Shape Based Feature Extraction in Detection of Image Email
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Abstract—Electronic mail is one of the important communication channels of information technology which serves as a systematic and universal communication mechanism across the globe. Though the functionalities of e-mail have been very helpful in serving both individuals and institutions, it encounters a major issue called ‘Spamming’. Spam mails are unwanted text or image-based messages, often sent without the consent of users so as to fill their mailboxes. In this paper, proposes Shape based feature extraction is used which tends to recognize the characters in the images and identify whether an image is Ham or Spam. In this paper at first elaborates on the methods of visual feature extraction (Text layout analysis) and the details of the algorithms used for Image Ham/Spam detection. Furthermore, the score and performance metrics of the identified images are provided which is the result of the experiments. The overall efficiency of the proposed system reached above 90 per cent which discerns the proposed work as a significant contribution to the research community.

1. Introduction
Email communication is one of the most efficient and most popular communication systems that enable people to communicate with each other. The total number of worldwide email accounts is expected to increase up to 4.3 billion accounts by the end of 2016 [4]. This signifies an typical yearly progress rate of 6% by 2020. In this regard with such an alarming usage of email communication, managing emails against fraudulent activities has become an important task. One such activity through emails is the impulsive posting of unwanted email to users known as spam messages. A spam mail is defined as an unsolicited/irrelevant/unwanted mail message received by users [2]. Spam mails usually contain commercial or profitable campaigns of uncertain products, dating services, get-rich-quick schemes and advertising. Spam emailing is also used to spread malicious or virus codes and is intended for fraudulence in financial transaction or phishing. Spamming is considered to regulate losses over the internet especially when they tend to turn malicious for business organizations. Several losses are mostly collateral damages not focusing a particular network or any organization. Spam mails occupy more network bandwidth during transmission. It also consumes user time in terms of searching. Statistical reports show, as of December 2014, spam messages accounted for 66.41 per cent of e-mail traffic worldwide and Asia constitutes 54% of the total percentage [5]. A recent study by [1] reveals the fact that most of the users receive more spam emails than non-spam emails.

Detection of spam email messages and quarantining it aside from the users are an important task. Spam detection consists of a series of steps- firstly, it starts with the tokenization phase in which the email content is parsed into a token. A token can be a word. The token is then transferred to the cleaning phase to process and form a single basic word without prefix and suffix. Then the processed tokens are sent to

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the spam detection phase to check whether the tokens are either spam or not. The clean token (not spam) is sent to the inbox folder and the infected known as ‘spam’ will be sent to the spam folder. The spam detection process requires understanding the message (token) (characters – alphabets, number, and symbols) written in the email. As a text email, the token is in ASCII character form for words and sentences therefore it is well understood and easily processed by the system for decision making.

Spammers are coming up with new routes towards sending spam email messages through images. Even though text-based spam emails are discovered by many methods of spam email detection. Such a form of sending spam email messages incorporated with images is called as image spamming and images embedded with spam characteristics are known as spam images or Image spam. Unsolicited text email have been identify in an easy way by many algorithms, however the same machine learning algorithms or techniques cannot be applicable for identifying image spam email, it is a daunting task. An image spam email carries a message which is projected to reach client systems and displays the same. Yet another challenge of spam detection techniques is irrespective of the thought that they are enhanced methods to detect spam; they may also aim to block legitimate email wherein the process is known as false positive [3]. Still, detection of image spam email is a challenging task as the words or characters is embedded within the images. The text occluded in image needs to be extracted and should be converted into ASCII form. In the concluding phase, ASCII forms are prepared to be managed for identifying unsolicited emails. Detecting spam mails especially image spam as shown in figure 1 is the focus of the present research which is challenging task when compared with other conventional spam detection techniques.

This research paper is structured as follows. Section 2 provides detailed literature review of shape based feature extraction. Section 3 presents in detail a detection algorithm for image based ham/ spam emails using the shape based feature extraction technique and discusses the entire approach with the discussion of the different algorithms used followed by testing the entire system based on various parameters. Section 4 concludes the investigation and gives recommendations for upcoming work with esteem to this work.

2. Literature review

This segment covers a brief demonstration of former work done by several researchers for classification of spam emails.

The beginning of the Shape Based Feature Extraction approach took place in the year 1992 when [6] examined the necessity for a content based image retrieval database system which emphasized more on the shape and color as the criteria for feature extraction. After the workshop at the National Science
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Foundation of United States, the concept of Feature extraction in image based systems gained momentum. In [7] several existing machine learning algorithms are obtained and evaluated. Constructed on content based features, transformed link based features, and link based features are absorbed towards classifying websites as ham or spam. Collection of dataset called WEBSPAM UK2006 used for testing. For training and testing, describes the dimension of Monte Carlo cross validation. As compared with other classifiers combination techniques like bagging of trees and adaptive boost produce expected result whereas SVM produce poor results.

A Complete case study [8] used to shape innovative multilevel classifiers. Base classifier is to provide innovative meta-classifiers by dissimilar meta-classifiers. AGMLMC are named as innovative set of classifiers. For spam e-mail classification AGMLMC classifiers, meta-classifiers and base classifiers are matched. To obtain multi-tier classifier, Adaboost, Multiboost and Bagging have been experimented. Top combination for AGMLMC, Adaboost at top level and Bagging at middle level have been experimented. Meta classifiers used for filtering phishing e-mails and AGMLMC found to be best amongst all other base classifiers. Various machine learning approaches for spam classification [9] algorithms have examined. E-mail spam dataset has been taken from TANAGRA data mining tool and UCI machine learning repository has been used to examine prevailing procedures. To select appropriate features from dataset, various feature selection algorithms such as RelieF Step disc Fisher filtering and Run filtering has been used. Before and after feature selection, various spam classification algorithms have been applied on the data set and then results are compared with existing work. It attains 99% of accuracy using Runs tree classification and considered as best classifier.

Now image retrieval based systems, feature extraction plays a crucial role; furthermore, feature extraction enables highly accurate selection of features. In the process of feature extraction, the visual information from the image is separated and then stored in the form of feature vectors in a database meant for features. The values in the feature database, also known as image based feature vectors aids identifying the information of the image from feature extraction. These features are in turn compared with the query image stored in the database. Feature extraction has extensive applications in pattern recognition as features are characterized in such a manner that one class of an object is distinguished from another. Each feature could have different representations wherein each aspect of representation enables appropriate retrieval of images [10]. In [11], only text features content are used for e-mail classification. Principal component analysis document reconstruction (PCADR) uses the classifier which is able to extract and yields the significant features of document. PCADR approach has been investigated on diverse e-mail corpora such as Ling Spam, Phishing, SpamAssassin, PU1, and TREC7 spam corpus. When training and testing data are from different sources, PCADR is well matched

Happening the recent years, it is evident that spammers attempt to insert junk information with the image mails wherein the message is attached to the body. This is an act to escape from traditional text-based spam detection techniques that could handle only text based spam mails. With the purview of dealing with Image spams, filtering techniques should possess the capability to acquire text based features from images and eradicate spam images by comparing the features [12]. Spam images are no longer just junk images and might include attachments such as spyware agents and viruses that may affect the recipient’s system. Hence, there is a need to combine spam detection techniques with machine learning algorithms which enable proper detection of spam/ ham image mails. In this regard, the present research combined the use of multi-SVM with shape based feature extraction which enables segregation of HAM/ SPAM based on feature based score. In the context of the present research, multi-Support Vector Machine (SVM) is used. SVM is a machine learning supervised model which is used for the purposes of classification and regression analysis. An SVM creates hyperplanes and an extreme fringe hyperplane is designated which is also known as binary linear classifier. It is used to classify the test data in to two different labels [13]. SVMs are established based on a strong hypothesis- the theory of statistical learning which enables the speculative execution of SVM. One of the most straightforward approaches
of SVM is considered in the present research-the classification of classes which are linearly separable [18]. Analysts [27] yield to a hybrid character partition method integrating Discrete Wavelet Transform (DWT) and Hough Transform to extract character from images. The performance of classifiers [14] have associated with or without the help of other boosting algorithms. Enron e-mail dataset are used for experimentation, which is selected 134 out of 1359 features. To select vital features, Genetic search algorithm has been used. Bayesian classifiers and Naïve Bayes algorithm have been evaluated first and to increase the performance of these classifiers, boosting algorithms are used. Bayesian classifier has achieved well than naïve bayes. 92.9% of accuracy has obtained using Bayesian classifier and boosting algorithm. Boosting algorithms can be used with other base classifiers to do the comparison of performance will be future enhancement of the work. A sequential approach [28] in segmentation and recognition techniques used to detect image based emails. The research testing have been implemented on assorted texture analysis and combined methods.

This section presents in detail the use of Shape based feature extraction which enables the identification of Spam/ Ham from Image emails. In this regard, this section at first elaborates on the methods of visual feature extraction (Text layout analysis) and the details of the algorithms used for Image Ham/ Spam detection. Furthermore, the score and performance metrics of the identified images are provided which is the result of the experiments. The need for Image based spam detection techniques emerged in the recent years wherein it was revealed that compared with text spam detection methods, image spam detection approaches are time consuming, more space, and resources has great destructive influence. Image spams cannot be filtered using traditional spam filtering techniques and hence becomes more difficult for recognition of spam image mails. According to [15], three requirements need to be satisfied by image spam detection systems- extensibility, high efficiency and high rate of accuracy. However, previous filtering techniques involving image spam are unable to detect spam images and hence suffer from low rate of accuracy. Over the years, several anti-spam technologies emerged which filter text based email spams; however the same is not feasible to be applied in image spam since most anti-spam software do not detect image spam. In this context, several image anti-spam systems are proposed to filter image spam.

A. Classification Based on contents

According to [16] probabilistic trees could be used for the detection of spam images in email wherein global image features are used to train the classifier and distinguish spam and ham images. However, [17] used low-cost and fast feature extraction and classification framework which enables identifying large sets of image spam using SVM and decision trees. The examination of the efficiency of both decision tree and SVM classifier revealed that SVM performs better than decision tree method.

B. Classification Based on text properties

Low-level image processing [1] techniques for the detection of one of the image spam characteristics. The proposed method detects noisy text in an image and the output was generated as a crisp value in the range or some real value. The presence of noisy text aids identification of spam in image mails.

C. Classification Based on image features

Several researchers have utilized images features for image-spam mail filtering [19] revealed the two different features of images which are classified as high-level features and low-level features. The high level features include file size, file name and file format whereas the low level features include color, shape, and so on. In this context, the present research considered shaped based feature extraction as the method to detect spam/ ham image emails.
Architecture for Image spam detection using Shape based feature extraction

Since spammers generally send image spam in the form of batches which consists of similar features, image based spam detection method can filter those images effectively on the basis of known image spams that are collected, stored, trained and classified. The underlying principle for the spam detection system is as follows: firstly, the features of the detected image such as low-level features (visual) and high-level features (semantics). Secondly, the features are compared with the features in two feature databases (DB with spam features and DB with ham-features). Finally, the image is judged whether it is spam or ham. The architecture for image spam detection is shown in figure 2.

![Architecture for image spam detection](image)

Figure 2. Architecture for image spam detection

The various processes involved in the image features extraction is shown in above figure. The color based features are extracted and then the texture and shape features are extracted in the detected image.

Examining the various spam images from the image spam dataset, it is revealed that spammers generally utilize the same text layout template for the generation of different advertisements wherein only the use of words/text in the images change based on the different products they attempt to advertise. For the analysis of the text layout, the minimum bounding box technique is used for the whole area, which is again dilated for connecting words that are in the same line. Scaling is then performed for the text area which is dilated and is then normalized for the comparison of text layout [20].

3. **Experimentation and results**

The image spam data set is collected from [21]. From the dataset, it is evident that there exists different kinds of image spam messages which are generated by spammers for the sake of escaping from spam filters. They are ‘text only’, ‘randomized’, and ‘wild background’ images. Text only images contain only texts whereas images with randomization are added with random color pixels, stripes and color shades. The last type is image with wild background wherein the images are embedded with noisy background. The image spam data set contains 2173 images in Spam Archive corpus, 2359 images in personal ham corpus, and 1248 images in personal spam. The additional data will be given the name...
non-benchmark data in this thesis. For the assessment of the proposed algorithms with respect to the
detection accuracy, the proposed algorithms are compared with existing individual methods. However,
there are other types of images which are even more appealing for users. They include animated gif,
multipart Images, and standard images which are attractive and are least filtered by spam filters.

Furthermore, to examine the performance of the proposed approaches (shape based feature extraction),
the values of false negative, false positive, true negative, true positive, precision, recall and F-measure
are measured and are compared with the values of the factors acquired in previous researches. Following
is the description of the performance analysis indicators used in the present research:

| Parameter Measures | Formula |
|--------------------|---------|
| False Positive Rate (FP) | \( FP = \frac{b}{b + d} \) |
| Recall (R) | \( R = \frac{\text{Correctly segmented characters}}{\text{Correctly segmented characters} + FN} \) |
| F-Measure (F) | \( F = 2 \times \frac{P \times R}{P + R} \) |
| Accuracy (A) | \( \text{Accuracy} (A) = \frac{TP + TN}{TP + TN + FP + FN} \) |
| Precision Rate (P) | \( P = \frac{\text{Correctly segmented characters}}{\text{Correctly segmented characters} + FP} \) |
| False Negative Rate (FN) | \( FN = \frac{c}{c + a} \) |

The shape features for each character segmented and recognized are extracted based on the region
properties wherein several features are examined which included- Area, Bounding box, Centroid,
Eccentricity, Euler’s number, Extent, Extremes, Major Axis length, Minor Axis length, Orientation and
Perimeter. Of all these features, the threshold average fit best for the feature ‘Area’ which is hence used
to detect whether an image is HAM or SPAM. The feature value of a testing input image is compared
with the trained feature values of multiple images using Multi-SVM algorithm which classifies and
produces the result whether an image is HAM/SPAM. However, the performance analysis of the
proposed system is measured using metrics such as Total positive rate/Sensitivity, Total Negative
Rate/Specificity and Accuracy. Table 1 provides the information of the performance metrics for each
image identified using the proposed Ham/Spam detection system. Here output of spam-free and ham
image shown in images 1 and 2 whereas table 2 shows detection of spam image shown in images 1 and 2.
### Table 1. Performance metrics of images detected as HAM using the proposed approach

| No. | Images | Performance metrics |
|-----|--------|---------------------|
| 1   | THIS IS SPAM-FREE AND HAM IMAGE | Correct Rate is: 82.2581%  
Error Rate is: 17.7419%  
True Positive is: 100  
False Positive is: 10  
True Negative is: 90  
False Negative is: 0  
True Positive Rate (TPR)/ Sensitivity is: 100%  
True Negative Rate (TNR)/Specificity is: 78%  
False Positive Rate (FPR) is: 22%  
False Negative Rate (FNR) is: 0%  
Precision is: 0.909091  
Recall is: 1  
Fmeasure is: 0.952381  
Accuracy of Linear Kernel SVM is: 96.7742% |
| 2   | THIS IS SPAM-FREE AND HAM IMAGE | Correct Rate is: 82.2581%  
Error Rate is: 17.7419%  
True Positive is: 100  
False Positive is: 10  
True Negative is: 90  
False Negative is: 0  
True Positive Rate (TPR)/ Sensitivity is: 83.3333%  
True Negative Rate (TNR)/Specificity is: 82%  
False Positive Rate (FPR) is: 18%  
False Negative Rate (FNR) is: 16.6667%  
Precision is: 0.909091  
Recall is: 0.833333  
Fmeasure is: 0.869565  
Accuracy of Linear Kernel SVM is: 95.1613% |

### Table 2. Performance metrics of images detected as SPAM using the proposed approach

| No. | Images | Performance metrics |
|-----|--------|---------------------|
| 1   | SPAM IS DETECTED | Correct Rate is: 80.6452%  
Error Rate is: 19.3548%  
True Positive is: 100  
False Positive is: 10  
True Negative is: 90  
False Negative is: 0  
True Positive Rate (TPR)/ Sensitivity is: 91.6667%  
True Negative Rate (TNR)/Specificity is: 78%  
False Positive Rate (FPR) is: 22%  
False Negative Rate (FNR) is: 8.33333%  
Precision is: 0.909091  
Recall is: 0.916667  
Fmeasure is: 0.912863  
Accuracy of Linear Kernel SVM is: 93.5484% |
Of all the 23 images tested from 560 images in the training dataset, an average F-measure value of 0.90 is obtained with the recall value of 0.91. The accuracy reached 0.95 and the precision value recorded is 0.91 as shown in figure 3.

The performance of the proposed system with respect to character segmentation and recognition accuracy is examined through comparison with previous researchers. A research by [22] proposed a character recognition system using OCR which could detect three different types of fonts wherein the accuracy reached 0.92 for Californian, 0.94 for Georgia and 0.97 for Tibbook antique. A comparison with similar researches in feature extraction based character detection method revealed that the proposed method operates with great precision and accuracy. A research by [23] revealed a precision value of 66 and recall value of 70. Similarly, researches by [24] [25] [26] revealed precision and recall values of (59, 55), (79, 76) and (100, 81). However, the present research could achieve 95 per cent accuracy and 87 per cent recall. Furthermore, the values of accuracy in comparison with other methods of image ham/spam detection are examined which revealed that the proposed system achieved an accuracy of 0.95. Figure 4 compares the results achieved by previous researchers and the proposed system.
Figure 4. Comparison of other image ham spam systems’ accuracy with the proposed system

4. Conclusion

The experiments carried out based on shape based feature extraction revealed the following findings; the performance of the proposed image ham spam detection approach is better than other classification algorithms such as Naïve Bayes and Decision Tree. By having more training samples, the accuracy of both classifiers will be improved. The validation and experiments have shown that the proposed method was successful for email classification. However, the algorithm can still be improved further. Here are the recommendations proposed for improving email classification performance. Integration of other machine learning algorithms could better improve spam or ham image email classification.

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