An Automated Fuzzy Logic Based Approach for Text Spam Detection

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Abstract- *With increased internet usage, one of the most prevalent problems faced is constant spamming. While web applications and mailing services are heavily spammed, the upsurge of handheld mobile devices has led to an outburst of heavy mobile spamming. The matter is more severe in mobile devices due to lesser sophisticated filtering mechanisms in built in mobile operating systems. Spam detection is challenging due to the need for semantic analysis of the mobile spam messages, which generally tend to have overlapping polarities. In this work, a mobile spam classification technique is developed based on Adaptive Neuro Fuzzy Inference System (ANFIS) comprising of Gini's index Fuzzy and Back-propagation in machine learning. The approach uses the Gini's splitting criteria for the data sets and backpropagation based neural network as the machine learning classifier. The evaluation of the proposed system is based on the accuracy of classification and number of iterations. The results obtained in the proposed work are compared with existing techniques and it is shown that the proposed technique outperforms them in terms of accuracy of classification.*

Keywords- Mobile Spam Classification, ANFIS, Gini's Index, Back Propagation, Training Iterations, Classification Accuracy

I. INTRODUCTION

Mobile spamming has become one of the most common techniques for promotions, customer churning and potential attacks targeting the frequently used handheld mobile devices which are more prone to such attacks. The ease of collecting mobile contacts, connected data bases and relatively lesser sophisticated filtering mechanisms for the mobile spam filtering makes its extremely challenging to thwart spamming attacks. A numeric estimation of the rising spamming attacks has been depicted in figure 1, for the 3rd quarter of 2020 citing an increasing trend.

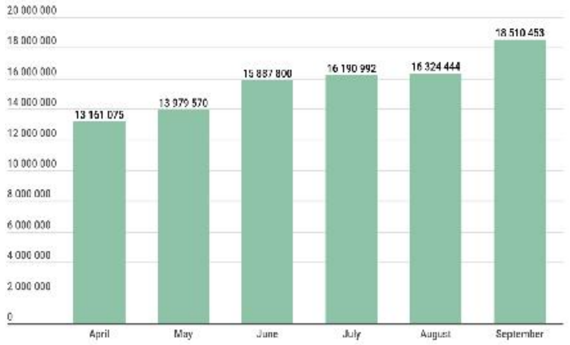


Fig.1 Number of Mobile Spams for Quarter-3, 2020 Courtesy: Kaspersky Labs Security Report

Some of the spamming attacks may be benign while others may be malignant trying to redirect mobile users to malicious websites where user security may be compromised. Since the amount of data is staggering large and complex, off late machine learning based approaches are becoming common to filter out spams. One of the challenges which machine learning based approaches face for mobile spamming platforms is the limited computational and processing capabilities of hand held mobile devices. This makes is necessary to design and test algorithms which are compatible with various versions of mobile operating systems and also supported by limited memory and processing hardware as there exists a lot of diversity in the mobile hardware of different devices. This paper is organized as:

Section I introduces the basic concepts pertaining to mobile spam classification and its necessities.Section II briefly summarizes the work done in the domain.Section III discusses the proposed approach.Section IV illustrates the obtained results. The findings of the paper are concluded in the conclusion.

II. RELATED WORK

Various approaches have been devised for mobile spam classification.

A spam classification mechanism based on text normalization and back propagation based neural network has been proposed by Jain et al. in [1]. The approach also compares the findings of the work with conventionally existing algorithms. Adewole et al. in [2] proposed a bio-inspired evolutionary machine learning based approach for the detection of spam. Different spamming features and sources are analyzed using standard machine learning algorithms using the Weka machine learning tools. The approaches used are the support vector machine (SVM), Ada-Boost, Random Forests, Multi-Layer Perceptron (MLP) Bayes' net. Barushka et al. in [3] proposed the use of regularized deep neural nets for the classification of spams. Sedhai et al. in [4] proposed a semi-supervise approach for spam classification. The data set used was that of Twitter. A similar approach was used by Chao et al. in [5] which aimed at analyzing drifted Twitter spam. Mirza et al. in [6] analyzed the effect of feature selection on spam filtering. A comparative analysis of addition and removal of features from the training data set was done. Afzal et al. in [7] proposed a techniques based on machine learning for bi-lingual data classification. Xu et al. in [8] developed an efficient machine learning based classifier for classification of multiple data sets corresponding to different social media platforms. Elssied et al. in [9] used a dual approach comprising of K-means clustering and support vector machine for spam classification. The clustering based approach was primarily used for data preparation and structuring while the multi-dimensional hyperplane based Support Vector Machine was used for the final classification. Vyas et al. in [10] presented a comprehensive review on the various supervised machine learning based approaches for email spam classification. The concepts of feed forward nets, convolutional nets, back propagation and recurrent nets were discussed in the context of spam filtering. Jatana et al. in [11] proposed a Bayesian classifier based approach for spam filtering. Kandasamy et al. in [12] proposed a natural language processing (NLP) based approach for spam classification using social media data. Prasad el al. in [13] compared the performance of Back Propagation and Resilient Propagation based machine learning approaches for spam classification. Indyk et al. in [14] proposed a Map Reduce based approach for collective spam classification.

III. PROPOSED SYSTEM MODEL

A. Data processing and normalization:

Since neural nets directly process numeric data sets, the processing of data is done prior to training a neural network. The texts are first split into training and testing data samples in the ratio of 70:30 for training and testing. Further, a data vector containing known and commonly repeated spam and ham words is prepared. The SMS spam collection v.1 dataset is used as a dataset for the proposed work. Text normalization is followed by removal of special characters and punctuation marks.

Subsequently the data set structuring and preparation is performed based on the feature selection. The features selected are:

1) Spam words
2) Ham Words
3) URLs in the message
4) Lengthy numerical strings which can be contact numbers
5) Character length
6) Special symbols
7) Presence of currency values
8) Self-answering texts

The feature vectors along with the list of commonly accepted spam and ham lists of words comprises of the training vector. A similar process is done for both the training and testing datasets.

B. Adaptive Neuro Fuzzy Inference Systems (ANFIS)

A very important tool that proves to be effective in several classification problems is fuzzy logic. It is often termed as expert view systems. It is useful for systems where there is no clear boundary among multiple variable groups. The relationship among the inputs and outputs are often expressed as membership functions expressed as [6]:

A membership function for a fuzzy set A on the universe of discourse (Input) X is defined as:

$$\mu A: X \rightarrow [0,1] \quad \textbf{(1)}$$

Here,
each element of X is mapped to a value between 0 and 1. It quantifies the degree of membership of the element in X to the fuzzy set A.

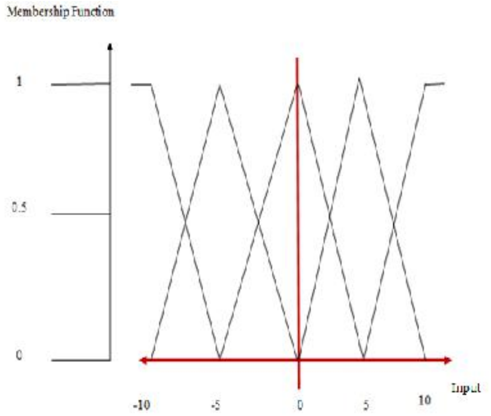


Fig.2 Graphical Representation of Membership Functions

Here,
x axis represents the universe of discourse (Input).
y axis represents the degrees of membership in the [0, 1] interval.
The final category is neuro fuzzy expert systems which governs the defining range of the membership functions.

The ANFIS can be thought of as a combination of neural networks and fuzzy logic. In this mechanism, the neural network module decides the membership functions of the fuzzy module. The ANFIS structure is depicted in figure 3.

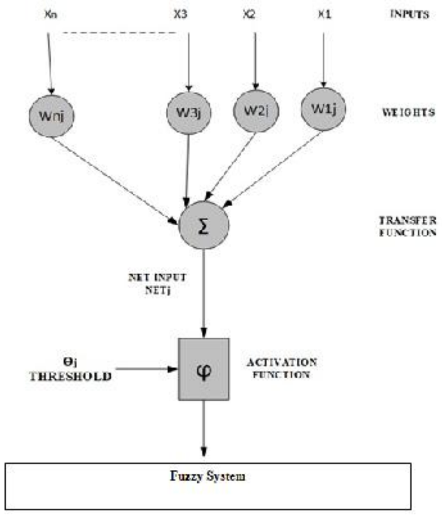


Fig.3 Block Diagram of Neuro-Fuzzy Expert Systems

The splitting can be done through the Gini's index which is especially useful for overlapping data sets since it can split data sets with overlapping classes based on conditional probability. The Gini's index for splitting is defined as:

$$GI = 1 - \sum_{i=1}^{n} p_i^2 \qquad \textbf{(2)}$$

Here,
GI represents the Gini's Index
P is the probability of a class

The prepared data vector for training is used for training wherein the weights are initialized randomly. A stepwise implementation is done as:

1. Prepare two arrays, one is input and hidden unit and the second is output unit.

Here, a two dimensional array W_{ij} is used as the weigt updating vector andoutput is a one dimensional array Y_i.

3. Original weights are random values put inside the arrays after that the output**.**

$$x_j = \sum_{i=0} y_i W_{ij} \qquad \textbf{(3)}$$

Where,
y_i is the activity level of the j^{th} unit in the previous layer and
W_{ij} is the weightof the connection between the i^{th} and the j^{th} unit.

4. Next, activation is invoked by the sigmoid function applied to the total weighted input.

$$y_i = \left[\frac{e^x - e^{-x}}{e^x + e^{-x}}\right] \qquad \textbf{(4)}$$

Summing all the output units have been determined, the network calculates the error (E)**.**

$$E = \frac{1}{2}\sum_i (y_i - d_i)^2 \qquad \textbf{(5)}$$

Where, y_i is the event level of the j^{th} unit in the top layer and d_i is the preferred output of the j_i unit.

C. Implementing Back Prop:

Calculation of error for the back propagation algorithm is as follows:

Error Derivative (EA_j)is the modification among the real and desired target:

$$EA_j = \frac{\partial E}{\partial y_j} = y_j - d_j \qquad \textbf{(6)}$$

Here,
E represents the error
y represents the Target vector
d represents the predicted output

Error Variations is total input received by an output changed given by:

$$EI_j = \frac{\partial E}{\partial X_j} = \frac{\partial E}{\partial y_j} X \frac{dy_j}{dx_j} = EA_j y_j(1 - y_i) \quad \textbf{(7)}$$

Here,
E is the error vector
X is the input vector for training the neural network
In Error Fluctuations calculation connection into output unit is computed as:

$$EW_{ij} = \frac{\partial E}{\partial W_{ij}} = \frac{\partial E}{\partial X_j} = \frac{\partial X_j}{\partial W_{ij}} = EI_j y_i \quad \textbf{(8)}$$

Here,
W represents the weights
I represents the Identity matrix
I and j represent the two dimensional weight vector indices
Overall Influence of the error:

$$EA_i = \frac{\partial E}{\partial y_i} = \sum_j \frac{\partial E}{\partial x_j} X \frac{\partial x_j}{\partial y_i} = \sum_j EI_j W_{ij} \quad \textbf{(9)}$$

The partial derivative of the Error with respect to the weight represents the error swing for the system while training. The gradient is computed as:

$$g = \frac{\partial e}{\partial w} \quad \textbf{(10)}$$

Here,
g represents the gradient
e represents the error of each iteration
w represents the weights.

The gradient is considered as the objective function to be reduced in each iteration. A probabilistic classification using the Bayes theorem of conditional probability is given by:

$$P\left(\frac{H}{X}\right) = \frac{P\left(\frac{X}{H}\right) P(H)}{P(X)} \quad \textbf{(11)}$$

Here,
Posterior Probability [P (H/X)] is the probability of occurrence of event H when X has already occurred
Prior Probability [P (H)] is the individual probability of event H
X is termed as the tuple and H is is termed as the hypothesis.
Here, [P (H/X)] denotes the probability of occurrence of event X when H has already occurred.

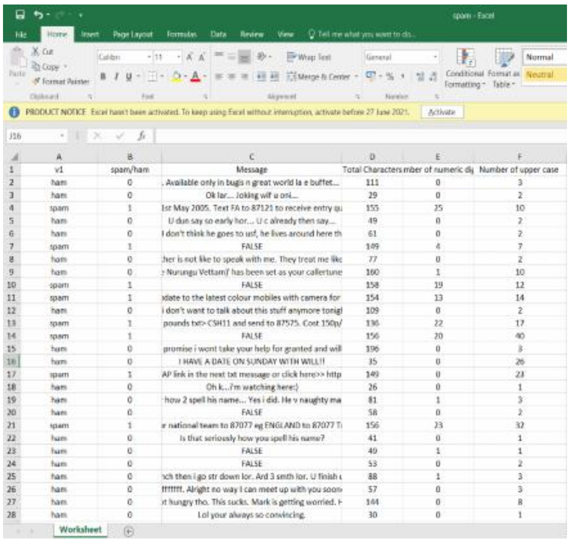
The final classification accuracy is computed as:

$$Ac = \frac{TP+TN}{TP+TN+FP+FN} \quad \textbf{(12)}$$

Here.
TP represents true positive
TN represents true negative
FP represents false positive
FN represents false negative

IV. RESULTS

The system is implemented on Matlab. The results obtained on implementing the proposed system is discussed in this section.



PRODUCT NOTICE Excel hasn't been activated. To keep using Excel without interruption, activate before 27 June 2021.

	A	B	C	D	E	F
1	v1	spam/ham	Message	Total Characters	mber of numeric di	Number of upper case
2	ham	0	. Available only in bugis n great world la e buffet...	111	0	3
3	ham	0	Ok lar... Joking wif u oni...	29	0	2
4	spam	1	1st May 2005. Text FA to 87121 to receive entry qu	155	25	10
5	ham	0	U dun say so early hor... U c already then say...	49	0	2
6	ham	0	I don't think he goes to usf, he lives around here th	61	0	2
7	spam	1	FALSE	149	4	7
8	ham	0	:her is not like to speak with me. They treat me like	77	0	2
9	ham	0	: Nurungu Vettam)' has been set as your callertune	160	1	10
10	spam	1	FALSE	158	19	12
11	spam	1	odate to the latest colour mobiles with camera for	154	13	14
12	ham	0	i don't want to talk about this stuff anymore tonigl	109	0	2
13	spam	1	pounds txt> CSH11 and send to 87575. Cost 150p/	136	22	17
14	spam	1	FALSE	156	20	40
15	ham	0	promise i wont take your help for granted and will	196	0	3
16	ham	0	I HAVE A DATE ON SUNDAY WITH WILL!!	35	0	26
17	spam	1	AP link in the next txt message or click here>> http	149	0	23
18	ham	0	Oh k...i'm watching here:)	26	0	1
19	ham	0	how 2 spell his name... Yes i did. He v naughty ma	81	1	3
20	ham	0	FALSE	58	0	2
21	spam	1	r national team to 87077 eg ENGLAND to 87077 T	156	23	32
22	ham	0	Is that seriously how you spell his name?	41	0	1
23	ham	0	FALSE	49	1	1
24	ham	0	FALSE	53	0	2
25	ham	0	ıch then i go str down lor. And 3 smth lor. U finish u	88	1	3
26	ham	0	fffffff. Alright no way I can meet up with you soon	57	0	3
27	ham	0	ot hungry tho. This sucks. Mark is getting worried. H	144	0	8
28	ham	0	Lol your always so convincing.	30	0	1

Fig.4 Raw data samples

The raw data samples are collected after which it is imported to the Matlab workspace.

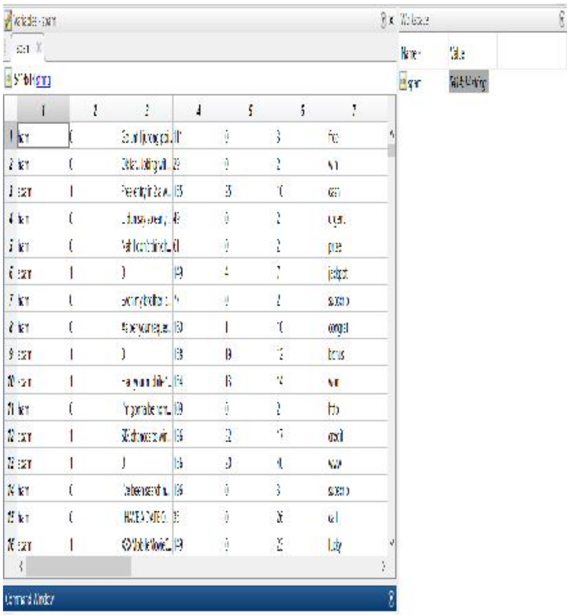
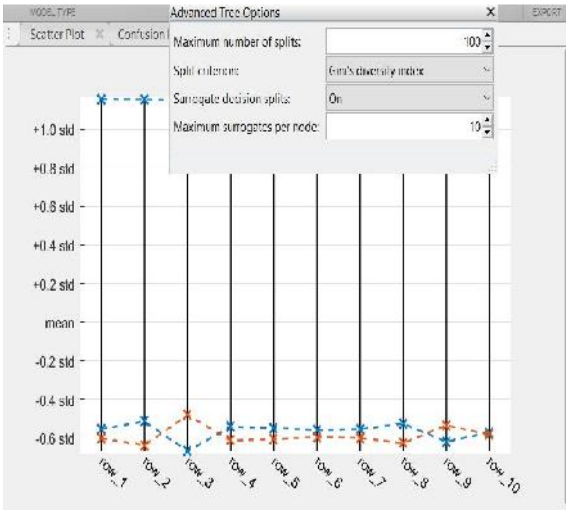


Fig.5 Conversion of Data into string

Subsequently, the data is converted into strings for ease of analysis of textural data. The data is split into training and testing data samples in the ratio of 70:30. While other data division ratios could have been uses, but in this work, the standard 70:30 ratio is adhered to.

The next process is invoking the Gini's split criterion.



Advanced Tree Options

Maximum number of splits: 100

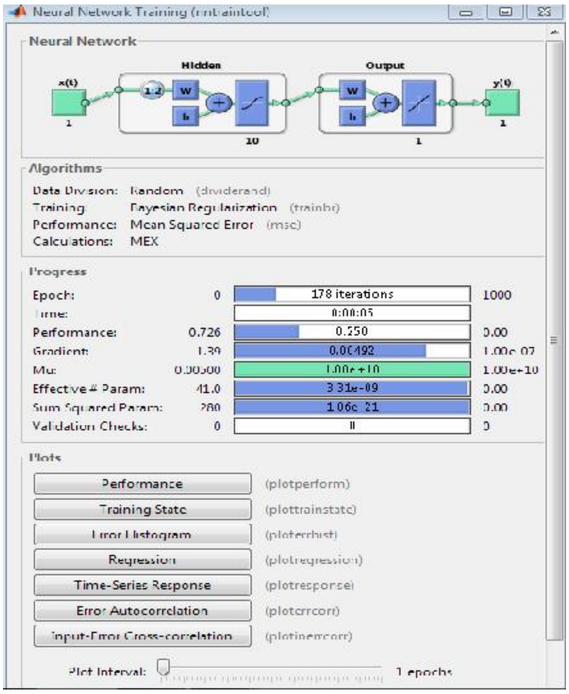
Split criterion: Gini's diversity index

Surrogate decision splits: On

Maximum surrogates per node: 10

Fig.6 Invoking the Gini's Split criteria

The Gini's split criteria is the precursor to the training of the system.



Neural Network Training (nntraintool)

Algorithms

Data Division: Random (dividerand)
Training: Bayesian Regularization (trainbr)
Performance: Mean Squared Error (mse)
Calculations: MEX

Progress

Epoch:	0	178 iterations	1000
Time:		0:00:05	
Performance:	0.726	0.250	0.00
Gradient:	1.39	0.00492	1.00e-07
Mu:	0.00500	1.00e+10	1.00e+10
Effective # Param:	41.0	3.31e-09	0.00
Sum Squared Param:	280	1.06e-21	0.00
Validation Checks:	0	0	0

Plot Interval: 1 epochs

Neural Network
Hidden
Output
x(t)
y(t)
1:2
w
b
1
10
1
1
Plots
Performance (plotperform)
Training State (plottrainstate)
Error Histogram (ploterrhist)
Regression (plotregression)
Time-Series Response (plotresponse)
Error Autocorrelation (ploterrcorr)
Input-Error Cross-correlation (plotinerrcorr)

Fig.7 Training Performance

Figure 7 depicts the training parameters of the proposed system which consumes 5 seconds to run 378 iterations of the back propagation algorithm. A 20 neuron hidden layer is designed for the system.

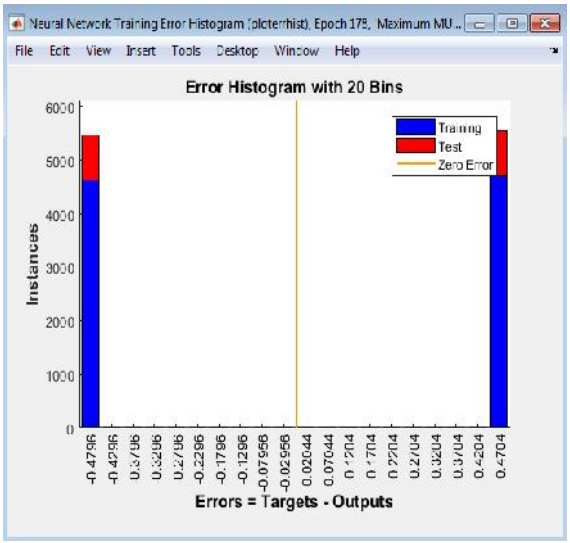
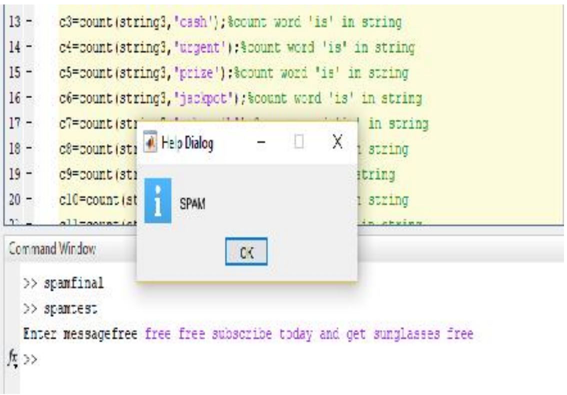


Fig.8 Training Error Histogram

The training error histogram is depicted in figure 7 which is an indicator of the errors occurring during the training process.



```
c3=count(string3,'cash');%count word 'is' in string
c4=count(string3,'urgent');%count word 'is' in string
c5=count(string3,'prize');%count word 'is' in string
c6=count(string3,'jackpot');%count word 'is' in string
c7=count(str                                  in string
c8=count(str                                  string
c9=count(str                                  tring
c10=count(st                                  string
```

```
>> spamfinal
>> spamtest
Enter messagefree free free subscribe today and get sunglasses free
>>
```

SPAM

Fig.9 GUI for detection

Figure 8 depicts the GUI for spam detection. A similar GUI represents that of the non-spam or ham case. A comparative analysis with existing approaches is tabulated in table I.

Table I: Comparative Accuracy Analysis of Proposed and Existing Algorithms

S.No.	Technique	Accuracy (%)
1.	SNAP	83.9
2.	AIR SENTI	80.5
3.	Naïve Baye's	64
4.	Random Forests	63
5.	ANN with BackProp	95.81
6.	**Proposed Approach: Gradient Descent with BackProp and Gini-Index**	**99.75**

It ca be observed from the tabulated results, that the proposed work outperforms the existing algorithms such as SNAPM AIR SENTI, Naïve Gayes', Random Forests and ANN with Back Prop.

V. CONCLUSION

It can be concluded from the aforesaid arguments that mobile spam classification is extremely challenging and non-trivial due to the constraints of computational power and memory at our disposal. Moreover, easier access to handheld devices makes systems more prone to spamming attacks. Text spam classification is non trivial in the sense that it generally belongs to non-clear or fuzzy boundary datasets. The proposed approach presents a mobile spam classification mechanism Using Gini's Index and ANFIS. It has been shown that the proposed approach outperforms the existing techniques in terms of classification accuracy. Additionally, the technique consumes moderate number of iterations and low execution time which are critical considerations for mobile devices. It can be observed that the proposed approach outperforms existing approaches in terms of accuracy.

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