

**INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH
TECHNOLOGY****SURVEY ON E-MAIL SPAM DETECTION USING SUPERVISED APPROACH
WITH FEATURE SELECTION****Harjot Kaur*, Er. Prince Verma**

* Research Scholar CT group of Institutions, Jalandhar, Punjab, India

Asst. Prof. CT group of Institutions, Jalandhar, Punjab, India

DOI: 10.5281/zenodo.496096

ABSTRACT

Electronic Mail (E-mail) has established a significant place in information user's life. Mails are used as a major and important mode of information sharing because emails are faster and effective way of communication. Email plays its important role of communication in both personal and professional aspects of one's life. The rapid increase in the number of account holders from last few decades and the increase in the volume of mails have generated various serious issues too. Emails are categorized into ham and spam emails. From past decades spam emails are spreading at tremendous rate. These spam emails are illegitimate and unwanted emails that may contains junk, viruses, malicious codes, advertisements or threat messages to the authenticated account holders. This serious issue has generated a need for efficient and effective anti-spam filters that filter the email into spam or ham email. Spam filters prevent the spam emails from getting into user's inbox. Email spam filters can filter emails on content base or on header base. Various spam filters are labeled into two categorizes machine learning and non-machine learning techniques. This paper will discuss the process of filtering the mails into spam and ham using various techniques.

KEYWORDS: Data Mining, KDD, E-Mail, Spam, Ham, Spam Filter, N-Gram based feature selection, MLP-NN and SVM classification algorithms.

INTRODUCTION

The generation in the growth of data from past few decades is increasing tremendously. Various sources like commercial sites, engineering field, facebook and other social links like twitter, you-tube contributes in the size and complexity of data. To handle and to extract relevance among the data various tool and techniques are used. Data Mining is a process used for extracting hidden and unknown information from the databases for seeking knowledge. Data can vary in size, complexity to structure. Data can be in the form of audio, video or simply a text data. To handle and to extract the desirable properties from the data, mining is carried out.

Knowledge Discovery Process

Knowledge form data can be achieved by undergoing various steps as mentioned below. Data mining term is also labelled as Knowledge discovery technique, which means a procedure of extracting useful information from a set of raw data. Data mining is a part of knowledge discovery as in [13], [14].

1. **Collection of Raw Data:** Dataset can be collected from various sources like online and offline, social media sources, banks, retail sector etc.
2. **Data Selection:** Relevant data that is of use is selected for analysis.
3. **Data Pre-Processing:** Cleansing of the data to remove any sort of noise, bogus or missing value from the data is carried out.
4. **Transformation:** The data is transformed into appropriate form so that mining operation can be carried out.
5. **Data Mining:** Extraction of relevant patterns from the data by using various data mining techniques.
6. **Evaluation:** Extracted patterns are analysed for the truth-worthiness of the patterns and its relevance.
7. **Knowledge:** The above procedure mines the relevant knowledge from the raw dataset. Knowledge can be represented by various techniques.

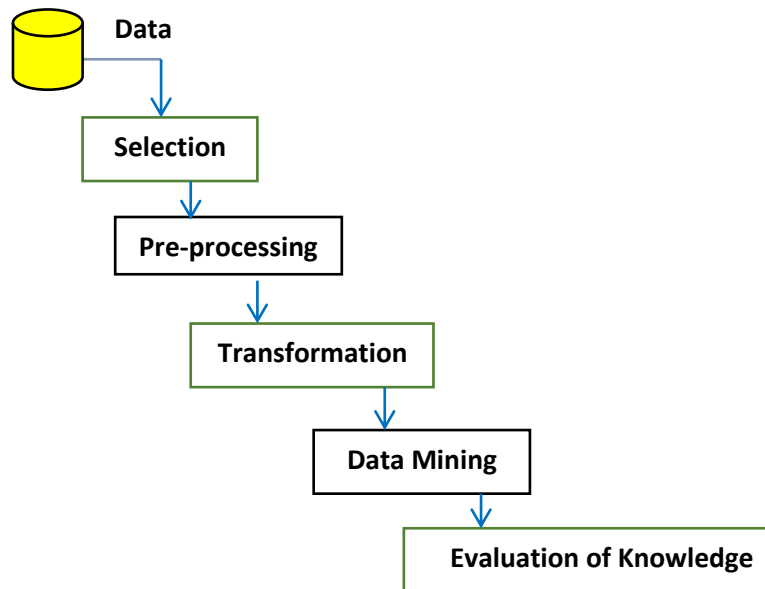


Fig. 1: Knowledge Discovery Process for mining data as in [13].

Various Techniques of Data Mining

The various techniques followed in data mining are classified as mentioned below as in [13]. The following steps are executed on irrelevant data to gain and access relevant information.

1. **Anomaly Detection:** Data information that is bogus or irrelevant is mined. Anomaly detection detects the information without any facts.
2. **Association Rule Mining (ARM):** It is a process of identifying relationship among the attributes present in the datasets.
3. **Clustering:** It is a process that groups the similar data in one cluster without using any predefined model. Clustering defines its own model and is descriptive procedure of grouping the data.
4. **Classification:** It is a process that has a predefined model and generalizes the data into known predetermined classes. Classification is a predictive model.
5. **Summarization:** A process of representing the data in a precise form for visualization.

Email Spam

Internet has become an important and essential part of human life. The increase in the utilization of internet has increased the number of account holders over various social sites. Email is the simplest and fastest mode of communication over the internet that is used both personally and professionally. Due to the increase in the number of account holders and increase in the rate of transmission of emails a serious issue of spam emails had aroused. From a survey it was analysed that over 294 billion emails are sent and received every day. Over 90% emails are reported to be spam emails as in [15].

Emails are labelled into two categories Spam emails and Ham emails. Spam emails are the junk mails received from illegitimate users that might contain advertisement, malicious code, virus or to gain personal profit from the user. Spam can be transmitted from any source like Web, Text messages, Fax etc., depending upon the mode of transmission spam can be categorised into various categories like email spam, web spam, text spam, social networking spam as in [3].

The rate at which email spamming is spreading is increasing tremendously because of fast and immodest way of sharing information. It was reported that user receives more spam mails than ham mails. Spam filtration is important because spam waste time, energy, bandwidth, storage and consume other resources as in [12]. Email can be categorised as a spam email if it shows following characteristics:

1. **Unsolicited Email:** Email received from unknown contact or illegitimate contact.
2. **Bulk Mailing:** The type of email which is sent in bulk to many users.
3. **Nameless Mails:** The type of mails in which the identity of the user is not shown or is hidden.

Spamming is a major issue and causes serious loss of bandwidth and cost billion of dollars to the service providers. It is essential for distinguishing between the spam mail and ham mail. Many algorithms are so far used to successfully characterise the mails on their behaviour but because of the changing technologies hackers are becoming more intelligent. So better algorithms with high accuracy are needed that successfully label a mail as spam or ham mail. Spam filter technique is used to label the mail as a junk and unwanted mail and prevents it from entering the authenticated account holder's inbox. Filters can be grouped in two categories as in [12]:

1. **Machine Learning Based Technique:** These techniques are Support Vector Machine, Multi-Layer Perceptron, Naïve Bayes Algorithm, Decision Tree Based etc.
2. **Non-Machine Learning Based Technique:** These techniques are signature based, heuristic scanning, black and whitelist, sandboxing, mail header scanning etc.

The success ratio of machine learning algorithms over non-machine learning algorithms is more. These techniques work by selecting the best features from the data to group the emails as spam or ham. Feature selection can be carried out in two ways:

1. **Header Based Selection:** Selecting the best feature from the header of the mail. It contains sender's address, BCC (Blind Carbon Copy), CC (Carbon Copy), To, From, Date and Subject.
2. **Content Based Selection:** Selecting the best feature from the content in the mail. It contains the main message either in the form of text, audio or video, attachments etc.

Content Based Feature Selection is proven as the most authenticated feature selection as compared to Header Based as Header Based Feature Selection can be easily tempered by the hackers or spammers.

The survey paper is outlined in different sections. Section 2 represents the literature survey introducing various papers in the field of email spam detection. Section 3 describes the best feature selection technique to label the email as spam mail or ham mail by using n-gram based feature selection technique. Section 4 and 5 describes various machine and non-machine learning algorithms for classification of mails and section 6 concludes the paper and prescribes the best algorithm with high accuracy for spam detection.

LITERATURE SURVEY

Bo Yu and Zong-ben Xu (2008) performed a comparative analysis on content-based spam classification using four different machine learning algorithms. This paper classified spam emails using four different machine learning algorithms viz. Naive Bayesian, Neural Network, Support Vector Machine and Relevance Vector Machine. The analysis was performed on different training dataset and feature selection. Analysis results demonstrated that NN algorithm is no good enough algorithm to be used as a tool for spam rejection. SVM and RVM machine learning algorithms are better algorithms than NB classifier. Instead of slow learning, RVM is still better algorithm than SVM for spam classification with less execution time and less relevance vectors as in [1].

Tiago A. Almeida and Akebo Yamakami (2010) performed a comparative analysis using content-based filtering for spam. This paper discussed seven different modified versions of Naïve Bayes Classifier and compared those results with Linear Support Vector Machine on six different open and large datasets. The results demonstrated that SVM, Boolean NB and Basic NB are the best algorithms for spam detection. However SVM executed the accuracy rate higher than 90% for almost all the datasets utilized as in [2].

Loredana Firté, Camelia Lemnar and Rodica Potolea (2010) performed a comparative analysis on spam detection filter using KNN Algorithm and Resampling approach. This paper make use of K-NN algorithm for classification of spam emails on predefined dataset using feature's selected from the content and emails properties. Resampling of the datasets to appropriate set and positive distribution was carried out to make the algorithm efficient for feature selection as in [3].

Ms.D.Karthika Renuka, Dr.T.Hamsapriya, Mr.M.Raja Chakkaravarthi and Ms.P.Lakshmisurya (2011) performed a comparative analysis on spam classification based on supervised learning using several machine learning techniques. In this analysis, the comparison was done using three different machine learning classification algorithms viz. Naïve Bayes, J48 and Multilayer perceptron (MLP) classifier. Results demonstrated high accuracy for MLP but high time consumption. While Naïve Bayes accuracy was low than MLP but was fast enough in execution and learning. The accuracy of Naïve Bayes was enhanced using FBL feature selection and used filtered Bayesian Learning with Naïve Bayes. The modified Naïve Bayes showed the accuracy of 91% as in [4].

Rushdi Shams and Robert E. Mercer (2013) performed a comparative analysis on classification of spam emails by using text and readability features. This paper proposed an efficient spam classification method along with

feature selection using content of emails and readability. This paper used four datasets such as CSDMC2010, Spam Assassin, Ling Spam, and Enron-spam. Features are categorized into three categories i.e. traditional features, test features and readability features. The proposed approach is able to classify emails of any language because the features are kept independent of the languages. This paper used five classification based algorithm for spam detection viz. Random Forest (RF), Bagging, Adaboostm 1, Support Vector Machine (SVM) and Naïve Bayes (NB). Results comparison among different classifiers predicted Bagging algorithm to be the best for spam detection as in [5].

Megha Rathi and Vikas Pareek(2013) performed an analysis on spam email detection through Data Mining by performing analysis on classifiers by selecting and without selecting the features as in [6].

Anirudh Harisinghaney, Aman Dixit, Saurabh Gupta and Anuja Arora (2014) performed a comparative analysis on text and images by using KNN, Naïve Bayes and Reverse-DBSCAN Algorithm for email spam detection. This analysis paper proposed a methodology for detecting text and spam emails. They used Naïve Bayes, K-NN and a modified Reverse DBSCAN (Density- Based Spatial Clustering of Application with Noise) algorithm's. Authors used Enron dataset for text and image spam classification. They used Google's open source library, Tesseract for extracting words from images. Results show that these three machine learning algorithms gives better results without preprocessing among which Naïve Bayes algorithm is highly accurate than other algorithms as in [7].

Savita Pundalik Teli and Santosh Kumar Biradar (2014) performed an analysis on effective email classification for spam and non-spam emails as in [8].

Izzat Alsmadi and Ikdam Alhami (2015) performed an analysis on clustering and classification of email contents for the detection of spam. This paper collected a large dataset of personal emails for the spam detection of emails based on folder and subject classification. Supervised approach viz. classification along-side unsupervised approach viz. clustering was performed on the personal dataset. This paper used SVM classification algorithm for classifying the data obtained from K-means clustering algorithm. This paper performed three types of classification viz. without removing stop words, removing stop words and using N-gram based classification. The results clearly illustrated that N-gram based classification for spam detection is the best approach for large and Bi-language text as in [9].

Ali Shafiqh Aski and Navid Khalilzadeh Sourati (2016) performed an analysis using Machine Learning". This paper utilized three machine learning algorithms viz. Multi-Layer Neural Network, J48 and Naïve Bayes Classifier for detection of spam mails from ham mails using 23 rules. The model demonstrated high accuracy in case of MLP with high time for execution while Naïve Bayes showed slightly less accuracy than MLP and also low execution time as in [10].

N-GRAM BASED FEATURE SELECTION

Feature selection is a dimensionality reduction method which is used for better classification results by selecting the most desirable feature from the preprocessed data. In this survey N-Gram based feature selection is discussed. N-Gram is a prediction based algorithm used for predicting the chance of occurrence of next word after making observations of N-1 words in a sentence or text corpus. N-Grams uses probability based methods for the prediction of next word. N-Gram is used in text mining and natural language processing. N-grams are the group of co-occurring words that move one or X (number of words in a corpus) steps or words ahead while computing N-Grams. Let X, be the number of words in a given text corpus T, the number of N-Grams can be calculated by:

$$N_{\text{grams}}(T) = X - (N-1) \quad (1)$$

N-Grams are collected from a text corpus and vary according to the size of N. In the above equation for the calculation of N-Gram, T represents the text, X represents the number of words in the text corpus, and N represents the size of the text.

1. **Uni-Gram:** The N-Gram of size one is termed as Uni-Gram. For example, the word "FOOD" in Uni-Gram can be represented by moving one step ahead viz. "F to O", "O to O", "O to D"
2. **Bi-Gram or Di-Gram:** The N-Gram of size two is termed as Di-Gram. For example, "FOOD" in Bi-Gram can be represented by moving two steps ahead in the string of data viz. "FO to OO", "OO to OD".
3. **Tri-Gram:** The N-Gram of size three is termed as Tri-Gram and so on for N= 4, N=5 etc.

N-Gram for a text corpus "Children are enjoying the sunny weather" using Bi-Gram (N=2) will be "Children are"; "Are enjoying"; "Enjoying the"; "The sunny"; "Sunny weather"

In the example of text corpus containing 6 N-grams were listed as we move two steps ahead for generating the possibility of occurrence of next word. N-Gram has a wide range of utilization in various application like spelling correction, plagiarism detection, summarization of words, feature selection, breaking the words in text etc. N-grams are the N number of characters in a text or string and are widely used model in various domains because of its ability to deal with noisy ASCII inputs and low error rate. Probability of N-Grams can be calculated by:

1. **Simple N-Gram:** Simple N-Gram is a non-smoothed N-Gram that predicts the probability of next word by labeling equal probability to all the number of words present in the corpus. Suppose if there are N words in a text their probability would be $1/N$ without taking into consideration about the frequency of occurrence of words.
2. **Markov Assumption:** The probability of occurrence of next word depends only on the previous word and this model was labeled as Markov Assumption. Markov Assumption calculates the probability by only considering the last word without taking into consideration about the history of words that occurred in the past. Markov assumption (Bi-Gram) can be upgraded to tri-gram by considering last 2 words in the past and bi-gram can be upgraded to N-Gram by looking N-1 words in the past history. The simplest way to calculate the probability of occurrence of next word is by using Maximum Likelihood Estimation (MLE) which takes counts from the text and normalizes the counts to lie in the range interval of [0,1].
3. **Smoothing:** The limitation of MLE is that it shows poor result for the words with low frequencies and for zero probability some N-Gram evaluation metrics does not works. Therefore smoothing is used along with MLE for making N-Gram efficient for those sequences of words with low frequency by borrowing the probability from higher frequencies.

Advantages of N-Gram

Words alone cannot provide information but using N-Grams provides informative combination of words which help in easy understanding of the meaning of text.

1. N-Grams can automatically capture the frequencies of words in the text that are repeated usually.
2. N-Gram is independent of the language used in the document. Also N-Gram can efficiently work with languages like Chinese and Urdu, where the words are not properly distinguished by borders.
3. N-Grams do not require any initial partitioning of text into bag-of-words.
4. N-Gram is highly tolerable towards any kind of words or spelling mistakes. For example if a word "Table" is written as "Talbe" N-gram can easily recognize the correct existence of the word "Table".
5. N-Gram effectively considers words and its ordering too.
6. Learning rate is fast in N-Gram as compared to other feature selection techniques.

NON-MACHINE LEARNING TECHNIQUES FOR SPAM DETECTION

Non-Machine Learning is a technique of establishing relationship among the variables using some self-proclaimed rules without relying on the data for knowledge. Non machine learning is a non-efficient technique for spam filtration and detection. Various Non-Machine Learning algorithms can be categorized as in [11], [12].

1. **Signatures:** Signatures contains the information taken from the documents. Signatures detect the spam or threats by generating a unique value called as hash value for each spam message. Signatures can be generated in two ways firstly by fragmenting the words into pairs and secondly by random generation of numbers. Signature uses the hash value with the new mail value to compare and analyze if the mail is spam or ham.
2. **Blacklist and Whitelist:** A blacklist is a list of spammers or any illegitimate contact that tries to send a spam or malicious mail while whitelist is a list that contains legitimate users or contacts that are known to an individual account holder.
3. **Heuristic Scanning:** This technique uses rules to detect malicious contents and threats. Heuristic scanning is a faster and efficient technique that detects the spam or threats without executing the file and works by understanding the behaviour. Heuristic scanning allows the user to change the rules.
4. **Mail Header Checking:** In this technique set of rules are developed that are matched with the mail header to detect if the mail is spam or ham. If the header of the mail matches the rules, then it invokes the server and directs the mails that contain empty field of "From", confliction in "To", confliction in "Subject" etc.

MACHINE LEARNING TECHNIQUES FOR SPAM DETECTION

Machine Learning Techniques enables the computer to learn by itself without being programmed. Machine learning algorithms are more efficient in contrast to those of non-machine learning. Machine learning work in similar way like data mining, both acquire knowledge from data and find relevance in the data. Machine learning algorithms can be categorized into supervised and unsupervised algorithms. Some of the supervised machine learning algorithms for classification of data is listed below:

Multi-Layer Perceptron Neural Network: Artificial neural networks are the part of artificial intelligence and MLP is a type of neural network. Multi-Layer Perceptron (MLP) is a feed-forward network that maps the group of inputs to their corresponding outputs. Fig. 2 demonstrates a feed-forward multi-layer perceptron neural network as in [10], [18]. MLP is made up of simple neurons termed as perceptron's. Neural network generates information by enabling input perceptron's consisting the values labelled on them. Activation function of neurons is calculated by the formula mentioned below in the output layer as in [10]:

$$a_i = \sigma(\sum_j W_{ij} O_j) \quad (2)$$

Where a_i represent level of activation for i th neurons; j is the set of neurons of the previous layer; W_{ij} is the weight of the connection between neurons i and j ; O_j represents the output of j th neuron and $\sigma(x)$ is the transfer function.

$$\sigma(x) = \frac{1}{1+e^{-x}} \quad (3)$$

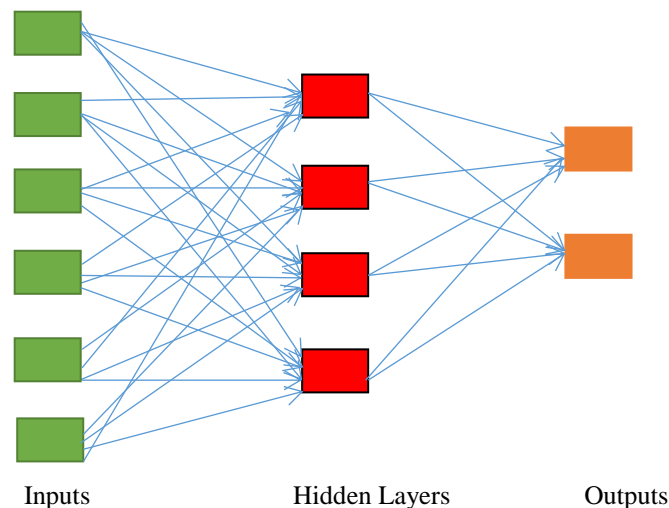


Fig.2: Multi-Layer Neural Network Architecture.

A back propagation strategy based on delta rule is used to train multilayer perceptron network. MLP consist of various neurons divided into various layers, as follows:

1. **Input Layer:** This layer generates the input for the network. The number of neurons depends upon the number of input given to the network.
2. **Hidden Layer:** The layers that maps the input to the corresponding output is named as hidden layer. Hidden layers vary in number.
3. **Output Layer:** The layer from where the resultant can be seen. The number of neurons in output layer depends upon the learning of the kind of problem.

The type of relationship between the input and output vectors in MLP is non-linear relationship. This is done by inter-connecting the neurons in the antecedent and succeeding layers. Outputs are achieved by multiplying them with weight coefficients. In the training phase, neural network is given the information of training only. Later on the weights of the network are tuned between $[-0.5, 0.5]$ to minimize the error rate between the expected and observed outputs and to enhance the frequency of training to a predicted level. A sequence untrained inputs is applied to the input to formalize the training. These input set are different from the inputs that are used for the training of the network. Training of the neural network is highly complex due to the large number of variables. MLP holds lots of advantages over other algorithms even if correct relationship is not induced between the input and output or if essential and exact information is not achieved as in [10]. Non-Linear Activation Function of

MLP makes MLP different from other networks. Algorithmic steps for MLP- Neural Network can be modeled as: Let a dataset D , consist of training samples and their target values, L be the rate of learning by the network to generate a trained network:

1. Initialize the weights and the biases of the layers using small random values.

2. Compute the weighted sum of the inputs where,

$$O_j = I_j \quad (4)$$

Output of the inputs is the true input values.

3. Compute the activation functions of hidden layers where,

$$I_j = \sum_i W_{ij} O_i + \theta_j \quad (5)$$

Compute the net input of j with respect to i (previous layer).

4. Compute the output of the layers where;

$$O_j = \frac{1}{1+e^{-I_j}} \quad (6)$$

5. Compute the error rate by Back-Propagation,

$$\text{Error for output layer: } \text{Error}_j = O_j(1 - O_j)(T_j - O_j) \quad (7)$$

Error calculation of next hidden layer, h :

$$\text{Error}_j = O_j(1 - O_j) \sum_h \text{Error}_h w_{jh} \quad (8)$$

$$\text{Weight update: } w_{ij} = w_{ij} + \Delta w_{ij} \quad (9)$$

$$\text{Bias update: } \theta_j = \theta_j + \Delta \theta_j \quad (10)$$

Where Δw_{ij} and $\Delta \theta_j$ are the change in weight and bias.

Support Vector Machine: Support vector machine (SVM) is a supervised approach for machine learning. The main idea used in SVM is constructing a hyper plane that is optimal for the classification of patterns that can be linearly separated as in [20]. This algorithm work by plotting each information point in n -dimensional workspace, where n represents the number of features which are equal to the co-ordinates in the workspace. The optimal hyper plan differentiates the classes at this point as in [21].

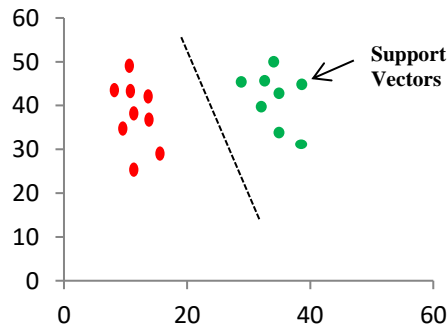


Fig. 3: SVM representing difference between two classes using hyper-plane.

In email spam detection the aim is to divide the email in two categorises spam or ham email by using an optimal hyper plane. The idea is to distinguish the two classes to achieve maximum marginal difference between two classes, viz. spam and ham. SVM represents the information points in the workspace, mapped so that the information points of the other categorises are partitioned by a maximum marginal difference. New information points are labelled to that same workspace and predictions are conducted to analyse the category of the new information point. SVM can efficiently perform non-linear classification by kernel trick (similarity function).

Algorithmic steps of SVM for the classification process are as follows, as in [19].

1. Train the initial SVM using all the training data to have support vectors decision functions.
2. Eliminate those support vectors generated from the training of initial SVM whose projections have greatest curvatures on the hyper surface by: finding the projection of the support vectors along the gradient of decision function used, calculate the notion of curvature for every support vector on the hyper plane, lastly sort the support vectors in the decreasing order and deduct the top N -percentage of the vectors of support.
3. Retrain the SVM by left over vectors for best decision.
4. Use the group of information point to finally train the SVM, generating support vectors.

SVM classifiers are grouped into linear and non-linear classifiers, as follows:

1. **Linear Classifiers:** Separating the data points in linear order by using a hyper-plane is classified as linear classifiers. There are different hyper-plane but the best way to separate the data using hyper-plane is by maximum margin difference viz. the distance of hyper-plane and the closest information point of any class.
2. **Non-Linear Classifiers:** Sometimes the data is not separated properly or linearly in high dimensional plane for such separation non-linear classifiers are used that correctly classify the information points and label them to their exact class by using kernel tricks. Some mostly used kernel tricks are as follows:

- a. **Homogenous kernels:** Polynomial kernels that are used for analysing the similarity of vectors are represented by the expression below:

$$k(\vec{a}_i, \vec{a}_j) = (\vec{a}_i, \vec{a}_j)^d \quad (11)$$

Where k is the kernel function and (\vec{a}_i, \vec{a}_j) are the vectors of the work space with d as the degree of the polynomial.

- b. **Non-Homogenous kernels:** In Non-homogenous kernels a free parameter is added that leverage the group of features combined together.

$$k(a, b) = (a^T b + c)^d \quad (12)$$

CONCLUSION

In this paper author illustrated various machine learning and non-machine learning algorithms. From last few decades the number of account holder has increased and this increased the amount of data and its complexity too. Various illegitimate sources spread its existence over the internet. The major problem user hold is of spam emails from unknown and illegitimate contacts. Various techniques to detect spam emails has discussed by the author in this survey. From various studies conducted so far by various authors it has been concluded that no algorithm guarantees 100% results in spam detection but still there are some algorithms that provide high accuracy for detection of spam emails when used with feature selection technique like MLP neural network but MLP has a limitation of selecting initial information point using a randomized approach which increases the execution and model building time of the MLP algorithm, so effective and efficient approach to solve the drawback of MLP will be considered and corresponding solution will be carried out in future research which will ensure high accuracy for the detection of spam emails with low execution time.

ACKNOWLEDGEMENT

The author expresses its humble thanks to CT group of Engineering, Management and Technology for their motivational participation and encouragement in research field. The author also presents its gratitude towards computer science research group for the support. The author is thankful to its mentor for guidance throughout the research work.

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