An Efficient Spam Filtering using Supervised learning SVM

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Abstract— With the growth of networking the usage of mails are also enhanced. Due to rapid growth of internet, dependency of communication is mostly based on electronics mails for both commercial and business purposes. According to today's scenarios electronics mails are also plays vital role in marketing or production advertisement. Hence numerous marketing firms used e-mails as a tool for promoting their products and services. These types of mails are generally called spam mails. Sometimes it is quite difficult to identify important mails among such group of spam mails. Because of this identification of such types of mails are essential so that they can keep away from important mails. The methodology implemented here is an efficient technique in which k-mean clustering is applied for the classification of spam.

I. Introduction

Now days networking or Internet is most widely used. The usages of e-mails are also enhanced. So that the large amount of text are usually transferred in form of e-mails to shear the data and message among people, organizations, companies and numerous departments. Emails can be used as powerful marketing tool and act as product or service promotions. In this scenario there can be spam which is unwanted messages or emails that sent electronically.

SPAM

Email spam or junk email or unsolicited bulk email i.e. UBE, is like electronic spam in which identical messages sent to many recipients by email. Spam email may include malware as scripts or other executable file attachments. “Spam generally includes the emails that are unsolicited and sent in bulk” The problem of junk email is becoming unmanageable now days because the unsolicited emails flood into corporate and consumer inboxes every day. Spam is generally used in commercial advertising like for dubious products, get-rich quick schemes, or quasi-legal services. [12]. some spam emails could hide viruses which can then infect the whole network. So that the mailing system should

Require more capable filters which help users to select of what to read and avoid us to spend more time on processing incoming messages.

Problems with spam

There can be two types of spam are the Email spam that is sent and received over the Internet and another is SMS spam is typically transmitted over a mobile network. The SMS spam can be a nuisance and also the mobile subscribers can suffer financial loss from SMS spam so it creates many problems to the users and network providers as resultant the subscribers can end up calling premium rate numbers or signing up to luxurious subscription services. They can unknowingly access suspect websites and be at risk of phishing attacks or malware downloads. Mobile network or service providers are suffering financially, facing higher operating costs and higher customer care costs in addition to damage to their brand and threat of regulation [3]

Spam Detection Methods

Duplicates detection Method

There are a large number of duplicate reviews and many of them are clearly spam. For example, different user ids posted duplicate or near duplicate reviews on the same product or different products. Duplicate detection is done using the shingle method [13] with similarity score > 0.9. '

Spam classification Method

Detection of spam reviews is done on the basis of 2-class classification. It uses machine learning model to classify each review and a classification model to labelled training like of spam reviews and non-spam reviews.

Dimensionality reduction methods

The dimensionality reduction methods are useful in the classification task to avoid dimensionality.

Feature selection (FS) - In this the dimensionality is reduced by selecting a subset of original features, and the removed features are not used in the computations anymore.

Feature extraction (FE) - in this the original vector space is transformed into a new one with some special proprieties, and the reduction is made in this new space.
In comparison of FS in FE all the original data features are present in a certain way but transformed to a reduced dimensional space, with replacing the original features by a smaller, but representative set of underlying features.

Feature Extraction
An e-mail can be a combination of text, graphics, hyperlinks, and even attached files. The feature extraction methods of spam more crucial to the filtering methods of spam. [1]. Feature Selection or feature extraction techniques works in a manner that the absolute values of the common vector elements are calculated for each class and on the basis of the indifference subspace projection, and justified by extensive testing the common vector elements which have large magnitudes correspond to more common, hence representative, properties of respective class. So the elements of the common vector that have small values carry relatively small information, their use in classification is redundant. [2]

Filtering of spam
There is some Simple filtering methods use traffic analysis to identify high volumes of messages from individual subscribers and there are also some anti-spam measures techniques like anti-spoofing and faking which can measures successfully the identity of SMS messages that have been manipulated to forge the originating details in order to keep away from charges. To get higher in non spoofed or faked SMS spam messages the more sophisticated filtering techniques is required. [3].

II. RELATED WORK

Yuanchun Zhu and Ying Tan proposed a Local-Concentration-Based Feature Extraction Approach for Spam Filtering [1]. They propose a local concentration (LC)-based feature extraction approach for anti-spam by taking inspiration from the biological immune system (BIS). The LC approach is considered to be able to effectively extract position-correlated information from messages by transforming each area of a message to an analogous LC feature. Two implementation approaches of the LC approach are designed using a fixed-length sliding window and a variable-length sliding window. To integrate the LC scheme into the whole process of spam filtering, a generic LC model is designed and presented. The performance of the LC approach is investigated on five benchmark corpora PU1, PU2, PU3, PUA, and Enron-Spam. Meanwhile, accuracy and F1 measure are utilized as evaluation criteria in analyzing and discussing the results [1].

BIS is an adaptive distributed system with the capability of discriminating “self cells” from “non-self cells.” It protects our body from attacks of pathogens. Antibodies, produced by lymphocytes to detect pathogens, play core roles in the BIS. On the surfaces of them, there are unambiguous receptors which can combine corresponding specific pathogens. Thus, antibodies can detect and destroy pathogens by binding them. All the time, antibodies circulate in our body and kill pathogens near them without any central controlling node. In the BIS, two types of immune response may happen: a primary response and a secondary response. The primary response happens when a pathogen appears for the initial time. In this case, the antibodies with resemblance to the pathogen are produced slowly. After that, a corresponding long-lived B memory cell (a type of lymphocyte) is created. Then when the same pathogen appears again, a secondary response is triggered, and a huge amount of antibodies with high resemblance to that pathogen are proliferated [1].

i. Structure of LC Model

To incorporate the LC feature extraction approach into the whole process of spam filtering, a generic structure of the LC model is designed, as is shown in Fig. 1. The tokenization is a simple step, where messages are tokenized into words (terms) by examining the existence of blank spaces and delimiters, while term selection, LC calculation and classification are quite essential to the model:

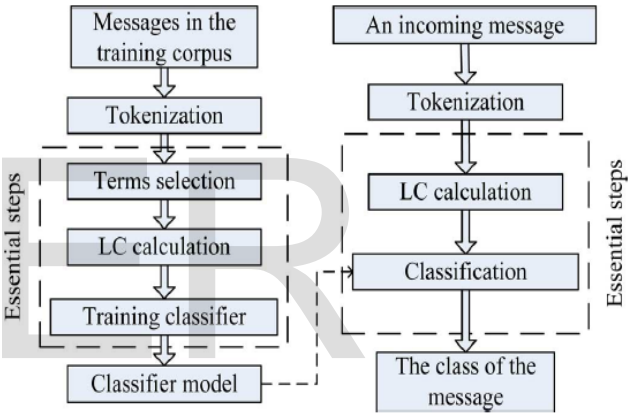


Figure 1: Training and classification phases of the LC model. a) Training stage of the model. b) Categorization phase of the model.

i. **Term selection:** In the tokenization step of the training phase, messages in the training corpus are transformed into a huge number of terms, which would cause high computational complexity. To reduce computational complexity, term selection methods should be utilized to remove less informative terms. Three term selection methods—IG, TFV, and DF were, respectively, applied to the LC model in our experiments. The experiments were conducted to compare their performances, aiming to show that the proposed model is compatible with various term selection methods.

ii. **LC calculation:** In BIS, antibodies distribute and circulate in bodies. Meanwhile, they detect and destroy specific pathogens nearby. In a small area of

a body, if the concentration of the antibodies with high affinity to a specific pathogen increases above some threshold, the pathogen would be destroyed. Thus, the local concentrations of antibodies determine whether the corresponding pathogens could be culled from the body.

iii. **Classification:** In the training phase, messages in the training corpus are at first transformed into feature vectors through the steps of tokenization, term selection, and LC calculation. Then the feature vectors are taken as the inputs of a certain classifier, after which a specific classifier model is acquired. Finally, the classifier model is applied to messages for classification.

Sarah Jane Delany et al [3] offered SMS spam filtering: Methods and data. They presented the state of the art in SMS spam filtering and have reviewed a number of different approaches to the problem which have been recommended and experienced. Using diverse data sets, a variety of researchers have shown that supervised learning algorithms can be effective for SMS spam classification, with reported accuracies of up to 97%. There is also some evidence of the use of non content-based approaches such as social network analysis and the identification of patterns of SMS submission. The results of the work published to date indicate that there is as yet no consensus on what the best techniques are for SMS spam filtering. Overall, the techniques which have been used to date are quite straightforward, applying what has been used in text classification in general to SMS filtering, and not necessarily taking the specific characteristics of SMS into account. One reason for this is simply the relative infancy of the field. Only recently have the ubiquity of SMS and the falling cost of delivery attracted the interest of spammers, so there has not yet been much time for academic research to identify and define the problem [3].

Alper Kursat Uysal et al [5] suggested The Impact of Feature Extraction and Selection on SMS Spam Filtering. They extensively analyses the effects of several feature extraction and feature selection methods together on filtering SMS spam messages in two dissimilar languages, explicitly Turkish and English. The whole feature set of the filtering scheme is composed of the features originated from the bag-of-words (BoW) model, and also an ensemble of structural features (SF) adopted for the spam problem. The distinctive features based on the bag-of-words model are determined using chi-square and Gini index based feature selection methods. The selected features are then combined with the structural features and fed into two separate pattern categorization algorithms, specifically k-nearest neighbor and support vector machine, to categorize SMS messages as either spam or legitimate. The filtering framework is evaluated on two separate SMS message datasets consisting of Turkish and English messages, respectively [5].

The impact of various feature extraction and selection methodologies on SMS spam filtering, particularly for Turkish and English languages was systematically observed in terms of cataloging accuracy and dimension reduction rate. Outcome of an in-depth experimental work indicated that the combinations of BoW and structural features, rather than BoW features alone, recommend better arrangement performance most of the time. Alternatively effectiveness of the utilized feature selection strategies was not significantly superior to each other for both languages. Since Turkish and English are the leading examples of agglutinative and non-agglutinative languages correspondingly, the conclusion of this study can also be an indicator for the other languages with similar characteristics as well [5].

Azadeh Beiranvand et al [6] offered Spam Filtering by Using a Compound Method of Feature Selection. They have focused on extracting words as features then we have introduced a method consisting of several feature selection methods and have evaluated the influence of reducing feature space dimensions and finally we have used Adaboost algorithm to learn about the system. Presenting documents is an important part in filtering process, or generally, the text categorization. In Spam filtering, the texts frequently are extracted from the message body although; it is also possible to use the topic or even the message header fields in this regard. One of the most famous displaying methods is Bag-Of-Word which can be named as Vector-Space [6].

After recognizing the features and gaining the vector space of the regarded data set, the feature selection stage is done and the related features are recognized in relation to the rest of feature, which have more ability of cataloging. In this consideration, the features are given to the first filter i.e. DF and the number of 658 features is remained after omitting those features that rarely appear in the dataset. Then this number of features is specified to the next filter i.e. IG and after performing this method repetitively, the number of errors appropriate for the features are gained by try and error [6].

Guyue Mi et al [7] suggested A Multi-Resolution-Concentration Based Feature Construction Approach for Spam Filtering. A multi-resolution-concentration (MRC) based feature construction approach for spam filtering is proposed, which progressively partitions an email into local areas on smaller and smaller resolutions, and the concentration features are constructed on each local area. The MRC approach depicts a dynamic process of gradual refinement in locating the pathogens by calculating concentrations of detectors on local areas and is considered to be able to extract the position-correlated and process-correlated information from emails. Furthermore, by introducing the different activity levels of detectors, a weighted MRC (WMRC) approach is presented. A generic structure of the MRC model is designed and the detailed implementations of MRC and WMRC are described. Experiments are conducted on five benchmark corpora PU1, PU2, PU3, PUA and Enron-Spam for investigating performance of the MRC and WMRC approaches. Accuracy

and □1 measure are selected as the main criteria in analyzing and discussing the results [7].

They [7] proposed a MRC based feature construction approach for spam filtering by taking inspiration from BIS. Feature construction is considered as a process of gradual refinement in locating the pathogens by dynamically calculating local concentrations of detectors on smaller and slighter declarations. By commencing activity level of detector, a WMRC based feature construction approach is presented. Sufficient experiments illustrate that the MRC and WMRC approaches outperform prevalent feature construction approaches in spam filtering and achieve high efficiency [7].

Sangeetha et al [8] offered Feature Extraction Approach for Spam Filtering. They propose a local concentration (LC)-based feature extraction approach for anti-spam by taking inspiration from the biological immune system (BIS). The LC approach is considered to be able to effectively extract position-correlated information from messages by transforming each area of a message to a corresponding LC feature. To incorporate the LC approach into the whole process of spam filtering, a generic LC model is designed and presented [8].

Nosseir et al [9] proposed Intelligent Word-Based Spam Filter Detection Using Multi-Neural Networks. This novel approach uses a multi-neural networks classifier to identify bad and good words in the textual content of an email. Words in the message are preprocessed before using the multi-neural networks classifier. The word goes through stop words and noise removal steps then stemming process step to extract the word root or stem. The experiment shows positive results [9].

The problem is that SPAM imposes direct cost in terms of time, money, and storage space and indirect cost to protect privacy and security breaches. Users are inconvenienced by the SPAM because of the time they spend to filter legitimate email from SPAM emails. These unproductive hours can be calculated “based on the number of SPAM emails users read [9].

In BIS, antibodies distribute and circulate in bodies. Meanwhile, they detect and destroy specific pathogens nearby. In a small area of a body, if the concentration of the antibodies with high affinity to a specific pathogen increases above some threshold, the pathogen would be destroyed. Thus, the local concentrations of antibodies determine whether the corresponding pathogens could be culled from the body. To construct an LC-based feature vector for each message, a sliding window of Wn-term length is utilized to slide over the message with a step of Wn-term, which means that there is neither gap nor overlap between any two adjacent windows [9].

Ying Tan et al [10] proposed Artificial Immune System Based Methods for Spam Filtering. They introduce and discuss several recent works which applied mixed principles to feature attraction, classifier combination, and classifier updating, so as to demonstrate the rationality of combining statistical and AIS methods for spam filtering. In addition, they present a generic framework of an immune based model for spam filtering, and online implementation strategies are given to demonstrate how to build an immune based intelligent email server [10].

There exist many explanations about the mechanisms of BIS. An explanation may be superior for analyzing some specific immune phenomena, but less persuasive for some other aspects. For AIS practitioners, it is not quite necessary to find which theory is better in explaining immune mechanisms. What matters most is the heuristic principles behind these explanations. Besides detecting antigens, dynamics of immune cells is also one of the most important properties possessed by BIS. Antibodies can evolve to recognize emerging antigens, and the recognition memory will be preserved to detect antigens more effectively next time. In addition, there are some ways in measuring the importance of antibodies, such as lifespan and weights. The dynamic change of lifespan and weights ensures that the existing antibodies give the best protection to the body [10].

The immune based model is built by borrowing some ideas from mechanisms of BIS. The effect of the model is not limited by the implementation details. Thus, it is natural and easy to extend the model using different implementation strategies. The essence of both LC and GC methods lies in the mechanism of concentration. It is concentration that endows the model with noise tolerance and robust properties. Besides characteristic terms, other attributes can also be taken as elements for calculating concentration. For instance, binary string or regular expression can characterize a message well. Thus, it is rational to use the concentration of them as messages’ features. In classification phase, other classifiers, e.g. NB, ANN, can be applied instead of SVM. The possible extensions may help us learn the mechanisms of the concentration method better [10].

In the classification phase, match signals, danger signals and danger zones play important roles. A match signal indicates a primary recognition of the message type, and a danger signal is a confirmation to the match signal. A danger zone defines a way of utilizing neighborhood information. In extending the model, more danger signals can be brought in to define a cascade way of combining multiple classifiers [10].

They [10] present a framework of an immune based spam filtering model, which demonstrate how to utilize these methods in real-world applications. In the model, immune mechanisms are brought in different phases of spam filtering model. First, concentration concept is utilized for extracting feature vectors from messages, and it is demonstrated that the concentration method is more robust and accurate than the prevalent BoW method. Mechanisms of DT are then shown to be effective in combining classifiers. Besides, dynamic mechanisms of BIS are adapted to updating classifiers of the

spam filter. Finally, implementation strategies of an immune based intelligent email server are also given [10].

Tarek M Mahmoud and Ahmed M Mahfouz proposed SMS Spam Filtering Technique Based on Artificial Immune System [11]. an anti-spam filtering technique based on Artificial Immune System (AIS) is proposed. The proposed technique utilizes a set of some features that can be used as inputs to a spam detection model. The inspiration is to categorize message using qualified dataset that contains Spam Words, Phone Numbers and Detectors. This anticipated technique utilizes a double collection of bulk SMS messages Spam and Ham in the training process to improve its efficiency.

They [11] proposed a mobile agent system for detecting SMS-Spam based on AIS. This system contains dataset, tokenizer, analysis engine, stop word filter, AIS engine, and training process. The system used AIS features to building the antibodies (detectors), by initial training phases. The generation, updating, and elimination of detector based on the AIS engine, the content of spam and non-spam SMS Messages used in training. The experimental results applied on 1324 SMS messages show that (on average) false positive rate, the detection rate and overall accuracy of the proposed system are 82%, 6%, and 91% respectively [11].

III. PROPOSED METHODOLOGY

Structure of LC Model

To incorporate the LC feature extraction approach into the whole process of spam filtering, a general structure of the LC model is designed. The tokenization is a simple step, where messages are tokenized into words (terms) by examining the existence of blank spaces and delimiters, while term selection, LC calculation and classification are

• **Term selection**: In the tokenization step of the training phase, messages in the training corpus are transformed into a huge number of terms, which would cause high computational complexity. To reduce computational complexity, term selection methods should be utilized to remove less informative terms.

• **LC calculation**: In BIS, antibodies distribute and circulate in bodies. Meanwhile, they detect and destroy specific pathogens nearby. In a small area of a body, if the concentration of the antibodies with high affinity to a specific pathogen increases above some threshold, the pathogen would be destroyed. Thus, the local concentrations of antibodies determine whether the corresponding pathogens could be culled from the body. Inspired from this phenomenon, we propose a LC based feature extraction approach.

• **Classification:** In the training phase, messages in the training corpus are at first transformed into feature vectors through the steps of tokenization, term selection and LC calculation. Then the feature vectors are taken as the inputs of a certain classifier, after which a specific classifier model is acquired. Finally, the classifier model is applied to messages for classifying in the classification phase. For classification I will modify previous Artificial Immune Reorganization system and propose new classification method Artificial Immune System with Local Feature Selection (AISLFS).

Algorithm for SVM

1: Input: (x1, y1) ... (xn, yn), C,∈
2. Si←∅ for all i=1 ...n
3. Repeat
4. For i=1 ...n do
5. H(y) =$\Delta(yi, y) + w^T\psi(xi, y) - w^T\psi(xi, yi)$
6. Compute Ÿ=argmaxy∈ $yH(y)$
7. Compute £i=max {0, maxy∈ $SiH(y)$
8. If H (Ÿ)>£i + ∈ $then$
9. Si←Si ∪ $\{\bar{Y}\}$
10. w←optimize primal over S=∪ iSi
11. End if
12. End for
13. until no Si has changed during iteration.

IV. RESULT ANALYSIS

Spam recall: It measures the percentage of spam that can be filtered by an algorithm or model. High spam recall ensures that the filter can protect the users from spam effectively. It is defined as follows:

$$R_s = \frac{n_{s\to s}}{n_{s\to s} + n_{s\to l}}$$

Where the number of spam is correctly classified, And is the number of spam mistakenly classified as legitimate e-mail.

Spam precision: It measures how many messages, classified as spam, are truly spam. This also reflects the amount of legitimate e-mail mistakenly classified as spam. The higher the spam precision is, the fewer legitimate e-mail has been mistakenly filtered. It is defined as follows:

$$P_s = \frac{n_{s\to s}}{n_{s\to s} + n_{l\to s}}$$

Where the number of legitimate e-mail is mistakenly classified as spam, and has the same definition as above.

Accuracy: To some extent, it can reflect the overall performance of filters. It measures the percentage of messages (including both spam and legitimate e-mail) correctly classified. It is defined as follows:

$$A = \frac{n_{l\to l} + n_{s\to s}}{n_l + n_s}$$

Where is the number of legitimate e-mail correctly classified, has the same definition as in above, and and are, respectively, the number of legitimate e-mail and the number of spam in the corpus.

Sliding Window	Existing Recall	Proposed Recall
5	0.947	0.9634
10	0.95	0.9843
15	0.936	0.9723
20	0.938	0.9752
25	0.942	0.9623
30	0.945	0.9762
35	0.926	0.9723
40	0.916	0.9643
45	0.913	0.9562
50	0.946	0.9743

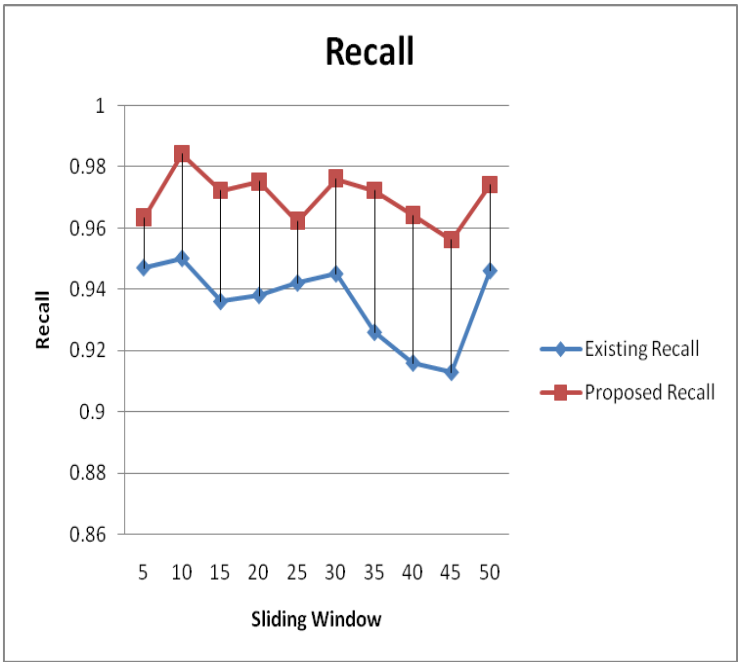
Table 1. Comparison of Recall

Sliding Window	Existing Precision	Proposed Precision
5	0.9643	0.9823
10	0.9623	0.97453
15	0.9643	0.98563
20	0.9646	0.9782
25	0.9649	0.9834
30	0.9629	0.9812
35	0.9637	0.9756
40	0.9523	0.9834
45	0.9578	0.9867
50	0.9628	0.98123

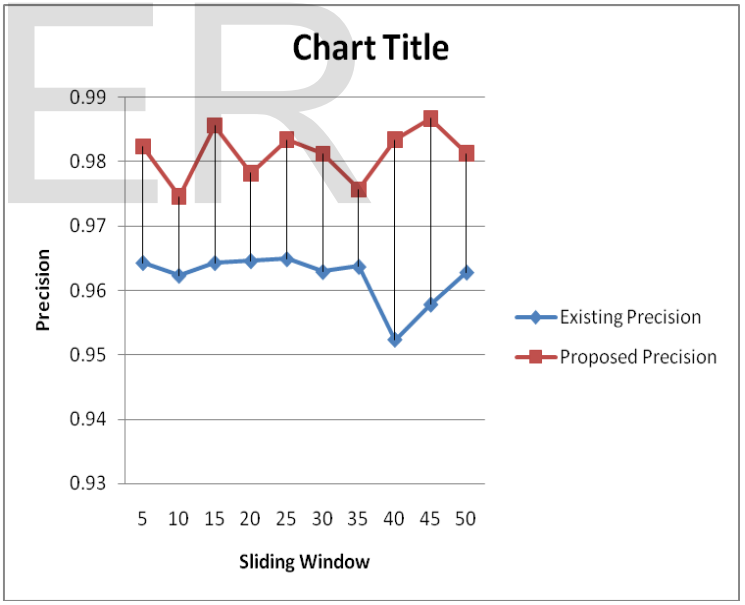
Table 2. Comparison of Precision

Sliding Window	Existing measure	Proposed measure
5	0.955571705	0.972758205
10	0.956110443	0.979390635
15	0.949939273	0.978919623
20	0.951114054	0.976697696
25	0.953312497	0.972735591
30	0.953866031	0.978693614
35	0.944473938	0.973947205
40	0.933797356	0.973756349
45	0.934863588	0.971210603
50	0.954326069	0.977752721

Table 3. Comparison of F-measure



Graph 1. Comparision of Recall



Graph 2. Comparison of Precision

V. CONCLUSION

When classifying email messages, often the data contained in messages are very complex, multidimensional, or represented by a large number of features. Then, the use of dimensionality reduction methods is useful in the classification task in order to avoid the curse of dimensionality. When using many features, we need a corresponding increase in the number of

annotated examples to train from to ensure a correct mapping between the features and the classes. The proposed methodology performs better in terms of precision recall and accuracy.

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