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Detecting Adverse Drug Reaction (ADR) Mentions from Social Media

K. Sornalakshmi, G. Sujatha, D. Hemavathi, S. Sindhu

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Abstract: Adverse Drug Reaction (ADR) can be described as undesired consequences resulting from consumption of medical prescribed drugs. Such reactions are often missed in clinical trials and are experienced by real world patients. If reported and corrected at early stages, it could be beneficial for other patients having the same disease. Many government agencies across different countries are aiming to collect the real time drug reactions from patients through surveys, reporting tools etc. The direct feedback from patients based on their experience is more relevant and informative in making decisions on restricting adverse drug reactions. This self-reported patient feedback in free flowing format is available from discussions in social media and medical blogs. Such data have more impact than government induced feedback, reporting and surveys. In this paper our primary focus is to utilize social media to mine the ADR mentions from patients. We filter tweets that might have adverse drug reaction mentions. We compare the performance of various classification algorithms in classifying accurately if a tweet comprises of ADR mention or not.

Keywords: Adverse Drug Reactions, ADR, Pharmacovigilance, Classification, Feature Selection, Tweets

INTRODUCTION

The safety of the usage of authentic drugs prescribed by practitioners is a significant issue in the domain of pharamacology. Some drugs cause unintended side effects that range from small problems like headache and dizziness to more complicated consequences like death. United states for the eight year period of 1999 to 2006 has reported 2341 ADR-related deaths [1]. It was also proven that the rate of death was higher in aged people who take drugs regularly. The clinical trials performed by government and industrial pharmaceutical agencies are carried out in a restricted environment where all possible conditions for ADR occurrence could not be addressed. So post-release surveillance of a drug's reactions is significant which are to be monitored by drug manufacturers, government agencies. This surveillance is carried out via forums where users can provide details about the adverse reactions like the United States government agency FDA's (Food and Drug Administration), Adverse Event Reporting System (FAERS). The information provided in such reporting platforms might not be enough to cover all possible adverse reactions corresponding to a drug group. To explore all the possible ADRs, the huge information available in social media and medical blogs directly from the stakeholders might be made use of to uncover new combinations of patient characteristics that cause ADRs. Also many NLP techniques could retrieve the context and meaning of user messages accurately.

Terms

Adverse Drug Reaction (ADR) –The general description of an Adverse Drug Reaction (ADR) is an unintended response to the consumption of a prescribed drug at normal dosage. The drug could have been administered for diagnosis, prevention or treatment. The unintended response could range from simple issues like headache or dizziness to more serious problems like death.

K. Sornalakshmi, Asst. Professor, Department of Information Technology, SRMIST, Kattankulathur.
G. Sujatha, Asst. Professor, Department of Information Technology, SRMIST, Kattankulathur.
D. Hemavathi, Asst. Professor, Department of Information Technology, SRMIST, Kattankulathur.
S. Sindhu, Asst. Professor, Department of Information Technology, SRMIST, Kattankulathur.

Pharmacovigilance – According to WHO, it is defined as the science and activities relating to the detection, assessment, understanding and prevention of adverse effects or any other drug-related problem [2]. It is a broader area that covers medication mistakes as well in addition to ADRs. It aims at curtailing the risks of harm to patients consuming suitable approved drugs.

Clinical Trials – These are research studies performed in people to evaluate a new drug, medical equipment, process or surgery or diet. It is used to learn if there are any unsafe side effects compared to the existing standard ones.

Post marketing Surveillance – This is a vital element of pharmacovigilance. Clinical trials are conducted in a restrained environment where the subjects might not cover all real world possibilities and characteristics. Monitoring the drug or device safety after it is put into use by the general population has the potential to unveil a wide range of ADRs.

Challenges in Pharmacovigilance

For the adverse drug reactions, clinical trials, post use surveillance and feedback reporting platforms were the primary source of information earlier. These practices are generally instigated and implemented by pharmaceutical companies or government agencies. All three have their own restrictions. Clinical trial does not guarantee all possible characteristics of patients. It guarantees to cover major effects to patients with general characteristics. The characteristics like demography, medical conditions with co-occurring diseases or medications, diagnosis, age are taken care in clinical trials. But still it is not enough or same as applying the same to the wide audience as in real time[11]. Investigations have shown that the patients who report about adverse drug reactions strongly believe that the health experts treating them have not given consideration to adverse reaction [5].

Importance of Social Media

Over the last few years, data deluge has increased tremendously. Information sharing and networking is done at a very high level that it could be used for many constructive purposes. Social media and internet has enabled sharing personal experiences in real time which could be leveraged for post use surveillance in pharmacovigilance. They can deliver early signals before affecting huge population. Collecting information from different sources where people share their information to mine ADRs is gaining more importance now because of the value of direct patient information. This information could benefit all stakeholders for safer healthcare delivery. More people refer internet for their health problems and try finding patients having similar issues or try reporting their problems to locate answers. This could provide information for mining ADRs.

For this work we choose Twitter, a free micro blogging service that connects millions of users to share short texts. It also provides APIs to retrieve live streaming public posts which could be used for analysis.

RELATED WORK

Social networks and medical blog websites are prominent among patients to share their experiences related to health concerns which might help other patients too. Tremendous amount of research has been committed to this area, and most of this work focuses on the study of social information exchanges and value, text mining and NLP. A summary of significant work done in ADR extraction from social media and publicly available annotated ADR data is presented as a methodological review in [21]. The benefits of using training data from multiple sources like medical blogs and databases were investigated and showed improvement in accuracy[14].The filtering of messages that could have ADR mentions from the huge set of messages is more difficult because tweets with ADR mentions are highly distributed and sparse. Semi supervised learning algorithms could improvise in building an early warning systems by using a small amount of labelled data to find suspicious ADR mentions from a huge corpus of unlabeled messages[18]. The word vectors are improvised using vector arithmetic to automatically identify additional ADR terms as opposed to fixed lexicons [20]. Dynamic lexicon based ADR mention extractions from tweets are also gaining importance. Lexicon and pattern based ADE extraction using semi supervised learning techniques were able to better identify problems like slang words, non-standard terms and incorrect spellings [9,16]. Sentiment analysis is used considering that negative sentiment along with drug usage could be ADR mentions [19]. Few authors have published annotated tweets publicly available and benchmark results for further research and comparison [15,17,]. Some studies used graph link association models to classify tweets as ADR and no ADR and matched directly with drug names[3]. Association rule mining was used to identify most proximal pairs of drugs and reactions for a subset of drugs[6,21] . Ensemble based kernel approaches combine many base models to produce one optimal classification model [7].

Other web based reporting ans summarizing tools were also developed. The SIDER is a resource for side effect that was created by extracting drug names [12]. However there is noteworthy literature and previous work done for exploring ore general terms like diseases. The primary lexical system for mapping concepts biomedical texts to concepts in the UMLS Metathesaurus [4] is MetaMap. The ConText system is used in categorizing findings in clinical records which are chronological, invalid or hypothetical [10]. BioCaster system is used for detecting infectious disease outbreaks by mining news reports which are posted in the web [8], while majority of the work concentrates on finding diseases concerning clinical records. However the FDA advocates are using MedWatch to report for any serious events. A patient self-reporting about the adverse drug reaction has a more important outlook that could not be found in a doctor's EHR, surveillance or reporting platforms or clinical trials.

EXPERIMENTS

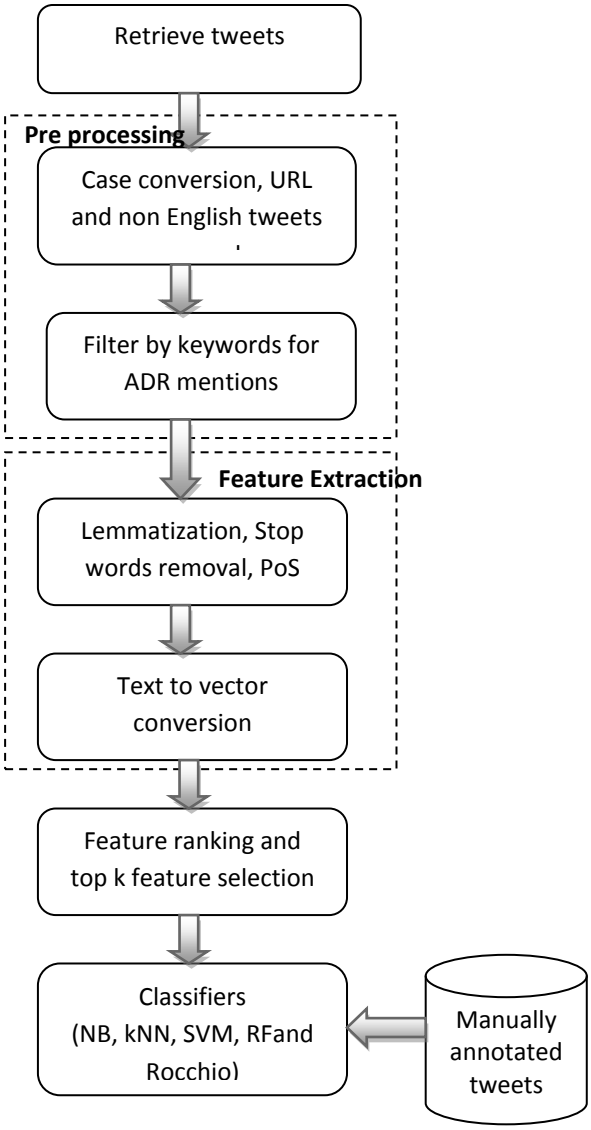

Fig. 1: Tweet classification methodology

Data

For social media data, we collected data from Twitter. Twitter is a popular social media platform whose data would be of high value to researchers to mine direct information from end users. 326 million people are using it every month and 9% more people are using it every day as of January 16, 2019 [13]. Our training data set has a collection of 2700 tweets which are manually annotated for binary classification of tweets with ADR and without ADR. We collected tweets from the 1% real live stream data provided by Twitter over a period of time. For extracting tweets from Twitter a special package has been used in Python programming language known as tweepy. Twitter only allows 1% of the live stream to be collected. To collect the tweets from Twitter a special application was created in the social networking site which in turn provides us with the consumer secret key which was needed to be used in the python

program. Hence with the help of the key and the package mentioned above, the user drug related comments were extracted.

Pre Processing and Feature Extraction

Data cleaning was done by removing non English tweets and URLs, case conversion. The methodology for classifying tweets is shown in Fig 1. Then tweets that have potential ADR mentions were filtered with keywords used in the annotated data set [9]. The resulting tweets were made more meaningful for classification by the techniques - lemmatization, stop words removal and Parts Of Speech (POS) tagging.

In the feature extraction phase, the words were converted to vector using frequency based vectorizers. The performance of any algorithm depends on the features and quality of data set. We used Term Frequency-Inverse document Frequency (TF-IDF) to compute the vectors. After extracting the features matrix we perform filter based feature ranking via chi squared test to select the best k features with k configurable. In the course of the experiment 2341 feature words were found. Each of these words when found in the text data will point to a possible conclusion. Initially we experimented with 250 feature words and the accuracy improved when we increased it step by step.

Classification

We compare the classification done by five classifiers namely – Naïve Bayesian (NB), k Nearest neighbour (kNN), SVM with linear kernel, Random Forest(RF) and Rocchio . Naive Bayes classifier requires less training data and is scalable. In kNN, an object is classified to the class that is common to most of its neighbours. There are many ways to choose the neighbours, we consider the brute force method. SVM for binary classification constructs a hyper plane, a line that separates the two classes. The linear SVM provided the best results for our classification problem. Rocchio classifier also known as nearest centroid classifier uses centroid to define boundaries so that intra class similarity is maximized. Random Forest classifier is an ensemble method that constructs many decision trees from randomly chosen sub sets of the training data. It then compares the output from different decision trees (called as votes) to decide the final output. This techniques addresses the over fitting problem of decision trees.

It is observed that among the five classifiers, linear SVM provided the best performance for classifying tweets as with ADR and no ADR.

RESULTS

The summary of results is shown in the graphs below. Fig 2 shows the performance of the five classifiers in classifying tweets with ADR. The Fig 3 shows the performance of five classifiers in classifying tweets without ADR mentions. The precision, recall and F-score comparison of the classifiers are shown in Fig, 4,5 and 6s

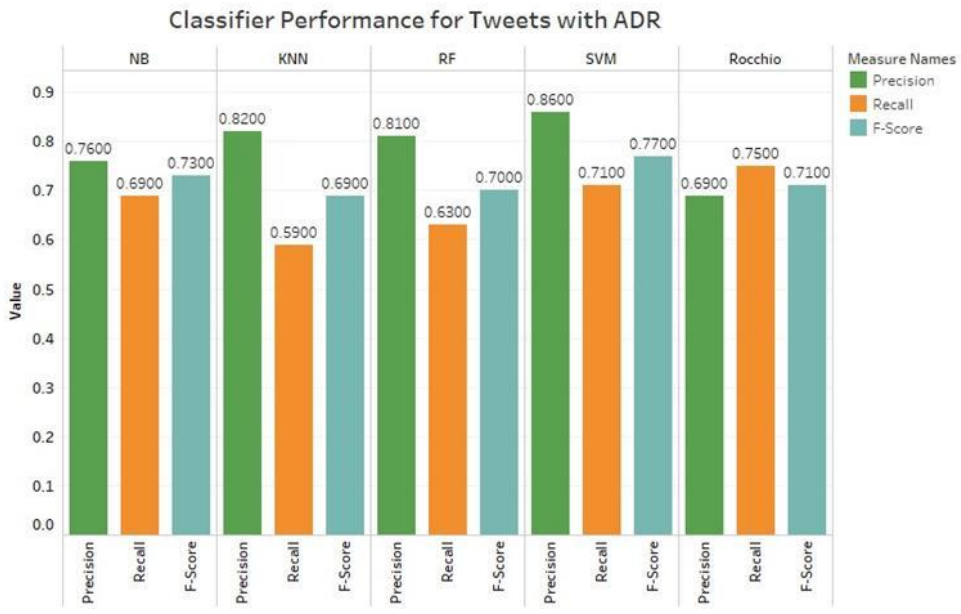

Fig. 2: Performance of classifiers in finding tweets with ADR

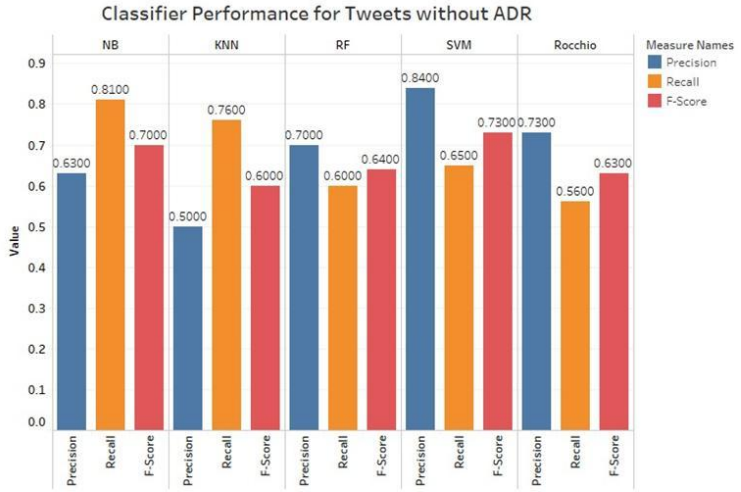

Fig. 3: Performance of classifiers in finding tweets without ADR



Fig. 4: Precision comparison of classifiers



Fig. 5: Recall comparison of classifiers



Fig. 6: F-Score comparison of classifiers

CONCLUSION AND FUTURE WORK

In this work we have retrieved real time tweets and filtered the ones with probable adverse drug reaction mentions. Later we analysed the performance of five classifiers on our data. In our future work we aim to improve the accuracy by exploring improved feature ranking and subset selection methods since better understanding of user tweets would boost the performance of classifier. We would like to analyse the application if deep learning algorithms like Recurrent Neural Networks for tweets classification with ADR mentions. Investigating possible relations or associations between specific drug names and reactions also would be interesting.

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