Support Vector Machines for Image Spam Analysis

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Abstract: Email is one of the most common forms of digital communication. Spam is unsolicited bulk email, while image spam consists of spam text embedded inside an image. Image spam is used as a means to evade text-based spam filters, and hence image spam poses a threat to email-based communication. In this research, we analyze image spam detection using support vector machines (SVMs), which we train on a wide variety of image features. We use a linear SVM to quantify the relative importance of the features under consideration. We also develop and analyze a realistic "challenge" dataset that illustrates the limitations of current image spam detection techniques.

1 INTRODUCTION

Electronic mail or email is one of the most common forms of digital communication today. Spam can be defined as unsolicited bulk email. The widespread use of email makes it an attractive target for spammers. According to a recent report from Symantec (Whitney, 2009), spam now accounts for a staggering 90.4% of all email. Therefore, spam email—which can include advertisements, malware, phishing links, adult content, and so on—represents a significant threat to the utility of email as a communication medium.

Initially, spam was virtually always in the form of text email. Strong classifiers have been developed to filter such spam, based on content, subject, header, and so on. For example, Lai and Tsai (Lai and Tsai, 2004) explore four machine learning algorithms that rely on different parts of an email message. Algorithms including k-nearest neighbors (k-NN), support vector machines (SVM), and naïve Bayes have been successfully applied to the text-based spam detection problem.

With the advent of strong text-based classifiers, spammers reacted by developing new techniques—one such technique is image spam. Spam text embedded inside an image can be an effective method to evade text-based filters (Gao et al., 2008).

In its simplest form, image spam contains text that has been converted to an image. To detect this type of image spam, optical character recognition (OCR) can be used to extract the text, which can then be subjected to text based spam detection techniques. As a reaction to OCR-based detection, spammers employed obfuscation techniques, which make OCR less effective (SpamAssasin, 2005).

Instead of detecting image spam based on OCR, it is possible to consider a more direct approach based on properties of the images themselves. In this research, we consider such an image spam detection strategy, where image processing techniques are used in conjunction with machine learning algorithms.

In this research, we improve slightly on the detection results in (Annadatha and Stamp, 2016) by considering more features. In addition, we have developed a synthetic image spam dataset, which provides a challenge (but realistic) test case for proposed image spam detection schemes.

The remainder of this paper is organized as follows. In Section 2, we give a brief overview of image spam and related work. In Section 3, we discuss the features used in our experiments. Section 4 gives a brief overview of the machine learning techniques used in our experiments. In Section 5 we discuss the process that was used to generate our synthetic dataset and to evaluate its effectiveness. Section 6 presents out detection results, while Section 7 gives our conclusions and suggestions for future work.

2 BACKGROUND

In this section, we briefly consider spam detection techniques. Then we discuss research that is most clo-

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sely related to the work presented in this paper.

2.1 Spam Detection Techniques

From a high level perspective, spam detection techniques can be loosely split into the following two categories. In practice, these approaches could be used in various combinations.

- Content based filtering — Content-based schemes can be used to filter text spam. These techniques extract the actual content from within each spam email and classifiers are built based on keywords, headers, payload, etc. Machine learning techniques have been extensively used for such classifiers (Dhanaraj and Karthikeyani, 2013).
- Non-content based filtering — Instead of analyzing content directly, we can consider other properties of email. For example, in the case of image spam, we can analyze image properties. As mentioned above, this is the approach that we follow in this paper.

2.2 Related Work

Machine learning techniques play a prominent role in spam detection. For most types of spam, a combination of image processing and machine learning techniques can yield good results.

Kumaresan et al. (Kumaresan et al., 2015) use several image features to construct image spam classifiers. They use a combination of support vector machines (SVM) and particle swarm optimization (PSO). PSO improves the results by iteratively scanning candidate solutions and moving "particles" in the search space. Due to its computational complexity, PSO can only deal with a relatively small dataset as compared to SVM. The authors of (Kumaresan et al., 2015) claim an accuracy of 90% on the Dredze dataset (discussed below) using 300 training images and 380 test images.

Another machine learning based approach is considered by Annadatha et al. (Annadatha and Stamp, 2016), where the feature set consists of 21 image properties. Each feature is associated with a weight, based on how much it contributes to a linear SVM classification. Based on these weights, the authors conduct various experiments primarily involving feature selection and feature reduction. These experiments are conducted on two datasets (Gao et al., 2008; **?**) and, as compared to (Kumaresan et al., 2015), significantly more features are used, and the accuracy is greater on the Dredze dataset. Additionally, an improved dataset was developed. We have also developed a challenge dataset, which can be viewed as an improvement on the dataset in (Annadatha and Stamp, 2016), in the sense that our image spam is more difficult to distinguish from benign images.

A detection architecture using neural networks is considered by Soranamageswari et al. (Soranamageswari and Meena, 2010), where the authors use back propagation neural networks (BPNN) for their image spam detection experiments. They achieve an accuracy of 92.82% on the Spam Archive dataset (Fumera et al., 2006) using color properties of the images.

Chowdhury et al. (Chowdhury et al., 2015) consider metadata features and they present a comparison of three machine learning algorithms: Naïve Bayes, SVM, and BPNN. The results show that neural networks achieve the greater accuracy, at the expense of increased complexity.

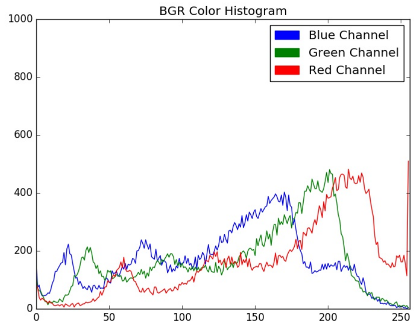
Gao et al. (Gao et al., 2010) analyze a "comprehensive" image spam technique that employs both server-side and client-side detection. Their strategy is based on a set of 23 image features and relatively complex detection strategies. In contrast, for the research presented in this paper, we utilize 38 features, of which 20 overlap with those in (Gao et al., 2010). We employ a straightforward SVM detector, which allows for a detailed analysis of the relative importance of the various features.

3 IMAGE FEATURES

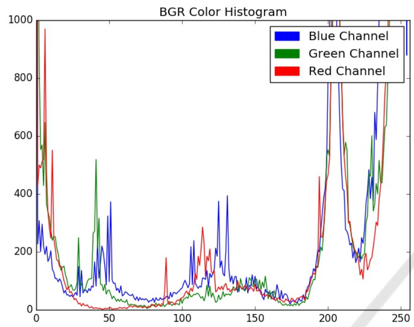
Spam images are typically computer generated and hence they tend to lack color properties and composition features of a normal "ham" image. For instance, brightness in ham images tend to vary more than in spam images.

We use image processing techniques to extract a total of 38 of features from images. Of these 38 features, 21 were considered in (Nixon, 2008). Table 1 gives a brief overview of all the features we have extracted, where the 21 features in (Nixon, 2008) are denoted with "†". The features under consideration can be loosely classified into the following five domains.

- Metadata features — Properties such as image size, height, width, aspect ratio, compression ratio, and bit depth are the most basic properties of an image. We consider six metadata features.
- Color features — Various histograms contain useful information about an image. For example, color histograms contain information about the usage of red, green, and blue colors. From Figure 1 we see that the RGB channels of ham and spam images tend to differ significantly.

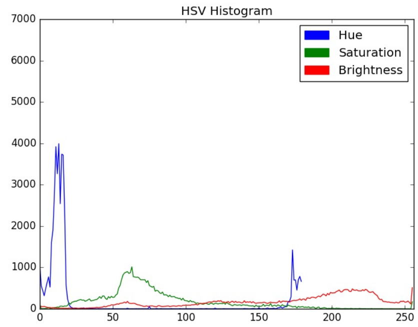


(a) Ham

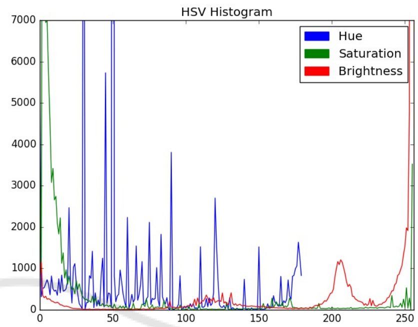


(b) Spam

Figure 1: RGB channels of color histogram.



(a) Ham



(b) Spam

Figure 2: HSV channels of HSV histogram.

Additional color features are related to hue, saturation, and value (HSV). The hue defines how close the color is to red—hue is in the range of 0 to 1, with 0 being red. Saturation is a measure of the “pureness” of the color, where higher values of correspond to deeper or richer colors. For example, white corresponds to 0 saturation. The value (or intensity) corresponds to brightness. Figure 2 compares the HSV channels of typical ham and spam images.

- Texture features — The local binary pattern (LBP) histogram captures information about the similarity of each pixel to its neighboring pixels. The LBP would appear to be a strong feature for detecting Image spam that is simply text set on a white background.
- Shape features — We consider a variety of shape features, including the histogram of oriented gradients (HOG) which describes how the intensity gradient changes in the image. The edges feature quantifies change in contrast, which serves to highlight boundaries of features in an image (Nixon, 2008). Figure 3 shows the Canny edge filter results for a spam image and a ham image. Spam images generally contain text, resulting in an increased number of clear edges as compared to ham images. Also, the edges in spam images tend to be smaller as compared to those in ham images. We consider the number of edges and average edge length as two separate features.
- Noise features — We consider two noise features. The Entropy of Noise is the amount of noise in an image—typically, spam images have less noise than ham images. The Signal to Noise Ratio (SNR) is defined to be the ratio of the mean to the standard deviation in the image histogram, based on a grayscale version of the image under consideration.

4 SVM MODELS

In this research, we rely on support vector machine (SVM) analysis. Neural networks and deep learning are popular today, and these techniques perform well in many classification tasks. However, when a careful comparison is done, the differences between deep learning and other machine learning approaches (such as SVM) is often quite small. For example, in recent research on malware detection based on image analysis (Yajamanam et al., 2018), it is found that a

Table 1: Feature set.

Feature Type	Feature	Description
Metadata	height	Height of the image
	width	Width of image
	aspect ratio †	Ratio of height and width
	compression ratio †	How compressed is image
	file size	Size on disk
	image area	Area of image
Color	entr-color †	Entropy of color histogram
	r-mean †	Mean of red histogram
	g-mean †	Mean of green histogram
	b-mean †	Mean of blue histogram
	r-skew †	Skew of red histogram
	g-skew †	Skew of green histogram
	b-skew †	Skew of blue histogram
	r-var †	Variance of red histogram
	g-var †	Variance of green histogram
	b-var †	Variance of blue histogram
	r-kurt †	Kurtosis of red histogram
	g-kurt †	Kurtosis of green histogram
	b-kurt †	Kurtosis of blue histogram
	entr-hsv	Entropy of HSV histogram
	h-mean	Mean hue of HSV histogram
	s-mean	Mean saturation of HSV histogram
	v-mean	Mean brightness of HSV histogram
	h-var	Variance of hue HSV histogram
	s-var	Variance of saturation HSV histogram
	v-var	Variance of brightness HSV histogram
	h-skew	Skew of hue HSV histogram
	s-skew	Skew of saturation HSV histogram
	v-skew	Skew of brightness HSV histogram
	h-kurt	Kurtosis of hue HSV histogram
	s-kurt	Kurtosis of saturation HSV histogram
	v-kurt	Kurtosis of brightness HSV histogram
Texture	lbp †	Entropy of LBP histogram
Shape	entr-hog †	Entropy of HOG
	edges †	Total number of edges in an image
	avg-edge-length †	Average edge length
Noise	snr †	Signal to noise ratio
	entr-noise †	Entropy of noise

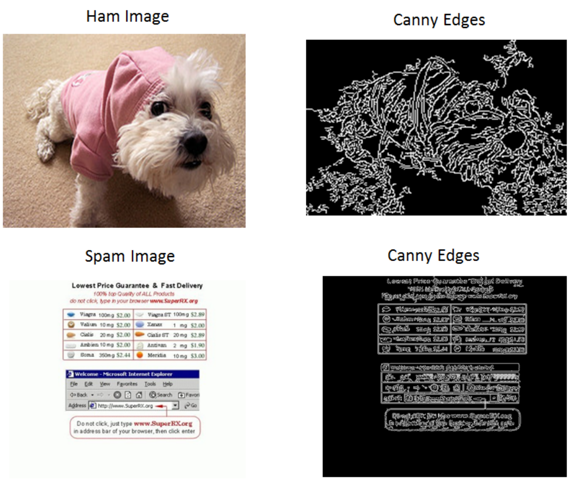


Figure 3: Canny edges.

simple *k*-nearest neighbor technique performs nearly as well as deep learning techniques based on transfer learning. And an advantage of SVM models is that they are extremely informative (in particular, linear SVMs), enabling us to easily determine the contribution of individual features, perform feature reduction, quantify interactions between features, and so on. In contrast, deep learning models tend to be opaque—essentially, black boxes that produce classification results. Therefore, we believe that SVM is an ideal technique for the research problems that we consider in this paper.

SVMs are a class of supervised learning algorithms, generally used for classification. SVMs have been applied to spam detection research in general (Lai and Tsai, 2004), and to the image spam detection problem in particular (Annadatha and Stamp, 2016). In this section, we give a brief overview of the

SVM algorithm.

There key concepts that define the SVM algorithm are the following (Stamp, 2017).

- Separating hyperplane — In the training phase, the SVM attempts to divide the labeled input data into two classes. In the ideal case, the data is linearly separable, that is, all data of one class lies on one side of a separating hyperplane and all data in the other class falls on the other side of the hyperplane.
- Maximize the margin — When constructing an optimal hyperplane, only a subset of training data is actually relevant. These special points are known as support vectors. An optimal hyperplane is defined as one that maximizes the separation or margin between the support vectors and the hyperplane.
- Work in higher dimensions — In general, the training data is not linearly separable in the input space. By transforming the input data to a higher dimensional feature space, linear separability can be improved.
- Kernel trick — A kernel function enables us to map the input space to a higher dimensional feature space without paying a significant cost in terms of efficiency.

4.1 Feature Selection

In a linear SVM, weights are determined for each input-space feature—the higher the weight, the more significance the SVM classifier places on that feature. Thus, we can use these weights to rank the features, and thereby reduce the dimensionality of the problem without any significant loss in accuracy. In fact, we can sometimes improve the accuracy through feature reduction, since some features may be so uninformative as to essentially act as noise.

In this research, we consider recursive feature elimination (RFE), where we initially train a linear SVM using all available features. Then we eliminate the feature with the smallest weight and train another linear SVM on the reduced feature set. We continue to reduce the number of features and retrain the SVM until the desired number of features has been obtained.

4.2 Scoring Metrics

Accuracy is the number of correct classifications divided by the total number of classifications, that is,

$$\text{accuracy} = \frac{\text{true positive} + \text{true negative}}{\text{total number of samples}}.$$

In our detection experiments, we use accuracy as one quantifiable measure of the success (or lack thereof) of our proposed techniques.

Given the results of any binary classification experiment, the receiver operating characteristic (ROC) curve is constructed by plotting the true positive rate versus the false positive rate as the threshold varies through the range of values. The area under the ROC curve (AUC) ranges from 0 to 1. An AUC of 1.0 indicates perfect separation, i.e., there exists a threshold for which no false positives or false negatives occur. On the other hand, an AUC of 0.5 indicates that the binary classifier is no better than flipping a fair coin. In general, the AUC gives the probability that a randomly selected match case scores higher than a randomly selected non-match case (Bradley, 1997; Stamp, 2017).

5 DATASETS

Two existing publicly available datasets have been used in this research. In addition, we have developed a realistic dataset that is designed to provide a challenging test for any proposed image spam detection scheme. All of these datasets contain both spam and ham images. For our datasets 1 and 2, the ham and spam images come from actual email, while the challenge dataset includes modified spam images.

5.1 ISH Dataset

The developers of Image Spam Hunter (Gao et al., 2008) collected a large sample of image spam and a similarly large sample of ham images. We refer to this data as the ISH dataset. After cleaning the data, 920 spam images and 810 ham images from the ISH dataset were retained for this research. All of these images are in `jpg` format.

5.2 Dredze Dataset

Dredze et. al (Dredze et al., 2007) created an image spam corpus which is publicly available. Here, we refer to this set as the the Dredze dataset. After cleaning the dataset, we retained 1089 spam and 1029 ham images from the Dredze dataset. As with the ISH dataset, all images are in the `jpg` format.

5.3 Challenge Dataset

As discussed above, previous research using publicly available image spam datasets has obtained strong results. We also obtain very strong results on these datasets. However, it is clear that image spam could be made much more difficult to detect. Therefore, we have also generated our own challenge dataset. As the name suggests, the purpose of this dataset is to provide a challenge to the detection of more advanced forms of image spam, which are likely to be seen in the near future.

We apply various image processing techniques to actual spam images to make the images look more like a ham image. We used the Dredze dataset for our spam corpus, and we overlay ham images from the ISH dataset.

We experimented with various approaches to develop our challenge dataset and ultimately found that a relatively simple and straightforward technique was most effective. To generate our spam images, we extract the content of an existing spam image, then simply overlay it on ham image. Figure 4 shows an example of a spam image generated using this approach. We see that the modified spam image looks like a ham image.

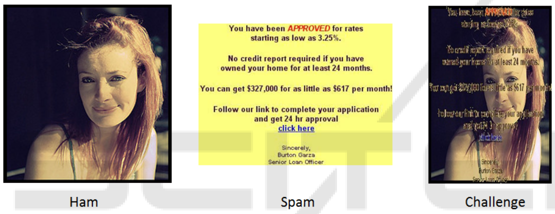
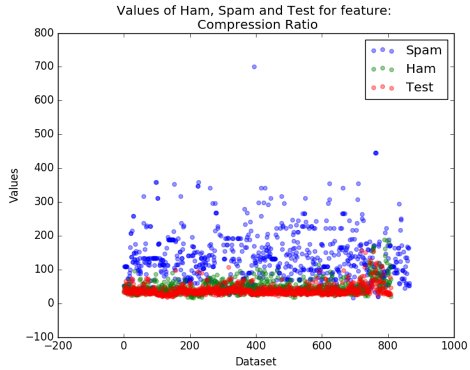


Figure 4: Challenge dataset example (second approach).

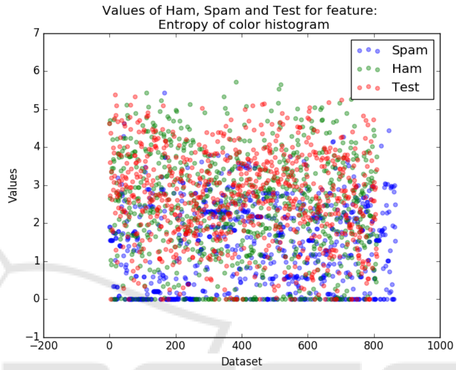
For the remainder of this paper, "challenge dataset" refers to the spam images that we have generated using the method discussed above. A straightforward SVM detection model was tested on our challenge dataset. We found that this SVM gave us a classification accuracy of 70%, while more complex techniques could only achieve an accuracy of 79%. Since our goal is to defeat the detection, this straightforward approach is better.

Figure 5 shows scatterplots of the compression ratio and color entropy for ham, spam, and our challenge dataset images. From these scatterplots, it is clear that the ham and challenge dataset images more closely align, as compared to those of ham and existing image spam.

Figure 6 shows differences in SVM weights associated with features in the ISH dataset, as compared to the same feature in the challenge dataset. The majority of these differences are near 0, indicating that the SVMs place nearly equal reliance on the corresponding features. This provides further evidence that it may be difficult to distinguish images in the challenge dataset from the ham images.



(a) Compression Ratio



(b) Entropy of Color Histogram

Figure 5: Feature value comparison scatterplots.

In the next section, we present and analyze our main experimental results for ham, spam, and our challenge datasets. These results are based on SVM classification experiments, and EM clustering experiments.

6 EXPERIMENTS & RESULTS

As previously noted, SVMs have been applied with success to the text-based spam detection problem (Dhanaraj and Karthikeyani, 2013). In this section, we first consider SVMs for image spam detection, and we use SVMs for feature reduction. Finally, we discuss results from clustering experiments.

Below, we conduct experiments on all of the datasets discussed above. We obtain strong results on the ISH and Dredze datasets. As expected, our results are poor on the challenge dataset, which indicates that it will present a significant challenge for research in this field.

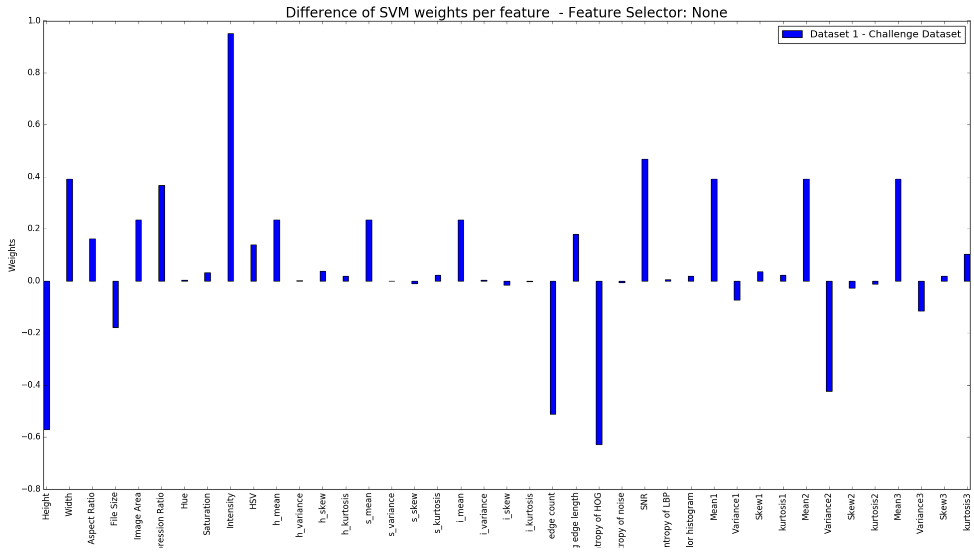


Figure 6: Comparing features of the ISH and challenge datasets.

6.1 SVM Experiments

We have extracted all 38 features from each ham and spam sample. We train various SVM classifiers based on selected subsets of these features. To measure the effectiveness of each model, a test set—disjoint from the training set—is passed to the SVM classifier, with the accuracy and the area under the ROC curve (AUC) used to quantify success. In this section, we also experiment with feature reduction to determine optimal subsets of features.

For each SVM experiment, five-fold cross validation is used. That is, for the dataset under consideration, we partition the ham images into five equal-sized subsets, which we denote as H_1,H_2,H_3,H_4,H_5, and we do the same for the spam images, and we denote these subsets as S_1,S_2,S_3,S_4,S_5. We then train an SVM classifier on the labeled datasets H_1,H_2,H_3,H_4 and S_1,S_2,S_3,S_4 with H_5 and S_5 reserved for testing the resulting SVM. Then we train an SVM on H_1,H_2,H_3,H_5 and S_1,S_2,S_3,S_5 with H_4 and S_4 used for testing, and so on, until each of the five pairs (H_i,S_i) have been used for testing. The results of all five "folds" are then combined when determining the result of the experiment. Cross validation serves to smooth any bias in the training data, while also maximizing the number of independent test cases.

As a first attempt to analyze the importance of each feature, we calculate SVM scores for each feature individually. That is, for each feature, we trained and scored using an SVM based only on that one feature. Figures 7 (a) through 7 (c) give the SVM results—in the form of AUC statistics—for each individual feature, over all three of the datasets. We see that dataset 1 generally gives the best results while, as expected, the challenge dataset is the most challenging from the perspective of individual features.

Next, we give results for SVMs where all 38 features are used. Again, we consider the ISH dataset, the Dredze dataset, and our challenge dataset.

Table 2 shows the accuracy and FPR for each of the three SVM kernels when tested on the ISH dataset. Here, we achieve the best results for linear kernel.

Table 2: SVM based on 38 features (ISH dataset).

Kernel	Accuracy	FPR
Linear	0.97	0.05
RBF	0.96	0.06
Poly	0.95	0.07

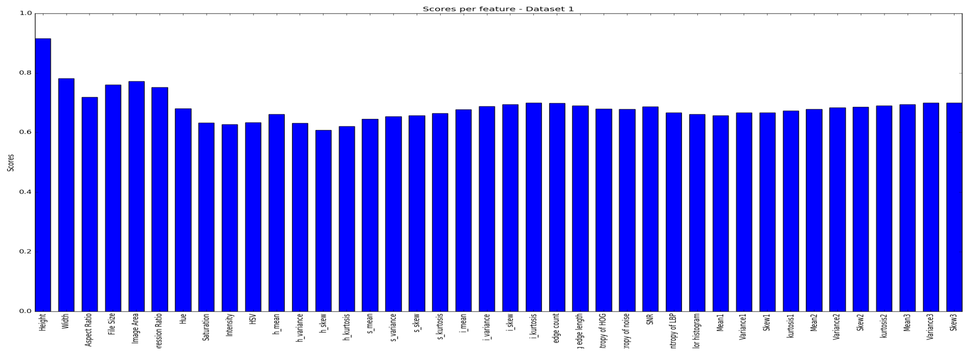
Table 3 shows the accuracies and FPR for the same three SVM kernels when tested on the Dredze dataset. In this case, we achieve equally strong results for the linear and RBF kernels.

Table 3: SVM based on 38 features (Dredze dataset).

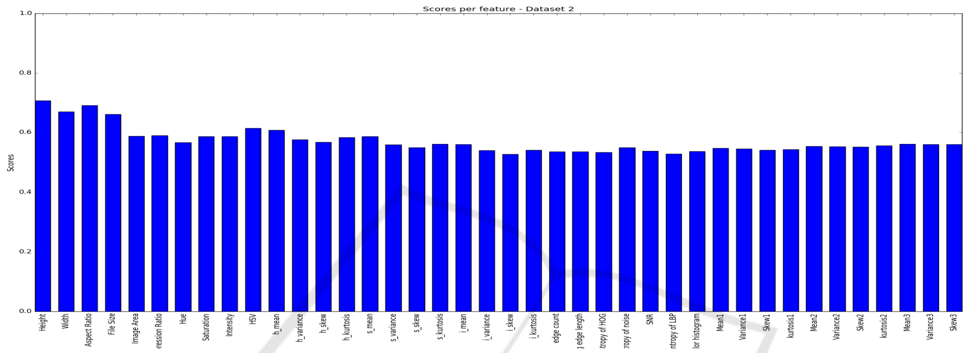
Kernel	Accuracy	FPR
Linear	0.98	0.01
RBF	0.98	0.01
Poly	0.95	0.09

Although we obtain good results for both the ISH and Dredze datasets when using the full 38 features, we obtain slightly better results for the Dredze dataset. This shows the strength of the SVM, as the results for individual features in Figure 7 (a), indicate that the ISH dataset may be the easier case.

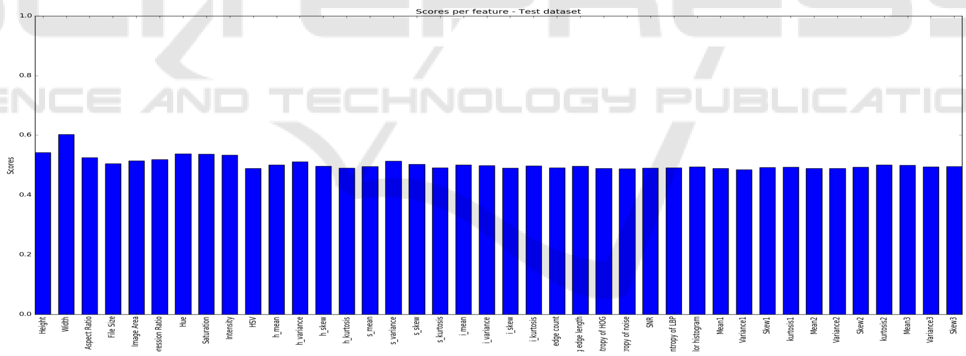
Table 4 shows the accuracies and FPR for each of



(a) ISH dataset



(b) Dredze dataset



(c) Challenge dataset

Figure 7: AUC for SVM (individual features).

the three SVM kernels when tested on our challenge dataset. Again, we achieve the best results using the linear kernel. As expected, the results are much worse for this challenge dataset, as compared to the ISH and Dredze datasets.

Table 4: SVM based on 38 features (challenge dataset).

Kernel	Accuracy	FPR
Linear	0.68	0.38
RBF	0.64	0.38
Poly	0.54	0.79

6.2 Feature Reduction

Since we have a large number of features, our next step is to explore techniques to reduce this number while maintaining (or improving) the overall accuracy. Also, reducing the number of features will increase the efficiency, which is particularly important in the detection (or classification) phase.

A linear SVM assigns a weight to each feature, where the weight directly corresponds to the relative importance of the feature in the SVM classifier. Therefore, a naïve approach to feature reduction is to simply rank the features based on these weights, eliminating those features with the smallest weights.

However, this is not an ideal strategy as the relationship between features can change whenever a feature is eliminated. In this section, we explore recursive feature elimination (RFE), which was discussed briefly in Section 4.1.

Recall that RFE is a straightforward modification to the naïve strategy mentioned in the previous paragraph. In RFE, we generate a linear SVM and eliminate the feature that corresponds to the smallest weight. Then we generate a new SVM based on this reduced (by one) feature set and again eliminate the feature that corresponds to the smallest weight. We continue this process until some stopping criteria is met (e.g., we reach the desired number of features, or the accuracy degrades, or we run out of features).

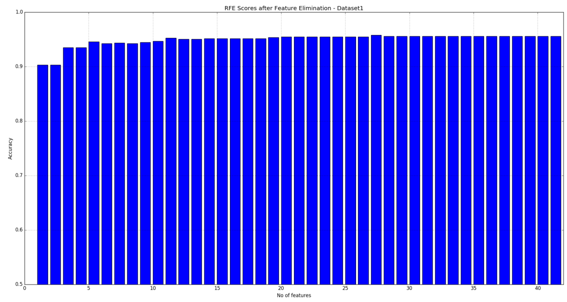
For each dataset, we performed a ranking of all 38 features. Figure 8 (a) shows RFE results for the ISH dataset. In this case, we achieve a maximum accuracy of 95.57% when eliminating 13 features.

Figure 8 (b) shows the RFE results for the Dredze dataset. For this particular dataset, the maximum accuracy is 98.02%, and this occurs when using only 16 features of the 38 features. In comparison to the ISH dataset, we require fewer features for the Dredze dataset and we achieve a higher accuracy.

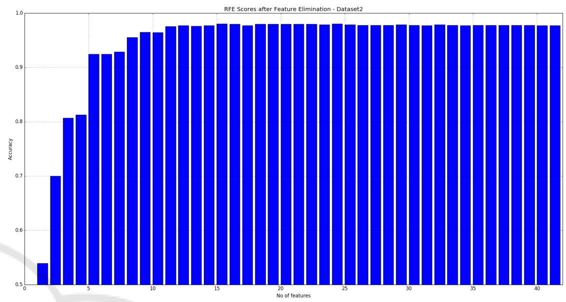
Finally, Figure 8 (c) gives RFE results for our challenge dataset. In this case, we achieve a maximum accuracy of 69.32% with 26 features which, again, points to the challenging nature of this dataset.

To summarize, our feature reduction experiments show that there is redundancy among our 38 features. This is not surprising, since there are many features used to measure very similar characteristics. Perhaps more interesting is the fact that in each case we can obtain near-optimal results with a small number of features. It is also interesting that the accuracy for the challenge dataset does not exceed 70%.

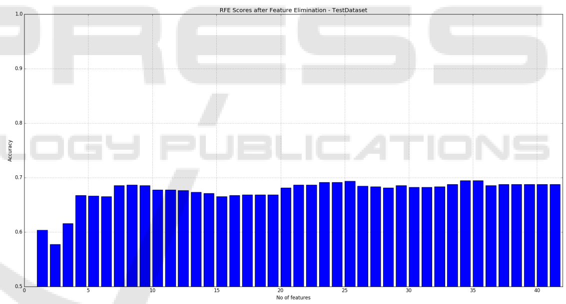
Next, we present clustering results for our datasets. These results provide another perspective on the inherent challenge of classifying image spam from each of the sets under consideration.



(a) ISH dataset



(b) Dredze dataset



(c) Challenge dataset

Figure 8: RFE results.

6.3 EM Clustering

Clustering is an unsupervised machine learning technique. The essential idea of clustering is to split the data into sets (or clusters) based on some concept of distance. The well-known K-means algorithm uses a simple iterative two-step hill climb which is based on a direct measure of distance. Expectation maximization (EM) clustering can be viewed as a generalization of K-means, where probability distributions are used to measure "distance" (Stamp, 2017). Another way to view the difference between K-means and EM is that the former generates spherical clusters, whereas the latter allows for more general shapes. Typically, Gaussian distributions are used in EM clustering, in which case the resulting clusters can take on elliptical shapes. In our EM experiments, we employ Gaussian distributions.

In effect, EM determines the parameters of unknown probability distributions which are used to determine the clusters. From a high level perspective, EM clustering consists of iterating the following two steps.

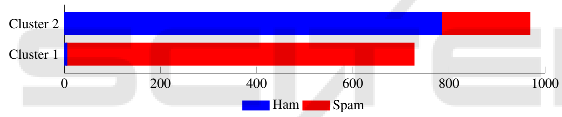
1. Expectation Step: Recompute the probabilities for

each datapoint based on the current estimates for the probability distributions.

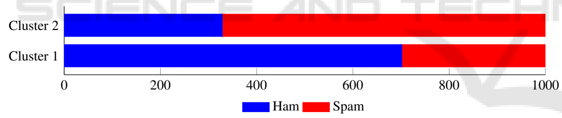
2. Maximization Step: Recompute the parameters of the probability distributions based on the probabilities computed in the expectation step.

Ideally, each cluster will contain only one type of data. We compute the purity (i.e., uniformity) of the clusters and use this as our measure of success. The purity ranges between 0 to 1 with ideal clustering (i.e., each cluster contains only one type of data) having a purity score of 1.0.

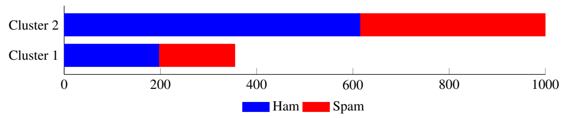
For EM clustering with Gaussian distributions and two clusters, and using all 38 features, we obtain the results in Figures 9 (a) through 9 (c). Ideally, one cluster should contain only ham and the other should contain only spam. As expected, for the ISH dataset, the results in Figure 9 (1) appear to be reasonably good, while the results for the challenge dataset in Figure 9 (c) are very poor. However, the results in Figure 9 (b) for the Dredze dataset are somewhat surprising. Using an SVM, we can classify the samples in Dredze dataset with an accuracy comparable to the ISH dataset, but the clustering results for the Dredze dataset are much worse than those for the ISH dataset.



(a) ISH dataset



(b) Dredze dataset



(c) Challenge dataset

Figure 9: EM clustering results.

Table 5 summarizes the purity scores corresponding to the experiments in Figure 9. These scores confirm the intuitive observations mentioned in the previous paragraph.

In the next set of clustering experiments, we combined the ISH and challenge datasets and subjected this combined set to EM clustering. Note that we have included the ham set, so there are three classes of data. Using three clusters, we obtain the EM results in Figure 10, with the corresponding numeric results summarized in Table 6. Cluster 2, in particular, indicates that a large percentage of the challenge dataset is indistinguishable from ham. This provides further strong evidence that the spam images in the challenge dataset will be difficult to detect using the features considered in this paper. That is, the challenge dataset represents a realistic challenge for future research in this field.

Table 5: Clustering results.

Dataset	Purity
ISH	0.87
Dredze	0.70
Challenge	0.52
Combined	0.62

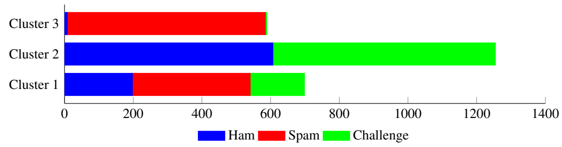


Figure 10: EM with three clusters on combined dataset.

Table 6: Cluster distribution.

Cluster	Ham	Spam	Challenge
1	7	577	4
2	606	0	648
3	197	343	158

We also performed EM clustering with the number of clusters varying from two to 20. The results of these experiments are summarized in the form of line graphs in Figure 11. Intuitively, the purity should increase as we add more clusters—in the extreme, every sample could be its own cluster, which would yield a purity of 1.0. Indeed, the purity score does generally rise as the number of clusters increases. More significantly, the gap between each pair of purity scores is consistent over the range of values tested, indicating that our results above are not an artifact of the number of clusters used.

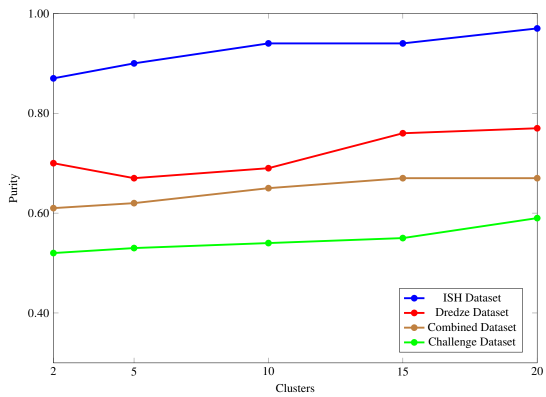


Figure 11: Purity scores vs number of clusters.

The results here indicate that even an unsupervised technique such as EM clustering could be quite strong against the current crop of image spam. However, if spammers use somewhat more advanced techniques, it is highly unlikely that the resulting image spam can be effectively detected using any combination of the 38 image processing based features we have considered in this paper.

7 CONCLUSION

Using samples of real-world ham and spam images, we showed that machine learning algorithms based on features extracted by image processing techniques can be used to construct strong classifiers. Our results on these real-world datasets improves slightly over the related work in (Annadatha and Stamp, 2016).

We also showed that it is not difficult to generate much stronger image spam, in the sense that the detection problem is significantly more challenging. In addition, we showed that such improved image spam cannot be reliably detected using the image processing based features considered here. These results improve over the challenge dataset presented in (Annadatha and Stamp, 2016), in the sense that the challenge dataset in this paper is significantly more difficult to distinguish from ham, even when using a richer and more informative feature set. These results indicate that we will likely need new approaches to detect image spam in the future.

More research is needed to develop and analyze improved methods for image spam detection. To this end, we have developed a large image spam challenge dataset that we will provide to any researchers in this field. By experimenting on this challenge dataset, it will be possible to directly compare results based on different proposed detection techniques. Additional experiments involving this dataset using neural networks and deep learning would be timely, and it would be interesting to have such a direct comparison between the SVM analysis in this paper, and deep learning techniques.

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