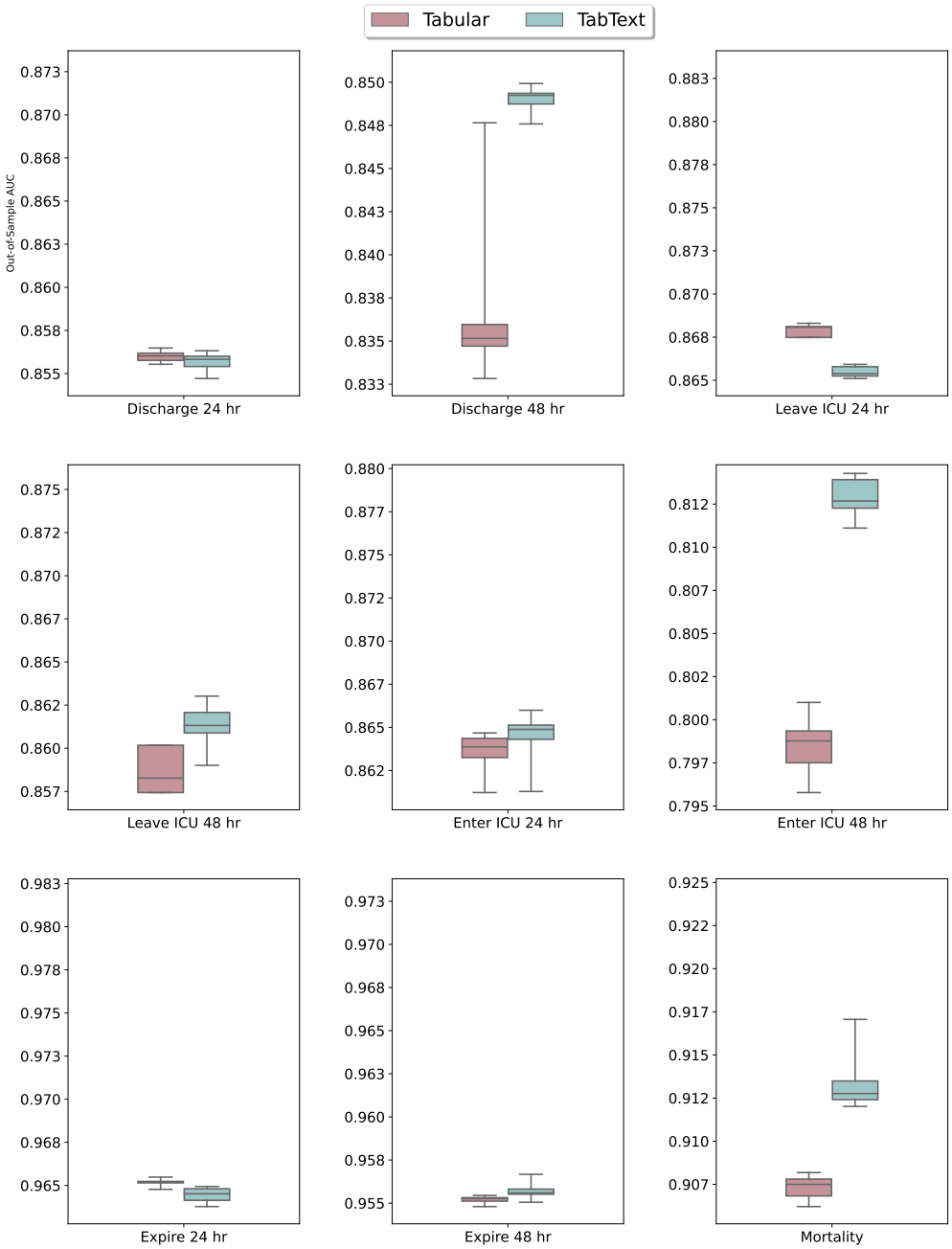
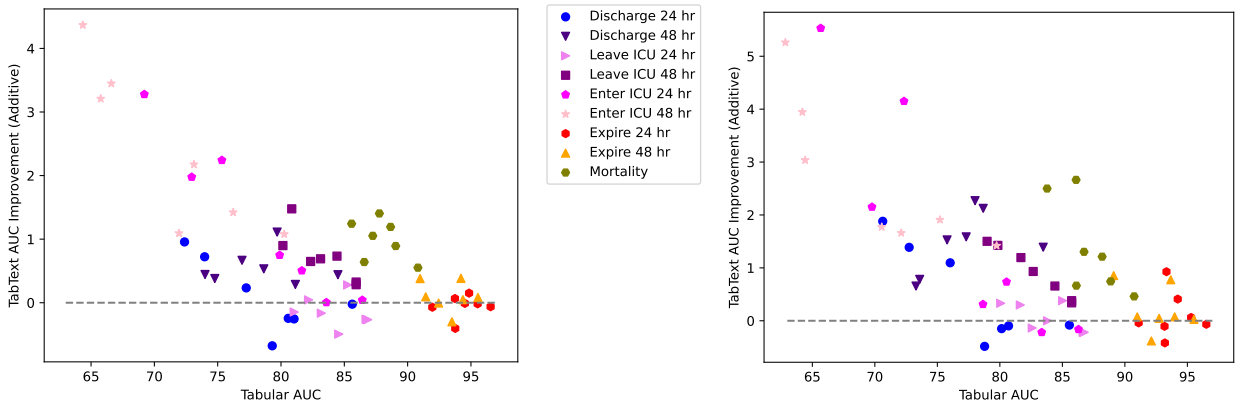


Figure 3: Boxplots for the out-of-sample AUCs across 10 random train-validation splits using Tabular vs. TabText models. We see that the largest TabText benefits occur for the classification tasks with high variability and low AUCs, while practically no effect was observed for the tasks with low variability and high AUCs.

3.1.3 Larger Benefits for Harder Predictions



(a) Average out-of-sample AUC improvement at varying data sizes.

(b) Worst-case out-of-sample AUC improvement at varying data sizes.

Figure 4: TabText AUC improvement over the standard Tabular approach at varying data sizes. We observe that the improvement of TabText is most prominent when standard Tabular models do not perform well. For high-performing tasks, the advantage is less pronounced.

To better understand the regimes in which TabText provides the largest improvements in AUC performance, we repeat this experiment using smaller and larger training data sets. For each prediction task, we consider the original training data size as well as smaller data sizes (ranging from 2000, 3000, 5000, 10000, 25000, and 50000 patient days). We plot in Figure 4a (resp. Figure 4b) the average (resp. worst-case) TabText additive AUC improvement across 10 random 75%-25% train-validation splits, where the x-axis corresponds to the average (resp. worst-case) AUC of the standard Tabular approach and the y-axis quantifies the additive improvement on average (resp. worst-case) AUC achieved with TabText. Each scatter point represents the result of a prediction task (denoted by legends) on one of the 7 different data subsets. As in Section 3.1.2, we observe larger improvements on the more difficult prediction tasks with Tabular AUCs below 85%. On easier prediction tasks, where Tabular models already achieve AUCs over 90%, the benefit of TabText is near or below zero. When the Tabular AUCs are less than 78%, TabText brings a positive improvement on all results, including several instances of additive improvement over 2–3%. This suggests more potential benefits of augmenting tabular models with TabText representations for tasks with low Tabular performance, such as challenging medical prediction tasks with a lack of difficult-to-observe risk factors or a small sample size.

3.2 Breast Cancer Recurrence Events Predictions

We next evaluate TabText performance using the publicly available Breast Cancer dataset from the UCI Machine Learning Repository (Zwitter & Soklic, 1988), originally obtained from the University Medical Centre, Institute of Oncology, Ljubljana, Yugoslavia. This data set consists of 286 instances, each described by 9 categorical attributes. The data is associated with a binary classification task, where 201 instances belong to one class (no-recurrence-events) and 85 to another (recurrence-events). The data set is used as it is without any pre-processing other than zero imputation and label encoding.

We apply our TabText framework to this dataset and classification task. Figure 5 presents the out-of-sample AUC results across 10 random splits of the data, using 70%-15%-15% train-validation-test data splits. The results show that TabText consistently outperforms the Tabular model, achieving superior average performance and decreasing the standard deviation of the results. TabText yields a 4.7% additive increase in average AUC, and 5.6% improvement on worst-case AUC, demonstrating its effectiveness in leveraging textual information to enhance predictive accuracy for other classification tasks in healthcare beyond patient flow prediction.

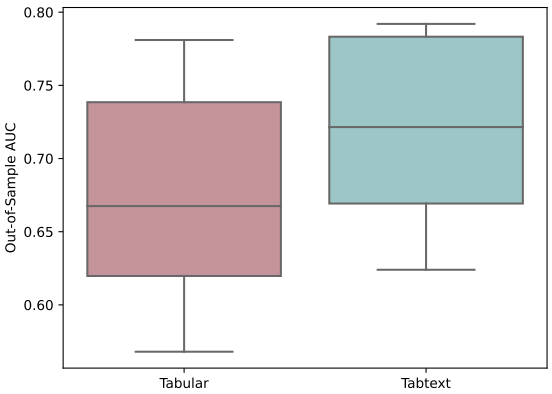


Figure 5: Out-of-sample AUC results across 10 random train-validation-test splits for Tabular and TabText models based on the Breast Cancer data set.

3.3 Glass Identification

Lastly, we evaluate the TabText framework using a publicly available dataset that is not associated with a healthcare-related task. Specifically, we use the Glass Identification data set from the UCI Machine Learning Repository (German, 1987), which is used to predict the types of glass (six classes in total) in terms of their oxide content. The data set contains 214 instances and 9 numerical features. The data set is used as it is without any pre-processing other than label encoding.

We evaluate the TabText framework exactly as described in our training methodology, except we use the Longformer LLM (Beltagy et al., 2020) instead of the Clinical-Longformer. We show in Table 6 the out-of-sample AUC results obtained by solving this binary classification task with both Tabular and TabText models. These results are across 10 random splits of the data, using a 70%-15%-15% train-validation-test partitioning strategy. The results show once more that TabText outperforms the Tabular model. TabText yields a 2.6% additive increase in average AUC and 5.2% additive increase in worst-case AUC, demonstrating that the TabText framework can also be used to solve classification tasks in other domains beyond healthcare.

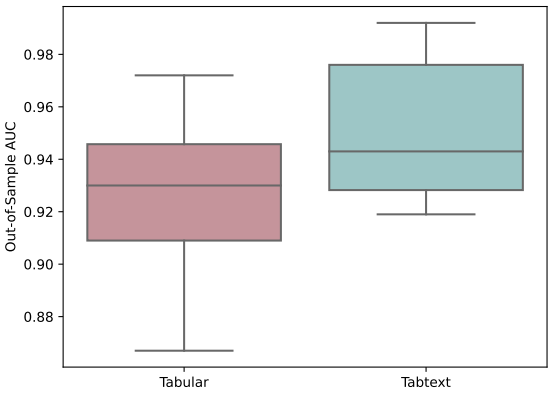


Figure 6: Out-of-sample AUC results across 10 random train-validation-test splits for Tabular and TabText models based on the Glass Identification data set.

4 Conclusions

This paper introduces TabText, a novel framework for processing tabular data by converting it into a text representation that captures important contextual information such as column descriptions. Our experiments show that augmenting standard tabular data with our TabText representations can improve the performance of standard machine learning models across 11 classification tasks, with larger improvements observed for the more challenging tasks. In addition, we demonstrate the efficiency of TabText in simplifying data preprocessing and cleaning, offering an alternative and flexible pipeline for generating high-performing baseline models.

Our experiments reveal the potential of TabText for improving the performance of standard machine learning models, and there are several research directions to further improve our framework. For instance, TabText relies on the use of NLP models that could generate high-quality embeddings for the input text, which motivates the development of more LLMs pre-trained with domain-specific data. Moreover, augmenting tabular data with TabText embeddings adds a layer of complexity to the interpretability of the model output, and developing tools to maintain the interpretability of the tabular data would be an interesting direction for future research. TabText is a general framework that can be particularly useful for difficult classification tasks, and we hope that this work motivates further research for leveraging language in general machine learning applications.

Data Availability

The patient-level data sets used for patient flow predictions are not publicly available due to the sensitive and confidential nature of hospital data. However, the data sets used in Sections 3.2 and 3.3 are publicly accessible. To support reproducibility, we provide the complete TabText framework code, along with the data and metadata necessary to replicate our results on the public data sets (`https://anonymous.4open.science/r/TabText-18F0`).

References

Emily Alsentzer, John R. Murphy, Willie Boag, Wei-Hung Weng, Di Jin, Tristan Naumann, and Matthew B. A. McDermott. Publicly available clinical bert embeddings, 2019. URL https://arxiv.org/abs/1904.03323.

Iz Beltagy, Matthew E Peters, and Arman Cohan. Longformer: The long-document transformer. *arXiv preprint arXiv:2004.05150*, 2020.

Tianqi Chen and Carlos Guestrin. Xgboost: A scalable tree boosting system, 2016.

Adam Ek, Jean-Philippe Bernardy, and Stergios Chatzikyriakidis. How does punctuation affect neural models in natural language inference, June 2020. URL https://aclanthology.org/2020.pam-1.15.

Lester Darryl Geneviève, Andrea Martani, Maria Christina Mallet, Tenzin Wangmo, and Bernice Simone Elger. Factors influencing harmonized health data collection, sharing and linkage in denmark and switzerland: A systematic review. *PLOS ONE*, 14(12):e0226015, December 2019. doi: 10.1371/journal.pone.0226015. URL https://doi.org/10.1371/journal.pone.0226015.

B. German. Glass Identification. UCI Machine Learning Repository, 1987. DOI: https://doi.org/10.24432/C5WW2P.

Yury Gorishniy, Ivan Rubachev, and Artem Babenko. On embeddings for numerical features in tabular deep learning, 2022. URL https://arxiv.org/abs/2203.05556.

Asaf Harari and Gilad Katz. Few-shot tabular data enrichment using fine-tuned transformer architectures, 2022.

Stefan Hegselmann, Alejandro Buendia, Hunter Lang, Monica Agrawal, Xiaoyi Jiang, and David Sontag. Tabllm: Few-shot classification of tabular data with large language models. In Francisco Ruiz, Jennifer Dy, and Jan-Willem van de Meent (eds.), *Proceedings of The 26th International Conference on Artificial Intelligence and Statistics*, volume 206 of *Proceedings of Machine Learning Research*, pp. 5549–5581. PMLR, 25–27 Apr 2023. URL https://proceedings.mlr.press/v206/hegselmann23a.html.

Jonathan Herzig, Pawel Krzysztof Nowak, Thomas Müller, Francesco Piccinno, and Julian Eisenschlos. TaPas: Weakly supervised table parsing via pre-training, July 2020. URL https://aclanthology.org/2020.acl-main.398.

Alistair EW Johnson, Tom J Pollard, Lu Shen, Li-wei H Lehman, Mengling Feng, Mohammad Ghassemi, Benjamin Moody, Peter Szolovits, Leo Anthony Celi, and Roger G Mark. Mimic-iii, a freely accessible critical care database. *Scientific data*, 3(1):1–9, 2016.

Jinhyuk Lee, Wonjin Yoon, Sungdong Kim, Donghyeon Kim, Sunkyu Kim, Chan Ho So, and Jaewoo Kang. BioBERT: a pre-trained biomedical language representation model for biomedical text mining. *Bioinformatics*, 36(4):1234–1240, 09 2019. ISSN 1367-4803. doi: 10.1093/bioinformatics/btz682. URL https://doi.org/10.1093/bioinformatics/btz682.

Yikuan Li, Ramsey M Wehbe, Faraz S Ahmad, Hanyin Wang, and Yuan Luo. Clinical-longformer and clinical-bigbird: Transformers for long clinical sequences. *arXiv preprint arXiv:2201.11838*, 2022.

Renqian Luo, Liai Sun, Yingce Xia, Tao Qin, Sheng Zhang, Hoifung Poon, and Tie-Yan Liu. BioGPT: generative pre-trained transformer for biomedical text generation and mining. *Briefings in Bioinformatics*, 23(6), sep 2022. doi: 10.1093/bib/bbac409. URL https://doi.org/10.1093%2Fbib%2Fbbac409.

Aamir Miyajiwala, Arnav Ladkat, Samiksha Jagadale, and Raviraj Joshi. On sensitivity of deep learning based text classification algorithms to practical input perturbations, 2022.

Liangyuan Na, Kimberly Villalobos Carballo, Jean Pauphilet, Ali Haddad-Sisakht, Daniel Kombert, Melissa Boisjoli-Langlois, Andrew Castiglione, Maram Khalifa, Pooja Hebbal, Barry Stein, and Dimitris Bertsimas. Patient outcome predictions improve operations at a large hospital network. *arXiv preprint arXiv:2305.15629*, 2023.

Yang Nan, Javier Del Ser, Simon Walsh, Carola Schönlieb, Michael Roberts, Ian Selby, Kit Howard, John Owen, Jon Neville, Julien Guiot, Benoit Ernst, Ana Pastor, Angel Alberich-Bayarri, Marion I. Menzel, Sean Walsh, Wim Vos, Nina Flerin, Jean-Paul Charbonnier, Eva van Rikxoort, Avishek Chatterjee, Henry Woodruff, Philippe Lambin, Leonor Cerdá-Alberich, Luis Martí-Bonmatí, Francisco Herrera, and Guang Yang. Data harmonisation for information fusion in digital healthcare: A state-of-the-art systematic review, meta-analysis and future research directions. *Information Fusion*, 82:99–122, June 2022. doi: 10.1016/j.inffus.2022.01.001. URL `https://doi.org/10.1016/j.inffus.2022.01.001`.

Inkit Padhi, Yair Schiff, Igor Melnyk, Mattia Rigotti, Youssef Mroueh, Pierre Dognin, Jerret Ross, Ravi Nair, and Erik Altman. Tabular transformers for modeling multivariate time series, 2021.

Gowthami Somepalli, Micah Goldblum, Avi Schwarzschild, C. Bayan Bruss, and Tom Goldstein. Saint: Improved neural networks for tabular data via row attention and contrastive pre-training, 2021. URL `https://arxiv.org/abs/2106.01342`.

Evan Sweeney. Experts say ibm watson's flaws are rooted in data collection and interoperability, Sep 2017. URL `https://www.fiercehealthcare.com/analytics/ibm-watson-s-flaws-trace-back-to-data-collection-interoperability`.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. *Advances in neural information processing systems*, 30, 2017.

Zifeng Wang, Chufan Gao, Cao Xiao, and Jimeng Sun. Meditab: scaling medical tabular data predictors via data consolidation, enrichment, and refinement. *arXiv preprint arXiv:2305.12081*, 2023.

Matjaz Zwitter and Milan Soklic. Breast Cancer. UCI Machine Learning Repository, 1988. DOI: https://doi.org/10.24432/C51P4M.

A Appendix

In this appendix, we provide additional information on the Results section.

The following are the hyperparameters that we grid-searched to obtain the optimal XGBoost model:

- Number of estimators: {100, 200, 300},
- Maximum depth: {3, 5, 7},
- Learning rate: $\{0.05, 0.1, 0.3\}$,
- L_2 regularization parameter: $\{1e^{-2}, 1e^{-3}, 1e^{-4}, 1e^{-5}, 0\}$.

Table 2: Summary of tabular data, which contains different aspects of a patient's admission stay from patient's high-level demographics to precise lab measurements.

Table #	**Table Meta Information**	**Example Columns**
1	Lab values	Platelet, Sodium
2	Chart measurements	Respiratory rate, oxygen concentration
3	Counting statistics	Number of medications, number of orders
4	Current condition	Oxygen device, is in ICU
5	Historical patient record	Previous admission, previous length of stay
6	Non-patient-specific data	Day of the week, ward census

Table 3: Data sizes (number of patient days) for training and testing sets across the nine patient-flow prediction tasks.

Prediction Task	**Training**	**Testing**
Discharge 24 hr	572,964	265,917
Discharge 48 hr	572,964	265,917
Enter ICU 24 hr	385,132	180,075
Leave ICU 24 hr	73,013	34,669
Enter ICU 48 hr	292,659	138,947
Leave ICU 48 hr	68,472	33,011
Expire 24 hr	572,964	265,917
Expire 48 hr	572,964	265,917
Mortality	572,964	265,917