Semi-self-supervised Automated ICD Coding

Anonymous ACL submission

Abstract

Clinical Text Notes (CTNs) contain physicians' reasoning process, written in an unstructured free text format, as they examine and interview patients. In recent years, several studies have been published that provide evidence for the utility of machine learning for predicting doctors' diagnoses from CTNs, a task known as ICD coding. Data annotation is time consuming, particularly when a degree of specialization is needed, as is the case for medical data. This paper presents a method of augmenting a sparsely annotated dataset of Icelandic CTNs with a machine-learned data imputation in a semi-self-supervised manner. We train a neural network on a small set of annotated CTNs and use it to extract clinical features from a set of un-annotated CTNs. These clinical features consist of answers to about a thousand potential questions that a physician might find the answers to during a consultation with a patient. The features are then used to train a classifier for the diagnosis of certain types of diseases. We report the results of an evaluation of this data augmentation method over three tiers of information that are available to a physician. Our data augmentation method shows a significant positive effect, which is diminished when an increasing number of clinical features, from the examination of the patient and diagnostics, are made available. We recommend our method for augmenting scarce datasets for systems that take decisions based on clinical features that do not include examinations or tests.

1 Introduction

When a patient consults a physician, communication is created in the patient's medical records. The physician notes down the patient's signs, symptoms, results of physical examination, the clinical thinking process, and if any diagnostic tests are warranted – in a free text format known as a Clinical Text Note (CTN). Then, the physician saves the diagnoses, using the International Classification of Diseases (ICD) code, that they made during the consultation. Thus, each CTN contains free text, from which clinical features can be extracted, in addition to the ICD classification code.

Previous work has shown the benefits of training machine learning classifiers on clinical features for automated ICD coding (Liang et al., 2019; Ellertsson et al., 2021; Zhang et al., 2020; Pascual et al., 2021; Kaur et al., 2021; Blanco et al., 2021). Ellertsson et al. (2021) hand-annotated features in 800 CTNs and trained a classifier to predict ICD codes for one of four types of primary headache diagnoses. Liang et al. (2019) hand-annotated a significantly larger set, i.e. about 6,000 CTNs, for the purpose of training a classifier to predict various types of diseases, i.e. 55 ICD codes in total. Additionally, Liang et al. developed a clinical feature extraction model (CFEM), for the purpose of automatically extracting features from the CTNs.

On its own, the CFEM is beneficial because it could solve the common clinical problem of getting a quick and comprehensive overview of a patient, when meeting a clinician for the first time. A clinician could search a patient's medical history with a question such as "Has the patient ever had a colonoscopy?". The ICD classifiers have, on the other hand, the potential of being integrated into a Clinical Decision Support System (CDSS), where they could, for example, predict if a physician should order an MRI for a patient when presented with a particular symptom, what kind of blood tests are warranted, or any other diagnostic test for that matter.

Generally, machine learning systems require large quantities of training data (Hlynsson et al., 2019) and ICD classifiers are no exception. In order to develop a high accuracy ICD classifier, without annotating large amount of CTNs, we experiment with a method of: 1) annotating a small subset of the CTNs with question-answer pairs which are used for training the CFEM, and then 2) use the

trained feature extractor to extract clinical features from a larger dataset of CTNs for training the classifier to predict one out of six ICD codes[1]. We call this method semi-self-supervised because it lies at the intersection of 1) semi-supervised learning, which combines a small amount of labeled data with large amounts of unlabeled data (Van Engelen and Hoos, 2020) and 2) self-supervised learning, which learns to predict missing parts of inputs (Mao, 2020).

In prior work on ICD coding, classifiers are trained on discharge summaries, after the patient has left the clinic (Liang et al., 2019; Zhang et al., 2020; Pascual et al., 2021; Kaur et al., 2021; Blanco et al., 2021). We instead focus on evaluating our model on stages in the primary health care pipeline where the recommendations of machine learning models would be the most effective. We thus introduce a novel three-tiered evaluation system that is designed to mirror the circumstances where ICD classification methods would actually be used and we evaluate our semi-self-supervised data augmentation method on these three tiers: 1) before the patient meets a physician, 2) after the physician performs the patient examination, and 3) after the physician has ordered diagnostic tests.

Our evaluation results show that the data augmentation method has a significant benefit for tier 1, i.e. before the patient meets a physician, but not for the other two.

2 Related Work

Liang et al. (2019) frame the problem of clinical feature extraction from CTNs as a question-answering task. Every clinical feature mentioned in a given CTN is marked, as well as the start and the end of the text span referring to a given clinical feature. A question is saved in the context of the text span, which contains the answer to that specific question. For example, given the text span "the patient has a fever", the question "Does the patient have a fever?" is saved with a binary value of 1. Out of 1.3 million CTNs from a single institution in China, Liang et al. annotated about 6,000 CTNs for training a CFEM, based on a Long Short-Term Memory (LSTM) network (Hochreiter and Schmidhuber, 1997) enriched with word embeddings. The feature extractor is trained on a batch of (CTN, question, text span) tuples as input with the goal of optimizing for the text span that contains the corresponding answer to the question in the given CTN. Thereby, the model learns to extract relevant clinical features from the questions put forward in the context of the CTN. Liang et al. used the CFEM to extract features from the whole set of un-annotated CTNs. The extracted features were then used to train a classifier, based on multi-class logistic regression, to predict an ICD code from a set of 55 codes.

Ellertsson et al. (2021) hand-annotated clinical features (in a similar manner as Liang et al.) in 800 CTNs from a common medical database of all primary care clinics in Iceland. Each CTN had an accompanying ICD code for one of four types of headache diagnoses. The resulting features (text spans) were then used to train a Random Forest classifier, for predicting one of the four possible ICD codes. Furthermore, they performed a retrospective study where the classifier was shown to outperform general practitioners on the four types of headache diagnostics.

In this paper, we expand upon the work of Ellertsson et al. The main difference between our work and theirs can be summarized as follows:

- We do not compare our ICD classifier to general practitioners.
- We hand-annotate questions-answers pairs in 2,422 CTNs, which includes a larger number of ICD codes, 42 in total (see Table 4 in the Appendix).
- Using the hand-annotated CTNs, we train CFEMs, based on Transformer models (Vaswani et al., 2017), for extracting clinical features, and compare them to a couple of LSTM models. These feature extractors are used to extract features from un-annotated CTNS as well as annotated CTNs.
- We perform a three-tiered evaluation of our classifiers on six of the ICD codes for pediatric (under 18) patients (see Table 5 in the Appendix).

Transformer-based models have rapidly become a popular choice for automated ICD coding. These models have been trained on CTNs in a fully end-to-end manner (Zhang et al., 2020; Pascual et al., 2021; Kaur et al., 2021; Blanco et al., 2021). A

[1]The ICD classes were chosen by doctors according to their perceived usefulness.

		Training Set	Validation Set	Test Set	Total
Adults	Total size	1700	199	220	2119
	Mean Age ± Std	45.33 ± 17.91	43.54 ± 17.86	44.24 ± 17.92	
	Min Age – Max Age	18.01 – 94.43	18.04 – 86.75	18.17 – 93.72	
Children	Total size	237	33	33	303
	Mean Age ± Std	10.01 ± 5.87	10.32 ± 5.82	9.39 ± 6.24	
	Min Age – Max Age	0.17 – 17.99	0.97 – 17.85	0.21 – 17.85	

Table 1: **Training data split statistics for the clinical feature extraction model.** The adult sets are 63% female and the child sets are 64% female. The different sizes of the adult validation and test sets came by to enforce a constraint of an equal proportion of notes corresponding to each ICD code within each set.

drawback of this approach is that physicians will often write down their hypothesized diagnoses which injects a serious bias to the data, a problem that our approach, of using one model for clinical feature extraction and another for clinical prediction, circumvents. For example, a fully end-to-end machine learning model might learn to associate the qualitative comment by a physician "the patient probably has a migraine without aura" in a patient with a migraine-without-aura ICD code. Our method avoids this by creating a bottleneck of information, where only specific questions are being answered.

Our approach also opens the door for interpreting the results of the ICD classifier, as the importance of each input feature to the classifier can be visualized, for example by portraying input coefficients in the case of linear models (e.g. logistic regression) or plotting other interpretability metrics, such as SHAP values (Lundberg and Lee, 2017).

3 Approach

3.1 Data and annotation

We use the dataset from the same source as Ellertsson et al. (2021), i.e. from the Primary Health Care Service of the Capital Area (PHCCA) in Iceland. The dataset consists of 1.2 million CTNs, written in Icelandic, from 200 thousand unique patients that were collected in clinical consultations taking place from January 2006 to April 2020. Physicians are instructed not to write anything that can uniquely identify their patients in the notes, but we also used a combination of a parsing system for Icelandic (Þorsteinsson et al., 2019) as well as a regex command to remove any personally identifiable information, such as names, personal identification numbers and phone numbers. This dataset contains CTNs that have an associated ICD code, but consist otherwise of unstructured text from which clinical features can be extracted.

In the same manner as described by Ellertsson et al., we reduced the full dataset by applying a filter which only keeps notes that contain any word from a medical keyword dictionary. From this reduced dataset, we randomly selected 2,422 notes which were manually annotated by a physician[2], resulting in question-answer pairs as described in Section 2.

As an example annotation, for a CTN containing the text "the patient is not coughing", one clinical feature is the pair consisting of the question "does the patient have a cough?" and the binary-valued answer "0", with the corresponding text span "not coughing". Some answers are continuous-valued, such as for the question "what is the patient's blood pressure?".

The number of clinical features that we use to train the extraction model to output is 942. There is typically a heavy class imbalance for each feature, where the binary questions have on average a 0.75 positive answer ratio, with a standard deviation of 0.2. The reason for this sweeping class imbalance is that physicians generally only ask questions that are relevant and with an affirmative answer.

For our three-tiered classifier evaluation, we define three strict subsets of these features, as described in Section 3.6. Each question is also paired with another binary variable which indicates whether an answer to that question can be found in the CTN or not.

The dataset is split into adults, that are 18 years old or older, and children. Within each age group, 80% of the dataset is allocated for training, 10% for development/validation, and hold out 10% for final testing (see Table 1). The split is stratified to ensure that each set has an equal proportion of sexes and ICD codes.

[2]The annotator is a white Icelandic male physician in his thirties, specializing in general practice / family medicine.

3.2 Pre-trained Transformer-based models

We compared four existing Transformer-based models in our experiments, based on the ELECTRA (Clark et al., 2020) and RoBERTa (Liu et al., 2019) architectures. We evaluated an ELECTRA-small[3], ELECTRA-base[4] and two RoBERTa-base models[5,6] (consisting of 14M, 110M and 125M parameters, respectively). All models have been pre-trained on the Icelandic Gigaword Corpus (IGC) (Steingrímsson et al., 2018), which consists of approximately 1.69B tokens from genres such as news articles, parliamentary speeches, novels and blogs. For one of the RoBERTa models, which we refer to as RoBERTa+, the IGC was supplemented with texts obtained from online sources, increasing the size of the pre-training corpus to 2.7B tokens. The RoBERTa models were pre-trained for 225k steps with a batch size of 2k. Otherwise, all models were pre-trained using default settings. The pre-training process and additional training data for the RoBERTa models is described in further detail by Snæbjarnarson et al. (2022).

3.3 LSTM architectures

For a baseline comparison, we created two LSTM models. The first one (LSTM 1) tokenizes and trains the embeddings from scratch, whereas the second one (LSTM 2) pre-processes the inputs with GloVe (Pennington et al., 2014) embeddings.

3.3.1 LSTM 1

The model splits up the tokenized input into question and content parts. The content part gets a 256-dimensional embedding and the question gets a 32-dimensional embedding. Each embedding is then passed to its own, uniquely parameterized two-layer bi-directional LSTM model, where each layer has 256 units.

The outputs from those two parts are then concatenated and used to 1) train a set of dense networks, where one is tasked with predicting whether an answer to the question can be found in the text and, if yes, the other dense network predicts the probability of the answer being affirmative (in the case of binary questions), and 2) predict the start and end indices of the tokens that mark the span of the answer in the context part.

3.3.2 LSTM 2

LSTM 2 has the same architecture as LSTM 1, except there is no embedding layer and the inputs have been processed by a pre-trained GloVe model. The GloVe embeddings[7] where pre-trained on the IGC.

3.4 Clinical feature extraction models

We fine-tuned the four Transformer-based models, mentioned in Section 3.2, on the hand-annotated data in order to develop a CFEM. The fine-tuning was carried out in the following manner: starting with the pre-trained transformers weights, the top layer was replaced with a randomly initialized network, and the whole system was then trained end-to-end for question-answering. We also trained the two LSTM models described in Section 3.3 from scratch for a CFEM comparison.

Each model learns to output the answer span for each question[8] as well as the probability of the answer being affirmative for binary-valued questions. The Transformer-based models were defined and trained using the Transformers (Wolf et al., 2019) and PyTorch libraries (Paszke et al., 2019) and the LSTM models were defined and trained using TensorFlow (Abadi et al., 2016).

3.5 Semi-self-supervised learning

Once our CFEMs were trained, we saved their outputs over all the CTNs (i.e. 2,422 annotated CTNs used for training and 750 randomly selected unannotated CTNs) to disk. The outputs define the matrix of independent variables X which is, along with the dependent variable array y of ICD codes, used to train our logistic regression ICD classifier (implemented in scikit-learn (Pedregosa et al., 2011)).

CTNs require expertise to interpret, which results in a high cost when labelling medical datasets. This is especially true for AI researchers that are working with a language with much fewer resources than English (Blanco et al., 2021), such as Icelandic.

[3] https://huggingface.co/jonfd/electra-small-igc-is. CC-BY-4.0 license.

[4] https://huggingface.co/jonfd/electra-base-igc-is. CC-BY-4.0 license.

[5] https://huggingface.co/mideind/IceBERT. AGPL 3.0 license.

[6] https://huggingface.co/mideind/IceBERT-igc. AGPL 3.0 license.

[7] https://github.com/stofnun-arna-magnussonar/ordgreypingar_embeddings/tree/main/GloVe

[8] If the question is not answered in the CTN, the model outputs an impossible span in the text, which is technically implemented as starting at the 0^{th} token (a special "start" token) and the 1^{st} token of the proper context.

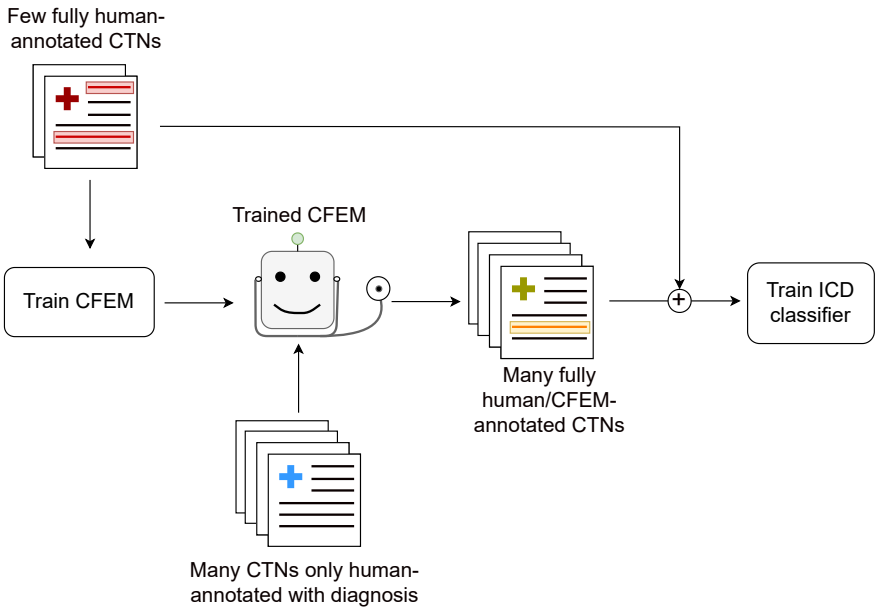

Figure 1: **Leveraging a Sparsely Annotated Dataset.** Our clinical feature extraction model learns to mark text spans (clinical features), containing an answer to a set of given clinical questions, from CTNs in which answer spans have been hand-annotated. The feature extractor is then used to extract answer spans – given the same set of questions – from a large set of CTNs that have diagnoses (ICD codes), but no marked answer spans. Finally, the extracted answer spans are used to train the ICD classifier. In this way, we make full use of a large set of CTNs that is only partly annotated and combine it with a much smaller set of human-annotated CTNs to learn automated ICD coding.

In our project, we have a large collection of CTNs, each of which is marked with a doctor's diagnosis, but does not contain answer spans for the set of questions for our clinical features. We input the un-annotated CTNs to a CFEM, that is trained on a much smaller subset of the data, to take advantage of the supervisory signal offered by the ICD code of each un-annotated CTN. This step keeps the interpretable clinical features and removes potential bias from the CTNs. This set of CTNs with imputed clinical feature values is then combined with our "gold standard" set of annotated CTNs, and both are used for training the ICD classifier (see Figure 1).

3.6 Three-tiered evaluation

To simulate the different stages of a physician's evaluation of a patient in real clinical circumstances, we limit the number of features that are available to the classifier at each stage:

- **Tier 1**: Before a patient meets with a physician. This includes the patient's main complaint, history, symptoms, and vital signs (420 features).
- **Tier 2:** After the patient has been examined by a physician (582 features).
- **Tier 3:** After results from diagnostics are available (608 features).

The full list of features is provided in the Appendix: Table 6 and Table 7 for tier 1, which are features that the patient could self-report. Tables 8 and 9 show the features for tiers 2 and 3, respectively. After tiers 2 and 3, decisions need to be taken regarding what further tests need to be ordered, for example imaging.

Note that our system could fit into a triage context at tier 1. The patient could fill out an online questionnaire and get recommendations depending on the results, for example, to go to the emergency room, to go the general physician, or maybe just rest at home with a set of self-care instructions.

4 Results and Discussion

4.1 Clinical feature extraction model training

The CFEMs were trained over three epochs on the subset of hand-annotated CTNs (see Table 1). For the ELECTRA-base and RoBERTa-base transformers, each epoch took approximately eight hours on Cloud TPU v3 with eight cores, and half that for

ELECTRA-small. The training took approximately three hours for each epoch for the LSTMs.

The RoBERTa+ model, which is pre-trained on the largest corpus, achieves the best results for all three metrics that we monitor (see Table 2): a span-based F_1-score, to evaluate the question-answering portion of the models, and the Matthews correlation coefficient (MCC) (Matthews, 1975; Chicco and Jurman, 2020) for the binary-valued clinical features (Binary MCC) and for predicting whether the question is answered in the text (Impossible MCC).

We chose the MCC metric because it is appropriate for imbalanced data (Chicco, 2017) (see discussion of our data in Section 3.1) and it offers a suitable combination of the four confusion matrix metrics: true positives, true negatives, false positives and false negatives.

Note in Table 2 that the high F_1-scores are due to the fact that most questions were correctly predicted to be not answered in any given context. This could be due to the fact that the 15.8 GB corpus, which was used to train RoBERTa+, contains 33 MBs of medical texts. Although this is not a large proportion, it could be enough for the model to have learned transferable representations of medical vocabulary.

To our surprise, the ELECTRA-base model was outperformed by RoBERTa (both are trained on equal-sized corpora), even though ELECTRA has, previously, been shown to outperform RoBERTa on question-answering tasks (Clark et al., 2020).

The LSTM variation whose inputs were not pre-processed by a pre-trained GloVe model (LSTM 1) performed better according to the MCC metrics (but slightly worse according to the F_1-score) than the other (LSTM 2). We hypothesize that it is due to the fact that the pre-trained embeddings are not trained with any tokenization, but rather on whole words. The free-text style of doctor's notes can include words or abbreviations that are not defined for the GloVe embeddings.

4.2 ICD classifier training

4.2.1 Transformer vs. LSTM

After training and evaluating the CFEMs, we validated the data augmentation scheme described in Section 3.5. We used the best-performing models from each category, RoBERTa+ and LSTM 1, to extract the clinical features from the children's notes[9]. These features, along with their associated ICD codes, were then used to train the classifier.

	F_1	Binary MCC	Imp. MCC
RoBERTa+	**0.993**	**0.846**	**0.872**
RoBERTa	0.991	0.780	0.823
ELECTRA-base	0.987	0.656	0.729
ELECTRA-small	0.982	0.553	0.650
LSTM 1	0.975	0.331	0.327
LSTM 2	0.979	0.313	0.257

Table 2: **Feature extraction model evaluation results.** Question-answering metrics and evaluation results for each clinical feature extraction model on the test set.

Table 3 shows the diagnostic metrics of the classifier for tier 3 depending on the feature extractor. Using RoBERTa+ yielded a higher weighted average for all diagnostic metrics compared to LSTM 1.

4.2.2 Qualitative analysis

To verify that the relationship between our features and the outputs of our models matches our clinical intuition, we use SHAP (Shapley additive explanation) values (Shapley, 1953) to show the impact of each feature in the prediction of our logistic regression classifier, trained on the features in tier 3 extracted by RoBERTa+.

The feature importance plot is shown in Figure 2. We see, for example, that the top four features are headache-related features and contribute to classifying a CTN as Tension-type headache, migraine with- and without aura. The two top features after that involve the doctor doing a physical examination of the patient's lung and contribute to predicting whether the patient has pneumonia or bronchitis. The sixth most impactful feature is then the result of an examination of the patient's ear, the result of which contributes to the diagnosis of Otitis media (a disease of the middle ear).

4.2.3 Data augmentation experiment

In the next set of experiments, we investigated the effect of augmenting a data set consisting of 303 human-labeled childrens's CTNs with a varying number of machine-labeled children's CTNs for the purpose of training an ICD classifier.

We trained logistic regression classifiers using 5-fold cross-validation over the whole children set. Each classifier had L1 regularization with the in-

[9]Due to time constraints, our evaluation of the data augmentation method is limited to only using the children CTNs.

Condition	*RoBERTa+* F_1-score	MCC	TPR	TNR	*LSTM 1* F_1-score	MCC	TPR	TNR
Migraine without aura	0.40	0.36	0.33	0.97	0.00	0.00	0.00	1.00
Migraine with aura	0.67	0.70	0.50	1.00	0.40	0.36	0.33	0.97
Tension-type headache	0.94	0.89	1.00	0.88	0.86	0.73	1.00	0.71
Otitis media, unspecified	0.00	0.00	0.00	1.00	0.57	0.60	1.00	0.90
Bacterial pneumonia	0.86	0.83	1.00	0.93	0.75	0.75	0.60	1.00
Acute bronchitis	1.00	1.00	1.00	1.00	0.33	0.29	0.25	0.97
Weighted average	**0.81**	**0.78**	**0.85**	**0.85**	0.64	0.56	0.70	0.70

Table 3: **Detailed ICD classification metrics.** Per-class metrics for clinical diagnosis prediction when a logistic regression classifier is trained on features extracted from CTNs by either our RoBERTa+ transformer or the baseline LSTM 1 model. MCC is the Matthews correlation coefficient, TPR is the true positive rate and TNR is the true negative rate.

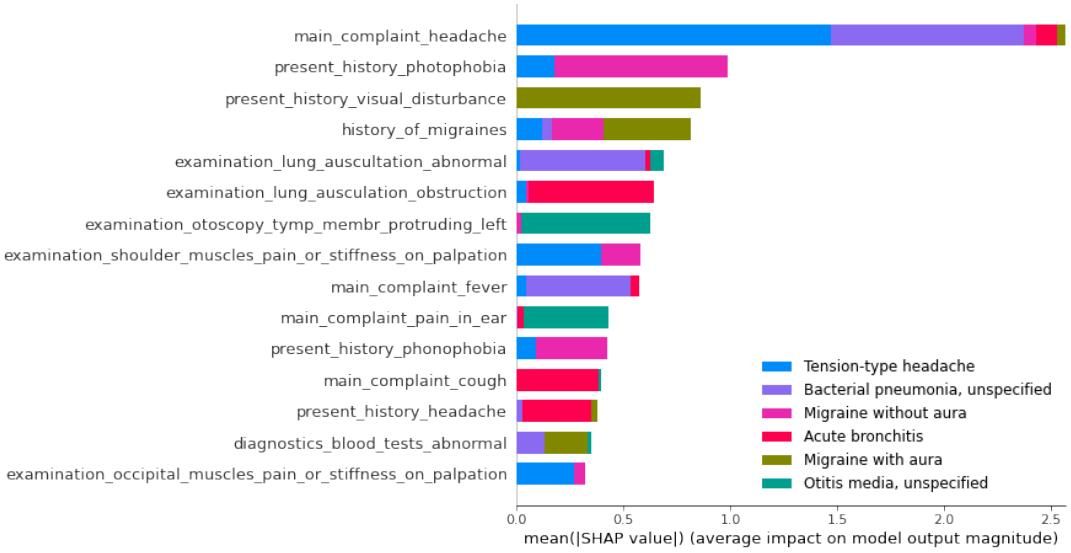

Figure 2: **Feature importance plot.** The features are scored by their SHAP values. The size of the colored bar in each feature's row indicates the contribution of that feature to predicting the disease with the corresponding color.

verse regularization parameter of $C = 0.2$, which was found to give good classification performance in early tests. We chose not to do hyper-parameter tuning as the scope of this project is not to get the best possible classifier in this context, but rather investigate the data augmentation and the three-tiered evaluation. The results are shown in Figure 3.

There is a clear benefit for using the data augmentation method in tier 1, but it looks rather harmful for tiers 2 and 3. We hypothesize that this is due to the fact that the classifiers place a high importance on the outcome of examination (tier 2) and test (tier 3) related features, making the classifiers more sensitive to prediction errors for these feature.

5 Conclusions and Future Work

Our results show that training a CFEM on a small annotated subset of CTNs and use it to extract features from a larger, un-annotated dataset can increase the performance of an ICD classifier. However, the effect is only positive and significant in the context before a patient has been examined by the physician.

A future line of work is to further validate different classifiers by performing prospective studies which allow us to get insight into how the classifier performs in real clinical situations. This can be done by integrating the classifier into a CDSS, where a patient can log into a secure portal, at home or at a medical institution, and answer targeted questions regarding their symptoms. The CDSS could build a list of differential diagnoses, recommend further diagnostics based on the patients symptoms, and then write out the CTN for the clinician. This does not disturb the clinical workflow, saves time for medical staff and poten-

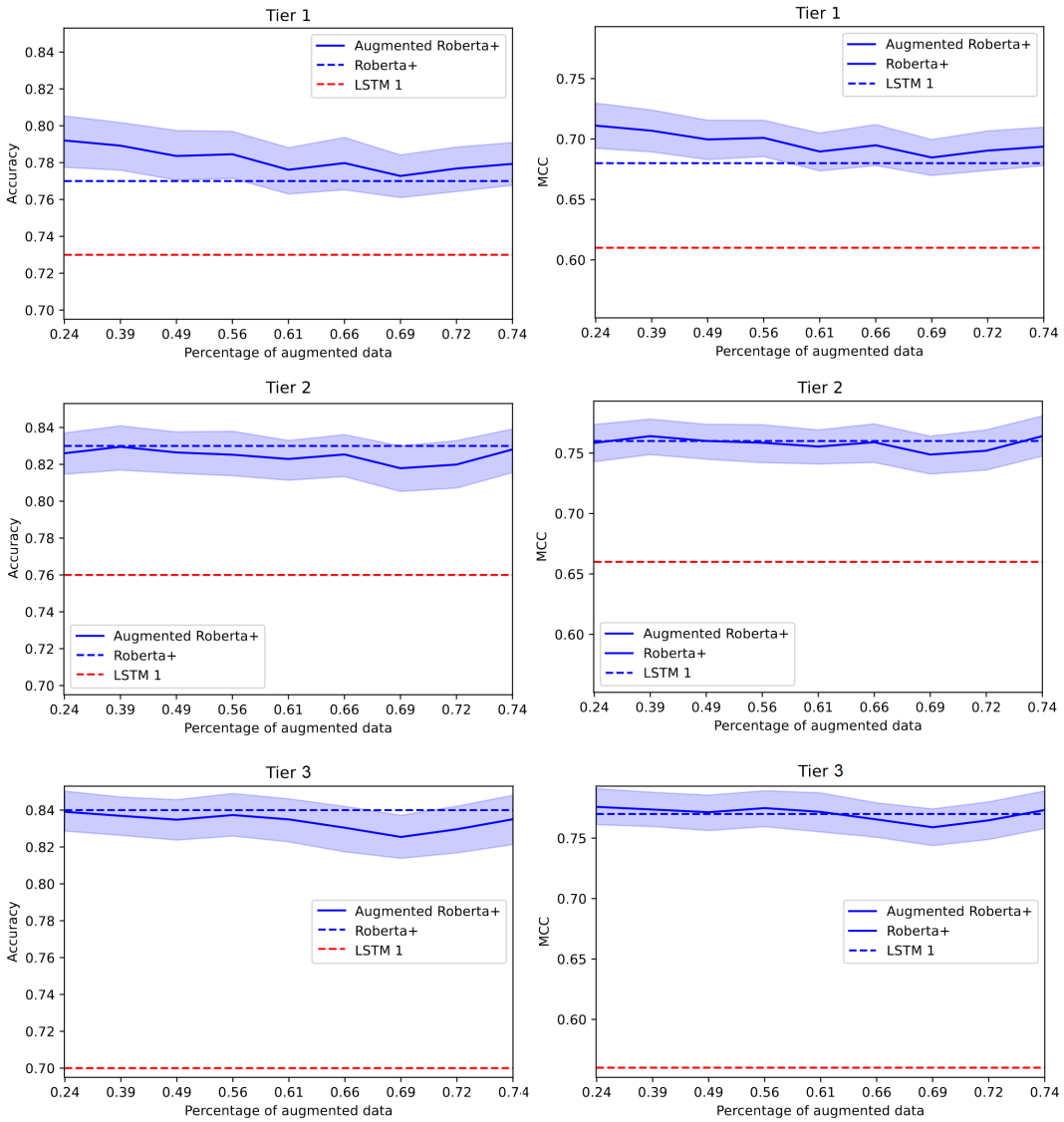

Figure 3: **Data Augmentation Results.** Each classifier is trained on fixed set of hand-annotated clinical features, in addition to a varying number of features automatically extracted by the RoBERTa+ model, i.e. machine-labeled features. There are 237 hand-annotated CTNs in each training set and each step along the x-axis adds 75 machine-labeled CTNs. Each point in the augmented curves shows the cross-validated metrics (accuracy in the left column and MCC in the right column) averaged over 20 random subsets of machine-labeled points that are added to the training set and the error band (the colored area around the Augmented Roberta+) signifies the 95% confidence intervals. The dashed lines indicate the performance of the classifiers trained only on hand-annotated data.

tially allows a much more detailed history taking, compared to the often time constrained clinician. This is important in all outpatient care, both public and private, since this kind of system has the potential to save money, increase the effectiveness and revenue for private clinics without losing the quality of care.

Acknowledgements

Acknowledgements will appear in the final version.

References

Martín Abadi, Paul Barham, Jianmin Chen, Zhifeng Chen, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Geoffrey Irving, Michael Isard, et al. 2016. Tensorflow: A system for large-scale machine learning. In *12th USENIX symposium on operating systems design and implementation (OSDI 16)*, pages 265–283.

Alberto Blanco, Sonja Remmer, Alicia Pérez, Hercules Dalianis, and Arantza Casillas. 2021. On the Contribution of Per-ICD Attention Mechanisms to Classify Health Records in Languages with Fewer Resources than English. In *RANLP 2021: Recent Advances in Natural Language Processing, 1-3 Sept 2021, Varna, Bulgaria*, pages 165–172. Association for Computational Linguistics.

Davide Chicco. 2017. Ten quick tips for machine learning in computational biology. *BioData mining*, 10(1):1–17.

Davide Chicco and Giuseppe Jurman. 2020. The advantages of the Matthews correlation coefficient (MCC) over F1 score and accuracy in binary classification evaluation. *BMC genomics*, 21(1):1–13.

Kevin Clark, Minh-Thang Luong, Quoc V Le, and Christopher D Manning. 2020. ELECTRA: Pre-training Text Encoders as Discriminators Rather Than Generators. *arXiv preprint arXiv:2003.10555*.

Steindor Ellertsson, Hrafn Loftsson, and Emil L. Sigurdsson. 2021. Artificial intelligence in the GPs office: a retrospective study on diagnostic accuracy. *Scandinavian Journal of Primary Health Care*, 39(4):448–458.

Hlynur Hlynsson, Alberto Escalante-B., and Laurenz Wiskott. 2019. Measuring the Data Efficiency of Deep Learning Methods. In *Proceedings of the 8th International Conference on Pattern Recognition Applications and Methods*. SCITEPRESS - Science and Technology Publications.

Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. *Neural computation*, 9(8):1735–1780.

Rajvir Kaur, Jeewani Anupama Ginige, and Oliver Obst. 2021. A Systematic Literature Review of Automated ICD Coding and Classification Systems using Discharge Summaries. *arXiv preprint arXiv:2107.10652*.

Huiying Liang, Brian Y Tsui, Hao Ni, Carolina CS Valentim, Sally L Baxter, Guangjian Liu, Wenjia Cai, Daniel S Kermany, Xin Sun, Jiancong Chen, et al. 2019. Evaluation and accurate diagnoses of pediatric diseases using artificial intelligence. *Nature medicine*, 25(3):433–438.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. RoBERTa: A Robustly Optimized BERT Pretraining Approach. *arXiv preprint arXiv:1907.11692*.

Scott M Lundberg and Su-In Lee. 2017. A Unified Approach to Interpreting Model Predictions. *Advances in Neural Information Processing Systems*, 30.

Huanru Henry Mao. 2020. A Survey on Self-supervised Pre-training for Sequential Transfer Learning in Neural Networks. *arXiv preprint arXiv:2007.00800*.

Brian W Matthews. 1975. Comparison of the predicted and observed secondary structure of t4 phage lysozyme. *Biochimica et Biophysica Acta (BBA)-Protein Structure*, 405(2):442–451.

Vilhjálmur Þorsteinsson, Hulda Óladóttir, and Hrafn Loftsson. 2019. A Wide-Coverage Context-Free Grammar for Icelandic and an Accompanying Parsing System. In *Proceedings of the International Conference on Recent Advances in Natural Language Processing (RANLP 2019)*, pages 1397–1404.

Damian Pascual, Sandro Luck, and Roger Wattenhofer. 2021. Towards BERT-based Automatic ICD Coding: Limitations and Opportunities. *arXiv preprint arXiv:2104.06709*.

Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. 2019. PyTorch: An Imperative Style, High-Performance Deep Learning Library. *Advances in Neural Information Processing Systems*, 32:8026–8037.

Fabian Pedregosa, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, et al. 2011. Scikit-learn: Machine learning in Python. *the Journal of machine Learning research*, 12:2825–2830.

Jeffrey Pennington, Richard Socher, and Christopher D. Manning. 2014. GloVe: Global Vectors for Word Representation. In *Empirical Methods in Natural Language Processing (EMNLP)*, pages 1532–1543.

Lloyd S Shapley. 1953. A value for n-person games. In Harold W. Kuhn and Albert W. Tucker, editors, *Contributions to the Theory of Games II*, pages 307–317. Princeton University Press, Princeton.

Vésteinn Snæbjarnarson, Haukur Barri Símonarson, Pétur Orri Ragnarsson, Svanhvít Lilja Ingólfsdóttir, Haukur Páll Jónsson, Vilhjálmur Þorsteinsson, and Hafsteinn Einarsson. 2022. A Warm Start and a Clean Crawled Corpus - A Recipe for Good Language Models. In *Proceedings of the 13th International Conference on Language Resources and Evaluation (LREC 2022)*, Marseille, France.

Steinþór Steingrímsson, Sigrún Helgadóttir, Eiríkur Rögnvaldsson, Starkaður Barkarson, and Jón Guðnason. 2018. Risamálheild: A Very Large Icelandic

Text Corpus. In *Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018)*.

Jesper E Van Engelen and Holger H Hoos. 2020. A survey on semi-supervised learning. *Machine Learning*, 109(2):373–440.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in Neural Information Processing Systems*, pages 5998–6008.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, et al. 2019. HuggingFace's Transformers: State-of-the-art Natural Language Processing. *arXiv preprint arXiv:1910.03771*.

Zachariah Zhang, Jingshu Liu, and Narges Razavian. 2020. BERT-XML: Large Scale Automated ICD Coding Using BERT Pretraining. *arXiv preprint arXiv:2006.03685*.

A Appendix

ICD code	Description
G43.0	Migraine without aura
G43.1	Migraine with aura
G44.0	Cluster headaches and other trigeminal autonomic cephalgias
G44.2	Tension-type headache
G44.4	Drug-induced headache, not elsewhere classified
G45.9	Transient cerebral ischemic attack, unspecified
H66.0	Acute suppurative otitis media
H66.9	Otitis media, unspecified
I10	Essential (Primary) Hypertension
I63.0+	Cerebral infarction
I63.1	Cerebral infarction
I63.2+	Cerebral infarction due to unsp. occl. or stenosis of precerebral arts.
I63.3	Cerebral infarction due to thrombosis of cerebral arts.
I63.4	Cerebral infarction due to embolism of cerebral arteries.
I63.5	Cerebral infarction due to unsp. occl. or stenosis of cerebral arts.
I63.6	Cerebral infarction due to cerebral venous thrombosis, nonpyogenic
I63.8	Other cerebral infarction
I63.9	Cerebral infarction, unspecified
I84	Haemorrhoids
J00	Acute nasopharyngitis [common cold]
J01	Acute sinusitis
J01.0	Acute maxillary sinusitis
J01.9	Acute sinusitis
J02.0	Streptococcal pharyngitis
J03.0	Streptococcal tonsillitis
J03.9	Acute tonsillitis
J05.0	Acute obstructive laryngitis
J10.1	Influenza due to other identified influenza virus w/ other resp. manifs.
J11.1	Influenza with other resp. manifs., virus not identified
J12.9	Viral pneumonia, unspecified
J15	Bacterial pneumonia, not elsewhere classified
J15.7	Pneumonia due to Mycoplasma pneumoniae
J15.8	Pneumonia due to other specified bacteria
J15.9	Bacterial pneumonia, unspecified
J20.9	Acute bronchitis
J44.1	Chronic obstructive pulmonary disease with (acute) exacerbation
J44.9	Chronic obstructive pulmonary disease, unspecified
J45.0	Predominantly allergic asthma
J45.9	Asthma, unspecified
M54.1+	Radiculopathy
M54.5+	Low back pain
S83.2	Tear of meniscus, current injury

Table 4: ICD codes associated with notes used during training of the clinical feature extraction model.

ICD code	Description
G43.0	Migraine without aura
G43.1	Migraine with aura
G44.2	Tension-type headache
H66.9	Otitis media, unspecified
J15.9	Bacterial pneumonia, unspecified
J20.9	Acute bronchitis

Table 5: ICD codes associated with notes using during classifier training.

History of migraines	History smoking	History smoking package years v	History of wiplash	History of alcoholism	History is regularly active	History of bells palsy
History of stroke	History of hypertension	History of migraines with descr	History active use alcohol mode	History active substance abuse	History of accident motor vehic	History of cigarette smoking
History of head trauma	History smoking active time	History smoking packages per da	History known allergy	History of cluster headache	History of depression	History of anxiety
History allergy pollen	History of fibromyalgia	History of headaches	History allergy penicillin	History of osteoarthritis	History of epilepsy	History of copd
History of pulmonary cancer	History of ischemic heart disea	History of diabetes mellitus 2	History of polio	History of hyperlipidemia	History of lupus	History of asthma
History of sinusitis	History of diabetes mellitus	History of hypothyrosis	History of palpitations	History of adhd	History of lower back disc prot	History of atrial fib flutter
History known medical allergy	History of chrons ds	History of dvt	History of bipolar disease	History allergy sulfa	History tonsillectomy	History appendectomy
History hepatitis c	History of prescription drug ab	History of streptococcal pharyn	History of sleep apnea	History of pad	History of lobectomy	History of heart failure
History of gastritis	History unilat or bilat catarac	History of pulmonary embolus	History of c section	History of reflux	History of ca mammae	History allergy tramadol
History o2 at home	History of heart attack	History of cabg surgery	History of renal cancer	History artificial heart valve	History has pacemaker	History copd gold stage
History cardiac catherization d	History of nephrectomy	History of cholecystectomy	History active substance abuse	History of psoriasis	History cancer prostata	History sick sinus
History of gerd	History hiatal hernia	History of recurrent otitis med	History of being prematurely bo	History has one kidney	History of diabetes mellitus 1	History hysterectomi
History of benign prostate hype	History of recurrent pneumonia	History of reumoatoid arthritis	History allergy morphine	History of pulmonary hypertensi	History joint proteses	History smoking time since quit
History of kidney stones	History of diverticulitis	History of gout	History allergy ibuprofen	History of substance abuse	History multiple sclerosis	History inactive subtance abuse
History active cancer	History of recurrent cystitis	History of chronic renal failur	History of aortic stenosis	History of chest pain	History breast wedge excision	History of glaucoma
History of colitis ulcerosa	History of diverticulosis	History of chronic diarrhea	History of compression fracture	History of spinal stenosis	History of dementia	History of heart valve disease
History is blind or close to bl	History of parkinsons disease	History has a single lung	History smoking stop year	History of tia	History of eczema	History of iron deficiency
History of backpain	History allergy voltaren	History allergy brown band aid	History of pneumonia	History of osteoporosis	History of accident type unkown	Present history nausea
Present history tinnitus	Present history shoulder and ba	Present history vomiting	Present history visual disturba	Present history aura	Present history photophobia	Present history recent head tra
Present history runny nose	Present history bulbar conjunct	Present history phonophobia	Present history chest pain	Present history dyspnea	Present history fever	Present history limb numbness
Present history dizziness	Present history recedes to quie	Present history facial or head	Present history limb reduced fo	Present history head trauma	Present history ptosis	Present history malaise
Present history diplopia	Present history flashing lights	Present history using analgesic	Present history aphasia	Present history nasal congestio	Present history wakes up with s	Present history is hearing chan
Present history abdominal pain	Present history feeling unbalan	Present history vertigo	Present history dizzyness on he	Present history syncope	Present history dysphasia	Present history memory problem
Present history visual disturba	Present history visual disturba	Present history headache	Present history insomnia	Present history diarrhea	Present history is pregnant	Present history pregnancy durat
Present history ear muffled bil	Present history back pain	Present history blood in stool	Present history common cold sym	Present history sore throat	Present history dysphagia	Present history cough
Present history melena	Present history dysuria	Present history snores	Present history nose bleeding	Present history palpitations	Present history treated by phys	Present history flulike symptom
Present history mate has notice	Present history body bone muscl	Present history pain in ear	Present history has iron defici	Present history has physiothera	Present history obstipation	Present history pain appears or
Present history sputum excretio	Present history chest tightness	Present history chest tightness	Present history two kinds of he	Present history chills	Present history pain after fall	Present history pain in chest o
Present history sputum excretio	Present history pleural pain	Present history recent fever	Present history recently finish	Present history ear muffled	Present history fluid out of ea	Present history tympanostomy tu
Present history involuntary los	Present history arrives with am	Present history has not taken t	Present history reduced fluid i	Present history reduced food in	Present history worst headache	Present history pain in joints

Table 6: **Tier 1 features.** Part 1 of 2.

Present history hemoptysis	Present history pollakisuria	Present history recent surgery	Present history reduced urine o	Present history uneasy	Present history itching	Present history pain in shoulde
Present history recent long fli	Present history night sweats	Present history pain in calve a	Present history recent stimulan	Present history is trying to qu	Present history dizziness nauti	Present history bed ridden bc o
Present history referred from p	Present history macroscopic hem	Present history inflammation in	Present history throat burn	Present history is using immuno	Present history abdominal pain	Present history vitals taken af
Present history urine incontine	Present history recently diagno	Present history repeated airway	Present history recently diagno	Present history increased o2 ne	Present history bedridden	Present history recently diagno
Present history increased leg e	Present history burn in throat	Present history chest pain resp	Present history trouble breathi	Present history feels feverish	Present history urinary stenosi	Present history hard to breath
Present history nocturnal dyspn	Present history unable to use r	Present history confusion	Present history hoarseness	Present history increased sweat	Present history visual field ab	Present history increased clums
Present history symptoms have r	Present history lower extremiti	Present history trauma	Present history unlike self acc	Present history hemi symptoms	Present history cough at night	Present history pain caused by
Present history back pain thora	Present history back pain lumbo	Present history neck pain	Present history pain in single	Present history pain in groin	Present history pain reduction	Present history saddle numbness
Present history morning stiffne	Present history leg length disc	Present history fecal incontine	Present history pain reduction	Present history unable to work	Present history pain in buttock	Present history pain increases
Family history migraine	Family history hypertension	Family history heart disease	Family history hemochromatosis	Family history multiple scleros	Family history stroke	Family history of brain tumour
Family history of diabetes mell	Family history of deep venous t	Family history of brain aneurys	Family history of lower back di	Pain character pulsating	Pain pain killers work well	Pain onset
Pain vas value	Pain stability	Pain character heavy	Pain character tension	Pain character pressure	Pain character sting	Pain radiation neck
Pain disturbs sleep	Pain radiation teeth	Pain over maxillary sinuses	Pain vas variable	Pain worsens or gets better wit	Pain radiation to left arm	Pain radiation to jaw
Pain radiation to right arm	Pain vas worst value	Pain radiation to back	Pain appears or worsens on vals	Pain changes with food intake	Pain appears or worsens when co	Pain over frontal sinuses
Pain appears or worsens with po	Pain appears or worsens on layi	Pain location thorax back	Pain character electrical	Pain appears or worsens when st	Pain appears or worsens when si	Symptom start a few weeks ago
Symptom duration 24 hrs or more	Symptom frequency a few times p	Symptom start a few days	Symptom duration one hour or le	Symptom frequency a few times p	Symptom start a few months	Symptom trigger
Symptom localisation on the rig	Symptom duration a few hours	Symptom start a year or longer	Symptom localisation on the lef	Symptom frequency every day	Symptom frequency a few times p	Symptom frequency a few times a
Symptom start a few hours	Symptom duration is variable	Symptom frequency is variable	Symptom localisation goes betwe	Symptom duration a few minutes	Symptom nsaids work well	Symptom duration a few seconds
Symptom start a specific date	Main complaint headache	Main complaint prescription ren	Main complaint nose bleeding	Main complaint visual disturban	Main complaint allergy	Main complaint dizziness
Main complaint multiple problem	Main complaint syncope	Main complaint numbness in head	Main complaint back pain	Main complaint pain in knee	Main complaint nausea	Main complaint common cold symp
Main complaint aphasia	Main complaint high blood press	Main complaint malaise	Main complaint pain around sing	Main complaint vomiting	Main complaint outside lesion o	Main complaint abdominal pain
Main complaint chest pain	Main complaint numbness in limb	Main complaint dyspnea	Main complaint physiotherapy re	Main complaint depression and o	Main complaint car accident	Main complaint shoulder and bac
Main complaint shoulder problem	Main complaint pain in joints	Main complaint certificate	Main complaint referral to spec	Main complaint constipation	Main complaint needs prescripti	Main complaint is pregnant
Main complaint cough	Main complaint re assessment	Main complaint resp. symp	Main complaint fever	Main complaint pharyngitis	Main complaint pain in chest or	Main complaint pain in ear
Main complaint maxillary skin i	Main complaint body bone muscle	Main complaint external tumour	Main complaint trouble breathin	Main complaint sputum excretion	Main complaint sputum excretion	Main complaint chest tightness
Main complaint pleural pain	Main complaint chills	Main complaint impared consciou	Main complaint dysuria	Main complaint migraine	Main complaint palpitations or	Main complaint asthma exacerbat
Main complaint nasal congestion	Main complaint limb reduced for	Main complaint face reduced for	Main complaint feeling unbalanc	Main complaint slurry speech	Main complaint pain in hip	Main complaint pain in lower ex
Main complaint pain in buttock	Cough disturbs sleep	Cough accompanying abdominal pa	Cough barking	Heart rate value	Heart rate value self measureme	Heart rate left side value
Heart rate value self measureme	Respiratory frequency value	Oxygen saturation value	Temperature value	Temperature at home value	Blood pressure value	Blood pressure value self measu

Table 7: **Tier 1 features.** Part 2 of 2.

Examination lung auscultation a	Examination proprioception abno	Examination is obese	Examination palpable neck lymph	Examination heart auscultation	Examination systolic heart murm	Examination systolic heart murm
Examination abnormal or absent	Examination abnormal neurologic	Examination abnormal neurologic	Examination pronator drift	Examination positive babinsky	Examination finger nose test ab	Examination rhomberg abnormal
Examination abnormal heel to to	Examination abnormal gait	Examination abnormal or asymmet	Examination abnormal neurologic	Examination abnormal sensation	Examination neurological reflex	Examination is blood pressure e
Examination abnormal abdominal	Examination pupils abnormal	Examination neck stiffness	Examination generally sick look	Examination spontant nystagmus	Examination disturbed eye movem	Examination dix hallpike positi
Examination pain with sinus pal	Examination occipital muscles p	Examination slurry speech	Examination is line walking abn	Examination vitals are abnormal	Examination edema	Examination audible carotis bru
Examination abnormal or reduced	Examination abnormal force uppe	Examination abnormal force lowe	Examination shoulder muscles pa	Examination restricted neck mov	Examination is overweight	Examination nystagmus
Examination abnormal or asymmet	Examination lung auscultation c	Examination abnormal sensation	Examination abnormal sensation	Examination abdomen epigastrium	Examination abdomen llq pain on	Examination abdomen rlq pain on
Examination lung auscultation w	Examination lung auscultation r	Examination mouth throat abnorm	Examination reflexes patella ab	Examination abnormal or asymmet	Examination ataxia	Examination spurlings test posi
Examination lasegue positive si	Examination heart rate irregula	Examination grasset test abnorm	Examination lymph nodes palpabl	Examination otoscopy abnormal b	Examination dysdiadochokinesia	Examination ram normal
Examination pain on scm palpati	Examination fundoscopy abnormal	Examination visual field abnorm	Examination renal pain on percu	Examination abdomen ruq pain on	Examination abdomen pain on rel	Examination otoscopy cerumen bi
Examination weak to see	Examination reflexes achilles a	Examination reflexes triceps ab	Examination reflexes biceps abn	Examination thyroid palpation a	Examination costal intercostal	Examination tonsils enlarged
Examination tonsils pus	Examination lumbosacral pain on	Examination face reduced force	Examination language understand	Examination reflexes brachiorad	Examination clonus	Examination rash on body
Examination pain on palpation b	Examination otoscopy redness in	Examination pain or no pulse on	Examination pain on palpation p	Examination capillary refill ti	Examination visible petechiae	Examination lung auscultation c
Examination lung auscultation c	Examination distal vascular sta	Examination lung auscultation p	Examination otoscopy visible ef	Examination tymp tube not in pl	Examination tymp tube not in pl	Examination otoscopy pus in ear
Examination lung auscultation r	Examination trismus	Examination lung ausculation ob	Examination neck venous stasis	Examination abdomen luq pain on	Examination struggles with brea	Examination otoscopy tympanic m
Examination abdomen suprapubic	Examination lung auscultation c	Examination lung auscultation c	Examination abdomen murphys sig	Examination systolic heart murm	Examination o2 value	Examination venous stasis derma
Examination skin pallor	Examination tonsils cryptic	Examination otoscopy visible va	Examination otoscopy tymp membr	Examination lung auscultation c	Examination calves pain on palp	Examination tympanic membrane r
Examination stridor	Examination using abdominal mus	Examination otoscopy tympanic m	Examination otoscopy visible ef	Examination fontanella abnormal	Examination otoscopy tymp membr	Examination otoscopy tymp membr
Examination tympanic membrane r	Examination otoscopy tympanic m	Examination central cyanosis	Examination abdomen diffuse pai	Examination lung auscultation m	Examination calves redness or i	Examination pitting edema lower
Examination tympanic membrane r	Examination nose alae flutter	Examination lung deafness on pe	Examination lymph nodes palpabl	Examination pus in eyes bilat	Examination cold extremeties by	Examination mucous membranes dr
Examination abdomen visible her	Examination intestinal sounds a	Examination neglect present	Examination sbs value	Examination soft gum abnormal a	Examination lumbo sacral pain o	Examination signs of scoliosis
Examination hip reduced range o	Examination pain on palpation t	Examination restricted movement	Examination trouble walking on	Examination signs of kyphosis	Examination signs of abnormal l	Examination pain on palpation g

Table 8: **Tier 2 features.** This tier also includes the previous tier's features.

Blood tests tnt value	Blood creatinine value	Blood alat value	Blood total cholesterol value	Blood hdl value	Blood pressure left upper arm v	Blood mcv value
Blood tsh value	Blood wbc value	Blood neutrophils value	Blood tests tnt 2 value	Blood d dimer value	Blood bnp value	Blood astrup abormal
Blood inr value	Diagnostics blood tests abnorma	Diagnostics blood tests tnt ele	Diagnostics blood status abnorm	Diagnostics blood tests d dimer	Diagnostics blood glucose value	Diagnostics blood esr value

Table 9: **Tier 3 features.** This tier also includes the two previous tiers' features.