Automatic ICD-10 Classification of Diseases from Dutch Discharge Letters

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Abstract: The international classification of diseases (ICD) is a widely used tool to describe patient diagnoses. At University Medical Center Utrecht (UMCU), for example, trained medical coders translate information from hospital discharge letters into ICD-10 codes for research and national disease epidemiology statistics, at considerable cost. To mitigate these costs, automatic ICD coding from discharge letters would be useful. However, this task has proven challenging in practice: it is a multi-label task with a large number of very sparse categories, presented in a hierarchical structure. Moreover, existing ICD systems have been benchmarked only on relatively easier versions of this task, such as single-label performance and performance on the higher "chapter" level of the ICD hierarchy, which contains fewer categories. In this study, we benchmark the state-of-the-art ICD classification systems and two baseline systems on a large dataset constructed from Dutch cardiology discharge letters at UMCU hospital. Performance of all systems is evaluated for both the easier chapter-level ICD codes and single-label version of the task found in the literature, as well as for the lower-level ICD hierarchy and multi-label task that is needed in practice. We find that state-of-the-art methods outperform the baseline for the single-label version of the task only. For the multi-label task, the baselines are not defeated by any state-of-the-art system, with the exception of HA-GRU, which does perform best in the most difficult task on accuracy. We conclude that practical performance may have been somewhat overstated in the literature, although deep learning techniques are sufficiently good to complement, though not replace, human ICD coding in our application.

1 INTRODUCTION

ICD-10 is the 10th edition of the International statistical Classification of Diseases, a repository maintained by the World Health Organization to provide a standardized system of diagnostic codes for classifying diseases (Atutxa et al., 2019; Baumel et al., 2018). These classification codes are vastly used in clinical research and are a part of the electronic health records (EHRs) in the University Medical Center Utrecht (UMCU), The Netherlands. Currently, the task of assigning classification categories to the diagnoses is carried out manually by medical staff. Manual classification of diagnoses is a labor-intensive process that consumes significant resources. For this reason, a number of systems have been proposed to automate the disease coding process with machine learning algorithms trained on data generated by medical experts.

The ICD coding task is challenging due to the use of free-text, multi-label setting of diagnosis codes and the large number of codes (Atutxa et al., 2019; Boytcheva 2011). Several attempts have been made to automatically assign ICD codes to medical documents, ranging from rule-based (Baghdadi et al., 2019; Boytcheva 2011; Koopman et al., 2015a; Nguyen et al., 2018) to machine learning approaches (Atutxa et al., 2019; Baumel et al., 2018; Cao et al., 2019; Chen et al., 2017; Du et al., 2019; Duarte et al., 2018; Karimi et al., 2017; Kemp et al., 2019; Koopman et al., 2015b; Lin et al., 2019; Liu et al., 2018; Miranda et al., 2018; Mujtaba et al., 2017;

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Mullenbach et al., 2018; Nigam et al., 2016; Pakhomov et al., 2006; Shing et al., 2019; Xie et al., 2019; Zweigenbaum and Lavergne, 2016). Rule-based methods have good performance when: (1) the terms to be categorized follow regular patterns, (2) the number of ICD labels is quite small, and (3) the task is limited to single-label classification (Atutxa et al., 2019). Unfortunately, with ICD classification these conditions seldom apply.

When a coded dataset is available and the range of the ICDs to label is large, machine learning based techniques have been successful (Atutxa et al., 2019; Baumel et al., 2018; Cao et al., 2019; Duarte et al., 2018; Miranda et al., 2018; Nigam et al., 2016). An approach for automatic matching of ICD-10 classification of Bulgarian free text (Boytcheva, 2011) was based on support vector machines (SVM). Zweigenbaum and Lavergne (Zweigenbaum and Lavergne, 2016) suggested a hybrid method for ICD-10 coding of death certificates based on a dictionary projection method and a supervised learning algorithm. They used the SNOMED (systemic nomenclature of medicine) and UMLS (unified medical language source) to set up the dictionary projection method. Koopman et al. (Koopman et al., 2015b) trained 86 SVM classifiers to identify cancers, first identifying the presence of a cancer by one classifier and later in a cascaded architecture classifying the cancer type according to ICD-10 codes using 85 different SVM classifiers.

Recently, deep learning methods boosted benchmarked results in various text mining studies (Gargiulo et al., 2018; Shickel et al., 2017; Subramanyam and Sivanesan, 2020; Xiao, 2018), including in automated ICD coding (Atutxa et al., 2019; Baumel et al., 2018; Du et al., 2019; Duarte et al., 2018; Karimi et al., 2017; Lin et al., 2019; Liu et al., 2018; Miranda et al., 2018; Mujtaba et al., 2017; Mullenbach et al., 2018; Nigam et al., 2016; Shing et al., 2019). Karimi et al. (Karimi et al., 2017) described a deep learning method for ICD coding, reporting on tests over a dataset of radiology reports. The authors proposed to use a convolutional neural network (CNN) architecture, attempting to quantify the impact of using pre-trained word embeddings for model initialization. The best CNN model outperformed baseline SVM, random forest, and logistic regression models using bag-of-words (BOW) representations. BOW is a vector representation method, demonstrating each document by one vector of features, i.e. words or combinations of words (n-grams). In (Nigam et al., 2016), recurrent neural networks (RNNs) have been applied to the multi-label classification task for assigning ICD-9 labels to medical notes, finding that an RNN with long short-term memory (LSTM) units shows an improvement over the binary relevance logistic regression model. Atutxa et al. (Atutxa et al., 2019) evaluated different architectures of neural networks for multi-class document classification as a language modeling problem. In their experiments, the results of ICD-10 coding using the RNN-CNN architecture outperformed alternative approaches. Baumel et al. (Baumel et al., 2018) investigated four models namely SVM, continuous-BOW (CBOW), CNN and hierarchical attention bidirectional gated recurrent unit (HA-GRU) for attributing multiple ICD-9 codes. The HA-GRU model achieved the best performance. A drawback of the existing literature is that the performance of different systems is difficult to compare, because the ICD classification task is often made easier by only considering the top-level "chapters" of the ICD hierarchy, or by only considering a single label as the output.

In the current application, we sought to implement a system to support human ICD coding of Dutch-language discharge letters at UMCU hospital. We explicitly aim at multi-label classification of three-digit ICD-10 codes, a task that is relatively difficult. Here, we present a benchmark of five state-of-the-art systems, all deep learning models, and two baseline methods based on BOW and pretrained embeddings with SVM. We aim to evaluate both the relative performance of these systems, which were all reported to outperform others, as well as the overall level of performance for potential support of human ICD coding, using a dataset of UMCU cardiology discharge letters.

2 METHODS

2.1 Case Study

Table 1 provides the characteristics of the dataset of discharge letters collected at the department of Cardiology in the UMCU. A hospital discharge letter is a medical text summary describing information about patient's hospital admission and treatments. UMCU cardiology discharge letters are coded based on the ICD-10 of cardiovascular diseases.

ICD-10 has a hierarchical structure, connecting specific diagnostic codes through *is-a* relations[1]. The hierarchy has several levels, from less specific to

[1] https://www.who.int/classifications/icd/

more specific. ICD codes contain both diagnosis and procedure codes. In this paper, we focus on diagnosis codes. ICD-10 codes consist of three to seven characters. For example, I50.0 shows the "congestive heart failure" disease, and I50 is its rolled-up code that shows the heart failure category in chapter IX: "Diseases of the circulatory system".

Table 1: UMCU dataset.

Feature	Description
Taxonomy	ICD-10
Language	Dutch
Nb of records	5,548
Nb of unique tokens	148,726
Avg nb of tokens / records	936
Nb of full labels	1,195
Nb of rolled-up labels	608
Label cardinality	4.7
Label density	0.0039
% labels with 50+ records	8.03%

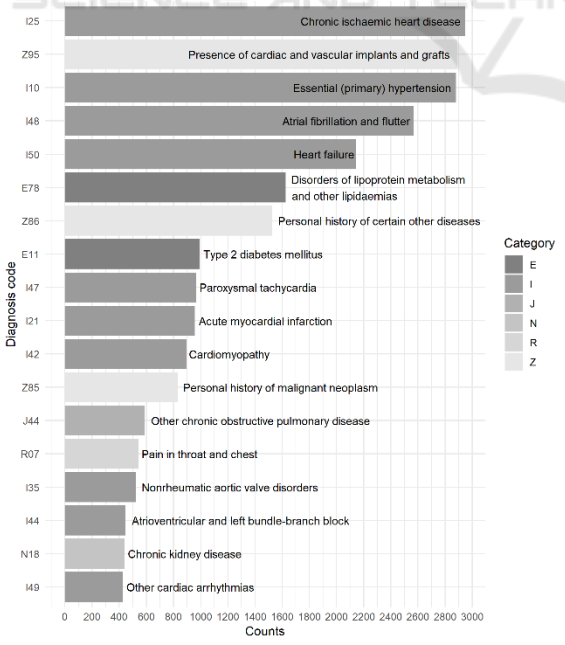


Figure 1: ICD rolled-up codes with more than 400 appearances in the UMCU dataset.

In Table 1, *cardinality* is the average number of codes assigned to records in the dataset. *Density* is the cardinality divided by the total number of codes. We filtered out ICD codes with less than 50 observations on their frequency. We note that there are approximately 64 frequent labels with at least 200 records in UMCU dataset. ICD codes in this dataset are mainly from chapters 4, 9, and 21. Figure 1 illustrates the ICD rolled-up codes with more than 400 appearance in the UMCU dataset. I25, Z95, I10, I48 and I50 are the top frequent rolled-up codes (at least 1000 counts) in our dataset.

In this study, we experimented with two versions of the label set: one with the 22 ICD chapters and one with the labels rolled up to their three-digit equivalent.

2.2 Preprocessing

Preprocessing the dataset of discharge letters comprised the following steps: (i) we anonymize the letters for legal and privacy reasons. We used *DEDUCE* (Menger et al., 2018), a pattern matching tool for automatic de-identification of Dutch medical texts; (ii) we use the *tm* (Feinerer, 2018) and *tidytext* (Silge and Robinson, 2016) packages in *R* to trim whitespace, remove numbers, and convert all characters to lower case; (iii) we tokenize all texts using the Python *scikit-learn* (Pedregosa et al., 2011) feature extractor, *gensim* library (Rehurek and Sojka, 2010) and the tokenizer in the *keras* library (Chollet et al., 2015).

2.3 Classification Methods

To employ the classification methods, we investigate two methods of vector representation:

- Bag-of-words (BOW; baseline)
- Word embeddings (average word vectors)

We use SVMs with each of the vector representations. We also assess the following neural network architecures for the automatic ICD coding of the Dutch discharge letters.

- CNN
- LSTM and BiLSTM
- HA-GRU

With these deep learning architectures, the first layer is the word embedding layer to represent patients' discharge letters. Hyperparameters of the models are formulated on the corresponding cited studies, while we tuned some based on the development set using a random parameter search.

2.3.1 Baseline: Support Vector Machines using Bag-of-Words

We use a one-vs-all, multi-label binary SVM classifier as the baseline learning method for ICD-10 classification. Baghdadi et al. (Baghdadi et al., 2019), Koopman et al. (Koopman et al., 2015a), Mujtaba et al. (Mujtaba et al., 2017) and Boytcheva (Boytcheva, 2011) applied SVM classifers for the task of ICD coding. We calculate the BOW representations using the preprocessed discharge letters. We also use the *tf-idf* vectorizer. The baseline model fits a one-vs-all binary SVM classifier with linear kernel for each ICD code against the rest of the codes.

2.3.2 Word Embeddings: Support Vector Machines using Average Word Vectors

Word embeddings (Mikolov et al., 2013a; Mikolov et al., 2013b) are vector representations for texts, representing words by capturing similarities between them (for a recent review on word embeddings in clinical natural language processing see Subramanyam and Sivanesan, 2020). Skip-gram and CBOW are two ways of learning word embeddings. Both approaches use a simple neural network to create a dense representation of words. The CBOW tries to predict a word (target word) from the words that appear around it (context), while skip-gram inverts contexts and targets, and tries to predict context from a given word. Baumel et al. (Baumel et al. 2018) examined the word embedding representations for ICD coding and achieved better scores comparing to the BOW representations. In this study, we train CBOW word embeddings in *gensim*. We set the vector dimensionality to 300, the window size to 5, and discard the words that appear only once in the training set. We then use the average of word embeddings to represent each discharge letter. These embeddings are then inputs to the classification model defined by the baseline SVM.

2.3.3 Convolutional Neural Networks

To be able to capture the order of the words as well as multi-word expressions, the next model we investigate is a CNN model. CNN has proven to be a good method for text classification and is also applied for the task of ICD coding (Baumel et al., 2018; Du et al., 2019; Karimi et al., 2017). The CNN represents texts at different levels of abstraction, essentially choosing the most salient n-grams. We perform one dimensional convolutions on the embedded representations of the words. The architecture of this model is very similar to the average word embeddings model, but instead of averaging the embedded words we apply a one dimensional convolution layer with filter *f*, followed by a max pooling layer. One dimensional convolution layers have proven effective for deriving features from sequences data (Du et al., 2019). In our experiments, we used the same embedding parameters as in the average word embeddings model. In addition, we set the number of filters to 128, and the filter size to 5. On the output of the max pooling layer, a fully connected neural network (two dense layers) was applied for the classification of the ICD-10 codes. The hidden dense layer contains 128 units and uses the *relu* activation function, and the output layer uses a *softmax* function to determine if the ICD code should be assigned to the letter. We also examine the CNN model with two convolution layers and two max pooling layers. In this setting, we employed a dropout layer after the first max pooling layer with rate 0.15.

2.3.4 Long Short-term Memory and Bidirectional Long Short-term Memory

Feedforward neural networks require fixed length contexts that need to be specified ad hoc before training (Chung et al., 2014). For automated ICD coding, this means that neural networks see relatively few preceding words when predicting the next one. RNNs avoid this problem by not consuming all the input data at once (Chung et al., 2014; Mikolov et al., 2010; Miranda et al., 2018). An RNN is a straightforward adaptation of the standard feed forward neural network to allow it to model sequential data (Hochreiter and Schmidhuber, 1997; Sutskever et al., 2011). At each timestep, the RNN receives an input, updates its hidden state, and makes a prediction (see Figure 2).

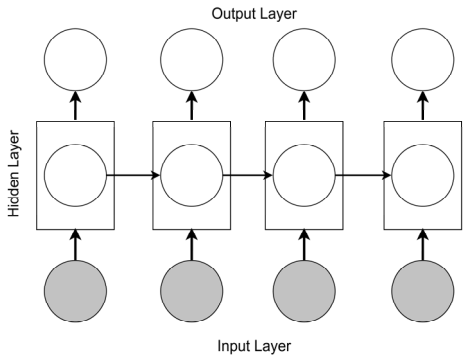


Figure 2: RNN architecture overview.

By using recurrent connections, information can cycle inside these networks for an arbitrarily long

time. LSTM (Hochreiter and Schmidhuber, 1997) models are variants of RNNs with memory gates that take a single input word at each time step and update the models' internal representation accordingly. RNN is extended to use LSTM units, simply replacing the nodes in hidden layers in Figure 2 with LSTM units.

To overcome the limitations in RNNs using all available input information in the past and future of a specific time frame, bidirectional LSTM (BiLSTM) model is introduced by Schuster and Paliwal (Schuster and Paliwal, 1997). The BiLSTM model as shown in Figure 3 is an extension of the RNN model using LSTM units, that combines two LSTMs with one running forward in time and the other running backward. Thus the context window around each word consists of both information prior to and after the current word.

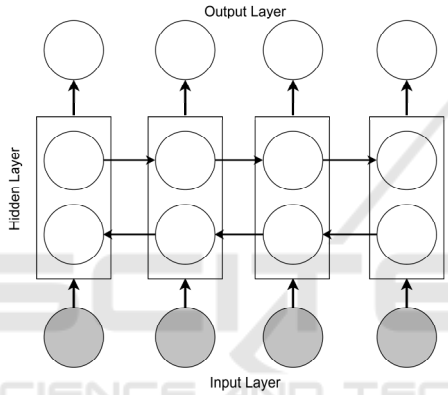


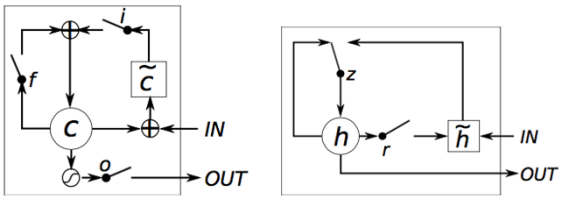
Figure 3: BiLSTM architecture overview.

RNN models have been applied extensively on textual data for natural language processing, as well as in the medical domain and ICD coding (Atutxa et al., 2019; Baumel et al., 2018; Du et al., 2019; Duarte et al., 2018; Miranda et al., 2018; Nigam, 2016).

In this study, we used the *keras* library to implement RNN models for automated ICD coding. We implemented LSTM and BiLSTM. We keep the same embedding parameters as in the average word embeddings model. We experimented with RNN models directly on the word sequence of all the discharge letters. However, as in previous studies on textual data, the fact that our data contains long texts creates a challenge for preserving the gradient across thousands of words. Therefore, we used dropout layers to mask the network units randomly during the training (Gal and Ghahramani, 2016). We set the number of hidden units in the RNN layers at 100. Dropout and recurrent dropout were added to avoid overfitting, both at a 0.2 rate. On the output of the recurrent layer, a fully connected neural network with the setting in CNN was applied for classification of the ICD-10 codes.

2.3.5 Hierarchical Attention Bidirectional Gated Recurrent Unit

GRU can be considered as a variation on the LSTM, that is a gating mechanism in RNN (Figure 4) aims to solve the vanishing gradient problem (Cho et al., 2014). Figure 4 compares the memory cell structures of the LSTM and the GRU.



(a) Long Short-Term Memory (b) Gated Recurrent Unit

Figure 4: (a) LSTM memory cell: c is the memory cell, $\tilde{c}$ is the new memory cell content. i, f and o are the input, forget and output gates, respectively. (b) h and $\tilde{h}$ are the activation and candidate activation, respectively. r and z are the reset and update gates.

The GRU has a slightly different architecture where it combines both the input (gate i) and forget (gate f) gates into a single gate called the update gate (gate z). Also, it merges the cell state and the hidden state. This results to a reduced number of parameters as compared to LSTM architecture and in some cases has resulted in faster convergence and a more generalized model (Duarte et al., 2018).

Baumel et al. (Baumel et al., 2018) proposed a HA-GRU model with label-dependent attention layer to classify diseases codes. Since the GRU model is too slow when applied to long documents as it requires as many layers as of the document length, they developed a HA-GRU to be able to handle multi-label classification. In this paper, we implemented the HA-GRU (Baumel et al., 2018) for the ICD-10 classification of cardiovascular diseases. The HA-GRU is a hierarchical model with two levels of bidirectional GRU encoding. The first bidirectional GRU operates over tokens and encodes sentences. The second bidirectional GRU encodes the entire document, applied over the encoded sentences. In this architecture, each GRU is applied to a much shorter sequence compared with a single GRU.

We applied the HA-GRU model using the *Dynet* deep learning library (Neubig et al., 2017) for ICD coding. The attention mechanism in the HA-GRU has the advantage that each label is invoked from different parts of the text. This allows the model to

focus on the relevant sentences for each label (Choi et al., 2016). As for our previous deep learning models, we kept the same embedding parameters in the average word embeddings model. We used a neural attention mechanism with 128 hidden units to encode the bidirectional GRU outputs. The first GRU layer encoded the sentences into a fixed length vector. Then the second bidirectional GRU layer uses 128 attention layers to generate an encoding specific to each class. Finally, we applied a fully connected layer with *softmax* activation.

2.4 Evaluation Measures

Two evaluation measures are considered: *accuracy*, and *F1*. In the single-label classification scenario, accuracy is the fraction of correctly classified discharge letters to the whole collection of discharge letters. *F1* is the harmonic mean of the fraction of positively coded discharge letters and the fraction of actual discharge letters that are positively classified. Accuracy is a simple and intuitive measure, yet *F1* takes both false positives and false negatives into account. *F1* score is a good measure for the ICD classification task as this task has a large number of catergories and usually contains imbalanced data. To evaluate the multi-label classification performance, we use the following sample-based metrics for accuracy and *F1*:

$$Accuracy = \frac{1}{n}\sum_{i=1}^{n}\frac{|Y_i \cap Z_i|}{|Y_i \cup Z_i|}$$

$$F1 = \frac{1}{n}\sum_{i=1}^{n}\frac{2|Y_i \cap Z_i|}{|Y_i| + |Z_i|}$$

Where:

$$|Y_i| = set\ of\ predicted\ ICD\ codes$$
$$|Z_i| = set\ of\ ground\ truth\ ICD\ codes$$
$$n = number\ of\ sample$$

We evaluate our experimental results in two scenarios: (1) single-label prediction: a model assigns one label to each patient letter; and (2) multi-label prediction: a model assigns multiple labels per patient letter.

3 RESULTS

We used the *train-test* split function from the model selection module implemented in the *scikit-learn* library to randomly split the dataset into train and test sets. We separate 25% of the data as the test set and the rest as for training. To evaluate the proposed models on the dataset of cardiovascular discharge letters, we conducted the following experiments. In the first setting, we trained the models on the training set separately using chapters as the labels. All models were evaluated on the test set according to the evaluation measures. In the second setting, we only considered the rolled-up ICD-10 codes to their three-digit codes.

3.1 Single-label Prediction Performance

Table 2 presents the obtained results for each model for both experimental settings (ICD chapters and rolled-up ICD codes) on the single-label scenario. In this case, a single code is predicted for every testing patient's letter. Bolded values in Table 2 indicate the best-performing model for each category.

Table 2: Single-label performance: accuracy and *F1* score on two settings (ICD chapters and rolled-up ICDs) for the models when trained on the UMCU discharge letters.

	ICD chapters		**Rolled-up ICD codes**	
	Accuracy	F1	Accuracy	F1
BOW SVM (baseline)	54.8	54.8	14.1	14.1
Average word embeddings (SVM)	54.9	**54.9**	18.2	18.2
CNN(1conv)	57.3	49.2	22.1	17.4
CNN(2conv)	59.2	54.0	22.5	18.1
LSTM	73.0	38.1	19.1	14.1
BiLSTM	**73.9**	41.3	23.2	**21.8**
HA-GRU	72.5	43.5	**23.7**	19.8

BiLSTM gives the best accuracy in the ICD-10 chapters i.e. 73.9%, while the SVM classifier using the average word embedding has the highest *F1* score of 54.9%. HA-GRU gives the best accuracy results in the rolled-up ICD-10 setting i.e. 23.7%, while the BiLSTM model has the highest value in *F1* score with 21.8%.

Table 2 shows that the difference between the results of the rolled-up ICDs and the ones for the chapters is considerable. This is expected given the large number of the rolled-up ICD codes comparing to the number of the ICD chapters. We note that the SVM classifier is still competitive with the deep learning architectures in our application.

3.2 Multi-label Prediction Performance

Table 3 presents the results for the multi-label task. In this scenario, corresponding to the prediction made by the classification models, every ICD label that presents a probability above a defined threshold is considered as a predicted output code. We assign the threshold in such a way that the label cardinality for the test set is in the same order as the label cardinality in the training set. Bolded values in Table 3 indicate the best-performing model for each category.

Table 3: Multi-label performance: accuracy and *F1* score on two settings for the models when trained on the UMCU discharge letters.

	ICD chapters		**Rolled-up ICD codes**	
	Accuracy	F1	Accuracy	F1
BOW SVM (baseline)	**62.3**	**74.3**	11.6	20.2
Average word embeddings (SVM)	60.4	72.6	12.5	**25.8**
CNN(1conv)	38.1	46.3	09.0	16.1
CNN(2conv)	42.2	49.0	12.4	19.1
LSTM	53.4	59.6	11.7	18.8
BiLSTM	55.0	70.1	13.7	23.2
HA-GRU	56.8	71.3	**15.9**	24.3

For the multi-label scenario, the SVM classifier gives the best results in *F1* score for the chapter labels and for the rolled-up codes with values equal to 74.3% and 25.8%, respectively. The former is the *F1* score for the BOW representation and the latter is the one for the word embeddings. In terms of accuracy, when the number of ICDs to be coded are large the HA-GRU has the best results with 15.9%.

By comparing Table 2 and Table 3, it is notable that the difference between the results on chapters and the results on the rolled-up codes is more consistent when we applied the CNN models using our case study. With regard to the single-label task, CNNs have the highest values of *F1* of about 54% and 18.1%, respectively, for the ICD chapters and the rolled-up codes. For the multi-label task these values are equal to 49% and 19.1%.

4 DISCUSSION

Automated ICD-10 classification can potentially save valuable time and resources in a clinical setting. In this study, we compared several state-of-the-art ICD coding systems on a dataset of Dutch-language discharge letters.

Classification performance of the 22 higher-level codes is very promising, especially when only a single label is considered. For this version of the task, RNNs (LSTM, BiLSTM, and HA-GRU) showed good performance, as reported in the literature. However, in many practical applications, including our own, a lower level of classification is required, and each letter receives multiple ICD codes. For this version of the task, performance was somewhat disappointing, and state-of-the-art systems failed to outperform the baseline BOW SVM with linear kernel. An exception is the HA-GRU system, which had the best accuracy, and showed an *F1* performance close to that of the baseline.

While none of the systems were able to achieve a level of classification accuracy on the most difficult versions of the ICD classification task that would allow them to completely *replace* a human coder, they do show performance that is good enough to *suggest* codes in an interaction with the human. Future work could investigate the performance of human-in-the-loop systems, for example by employing active learning.

A question that may arise is whether machine learning could be supplanted with a rule-based system. This is possible for the higher-level codes using information retrieval and natural language processing methods (Pakhomov et al., 2006). However, developing rule-based systems with manually coded rules is tremendously difficult for the lower levels of ICDs. There are a large number of ICD codes in lower levels of the ICD hierarchy, and a small number of observations per ICD code. Deep learning-based models are useful here because they obviate the need for manual feature engineering (Atutxa et al., 2019). For this reason, we believe machine learning remains an attractive alternative to rule-based systems.

A second consideration is the question of model interpretability. Here, the deep learning models that form the current state of the art are especially challenging in this regard, and this may be a point in favor of “simpler” methods such as BOW: the more opaque the model, the less willing clinicians may be to accept artificial intelligence recommendations. Although it is not clear whether this is a problem for ICD-10 coding specifically, future work could focus

on developing more interpretable systems or generic prediction explanation methods that mitigate this problem. Moreover, such systems could be very powerful when combined with a human-in-the-loop approach, by allowing the human to learn how text can be written to teach the correct code to the system.

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