Clinical Document Classification Using Labeled and Unlabeled Data Across Hospitals

Hamed Hassanzadeh, PhD¹, Mahnoosh Kholghi, PhD¹, Anthony Nguyen, PhD¹, Kevin Chu, MBBS FACEM²
¹Australian e-Health Research Centre, CSIRO, Brisbane, QLD, Australia; ²Royal Brisbane and Womens Hospital, Brisbane, QLD, Australia

Abstract

Reviewing radiology reports in emergency departments is an essential but laborious task. Timely follow-up of patients with abnormal cases in their radiology reports may dramatically affect the patient’s outcome, especially if they have been discharged with a different initial diagnosis. Machine learning approaches have been devised to expedite the process and detect the cases that demand instant follow up. However, these approaches require a large amount of labeled data to train reliable predictive models. Preparing such a large dataset, which needs to be manually annotated by health professionals, is costly and time-consuming. This paper investigates a semi-supervised transfer learning framework for radiology report classification across three hospitals. The main goal is to leverage both vastly available clinical unlabeled data and already learned knowledge in order to improve a learning model where limited labeled data is available. Our experimental findings show that (1) convolutional neural networks (CNNs), while being independent of any problem-specific feature engineering, achieve significantly higher effectiveness compared to conventional supervised learning approaches, (2) leveraging unlabeled data in training a CNN-based classifier reduces the dependency on labeled data by more than 50% to reach the same performance of a fully supervised CNN, and (3) transferring the knowledge gained from available labeled data in an external source hospital significantly improves the performance of a semi-supervised CNN model over their fully supervised counterparts in a target hospital.

Introduction

Emergency departments (EDs) in hospitals are usually overcrowded by patients with various severity of health problems. Prompt diagnosis and therapeutical decisions in such streaming environment might not be always based on the best available expert opinions. For example, patients with potential limb fractures may be treated by only examining the radiology images and prior to the availability of reports written by the radiologists. The manual reconciliation of the initial diagnosis with the formal radiology report usually occurs after the patient has been discharged from the ED. As a result, timely follow-up of patients with abnormalities in their reports is a critical task.

Natural Language Processing (NLP) in conjunction with Machine Learning (ML) has been widely applied to facilitate manual information extraction and classification of clinical documents. However, supervised ML approaches require a large number of labeled data to effectively capture useful information from clinical text and build robust classifiers. Manually annotating such dataset incurs considerable expenses, especially in the clinical domain as it requires significant efforts from highly qualified and busy health professionals.

Semi-supervised learning (SSL) and transfer learning are feasible alternatives to standard supervised machine learning approaches to alleviate the manual annotation cost. SSL approaches incorporates the information of the unlabeled data into the learning process as a solution for dealing with scarcity of the labeled data. Another way to minimize the workload of the manual annotation and maximize the classification performance is transferring the knowledge gained from available labeled data from one hospital (source) to a similar task at a different hospital (target). These approaches have been successfully applied to many real-world applications, where manual data labeling is a labour-intensive and expensive task. Examples include sentiment analysis, pharmacogenomics and personalized medicine, cancer case management, email classification, language translation, named entity recognition, clinical concept extraction, and data stream classification.

In this paper, we study a combined semi-supervised transfer learning approach for abnormality detection from radiology reports across three major hospitals in Australia with different demographic characteristics (i.e., adult, children, and mixed general hospitals). We investigate the effect of unlabeled data in reducing the dependency on labeled data using self-training as our SSL approach. Self-training follows an iterative process in which an initial model that is build
over a small set of labeled data uses its own predictions on unlabeled data for further learning in successive iterations. Furthermore, in order to improve the effectiveness of the learning model, we explore a transfer learning approach that leverages the knowledge gained from available labeled data in an external source hospital. We specifically address the following questions in this paper:

**RQ1.** Which conventional supervised or deep learning approach can build a more effective learning model for clinical document classification?

**RQ2.** To what extent does semi-supervised learning help to deal with the scarcity of labeled data to build an effective learning model for clinical document classification?

**RQ3.** How can the knowledge from already built models from an external source hospital be used in the SSL framework to further increase the performance of the classification task?

**Related Work**

The two primary areas that relate to this study are: (i) semi-supervised learning, and (ii) transfer learning for document classification. Semi-supervised learning is an efficient way to cope with the lack of labeled data, where an abundance of unlabeled data is available at low cost. Such approaches aim to maximize the effectiveness of the learning model and minimize the manual annotation effort by incorporating the information from unlabeled data into the learning process. Many semi-supervised approaches have been developed for classification tasks, for example, self-training, co-training, transductive support vector machine, graph-based method, and Expectation-Maximization (EM) with generative mixture models. Self-training is a commonly used approach, in which a classifier is first built on a small set of labeled data. Then, in an iterative process, those unlabeled samples with their predicted labels, for which the current classifier has higher confidence about their labels, are added to the labeled set. The extended labeled set is used to retrain and update the underlying classifier in each iteration. In this study, our approach conforms to the main concept of the self-training algorithm. Although semi-supervised learning has been widely used in several domains (as listed above), its application in the realm of medical text analytic was limited to a small number of document classification and information extraction tasks.

For clinical document classification, Garla et al. developed a semi-supervised framework using Laplacian SVM to recognize potentially malignant liver lesions from CT, MRI, and ultrasound reports. They showed that semi-supervised learning using Laplacian SVM significantly improved the effectiveness of the clinical text classification (Macro-F1 0.773) when compared to a supervised SVM (Macro-F1 0.741). Although they presented encouraging results by employing unlabeled data, their classifier trained on a set of complex rule-based features narrows the application of such approach to a particular type and style of reports from a specific institution. In contrast, the proposed semi-supervised framework in this work employs simple vector representation of documents and is validated over multi-institutional data.

Another approach addressed drug-drug interaction (DDI) extraction from medical literature using distant supervision. They presented a Bayesian model in a knowledge-driven distant supervision setting that incorporates available clinical knowledge resources. Drugbank and DailyMed resources were used as sources of unlabeled drug-drug relationships. Sentences that include components that have already-known relations were assumed to be the evidence of true relationships. This provides a semi-supervised learning approach that employs unlabeled data, although from a different perspective than our approach.

Semi-supervised learning has been also used for medical information extraction tasks; Dligach et al. presented a semi-supervised algorithm based on Expectation Maximization (EM) to address phenotyping tasks. They used a bag of Unified Medical Language System (UMLS) concept unique identifiers to represent the patients’ phenotype information. They evaluated their approach over four datasets of 600 annotated patients’ records. Their experiments showed that using unlabeled data improved the accuracy of the model. Similarly, Beaulieu-Jones et al. presented a semi-supervised learning approach based on denoising autoencoders (DA) for phenotype stratification that was evaluated on multiple simulation models.

Another solution to cope with the lack of training data is transfer learning, which uses available training data from source hospitals to augment the learning process in a target hospital. Given a source domain and its corresponding
learning task, denoted by $D_s$ and $T_s$, respectively, transfer learning aims to improve a target learning task ($T_t$) in a target domain ($D_t$) by applying the knowledge learned from $T_s$ in $D_s$. The degrees of similarity between $D_s$ and $D_t$, and their corresponding tasks $T_s$ and $T_t$ lead to different transfer learning cases; two common forms of transfer learning in a supervised learning setting are: Inductive transfer learning and Transductive transfer learning. In the former method, it is considered that $T_s = T_t$ (regardless of the similarity of $D_s$ and $D_t$), while in the Transductive method, also known as domain adaptation, $D_s \neq D_t$ and $T_s = T_t$. Since the source and target tasks in our case study are similar (i.e., detecting abnormalities from radiology reports) but the domains are different (i.e., different patient demographic focus of the hospitals that is reflected in their reports), we employ the Transductive transfer learning in our approach. From a deep learning perspective, such knowledge transference is usually performed by transferring weights or features learned in different layers of a source model to a target model. Degrees of similarity between the source and target domains’ data and tasks affect the extent of the feature transference.

Methodology

Dataset

We use a set of limb radiology reports that was collected within a one-year period from the EDs of Royal Brisbane and Women Hospital (RBWH), Royal Children Hospital (RCH), and Gold Coast Hospital (GCH) (Ethics approval was granted by the Human Research Ethics Committee at Queensland Health to use the non-identifying data). The radiology reports were classified as either “normal” (i.e., those without any fracture, dislocation, presence of a foreign body, or incidental findings) or “abnormal” (i.e., those with some fracture, dislocation, foreign body, or incidental findings) by two annotators and one adjudicator (all medical experts). The inter-annotator agreement between the two annotators was 0.85 Fleiss’ kappa ($\kappa$), which exhibits a strong agreement. Table 1 shows the distribution of normal and abnormal cases for each hospital’s data. In addition, a combined set of 11,802 unlabeled data, available from two of the hospitals, was used in our semi-supervised approach. The differences in the domain of these hospitals, explained by institutional demographic variations, reflected the variations in needs and services required to care for children, adults or both.

| Dataset | # Reports | Normal | Abnormal |
|---------|-----------|--------|----------|
| RBWH    | 1,480     | 58%    | 42%      |
| RCH     | 498       | 66%    | 34%      |
| GCH     | 400       | 62%    | 38%      |

Self-training

Semi-supervised learning approaches have been devised to utilize the huge amount of unlabeled data that is available in the majority of the domains demanding automation. One of the most common semi-supervised approaches is self-training. Figure shows the learning process in a self-training algorithm. First, an initial learning model is built using available training data (usually a small set of data). This model is then used to predict labels for the set of unlabeled data. The aim is to boost the performance of the model using unlabeled data through an iterative process. A selection criterion is employed to decide which subset of unlabeled samples and their predicted labels are qualified to be used for retraining the model. Such self-training idea is used in our combined semi-supervised transfer learning approach that is described in the following subsection.

Semi-supervised Transfer Learning

In order to build a more robust initial model, we integrate a transfer learning method into the self-training process. The intuition behind such a combined framework is to leverage prior knowledge that is gained from the training data available in a source domain, in addition to the freely available unlabeled data in the target domain. The details of the self-trained transfer learning approach is described in Algorithm.

In the first step in Algorithm, a model ($\Theta_t$) is trained on the available labeled data in a source domain (i.e., $A_s$).
In the first iteration of a self-training algorithm (shown as the SSL Loop), this source model is fine-tuned using the available labeled samples in the target domain ($\Lambda_t$). Fine-tuning in this setting means tuning the already learned weights according to the new labeled data. This model is then used for predicting labels for all the samples in the unlabeled data ($\upsilon \in \Upsilon$). In the fifth step, the confidence of the model for predicting labels is assessed using a selection criterion. This criterion is based on the probability of the model ($P_{\Theta_i}(y|\upsilon)$): the higher the probability, the more confident the model is. A probability threshold ($\tau$) is set to identify confidently predicted cases. After an empirical analysis and in order to ensure selection of samples with high precision, the $\tau$ was set to 0.99 in our approach.

**Algorithm 1** Self-trained transfer learning

| Input |
|-------|
| $\Lambda_s$: set of labeled samples in the source domain |
| $\Lambda_t$: set of labeled samples in the target domain |
| $\Upsilon$: set of unlabeled samples in the source or target domain |
| $\tau$: a probability threshold used for assessing the model’s confidence |
| $i$: loop’s indicator ($= 0$) |

| Output |
|-------|
| Trained model for the target task $\Theta_t$ |

1: Train a model $\Theta_i$ on $\Lambda_s$
2: **procedure** SSL LOOP
3: Fine-tune the model $\Theta_i$ on $\Lambda_t$
4: $\forall \upsilon \in \Upsilon$ predict $y \leftarrow \Theta_i(\upsilon)$
5: $\Gamma \leftarrow$ Select a subset of $\upsilon$ from $\Upsilon$ where $P_{\Theta_i}(y|\upsilon) > \tau$
6: $\Gamma \leftarrow$ Balancing($\Gamma$)
7: $\Lambda_t \leftarrow \Lambda_t \cup \Gamma$
8: $\Upsilon \leftarrow \Upsilon - \Gamma$
9: **if** Accuracy($\Theta_i$) $>$ Accuracy($\Theta_{i-1}$) **then**
10: $i \leftarrow i + 1$
11: **goto** 2
12: **else**
13: $\Theta_t \leftarrow \Theta_{i-1}$
14: **exit loop**

In the self-training iterations, a model can be biased towards its predictions of a particular class than the rest of the
classes\textsuperscript{30}. To avoid this problem, we use a balancing strategy. In step 6, highly distributed predicted classes are under-sampled to reach a balanced version of $\Gamma$ with the same number of samples for all classes. In a binary setting, this means keeping the same number of samples of both classes. In the seventh step, the newly selected and balanced set of samples (i.e., $\Gamma$) and their predicted labels are then used to augment the initial labeled data ($\Lambda \cup \Gamma$) and the model is subsequently retrained over the updated version of the training data. The performance of the retrained model (i.e., $\text{Accuracy}(\Theta_i)$) was examined (by monitoring its learning curve) to keep or roll back the model (i.e., stopping criterion to exit the loop).

**Supervised Learning Baselines**

We investigated the performance of five state-of-the-art conventional supervised learning approaches and one artificial neural network for the abnormality identification task from radiology reports. Choice of algorithms was supported by the literature and their applicability for clinical document classification tasks\textsuperscript{2, 5, 27}. These approaches are described in Table 2. The parameters of the models were tuned using a grid search approach.

The CNN model that is devised for this study (adapted from\textsuperscript{31}) employed a word2vec model (using Skip-gram algorithm\textsuperscript{32}) that was trained on a corpus of clinical documents (approx. 5 million progress notes)\textsuperscript{27}. Other hyper-parameters were tuned to optimize its performance; the final tuned values using a grid search approach were as follows: filter sizes = 10, 15; number of filters = 400; embedding model = Skip-gram on the corpus of clinical documents (mentioned above); embedding dimension = 300; learning rate = 0.0005; optimizer function = Adam; dropout rate = 0.7; batch size = 16; number of epochs = 10.

In order to provide better comparisons between the supervised approaches, all conventional classifiers in our experiment were also trained over the same vector representations that was used as the input for the CNN model. As a result, each document is represented with a vector of size 300, which equals to the embedding dimension size. This vector is an element-wise average of vectors of all constituent words in a given document.

**Table 2:** Classification algorithms and their description

| Algorithm                  | Description                                                                 |
|----------------------------|-----------------------------------------------------------------------------|
| Support Vector Machine (SVM)| One of the most commonly used ML algorithms for addressing classification problems. It represents the data samples in a high-dimensional space and finds the optimal hyper-plane that can separate categories of samples\textsuperscript{33} |
| Naïve Bayes (NB)           | A probabilistic classifier that is based on Bayes’ theorem and conditional probabilities. It applies Bayes' theorem over the features of a given sample and calculates the probability of each class\textsuperscript{34} |
| Stochastic Gradient Descent (SGD) | A stochastic gradient descent learning routine that supports different loss functions and penalties for classification. It updates the weights after seeing each sample based on the gradient of the loss function\textsuperscript{35} |
| Random Forest (RF)         | An ensemble learning method that takes both bagging and random feature selection techniques to build an ensemble of tree-based classifier\textsuperscript{36} |
| Logistic Regression (LR)   | A simple classification algorithm for predicting a binary discrete variable. It uses a “sigmoid” or “logistic” function to predict the probability that a given example belongs to each of the classes\textsuperscript{37} |
| Convolutional Neural Netwrok (CNN) | A feed-forward neural network that passes the information from the input layer through one or multiple intermediate convolutional functions to the output layer. The input is a grid-like representation of the data (e.g., a matrix of numerical representation of the constituent words of a document)\textsuperscript{38} |

**Experimental Setup and Evaluation Measures**

The deep learning algorithm was implemented using Keras 2.0,\textsuperscript{40} with a Theano 0.9 backend.\textsuperscript{41} The results were obtained using a GPU cluster. The cluster has 114 nodes, each of them has 4 NVidia Tesla P100 GPUs, 256 GB of RAM and 1TB of local SSD drive. The program was written in Python 3 and the word2vec models were generated using the Gensim library\textsuperscript{42}. The scikit-learn implementation of conventional algorithms (Table 2) were used in our
Table 3: Supervised ML performances on each hospital data. Statistically significant improvements ($p$-value $< 0.05$) for F1 when compared with all other supervised models are indicated by *.

|       | RBWH                  | RCH                  | GCH                  |
|-------|-----------------------|----------------------|----------------------|
|       | P        | R        | F1       | P        | R        | F1       | P        | R        | F1       |
| SVM   | 0.8539   | 0.8122   | 0.8325   | 0.9366   | 0.8811   | 0.9080   | 0.9347   | 0.8810   | 0.9071   |
| SGD   | 0.8575   | 0.7329   | 0.7903   | 0.9104   | 0.8276   | 0.8670   | 0.8713   | 0.7951   | 0.8315   |
| NB    | **0.9353** | 0.7102   | 0.8074   | 0.8409   | 0.9048   | 0.8717   | 0.8049   | 0.9281   | 0.8621   |
| RF    | 0.8508   | 0.7524   | 0.7986   | 0.9182   | 0.7552   | 0.8288   | 0.8654   | 0.8210   | 0.8426   |
| LR    | 0.8872   | 0.6912   | 0.7770   | 0.7003   | 0.0725   | 0.1314   | **0.9751** | 0.5043   | 0.6648   |
| CNN   | 0.9159   | **0.9028** | **0.9085** | **0.9370** | **0.9408** | **0.9367** | 0.9359   | **0.9342** | **0.9335** |

We performed stratified 10-fold cross validation experiments to evaluate the performance of classifiers using standard text classification measures, namely, Precision, Recall, and F1-Score:

**Precision (P):** $\frac{TP}{TP + FP}$;

**Recall (R):** $\frac{TP}{TP + FN}$;

**F1-Score (F1):** $\frac{2 \times R \times P}{R + P}$; i.e, harmonic mean of Precision and Recall;

where true positive (TP) indicates that a model correctly identified a radiology document with a reported abnormality, false positive (FP) refers to the identification of an incorrect abnormal case, and false negative (FN) indicates that a model failed to identify an abnormality according to the ground truth data. To demonstrate statistically significant improvements on F1-Score, we performed a paired t-test.

**Results and Discussion**

**Supervised Learning Performance**

In order to answer the **RQ1**, the comparative performance of the conventional supervised ML and deep learning approaches on abnormality detection has been investigated across three hospitals (Table 3). The best-performing systems in terms of Precision, Recall, and F1-Score are shown in boldface numbers.

The results in Table 3 shows that Logistic Regression (LR) achieved the lowest Recall across all datasets, which led to the worst supervised system in terms of F1-Score. It should be noted that in such tasks, missing abnormal cases are more critical than misclassifying normal cases. Among the conventional supervised approaches, SVM and Naive Bayes (NB) achieved better performances in terms of F1-Score across all three hospitals.

The CNN model obtained the highest Recall across all datasets and significantly outperformed all conventional supervised approaches with the highest F1-Score of 0.9085, 0.9367, and 0.9335 across RBWH, RCH, and GCH, respectively. Therefore, the CNN algorithm, as the best performing approach, was used in self-training and the semi-supervised transfer learning experiments to build classifiers.

**Semi-supervised Learning Performance**

Table 4 presents the performance of the self-trained CNN across RBWH, RCH, and GCH. For each dataset, the self-training experiments were performed with different random portions (i.e., 30%, 50%, and 70%) of the labeled set to build different initial learning models. The aim is to investigate the effect of using unlabeled data to learn a model that reaches at least the same performance of a fully supervised CNN model (as shown in Table 3). We also examined the self-trained CNN approach using 100% of the labeled data (i.e., the whole training data) available for each dataset. This was done to investigate whether using the whole labeled set along with the unlabeled data would lead to a significant improvement in classification performance compared to a fully supervised CNN. The best self-trained CNN with a significant improvement over the fully supervised CNN model is indicated by an asterisk symbol and those models.
Table 4: Self-trained CNN performance. Statistically significant improvements \((p\text{-value} < 0.05)\) for F1 when compared with supervised CNN model are indicated by *.

| Used Labeled Data | RBWH       | RCH       | GCH       |
|-------------------|------------|-----------|-----------|
|                   | P R F1     | P R F1    | P R F1    |
| 30%               | 0.8652 0.8835 0.8725 | 0.9325 0.9471 0.9379 | 0.9069 0.9275 0.9157 |
| 50%               | 0.9155 0.8866 0.8994 | 0.9403 0.9467 0.9403 | 0.9098 0.9275 0.9178 |
| 70%               | 0.9196 0.8804 0.8894 | 0.9443 0.9463 0.9429 | 0.9198 0.9475 0.9317 |
| 100%              | 0.9026 0.9224 0.9121 | 0.9295 0.9643 0.9443 | 0.9541 0.9475 0.9499* |

that reached the same effectiveness as the fully supervised CNN with no significant difference (in terms of F1-Scores) are highlighted in gray.

By comparing the results in Table 4 with the CNN results in Table 3 it can be observed that a self-trained CNN model can achieve the performance of a fully supervised CNN (in terms of F1-Score) by only using a maximum of 50% of the training data. This demonstrates the benefit of using unlabeled data in training an effective classifier with less labeled data, which means less manual annotation effort \((RQ2)\). On the RCH dataset, the self-trained model reached the fully supervised performance using only 30% of the randomly selected labeled data. When using the whole training data available for each dataset in the self-training approach, only the model built on GCH training data significantly outperformed the fully supervised CNN model \((i.e., 0.9499 cf. 0.9335)\). The following subsection presents the results of our semi-supervised transfer learning approach in which we use labeled data available from other source hospital to further improve the classifiers’ performance while addressing lack of training data in target hospitals.

### Semi-supervised Transfer Learning Performance

In the semi-supervised transfer learning experiments, we selected RBWH as the source domain, mainly due to the provision of more labeled data, and the other two hospitals as the target domains where limited labeled data is available. Table 5 shows the results of the self-trained transfer learning approach on the RCH and GCH datasets. In addition to examining different random portions \((30\%, 50\%, 70\%, \text{ and } 100\%)\) of the target labeled sets, we also examined the case that no labeled data \((i.e., 0\%)\) is available from target datasets for the learning process. The intuition is to show the effect of knowledge transferred from other source hospitals without any available labeled data in the target domain. The best performing settings are highlighted in boldface, which are also significantly better than the fully supervised result.

As shown in Table 5, the self-trained transfer learning approach \((F1\text{-Score} = 0.9744\text{ and } 0.9643)\) significantly outperformed the fully supervised CNN model \((F1\text{-Score} = 0.9367\text{ and } 0.9335)\) on both RCH and GCH datasets, while only using 70% of the randomly selected labeled data from each dataset \((RQ3)\). Comparing the results in Table 5 with the performance of self-trained CNN in Table 4 shows that using labeled data from other source hospitals along with the unlabeled data from the target hospital leads to further significant improvements \((indicated by \dagger\text{ in Table 5})\).

Table 5: Self-trained transfer learning performance. Statistically significant improvements \((p\text{-value} < 0.05)\) for F1 when compared with supervised CNN model are indicated by * and when compared with the self-trained CNN are indicated by †.

| Used Labeled Data | RCH       | GCH       |
|-------------------|-----------|-----------|
|                   | P R F1    | P R F1    |
| 0%                | 0.9561 0.9824 0.9678 | 0.9378 0.9738 0.9548 |
| 30%               | 0.9542 0.9526 0.9515 | 0.9239 0.9604 0.9398 |
| 50%               | 0.9405 0.9941 0.9660 | 0.9480 0.9671 0.9553† |
| 70%               | 0.9570 0.9941 0.9744*† | 0.9570 0.9738 0.9643*† |
| 100%              | 0.9552 0.9941 0.9739† | 0.9312 0.9738 0.9516 |

In order to better understand the behaviour of our learning model, we study a number of misclassified reports by the
semi-supervised transfer learning model. The classification errors regarding misclassifying abnormal reports as normal were mainly related to reporting and linguistic diversity in the clinical domain that makes such document classification task even more challenging. For example, a report may contain a statement like “no bony abnormality”, however, there may also be a speculative statement that refers to a “slight lateral deviation of the patella”. This introduces a complex and challenging case for the model to automatically detect the reported abnormality. Other similar observed cases included conditional propositions (e.g., “If clinical suspicion persists for a fracture, further evaluation with CT is advised.”).

These problems, known as “ambiguity” in natural language processing, could be challenging for both human and machine to detect. Clinical free text resources, such as radiology reports, are often unstructured, ungrammatical, fragmented, and exhibit ambiguities that need to be effectively tackled when being automatically processed. As a result, employing more sophisticated NLP features is warranted in order to minimize such misclassification errors.

A limitation of our experiment is related to the availability of unlabeled data from all hospitals. Despite only having unlabeled data from two of the three hospitals, our transferred learning model exhibited considerable flexibility in not only employing the source labeled model but also getting advantages of unlabeled data regardless of their domains and reporting style. Further investigation is warranted to understand the effects of quality and quantity of the unlabeled data on our approach.

Conclusion

This paper presented a combined semi-supervised transfer learning approach to improve the performance of the abnormality detection from radiology reports. The information embedded in the unlabeled data was employed in the learning process in order to address the lack of labeled data. Furthermore, the potential of the labeled data available from other source hospitals was studied in order to augment the classification performance.

The results of our empirical investigation highlighted the key role of the combined semi-supervised transfer learning approach in dealing with the scarcity of labeled data and improving the classification performance. Our results suggested that such combined approach reduces the amount of labeled data required for training an initial learning model, which can further translates into less manual annotation effort.

The future work will explore more effective sample selection techniques for both generating the initial labeled set in the semi-supervised learning process and for selectively transferring informative samples from a source domain. Furthermore, we will also examine the effects of language styles and conventions used in writing the reports across institutions by using local hospital’s unlabeled data instead of the combined unlabeled dataset.

References

1. Filipe R Lucini, Flavio S Fogliatto, Giovani JC da Silveira, Jeruza L Neyelloff, Michel J Anzanello, Ricardo de S Kuchenbecker, and Beatriz D Schaan. Text mining approach to predict hospital admissions using early medical records from the emergency department. *International Journal of Medical Informatics*, 100:1–8, 2017.

2. Bevan Koopman, Guido Zuccon, Amol Wagholi, Kevin Chu, John ODwyer, Anthony Nguyen, and Gerben Keijzers. Automated reconciliation of radiology reports and discharge summaries. In *American Medical Informatics Association Annual Symposium*, pages 775–784, 2015.

3. Özlem Uzuner, Imre Solti, and Eithon Cadag. Extracting medication information from clinical text. *Journal of the American Medical Informatics Association*, 17(5):514–518, 2010.

4. Mahnoosh Kholghi, Laurianne Sitbon, Guido Zuccon, and Anthony Nguyen. Active learning: a step towards automating medical concept extraction. *Journal of the American Medical Informatics Association*, 23(2):289–296, 2015.

5. Sarvnaz Karimi, Xiang Dai, Hamed Hassanzadeh, and Anthony Nguyen. Automatic diagnosis coding of radiology reports: A comparison of deep learning and conventional classification methods. *BioNLP 2017*, pages 328–332, 2017.
6. Mohamed Farouk Abdel Hady and Friedhelm Schwenker. Semi-supervised learning. In *Handbook on Neural Information Processing*, pages 215–239. 2013.

7. Sinno Jialin Pan and Qiang Yang. A survey on transfer learning. *IEEE Transactions on knowledge and data engineering*, 22(10):1345–1359, 2010.

8. Jonathan Ortigosa-Hernández, Juan Diego Rodríguez, Leandro Alzate, Manuel Lucania, Iñaki Inza, and Jose A Lozano. Approaching sentiment analysis by using semi-supervised learning of multi-dimensional classifiers. *Neurocomputing*, 92:98–115, 2012.

9. Rong Xu and QuanQiu Wang. A semi-supervised approach to extract pharmacogenomics-specific drug–gene pairs from biomedical literature for personalized medicine. *Journal of biomedical informatics*, 46(4):585–593, 2013.

10. Vijay Garla, Caroline Taylor, and Cynthia Brandt. Semi-supervised clinical text classification with laplacian svms: an application to cancer case management. *Journal of biomedical informatics*, 46(5):869–875, 2013.

11. Svetlana Kiritchenko and Stan Matwin. Email classification with co-training. In *Proceedings of the 2011 Conference of the Center for Advanced Studies on Collaborative Research*, pages 301–312, 2011.

12. Nicola Ueffing, Gholamreza Haffari, and Anoop Sarkar. Semi-supervised model adaptation for statistical machine translation. *Machine Translation*, 21(2):77–94, 2007.

13. Hamed Hassanzadeh and Mohammadreza Keyvanpour. A two-phase hybrid of semi-supervised and active learning approach for sequence labeling. *Intelligent Data Analysis*, 17(2):251–270, 2013.

14. Xinbo Lv, Yi Guan, and Benyang Deng. Transfer learning based clinical concept extraction on data from multiple sources. *Journal of biomedical informatics*, 52:55–64, 2014.

15. Mahnoosh Kholghi and MohammadReza Keyvanpour. Active learning framework combining semi-supervised approach for data stream mining. *Intelligent Computing and Information Science*, pages 238–243, 2011.

16. Kamal Nigam and Rayid Ghani. Analyzing the effectiveness and applicability of co-training. In *Proceedings of the ninth international conference on Information and knowledge management*, pages 86–93, 2000.

17. Avrim Blum and Tom Mitchell. Combining labeled and unlabeled data with co-training. In *Proceedings of the eleventh annual conference on Computational learning theory*, pages 92–100, 1998.

18. Thorsten Joachims. Transductive inference for text classification using support vector machines. In *Proceedings of the 16th International Conference on Machine Learning (ICML)*, pages 200–209, 1999.

19. Xiaojin Zhu, Zoubin Ghahramani, and John D Lafferty. Semi-supervised learning using gaussian fields and harmonic functions. In *Proceedings of the 20th International conference on Machine learning (ICML-03)*, pages 912–919, 2003.

20. Kamal Nigam, Andrew Kachites McCallum, Sebastian Thrun, and Tom Mitchell. Text classification from labeled and unlabeled documents using EM. *Machine learning*, 39(2):103–134, 2000.

21. Dmitriy Dligach, Timothy Miller, and Guergana K Savova. Semi-supervised learning for phenotyping tasks. In *AMIA Annual Symposium Proceedings*, page 502, 2015.

22. Brett K Beaulieu-Jones, Casey S Greene, et al. Semi-supervised learning of the electronic health record for phenotype stratification. *Journal of biomedical informatics*, 64:168–178, 2016.

23. Zhuoran Wang, Anoop D Shah, A Rosemary Tate, Spiros Denaxas, John Shawe-Taylor, and Harry Hemingway. Extracting diagnoses and investigation results from unstructured text in electronic health records by semi-supervised machine learning. *PLoS One*, 7(1):e30412, 2012.
24. Dingcheng Li, Sijia Liu, Majid Rastegar-Mojarad, Yanshan Wang, Vinip Chaudhary, Terry Therneau, and Hongfang Liu. A topic-modeling based framework for drug-drug interaction classification from biomedical text. In AMIA Annual Symposium Proceedings, volume 2016, page 789, 2016.

25. Olivier Bodenreider and Alexa T McCray. Exploring semantic groups through visual approaches. Journal of biomedical informatics, 36(6):414–432, 2003.

26. Jie Lu, Vahid Behbood, Peng Hao, Hua Zuo, Shan Xue, and Guangquan Zhang. Transfer learning using computational intelligence: A survey. Knowledge-Based Systems, 80:14–23, 2015.

27. Hamed Hassanzadeh, Anthony Nguyen, Sarvnaz Karimi, and Kevin Chu. Transferability of artificial neural networks for clinical document classification across hospitals: A case study on abnormality detection from radiology reports. Journal of Biomedical Informatics, 85:68–79, 2018.

28. Jason Yosinski, Jeff Clune, Yoshua Bengio, and Hod Lipson. How transferable are features in deep neural networks? In Advances in neural information processing systems, pages 3320–3328, 2014.

29. Ross Sheldon et al. A first course in probability. Pearson Education India, 2002.

30. Hamed Hassanzadeh, Tudor Groza, Anthony Nguyen, and Jane Hunter. Load balancing for imbalanced data sets: Classifying scientific artefacts for evidence based medicine. In Pacific Rim International Conference on Artificial Intelligence, pages 972–984, 2014.

31. Yoon Kim. Convolutional neural networks for sentence classification. arXiv preprint arXiv:1408.5882, 2014.

32. Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. Distributed representations of words and phrases and their compositionality. In Advances in neural information processing systems, pages 3111–3119, 2013.

33. Vladimir Vapnik. The nature of statistical learning theory. Springer science & business media, 2013.

34. Oded Maimon and Lior Rokach. Data mining and knowledge discovery handbook. 2005.

35. Léon Bottou. Stochastic gradient learning in neural networks. Proceedings of Neuro-Nımes, 91(8), 1991.

36. Leo Breiman. Random forests. Machine learning, 45(1):5–32, 2001.

37. Saskia Le Cessie and Johannes C Van Houwelingen. Ridge estimators in logistic regression. Applied statistics, pages 191–201, 1992.

38. Ian Goodfellow, Yoshua Bengio, and Aaron Courville. Deep Learning. MIT Press, 2016. [http://www.deeplearningbook.org]

39. François Chollet et al. Keras. [https://github.com/fchollet/keras] 2015.

40. Theano Development Team. Theano: A Python framework for fast computation of mathematical expressions. arXiv e-prints, abs/1605.02688, May 2016.

41. Radim Řehůrek and Petr Sojka. Software Framework for Topic Modelling with Large Corpora. In Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks, pages 45–50, 2010.

42. Fabian Pedregosa, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, et al. Scikit-learn: Machine learning in python. Journal of Machine Learning Research, 12(Oct):2825–2830, 2011.