Certificate

This is to certify that the work contained in this dissertation entitled **"Sentiment Analysis Using Neural Network"** submitted in the partial fulfilment, for the award for the degree of M.Tech in Computer Science and Technology at **DELHI TECHNOLOGICAL UNIVERSITY** by **RITU RANI, Roll No. 2K14/CSE/17**, is carried out by her under my supervision. This matter embodied in this project work has not been submitted earlier for the award of any degree or diploma in any university/institution to the best of our knowledge and belief.

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Declaration

I hereby declare that the major Project-II work entitled "Sentiment Analysis using Neural Network" which I being submitted to Delhi Technological University, in partial fulfilment of requirements for the award of degree of Master of Technology (Computer Science and Engineering) is a bonafide report of Major Project-II carried out by me. The material contained in the report has not been submitted to any university or institution for award of any degree.

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Abstract

In last few years, there has been a rapid growth in the use of social networking sites so this become a significant medium for people to express their views or opinions. Sentiment Analysis is used to identifying and classifying the polarity of an opinion, such as positive, neutral or negative. Twitter is one of the social media site which is gaining the popularity. Twitter Sentiment Analysis has application such as political sentiment analysis, companies getting their customer's perspective on their products or opinions on current issue, movie reviews. Recent research has involved looking at text from online tweets, online movie reviews, etc. to try and classify the text as being positive, negative, or neutral.

For this research work, a Supervised Machine Learning Based approach is realised for Sentiment Analysis of tweets. The approach used here is Probabilistic Neural Network because PNN is a multi-layered feedforward neural network due to which it is fast as compare to other approaches. PNN is developed based on an estimation method that is probability density function for Parzen window and Bayes classification rules. Probabilistic Neural Network has feature of adaptive learning, fault tolerance, parallelism and generalization which provides a superior performance. Smoothing parameter of PNN plays a great role for predicting an accurate class of classifier. So a self-adaptive algorithm is used to calculate and optimize the smoothing parameter. Training and Testing dataset is collected from twitter using Twitter API based on a keyword "#NSG". This classifier is used to determine the opinion of a tweet whether this tweet is about to good effort of Indian Prime Minister or a diplomatic failure of not getting a NSG membership. Probabilistic Neural Network is trained with the smoothing parameter which is adjusted self-adaptively so that best parameter is selected and according to that results are obtained for testing data set after that accuracy of classifier is determined.

CHAPTER 1 INTRODUCTION AND OUTLINE

This chapter gives the brief introduction to research work proposed in this thesis. Section 1.1 gives overview of introduction to the work undertaken in this research. Section 1.2 and section 1.3 describe the motivation and scope of research work which is proposed. Section 1.4 define the research objectives and section 1.5 present outline of thesis organization.

1.1 Introduction

In today's world, excessive volume of information is available on microblogging sites such as twitter, Friend Feed, Tumblr.com, Meetme, etc. Microblogging are gaining their popularity over the online world. Mainly Microblogging sites are used for the world news, for product publicity, to share information and many more. Among all the microblogging sites, Twitter is most popular one. Twitter is an online social networking sites with help of which one can send or read messages of character length 140 called 'tweets'. Twitter also stipulate to develop a user friendly streaming API so that real time tweets from different user could be retrieved for data analysis purpose.

The rise of social media such as twitter and blog has generate the interest in sentiment analysis. People, over the social media, share their opinion and feeling about variety of subjects like an issue, news, product, movie etc. Among the countless or multitude information or opinion exist on social media, peoples wants to conclude the opinion or sentiment of text in that information or document. For this purpose, Sentiment Analysis is used to classify the polarity of a sentence whether the sentiment or opinion of that sentence is positive, negative or neutral. Sentiment analysis is the computational study of sentiments, opinions, and emotions expressed in the given text at document, feature or sentence [1].

Sentiment analysis of tweets could be performed using three techniques. These techniques are Lexical analysis, Machine learning based analysis and Hybrid/Combined analysis. Lexical analysis process is governed by tokenizing the input stream into sequences of tokens using POS tagging to a predefined dictionary. Lexical analysis does not need any prior training of data, it is a ready to go approach. Machine learning based analysis consist of data extraction, data pre-processing, training data to machine, classification of data and testing of data process. Machine learning is classified into supervised learning and unsupervised learning. In supervised learning training document is labelled whereas no labelling is performed in

unsupervised learning. Hybrid analysis could collectively use accuracy of machine learning based analysis and speed of lexical analysis approach [2].

1.2 Motivation

Opinion has a key role in almost all the human activities because they are influenced by others behaviour and opinion. In real world when they take a decision they wants to find others opinion. Like in business or in organisation when a new product is launched by a company or an industry, after that they wants to know costumer review about the product. Also one customer wants to know others' opinion before purchasing a product and people also wants to know others' opinion about a political candidate before casting their vote. Thus there is a need of sentiment analysis of people's review and comments that identify their opinion.

Here sentiment analysis is performed using machine learning based analysis. However using machine learning process of sentiment analysis become slow as compare to lexical analysis but accuracy of result higher then lexical analysis so supervised machine learning using neural network is used to exhibit opinion or sentiment analysis. Main motivation using probabilistic neural network in this field is accuracy of output and higher speed of training neural network due to only feedforward training.

1.3 Scope

Sentiment analysis is used to detect the polarity of people's thoughts and opinions who are accessing social media. Businessman and researcher are interested in the thoughts and opinions of people and how they respond to things happens around them. Companies use this approach to estimate their advertisement promotions and to improve their products quality. This will help to companies to change their strategies regarding things for which people have negative view and opinion and also to political parties to change the agenda regarding to schemes and issues for which people's view are not favour to them.

In the recent time, probabilistic neural network classifier in sentiment analysis has more scope because training process is fast due to PNN learns from the training data instantaneously. The major features of neural networks such as adaptive learning, fault tolerance, parallelism and generalization deliver superior performance [3].

1.4 Research Objectives

Statement of Research Question

"Can accuracy of Sentiment Analysis of microblogging sites like twitter could be enhanced using probabilistic neural network?"

The goal of Sentiment analysis is to competently identify the feeling or emotion expressed in the text documents of tweets. In order to explain the Statement of research, this research question can be broken down into the succeeding questions, explanation of which will be accomplished by this research:

- How neural network based model can be applied for text classification?
- How text classification can be implemented using probabilistic neural network?
- How self-adaptive smoothing parameter is realised in PNN?
- What is the accuracy rate of output of Twitter Sentiment Analysis using PNN?

Therefore, the main research objectives of proposed approach undertaken are:

- i. Research Objective 1 To propose a classifier with improvement in accuracy of Sentiment Analysis.
- **ii. Research Objective 2** To implement a text classification or Sentiment Analysis with a faster classifier.
- iii. **Research Objective 3** To propose an algorithm to determine the best self-smoothing parameter for PNN classifier.

The objective of this thesis is to determine the mood or opinion of tweets posted by public on a particular issue or topic using faster classifier with improved accuracy.

1.5 Organisation of Thesis

This thesis is composed of 5 chapter followed by references.

Chapter 1 present the introduction of work undertaken, motivation and scope of proposed approach and research objective of thesis.

Chapter 2 provide the essential background of work to implement proposed work in this thesis and research work related to Sentiment Analysis.

Chapter 3 present the details of framework and methodology employed and summary of proposed approach which is Probabilistic Neural Network with self-adaptive approach for Sentiment Analysis of tweets.

Chapter 4 describe the experimental results which are obtained from text classifier which is employed and analyse the accuracy of the result of testing data.

Chapter 5 give the conclusion based on the thesis and future scope of the research which is proposed in this thesis.

CHAPTER 2 LITERATURE REVIEW

This chapter focus is to review the protuberant and relevant research that has been take on related to proposed approach. Section 2.1 focus on the introduction of sentiment analysis, type of Sentiment Analysis and the methods with the help of Sentiment Analysis of text and a document could be evaluated. This is followed by section 2.2 which gives details of neural network and type of neural network used for analysis.

2.1 Sentiment Analysis

In recent years, Sentiment Analysis has awakened the curiosity in many researchers, because text classification is used in many applications. Natural Language Processing (NLP), computational linguistics and text analytics are the challenges of Sentiment Analysis. In general words, Sentiment Analysis determine the attitude of online users regarding subject/object in discussion. With the rapid growth of internet applications such as social network, microblogging sites, forums, study of this area gained limelight [4].

Sentiment Analysis is an interdisciplinary area which consist of text analysis, natural language processing, and computational linguistics to classify the text sentiment. With explosive increase in web, online user express their feeling and sentiment in form of text. There are huge amount of text messages due to which to make a decision for people become difficult. For this purpose, sentiment classification method is required to determine the sentiment orientation category (e.g. neutral/positive/negative) of the text messages. There are two types of textual information from sentiment viewpoint, namely, facts and opinions. Facts gives the objective declarations about the behaviour of product while opinion refer to appraisals, attitudes, emotions and feelings regarding a service, topic, product, or an issue. Although the mainstream of research attention is toward implementing applications related to facts but recent trend has been focused toward the implementing application related to opinions in area of text mining [5].

The processing of opinions in text format is easier than other format, since most of opinion are obtainable in text format and sentiment analysis has arose as one of subfield of text mining. It identify the opinions of people conveyed in text. That opinions could be evaluations, judgments, beliefs, affective (or emotional) states, or wishes. First time in literature, Sentiment Analysis give the impression in 1990 and then in 2000, it become major research area. Due to

its many features it is often mentioned with different names such as sentiment classification, opinion mining, sentiment extraction and sentiment analysis.

With the help of following techniques, Sentiment Analysis (sentiment extraction) is implemented on twitter posts [6].

- Lexical analysis
- Machine Learning based analysis
- Hybrid/Combined analysis



Fig. 2.1 Technique of Sentiment Analysis

2.1.1 Lexical analysis

This analysis technique is accomplished by use of a dictionary comprising of pre-tagged lexicons. By the Tokenizer, input text is divided into tokens. For the lexicon, every new token which is encountered is matched in dictionary. Total score of pool is increased by 1 if encountered token match is positive for input text. Otherwise there is decrement in score or tagged the word as negative. Working of lexical analysis technique is shown in fig. 1.

Final total score achieved decide the classification of text. Dictionary of sentiment contains the words along with their polarities which is used to classify the text into neutral, positive and negative class. The dictionary used in sentiment is domain specific i.e. in dictionary, polarity of word is set according to topic which is used to sentiment analysis e.g.

movie review, specific topic opinion, product review [8]. This approach perform well in term of speed because there is no need of training of data. Lexical approach has a limitation and which



Fig. 2.2 Lexical Analysis

is that the performance (in terms of accuracy and time complexity) of this approach decrease drastically as the size of dictionary grow exponentially [7].

2.1.2 Machine Learning Based Analysis

Machine learning based analysis is a subfield of Artificial Intelligence which deal with algorithms that allow a model to learn. Which means an algorithm is given with a data set and successively concludes statistics about the behaviour of the given data; prediction is made, on basis of this information, about the data which may arise in future. Due to accuracy and adaptability of this approach, this technique is gaining the interest of researchers [9]. Machine learning approach is classified into three learning methods:

- Supervised Learning
- Unsupervised Learning
- Semi-supervised or Weakly Supervised Learning

2.1.1.1 Supervised Learning

In supervised learning technique, training data is labelled to train some classification function. Content of training data set are input feature vector and corresponding class labelling. The output from this function either can predict label or category of input data called as classification or a continuous value called as regression. Here all focus is only on classification. To the quantity and quality of training data this technique is quite sensitive so when training data is insufficient and biased this technique may fail [10]. Mostly used supervised learning classifiers are: Maximum Entropy, Naïve Bayes, Support Vector Machines Decision Trees, (Artificial) Neural Networks and TiMBL (Tilburg Memory-Based Learner).

2.1.1.2 Unsupervised Learning

In unsupervised learning technique, training data is not labelled for training purpose. Model or function receive unlabelled data set. Sometime it become quite difficult to create a labelled data and it is easy to gather unlabelled data so at that time this technique can be used. An analyser cannot lean about final output purely based on unsupervised methods because it has no information about what constitute a desired output state and a correct action [11]. Unsupervised learning classifier methods are: clustering or cluster analysis (k-means), the expectation-maximization algorithm and an algorithm to finding out the maximum likelihood of examples.

2.1.1.3 Semi-supervised or Weakly Supervised Learning

In semi-supervised learning technique, training task is accomplished by small labelled data set and a large pool of data from unlabelled data. Commonly used semi-supervised or weakly supervised learning algorithm include multi-view learning, generative models, self-training, and graph-based methods and co-training [12]. Typical number of step followed in machine learning techniques are shown in fig. 2



Fig. 2.3 Machine Learning Based Analysis

Explanation of working of machine learning technique is given as:

First Step: Data Extraction – in this step, data which has to be analysed is crawled from several sources like Social network (MySpace, Twitter etc.), Blogs depending on source for application.

Second Step: Pre-Processing – in this step, collected data is cleaned, pre-processed and made ready for input in classifier. Cleaning comprise of removing URL, hashtag, stop words, unnecessary tab and white space and extracting keywords and useful symbols.

Third Step: Training Data – in this step, firstly a manually tagged collection of data is prepared and that data set is input for classifier. For learning purpose, this input data set is feed to algorithm of classifier.

Forth Step: Classification – This step is the heart of this technique. According to requirement of application Naïve bayes, SVM or neural network is implemented for analysis. After completing training process, classifier is ready for real time text/tweet sentiment analysis.

Fifth Step: Result – Result is prepared according to requirement in term of recall, precision and accuracy.

However there are some challenges in this techniques like preparing training data to fuel in classifier, designing classifier and a correct interpretation of unseen data or phrase. But it

overcome the drawback of lexical technique of performance degradation and it perform well when size of data grow exponentially [13].

2.1.3 Hybrid Analysis

Hybrid analysis is combination of machine learning based analysis and lexical analysis. Hybrid approach collectively gain the speed of lexical approach and accuracy of machine learning approach. Performance of classification is improved by the combination of these two. In this technique, initial sentiment detection is performed by lexicon and after this these sentiment lexicon are used as feature for machine learning. Performance of this approach can be improved by increasing number of classifier to be used [6].

Training data set and test data set are used in machine learning technique for classification. Training data set consist of input vector and corresponding label of class. A classification model is prepared using this training data set which classify the input feature vector of unseen data of test data set into corresponding class label.

Different type of machine learning approaches or techniques are used like Naive Bayes (NB), Neural Network, Support Vector Machines (SVM) and Maximum Entropy (ME) are used for text classification which can be applied for twitter sentiment analysis.

Naive Bayes Classifier

Most commonly used and simplest classifier is the Naïve Bayes classifier. This classifier use all the features present in the feature list and analyses these features independently to each other and indivisibly. On bases of the word distribution in text document, this classification model calculate the posterior probability of a class. Working of this model is based on the bag of word (BOW) feature extraction in which location of word in document is ignored [14]. The Bayes Theorem which used to predict the probability for a given feature set goes to a particular class or label.

$$P (label | features) = \frac{P(label) * P(features | label)}{P(features)}$$

P (label) refer to the prior probability of a class or label or chance of feature set belong to a label. P (feature | label) refer to the prior probability to a given feature vector or set is going to be classified as a class or label. P (features) refer to the prior probability to occurrence of a given feature vector or set [15]. According to assumption of Naïve Bayes, all the feature vectors are independent to each other so equation can be rewrite as

$$P (label | features) = \frac{P(label) * P(f1|label) * \dots * P(fn|label)}{P(features)}$$

In spite of simplicity and assumption of being independent features clearly not hold in real world problem, indeed this model is optimal for some problem which have highly dependent features [16].

Maximum Entropy

In Maxent Classifier, labelled features set are converted to a vector set using encoding. The weights of each feature are calculated using this encoded vector set then that combined weight can be used to decide the most probabilistic label of feature set [17]. Parameters used in this classifiers are set of X {weights}, which consist of the combination of joint features which are generated by a set of features by an X {encoding}. Each C {feature set, label} pair mapped to a vector by encoding. The following equation is used to calculate the probability of a class of label.

$$P(fs \mid label) = \frac{dotprod(weights, encode(fs \mid label))}{sum(dotprod(weights, encode(fs \mid l))forlinlabels)}$$

In this classifier, entropy of system is maximised by approximating the conditional distribution of label of class. Conditional distribution is given as:

$$P(y \mid X) = \frac{1}{Z(X)exp\{\sum_{i} \lambda_{i} f_{i}(X, y)\}}$$

Where X refers to feature vector and y refers to the class label. Z(X) refers as a normalisation vector, λ_i as a weight coefficient $f_i(X, y)$ as a feature function that defined as

$$f_i(X, y) = \begin{cases} 1, & X = x_i \text{ and } y = y_i \\ 0, & otherwise \end{cases}$$

This classifier can also be called conditional exponential classifier. In this classifier, no assumption is considered regarding to the relationship between features so there is no issue regarding to "independent assumption" in this model [18].

Support Vector Machine

SVM is a classification technique which use supervised machine learning approach in which kernel functions are used to map an input feature space, in which classes are linearly distinguishable, into new space. A large margin is used by SVM classifier for classification. The discriminative function used by SVM is defined as [19]:



Fig. 2.4 Support Vector Machine

$$g(X) = w^T \phi(X) + b$$

'X' refers to feature vector, 'w' refers to weight vector and 'b' refers to bias vector. ϕ () is a function of non-linear mapping type in which input space is mapped to a high dimensional feature space. When a linear kernel is used for classification then a wide gap is maintained between two classes. This classifier have a potential which can handle large feature space having a large number of dimensions. Also SVM have an independent learning ability to dimension of feature space.

Training in SVM is relatively easy. Unlike to neural network, there is no local optima. It perform relatively well in case of high dimensional data and trade-off can be controlled between error and classifier complexity explicitly. For better performance, this model need to choose a good kernel function [20].

2.2 Neural Network

Neural Network is a computational system of 'connectionist'. The word network refer to interconnections between neuron present in different layers of a model. If a model have three layer. The first layer containing input neuron sent information or data to neuron of second layer via synapses then to final layer of output neuron via more synapses. If a model is more complex it contain more number is neuron layers. The parameter value store in synapses is 'weights' that is manipulated in data calculation. Neural Network is an adaptive complex system, not just a complex system, means it can adapt or change its internal weight or structure depending on the information flowing through it [21] [22].

Neural Network Layers

A common type of neural network is combination of three layers or units and these units are input, hidden and output units. First unit is 'input layer' which is linked to a unit called 'hidden layer' and that is linked to final unit called 'output layer'.

- Functionality of input layer is to feed raw information to neural network.
- Functionality of hidden layer is to find out the activities of input layer neuron and assign weights to connections between input layer and hidden layer.
- Functionality or output of output layer depends on the functionality of hidden layer and weight assigned between hidden unit and output unit.



Fig. 2.5 Neural Network Architecture

Neural Network varies from those which has one or two single directional logic layers, to complicate with multi input and many directional feedforward, backpropagation loops and layers. Model use the algorithm used for functionality to determine to organisation of their function or to control. Some neural network used for sentiment analysis are: Feedforward neural network (FNN), Backpropagation, Recurrent neural network (RNN), Time delay neural network (TDNN), Probabilistic neural network (PNN) and Deep Learning neural network.

2.2.1 Probabilistic Neural Network

Probabilistic neural network (PNN) is derived from a radial basis function type based model which is used in data classification effectively. Donald Specht proposed this model. PNN is supervised neural network which is widely used in many areas like: nonlinear mapping, pattern recognition, digital image watermarking, image classification and recognition, classification in a time-varying environment and text classification [23].

Bayesian Classifier

The classification performed by probabilistic neural network is derivative by the Bayes theorem. This theorem state that a vector x given to a class g if for which $g \neq h$ for the all classes holds the following:

$$p_g e_g y_g(x) > p_h e_h y_h(x)$$

Where x belongs to the one of example or sample of predefined class g. where $g \in (1, 2, ..., G)$. p_g refers to the probability of a vector x to be contained in class g. e_g refers to the error which is associated to vector x which is classified into class g. $y_g(x)$ is a PDF for class g which gives the concentration of gth class's data around the x vector. If it is assumed that $e_g = e_h$ and $p_g = p_h$, then to the class g, vector x is assigned if in the neighbourhood of x, the PDF for $y_g(x)$ takes higher value than the pdf for $y_h(x)$ [24].

In case of real classification problem, there is no knowledge about the PDFs because distribution of data set is usually unknown. Therefore need to determine some approximation of PDF. Using Parzen method, these approximation can be found. For multiple variables, PDFs can be expressed as:

$$y(x, \sigma) = \frac{1}{l\sigma_1 \dots \sigma_n} \sum_{i=n}^l W(u)$$

Where

$$\mathbf{u} = \begin{bmatrix} \frac{x_{i1} - x_1}{\sigma_1}, & \dots, & \frac{x_{in} - x_n}{\sigma_n} \end{bmatrix}$$

Where 1 refers to the number of input vectors, W (.) denotes a function called weighting function which should be selected appropriately and $\sigma = [\sigma_1, \ldots, \sigma_1]$ refers to smoothing parameter which is associated to n variables x_1, \ldots, x_n [25].

PNN has a complex structure with multi-layered feed-forward neural network. PNN is consist of four layers such as input layer, pattern layer, summation layer and output layer.

2.2.1.1 Layers of PNN

Input layer: The input node which are measurement set comprise the input layer. Training sample is received by this and feature vector is transferred to network. When input is present, this layer calculate the distance between input vector and training vector.

Pattern Layer: Neuron of pattern layers are divided into a number which is equal to the number of classes. Total neuron in this layer is equal to training sample. Neuron of this layer are fully connected to neuron of input layer. Neuron of this layer calculate the Euclidean distance for each teat case from centre point of neuron and which is applied to a Gaussian function using sigma value. Output of this layer by each neuron is given as:

f(X, W_i) = exp
$$\left[-\frac{(X-W_i)^T(X-W_i)}{2\sigma^2}\right]$$

Summation layer: Working of this layer is simply sum up the inputs which it got from pattern layer that correspond to a category from a selected training pattern. This layer find out the maximum like hood of a pattern to be classified into a class by summarizing.

Output Layer: This layer select the maximum value from the input which it get form summation layer and determine the class of test case [26].

Steps involved in PNN model are:

Step 1: In this step all the neuron measurement are distributed to neuron of pattern layer by input layer.

Step 2: Gaussian kernel function is applied to all the given data set using sigma.

Step 3: Here average or summarizing operation of output are performed for each target class.

Step 4: Maximum value is selected from input from previous layer and label of class is determined [3].



Fig. 2.6 Layers of PNN

There is only single training parameter for PNN. This is called smoothing parameter of probability density function (PDFs) which is used to activate the neuron of pattern layer. So training process of PNN require only single pass of input-output signal to compute neural network response. Therefore possibility of correctness of output of model depends on the optimum value of smoothing parameter. In this neural network, there is no requirement of any iterative training due to which it learn quite quickly which is one of greatest benefit of this network. As well as this network has a disadvantage which is that in this network for every training instance it contain a hidden node so due to which it need additional computational resources, in term of time and storage, during execution time then other model [27] [28].

In probabilistic neural network, a crucial role is played by choice of smoothing parameter in training parameter. A PNN has different smoothing parameter for: each attribute, each class and each attribute and class. Selection of smoothing parameter for PNN according to four different types' strategies: for whole network there is a single smoothing parameter σ , for each class single σ , for each attribute single σ , for each class and each attribute single σ .

PNNS model:

Commonly for the choice of PDF function, Gaussian function is used because all the condition and requirement of Parzen's method is satisfied by this function. The assumption which is used in Gaussian density function for PDF fulfil all the possibility for construction of a feed forward classifier. This classifier consist of a input layer containing attributes of x, pattern layer followed by summation layer which contain G neurons in which signal for pattern belonged to the g-th class is computed by each of these neuron. Depending on the value of smoothing parameter, this type of PNN hereafter is called PNNS.

$$y_g(x;\sigma) = \frac{1}{l_g(2\pi)^{n/2}\sigma^n} \sum_{i=1}^{l_g} \exp\left(-\sum_{j=1}^n \frac{(x_{ij}^{(g)} - x_j)^2}{2\sigma^2}\right)$$
(1)

Where l_g is no training data belong to class g. σ refers to smoothing parameter. In i-th training vector (i= 1, 2, ..., l_g) which belong to class g, $x_{ij}^{(g)}$ is the j-th element. x_j is j-th coordinate of x unknown vector. So according to Bayes' decision law, output layer calculate the class of x vector which is based on the neuron of all summation layer's output.

$$G^*(x) = \arg \max\{ y_q(x) \}$$

Where $G^*(x)$ refers to the class of vector x to be predicted.

PNNC model:

Signal of summation layer which is defined in (1) has different shape, if pattern differs in term of densities of a specific class, depending on smoothing parameter value of related class. This type of PNN model is called PNNC.

$$y_g(x; \sigma_c) = \frac{1}{l_g(2\pi)^{n/2}(\sigma^{(g)})^n} \sum_{i=1}^{l_g} \exp\left(-\sum_{j=1}^n \frac{(x_{ij}^{(g)} - x_j)^2}{2(\sigma^{(g)})^2}\right)$$

Where σ_c is a vector of smoothing parameters $\sigma_c = [\sigma^1, \ldots, \sigma^{(G)}]$, where G is no of class to be classified. In this vector element $\sigma^{(g)}$ is associated with the smoothing parameter of g-th class.

PNNV model:

There is also a chance of differentiating smoothing parameter on bases of each attribute of input vector. According to this, the changed formula is as:

$$y_g(x; \sigma_V) = \frac{1}{l_g(2\pi)^{n/2} \sum_{j=1}^n \sigma_j} \sum_{i=1}^{l_g} \exp\left(-\sum_{j=1}^n \frac{(x_{ij}^{(g)} - x_j)^2}{2(\sigma_j)^2}\right)$$

Where σ_V is a smoothing parameter vector which is $\sigma_V = [\sigma_1, \sigma_2, \dots, \sigma_n]$ in which element σ_j is linked to the j-th variable of the input. The PNN model which contain different smoothing parameter for each input variable is called as PNNV model.

PNNVC model:

The PNN model which contain different smoothing parameter with respect to each class and each data attribute. The signal of summation layer of this network are represented as:

$$y_g(x; \sigma_{VC}) = \frac{1}{l_g(2\pi)^{n/2} \sum_{j=1}^n \sigma_j^{(g)}} \sum_{i=1}^{l_g} \exp\left(-\sum_{j=1}^n \frac{(x_{ij}^{(g)} - x_j)^2}{2(\sigma_j^{(g)})^2}\right)$$

$$\sigma_{VC} = \begin{bmatrix} \sigma_1^{(1)}, & \dots & , & \sigma_j^{(1)} & \dots & , & \sigma_n^{(1)} \\ \ddots & \ddots & \ddots & \ddots & \ddots & \ddots \\ \vdots & \ddots & \ddots & \ddots & \ddots & \vdots \\ \sigma_j^{(g)}, & \dots & , & \sigma_j^{(g)} & \dots & , & \sigma_j^{(g)} \\ \vdots & \ddots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots & \vdots \\ \sigma_1^{(G)}, & \dots & , & \sigma_j^{(G)} & \dots & , & \sigma_n^{(G)} \end{bmatrix}$$

Where

is a matrix containing values for smoothing parameters in which element $\sigma_j^{(g)}$ is the value of smoothing parameter associated with j-th input attribute of data in g-th class. This type of PNN model is named as PNNVC.

Considering all the above four possibilities of calculating the signal of summation layer, the generalised output form of PNN model is defined as:

$$G^*(x; sigma) = \arg\max\{y_g, (x; sigma)\}$$

Where

$$Sigma = \begin{cases} \sigma & for PNNS \\ \sigma_{C} & for PNNC \\ \sigma_{V} & for PNNV \\ \sigma_{VC} & for PNNVC \end{cases}$$

And y_g is calculated according to equations of PNNS, PNNV, PNNC and PNNVC depending on the requirements [30] [31].

2.3 Related Work

Even though a broad research has been carried out in area of sentiment analysis from last few years even then this field keep holding the attention or interest of researcher. Enormous amount of data available on social sites where people express their feeling, emotions or view about a topic which give inspiration to researchers to do experiment with help of using different models for sentiment analysis to retrieve sentiment with a better accuracy.

In [32], focus is placed on the sentiment analysis using neural network. The neural network used for sentiment analysis is feedforward pattern network for neural network toolbox of MATLAB. Before feeding the tweets to network they are pre-processed. In this step, the item which are removed from tweets are: symbols, punctuation, URL, single word and stop words. In next step, using Porter's Stemming algorithm all the pre-processed tweets are stemmed. All the unique words for pre-processed tweets are added to 1-D list called vocabulary list. Training data is stored in form of 2-D matrix. A map variable is generated which maps the words from training vocabulary key to the index of vocabulary list where word is located. In this way a numeric input training vector is generated. A numeric vector whose size is number of words inn vocabulary * numbers of tweets, is generated and feed to neural network for purpose of training. MATLAB provide a pattern recognition neural network that is feedforward network in which for regulating the biases and weights, a scaled conjugate gradient method is used. For this experiment 10 neurons are used in hidden layer of network and two neuron for output layer, one for the probability of positive tweets and other for negative tweet probability. A set of 200 tweets in which 100 are positive tweets and other 100 are negative is used of training neural network. For these tweets, a vocabulary list of 288 words is created. And a test set for this experiment is of 100 tweets. The average accuracy of this classifier is 74.15 % according to setup of this experiment. In training of feedforward network, memory become an issue when size of vocabulary list is increased.

In [33], probabilistic neural network is applied in order to classify the network intrusion. An intrusion detection model is given to perform for classification of network intrusion. KDD cup dataset is used for the experiment. Advantage of using PNN is simple operation and fast convergence speed. KDD Cup 99 is standard data set for network intrusion which is used for training and testing purpose. The data contain 41 different data attributes. For input to network 41 data attribute are used and output is attack type. The data before feed to network need to be normalised to nullify the difference between the magnitudes of data dimension and avoid the large prediction error off network. To create PNN, MATLAB toolbox function which are for neural network purpose are used where netwpnn() function is used for training of data and sim() is used for testing of data. Classification is carried out for two type of problem, one having two classified class and other have 5 class. According to experiment, 1st problem have 97.75 % detection rate while 2nd have 98% detection rate.

In [34], PNN with the help of Discrete Cosine Transformation is used for Brain Tumor classification. In the central spinal canal or the brain, an intracranial solid abnormal or neoplasm growth of a cell is called as brain tumor. PNN is used to identify the type of brain tumor from which a patient is suffering with the help of images of brain tumor which are received form Computed Tomography (CT) scan and Magnetic Resonance Imaging (MRI).

Discrete Cosine Transformation is a discrete sinusoidal unitary transform which is a set of basic vectors which consist of sampled cosine function. For a typical image, DCT has a property with the help of which it concentrate the most significant information in just a few coefficients. The database used for proposed model contains 5 classes and 4 images in each class of size 70 * 60 pixel each with a different background conditions. MATLAB is used for simulation purpose. This data base is feed to Discrete Cosine Transformation to reduce the size of images and feature extraction. DTC extract 16 features per image and reduce size to 4 * 4. The feature vector which is generated as output of DTC if feed to PNN for classification purpose. An accurate and fast result is given by PNN for classification of brain tumor images. The average training time for a training sample of 15 images is 3.2760 sec and testing time for a 5 test sample is 1.076 sec. The recognition rate is 100% of purposed model for Brain tumor database.

In [35], use NLP technique to analyse the performance of ensemble method for twitter sentiment analysis. Ensemble classifier combines the effect or involvement of various independent classifiers for a problem of classification. For mining the sentiment two main approaches are used: dictionary based (DB) and machine learning based. Pre-built dictionary is required for DB. DB has a potential limitation that the classification strength of DB depends on the pre-built dictionary used. In proposed model NLP techniques are applied on the data which is gathered from twitter to frame the feature vector. Then for a training model, Ensemble method is realised to training data. Four modules constitute the system: data extraction, data pre-processing, training and classification model and classification output. With help of Twitter API, tweets are fetched and pre-processed to extract the features. Performance of ensemble method is compared against machine learning algorithm like Baseline, SVM, Naïve Bayes and Maximum Entropy. The parameters used for performance calculation are: Recall, Precision and F- score. Database used for classification is an election dataset of 7086 tweets for training

and testing. As a result, it is observed that Ensemble method perform better than other traditionally classification methods.

In [36], a PNN model is proposed which is self-adaptive. In this model sigma parameter for PNN is optimised by using Particle Swarm Optimization (PSO) algorithm to enhance the performance. POS is an optimization algorithm which is based on population. In this case swarm is population and particles are the individual search points. A memory of best position of particle is retained which it encountered when it move in search space with an adaptive velocity. In global variant case, the best position which is attained by the all particle of swarm is transferred to all other particle after each iteration.

In PNN sigma play a critical role in classification. So determination of sigma is completed using PSO. A specific sample from dataset is required to perform the optimization. So that value of sigma which is obtained from PSO is best for the respected data set. The data set of bioinformatics field is used for proposed model. For evolution of 100 generation, a swarm of 20 particle is allowed. Because of faster exhibition convergence, a global variant algorithm is considered as compare to local variant. To avoid possible explosion of velocities, particle are constrained in box [0, 1]. For different sampling techniques, performance of SA-PNN is examining with the help of the Stratified Random Sampling and the 10-Fold Cross-Validation sampling techniques, as well as, a Train-Validation-Test partitioning on the data set. Out of these three technique of samplings, best classification performance is produced by stratified random sampling despite of that the training sets it produces as compare to 10-fold cross validation are smaller in magnitude. The obtained results shows that the performance achieved using self-adaptive PNN is significantly superior on data set which is used for this experiment.

CHAPTER 3 PROPOSED APPROACH

This chapter exemplify the techniques which is used to realise of the proposed approach for sentiment analysis by building a classifier. Section 3.1 describe the general idea of the research undertaken. Section 3.2 illustrates the architecture or flow diagram of proposed approach. Section 3.3 explain proposed framework with description of each component of model and shows the contribution of these component for classification to Sentiment Analysis model.

3.1 Proposed framework

For researcher in area of text mining, Sentiment Analysis is an enduring field. Sentiment Analysis (SA) is a computational study of attitudes, opinion and emotion of peoples towards an entity. This entity can be a topic, event or individual. SA can be applied on news articles, product reviews, political debates and stock markets. In last few years, many enhancement or application the techniques and algorithm on SA are proposed. Machine learning based technique for sentiment classification is studied extensively because of its predominant performance in classification. This research focus on the neural network based sentiment analysis which is a type of machine learning based technique. Neural network is a rapidly growing area in the recent time because of two reasons. First one is that the neural network has a deep architecture with layers that represents an intelligent behaviour and more efficient and effective than a shallow architecture like SVM (Support Vector Machine). And second is that neural network has feature of adaptive learning, fault tolerance, parallelism and generalization which provides a superior performance.

To classify the sentiment analysis of tweets which are based on a topic, we propose a probabilistic neural network with a self-adaptive approach. PNN is like a parallel algorithm. PNN is developed based on an estimation method that is probability density function for Parzen window and Bayes classification rules. A linear learning algorithm of PNN is also capable for solving non-linear algorithm problem. Operation of PNN are structured into a multi-layered feedforward network. First layer of PNN calculate the distance of input vector from the training vector which generate the result in form of vector that indicate how the input is close to training input. Next layer sum up the contribution of an input from the previous layer for each class and produce a vector of probability as output. Next layer pick up the maximum value out of these probability to produce output of classifier.

A parameter which has great influence on the performance of PNN, called smoothing parameter (σ) or spread, need to be optimized. This parameter determine the receptive width for PDF of the set of training of Gaussian window. So in this propose work, a self-adaptive technique for smoothing parameter is incorporated into PNN. So the best smoothing parameter can be selected by self-adaptively all the time to enhance to performance.

3.2 System Architecture

The proposed model is mean to extract the tweet from twitter based on a topic for Sentiment classification. Tweets are then classified into neutral, positive and negative class using classifier model. The architectural view of proposed model is shown in the figure.

3.3 PNN Classifier Model

After having a detail study of objective and principals of Sentiment Analysis and Classification we propose a Probabilistic Neural Network with self-adaptive approach system which realises the Sentiment Analysis of tweets.

The main modules or components of PNN classifier model are:

- Data Retrieval Module: This component is used to extract the tweets from Twitter with the help of Twitter Streaming API based on a topic decided by user.
- Pre-processing Module: This module or component removes the unwanted text for sentiment analysis from tweets so that complication for classifier can be reduced. After processing this module tweets contains only relevant text to classifier.
- Input vector Module: This prepare the input which could feed to Probabilistic Neural Network or to the form which is compatible to classifier.
- Training and Testing Data Module: In this component or module, training data set is prepared with the help of labels means a label or class is assigned to every tweet of set of training and testing data set is also defined.
- Optimize Module: This module or component optimize the value of smoothing parameter of classifier with help of self-adaptive algorithm. An optimized value of this parameter gives improved result of classification.

- Classification Module: This module is 'brain' of this classification model. Classification algorithm is implemented in this component. This module determine the class or sentiment orientation of tweets.
- Result Module: This module gives the final Sentiment Analysis of a tweets of all the input vector of testing data set.



Fig. 3.1 Architecture of PNN Classifier Model

The detail explanation of PNN classifier modules is given in following sub-sections.

3.3.1. Data (Tweet) Retrieval Module

An interface is provided by Twitter platform, called as Twitter API, with help of which websites or application connects to the worldwide conversations which is happening or trending on Twitter. API is class which provides the access to twitter. A limited amount of data is delivered using Twitter Streaming API via two types of data stream: filtered stream and sampled stream. In streaming API, data delivered is closer to real-time data. Tweets delivered in sampled stream are random sampling at 100% firehose with statically valid percentage. Filtered stream is of second type stream. Tweets delivered by this stream type are the one which match to the filter selected by users. This stream is used where a limited amount of tweets are required based on a keyword. Only limited amount of tweets are accessible through this stream. A separate process is required to run streaming connection apart from that process which is used to handle the HTTP requests. After establishing a successful twitter connection, streaming process retrieve the tweets based on the filtered keyword and store to a database. Figure shows the diagrammatic view of Twitter API model [37].



Fig. 3.2 Data streaming of Twitter API module

Twitter requires OAuth for authentication to use all the requests. Here R tool is used for tweet extraction. twitteR is an R package which provides access to the Twitter API. Twitter streaming API is made easier by twitteR by handling authentication, creating and destroying session, connection, reading incoming messages. A searchTwitter() method of twitteR in R is used

extract the tweets whose arguments are search keyword or string, language, no of tweets required, since when and up until which date the tweets required. These commands returns any authorized tweets which match the search criteria. Authorized tweets are public tweets as well as those protected tweets that are available to the user after authenticating via registerTwitterOAuth.

3.3.2 Pre-processing Module

Because of presence of language irregularities in the Twitter messages, pre-processing has to be applied. Several pre-processing steps are applied to remove the noise from tweets. These steps are:

• Remove web links: In pre-processing step, the web links which are contained in tweets are removed because there is no need of web links in Sentiment Analysis.

```
tweet = re.sub('((www\.[^\s]+)|(https?://[^\s]+))','',tweet)
```

• Remove user name and # tag: This step remove username present with @ and #tag present with the keyword in the tweet.

```
tweet = re.sub('@[^\s] | #[^\s]+','',tweet)
```

• Remove whitespace: This step remove unwanted whitespace present within tweet. Due to this may increase the complexity.

```
tweet = re.sub('[\s]+', ' ', tweet)
```

• Convert to lower case: Before processing the tweets, all are converted into lowercase for a better understanding.

```
tweet = tweet.lower()
```

• Replace two or more words with one: If there is repetition of words then this step replace two or more words with a single word.

```
def replaceTwoOrMore(s):
    #look for 2 or more repetitions of character and replace with the character itself
    pattern = re.compile(r"(.)\1{1,}", re.DOTALL)
    return pattern.sub(r"\1\1", s)
```

• Remove duplicate tweets or retweets: When tweets are extracted from twitter there are lots of retweet or redundant tweets so these redundant tweets has to be removed to avoid repetition of tweets and for better performance.

```
lines_seen = set() # holds lines already seen
outfile = open('New1.txt', "w")
lfor line in open('New.txt', "r"):
    line = re.sub('((www\.[^\s]+)|(https?://[^\s]+))', '', line)
    if line not in lines_seen: # not a duplicate
        outfile.write(line)
        lines_seen.add(line)
outfile.close()
```

• Remove stop words: The stop words like a, an, the, you, we, are, is, etc. are of no use

for tweet Sentiment Analysis so these words are removed.

```
idef getStopWordList(stopWordListFileName):
    #read the stopwords file and build a list
    stopWords.append('AT_USER')
    stopWords.append('URL')

    fp = open(stopWordListFileName, 'r')
    line = fp.readline()
    while line:
        word = line.strip()
        stopWords.append(word)
        line = fp.readline()
    fp.close()
    return stopWords
```

After pre-processing tweets are ready for further operations.

3.3.3 Input Vector Module

In this module pre-processed tweets are transform into a vector which is compatible to feed into a classifier. This module comprise of two section: Bag of Words and Feature Vector.

Bag of Word: Bag of words is a vocabulary list which is learn from all the tweets. This list contains most frequent words from pre-processed tweets. This bag collects the occurrence of words of a document without any regard of grammar of a text. Occurrence of each word in bag is used as feature in training of a classifier. Bag of word is used to calculate the frequency of term that appeared in a text.

```
def extract features(tweet):
    tweet words = list(tweet)
    features = {}
    print featureList
    for word in featureList:
        features['contains(%s)' % word] = (word in tweet_words)
    print features
    return features
#end
# Remove featureList duplicates
featureList = list(set(featureList))
input_file = 'preprocess.txt'
out_file = 'preprocess1.txt'
with open(input_file) as f:
    lines=f.readlines()
for line in lines:
    filtered_line=[w for w in line.split() if not w in stopWords]
    filtered line=' '.join(filtered line)+ '\n'
    with open(out_file, 'a') as myfile:
       myfile.write(filtered_line)
```

Feature Vector: A classifier algorithm expect input to be feed to it in form of a numeric feature vector rather than a sequence of text and symbols with a vector of fix size rather than a variable size of raw text document. Size of feature vector is size of Bag of Vector * no of tweets. No of column is same as the no of item in the bag of words so that if a tweet contain that item or word place 1 in that row corresponding to that column otherwise place 0 at that place. So in this way feature vector or input vector is created.

```
inpt=open('inputvector.csv','a')
writer =csy.writer(inpt,dialect='excel',delimiter='\n')
with open('inputvector.csv','r') as csvinput:
     with open('output.csv', 'wb') as csvoutput:
            writer = csv.writer(csvoutput, lineterminator='\n')
            reader = csv.reader(csvinput)
            all = []
            row = next(reader)
            for j in range(1, rows):
                 for i in range(0,lines):
                    row.append('0')
                all.append(row)
                row = next(reader)
            writer.writerows(all)
csvinput.close()
csvoutput.close()
pre=open('preprocess1.txt','r')
out=open('outputvector.csv','w')
wrt=csv.writer(out)
arr=[]
#collected = []
for line in pre:
    arr=line.split()
    arr1=[0]*rows
    for i in range(len(arr)):
        if arr[i] in featureList:
            print___arr[i]
            print__featureList.index(arr[i])+1
            arr1[featureList.index(arr[i])]+=1
    wrt.writerow(arr1)
```
This module generate the output which is compatible to feed into a classifier algorithm. One row of feature vector is an input vector corresponding to one tweet.

3.3.4 Training and Testing Data Module

The tweets which has been collected through Tweeter API based on a keyword are unlabelled which means sentiment class of these tweets is not defined along with them. To train a classifier, training data need to be labelled so a labelled data has to be constructed. Class or label of the tweet can be positive, neutral and negative so these label has to be defined along with input vector. This labelling process is completed manually. User decide the label or class of a tweet by analysing the sentiment of that tweet [38]. Out of feature vector data, 67% data is used for training so labelling of that data is necessary and remaining 33% use for testing operation.

3.3.5 Classification Module:

In the propose approach probabilistic neural network is used as a classification model which is a machine learning based technique. PNN is a network which is based on the theory of Bayesian decision and Probability Density Function (PDF) which estimate the nonparametric technique. Probabilistic neural network is a feedforward, there is no need of backpropagation so parameters or weight can't be optimized after many iterations. So a single parameter is used for classification. This parameter is known as smoothing parameter or sigma (σ). By adjusting the value of smoothing parameter prediction accuracy of classifier can be enhanced. For a feature vector (X) belongs to a class, the PDF is given as:

$$f_a(x) = \frac{1}{n_a(2\pi)^{p/2}(\sigma)^p} \sum_{i=1}^{n_a} \exp\left(-\sum_{j=1}^n \frac{(x_{ij}^{(g)} - x_j)^2}{2(\sigma)^2}\right)$$

Where $f_a(x)$ is value of PDF at point X for a class A.

x refers to the test vector to be classified.

i is a numbering of training vector.

j is index numbering in feature list.

p is size of training vector.

 n_a is number of training vector which belong to class A

 σ is smoothing parameter.

Final class of x is decided according to Bayes' decision rule according to output of all neuron of summation layer. PNN architecture is consist of four layers. First one is input layer which comprise of neuron equal to length of input vector. Testing data is feed through input layer. This layer is followed by pattern layer in which all neuron are categorised into number of classes or labels and one category contain neuron equals to no of training tweet corresponding to that class. After that summation layer follow that layer in this number of neuron equal no of classes. Result of each category of classes of pattern layer is feed into summation layer. This layer gives the output as maximum of outputs of pattern layer. Final layer is output layer which give the sentiment result according to output of summation layer [39] [40].

```
testvector=list(csv.reader(open('test.csv')))
testreader = csv.reader('test.csv',delimiter=';')
res=[]
n = len(testvector[1])
final=[]
for i in range(0,len(testvector)):
    v = 0
    trainvector = list(csv.reader(open('positive.csv')))
    trainreader = csv.reader('positive.csv', delimiter=';')
    l = len(trainvector)
    leng = len(trainvector[1])
    print 1
    print int(trainvector[1][1])
   for j in range(0,len(trainvector)):
        for k in range(0,leng) :
            a=(int(trainvector[j][k])-int(testvector[i][k]))
            x=(math.pow(a,2))/(2*math.pow(s,2))
            y=y+x
        r=math.exp(-y)
    res=r/(l*(math.pow(2*math.pi,n/2))*math.pow(s,n))
    print res
```

3.3.6 Optimisation Module:

Smoothing parameter plays a great role for predicting an accurate class of classifier. This parameter has great influence on the performance on Probabilistic Neural Network. Manually selection of this parameter is quite difficult. So a self-adaptive algorithm is used to calculate and optimize the smoothing parameter. So this approach is called Probabilistic Neural Network with self-adaptive. Smoothing parameter is adjusted self-adaptively and best parameter is selected to train and test the Probabilistic Neural Network. In algorithm $sigma_{min}$ and $sigma_{max}$ specifies the minimum and maximum value of smoothing parameter. And $sigma_{interval}$ is the interval of smoothing parameter.

 $sigma_1 = sigma_{min}$, $sigma_2 = sigma_{min} + sigma_{interval}$, $sigma_2 = sigma_{min} + 2*sigma_{interval}$ and so on.

$$sigma_j = sigma_{min} + (j-1) * sigma_{interval}$$

 $sigma_M = sigma_{max}$

Where j=1, 2, 3, ..., M.

M is the number of smoothing parameter which is given as:

$$M=round\left(\frac{sigma_{max}-sigma_{min}}{sigma_{interval}}\right)+1$$

Algorithm for self-adaptive smoothing parameter is given as:

Begin

Step 1: Initialization of variables. Set maximum and minimum value of smoothing parameter $sigma_{max}$ and $sigma_{min}$. Set maxIter equal to no of test case, counter of current iteration t=1, counter of current generation G=1 and interval of smoothing parameter $sigma_{interval}$.

Step 2: While t<=2 do

Compute all possible smoothing parameter $(sigma_1, ..., sigma_M)$ according to $sigma_{min}$, $sigma_{max}$ and $sigma_{interval}$.

For j=1 to M

While G < maxIter

Construct basic PNN using *sigma_j*.

Train and test the data set.

Compute prediction result.

```
G=G+1.
```

end while

end for j

Select the best smoothing parameter *sigma*_{best} with minimum error.

Update $sigma_{min}$ and $sigma_{max}$ according to update equation.

 $sigma_{interval} = 0.1.$

t=t+1.

Step 3: end while

Step 4: Output the best smoothing parameter *sigma*_{best}.

End.

For each value of smoothing parameter this algorithm perform training and testing process. After each iteration best smoothing parameter $sigma_{best}$ is selected with minimum error. According to this $sigma_{best}$ the other parameters like $sigma_{min}$, $sigma_{max}$ and $sigma_{interval}$ are adjusted as given in the equations.

 $sigma_{min} = \max (sigma_{best} - sigma_{interval}, sigma_{min})$ $sigma_{max} = \min (sigma_{best} - sigma_{interval}, sigma_{max}).$

3.3.7 Output Module

This module give the Sentiment Analysis of data which is used for testing dataset. This module assign the positive, negative and neutral opinion according Sentiment Analysis of tweet provided by the output of the Probabilistic Neural Network.

```
result=max(res,res1,res2)
print "result is ::"
print result
if result == res:
    print "positive"
    final.append(1)
elif result == res1:
    print "negative"
    final.append(-1)
elif result == res2:
    print "neutral"
    final.append(0)
    print "final result"
print final
```

CHAPTER 4 EXPERIMENTAL RESULT AND ANALYSIS

This chapter describes the experimental results realised from the proposed approach. It also analyse the result on behalf of test dataset.

4.1 Illustration

Stepwise execution of Classifier for Sentiment Analysis is given as:

4.1.1 Extraction of tweets:

Tweet are extracted from Twitter using Twitter API. The keyword used for tweet extraction is "#NSG". NSG abbreviate for Nuclear Supplier Group. Tweets are related to whether India should get the membership for NSG or not.

RT @INCIndia: Don't know why India showed so much desperation. PM Modi needs to realise diplomacy needs depth not public tamashaa: Anand Sh... #NSG indicates no exception will be made in the case of #India - https://t.co/7Pz6IG9V02 @EconomicTimes #NPT #China @narendramodi #Nuclear RT @shammybaweja: #NSG How sensible was it for India to stake its all and what diplomatic sense is there in blaming one country in an offic... Who'll be the scapegoat now that India didn't get into #NSG ? May be #subramaniamswami will decide! <ed><U+00AE><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><ed><U+00BE><<U+00BE><<U+00BE><<U+00BE><<U+00BE><<U+00BE><<U+00BE><<U+00BE><<U+00BE><<U+00BE><<U+00BE><<U+00BE><<U+00BE><<U+00BE><<U+00BE><<U+00BE<<<U+00BE<<U+00BE><<U+00BE<<U+00BE<<U+00BE<<u+00BE<<u+00BE<<u+00BE<<u+00BE<<u+00BE<<u+00BE<<u+00BE<< RT @gauravcsawant: Well fought India. Its clear who are our real friends & amp; Back stabbers identified. Will there be consequences? Or busines... RT @INCIndia: World saw PM make a spectacle of himself & amp; India. Now India faces embarrasment unnecessarily: Anand Sharma on #NSG https://t... RT @ShivAroor: Knew our politics was rotten. Didn't think it so far gone that India's #NSG fight would be a topic of political derision and... RT @Smita Sharma: India's #NSG bid dashed against the Great Wall-China & others make #NPT big sticking point.My report https://t.co/bOGEMvL... #NSG Again most countries will support was false propaganda @Myth_busterz @geetv79 @alamgirizvi @BibiPakhii @MehekF https://t.co/EthE6XzkSG "RT @firstpost: India's #NSG bid: Most countries have expressed support, claims MEA https://t.co/sLyFF1NWjb https://t.co/QVUeMLecHT" RT @EconomicTimes: We understand that procedural hurdles were persistently raised by one country: MEA on #NSG https://t.co/dp2AT0tSmw RT @Smita_Sharma: My report for @mail_today earlier on the Thursday deadlock in #NSG special meet in Seoul https://t.co/aPIv735wpv https://... RT @vidyarthee: So much hoopla for #NSG. But #ModiGovt gets blocked by China wall and the 'U-turn' by Switzerland. Failed diplomacy! https:... RT @EconomicTimes: There is thus no contradiction between the NPT and India's closer engagement with the NSG: MEA on #NSG https://t.co/fSbq... RT @INCIndia: Don't know why India showed so much desperation. PM Modi needs to realise diplomacy needs depth not public tamashaa: Anand Sh... RT @ShivAroor: (2/2) This attempt at the #NSG hasn't worked. But it's made our adversaries/traitors stand out much more clearly. India shou... RT @ShivAroor: India's #NSG fight is the good fight. It's rightful & important. The nuclear world is less governed without India in the NSG... The real game has just begun! #NSG down. #UNSC / #Chabahar / #SouthChinaSea is next. https://t.co/DUArc5v6aG RT @shammybaweja: #NSG How sensible was it for India to stake its all and what diplomatic sense is there in blaming one country in an offic... Every true Indian now must #boycottChineseProducts also these are 3rd quality products too! Ban them like they do with our pm Modi in #NSG "#nuclear order will collapse if #India joins #NSG : #China https://t.co/HXFWDyxwC5 https://t.co/LVvWuogR3M" RT @laidback1954: China is not our well-wisher & has never been. Accept & respond accordingly. #NSG RT @gauravcsawant: Well fought India. Its clear who are our real friends & amp; Back stabbers identified. Will there be consequences? Or busines... RT @JhaSanjay: #NSG different from #MSG (Madison Square Garden). There are limits to event management. Pakistan nation to give standing Salute to Chinese President for his magnanimous support for our Country #NSG #India https://t.co/ECn02rYj7J RT @s navroop: #China #SunTzu #Chanakya on #NSG (Thread) https://t.co/JwqJBWZ305 "RT @ANI news: #Flash Meeting of Heads of delegations of #NSG in Seoul, to continue tomorrow." "RT @ANI news: #Flash Special #NSG meeting in Seoul, ends." RT @ANI news: Brazil also said that India has by far a better nuclear proliferation record than Pakistan: Sources #NSG RT @shammybaweja: #NSG How sensible was it for India to stake its all and what diplomatic sense is there in blaming one country in an offic... RT @ANI news: Brazil today supported India's bid for #NSG but called for a common criteria for all non-NPT states: Sources Pakistan daily lambasts Sharif govts handling of #NSG Issue https://t.co/JS5qoY534k #Liberal #Democrat https://t.co/6mOZTdd4pD RT @CNNnews18: The World saw PM make a spectacle of him & amp; India. Now India faces embarrassment unnecessarily: Anand Sharma #NSG "RT @abaruah64: Meanwhile, #Brexit drowns the #NSG fiasco" RT @NaIna0806: Mr @anandsharmamp Care to tell the world abt Nehru's refusal of Kennedy offer kept India out of #NSG Huge blunder https://... Fig. 4.1 Extracted Tweets

4.1.2 **Pre-processing of tweets**

A file is created of pre-processed tweets which reduce the complication for classification

process.

rt so china was not the only opponent to india's nsg membership. at least ten other countries torpedoed the move rt pakistan efforts against india on nsg proved that both pak & amp; ind must solve kashmir issue to move forward... bastard ridiculing pm on india failing to get into nsg shows his low character! country needs to be purged of such gutter pests!" india will get nsg membership someday, may b next year hopefully, but what abt brexit ? mam, yaha toh permanent ""talakh ho gaya" its not all about india or nsg, but having military ties w/ the us, aus, jap and skorea is of most importance against hegemony or some (2/3)" nuclear order will collapse if india joins nsg: china... you can behave like me but cant be like me"", arvind kejriwal to switzerland after their u turn from india's bid for nsg" miss.you.india nsg lets ban all goods from china, withdraw their priority visas and also lets bycot swiss as india is top of their tourism! nsg" we the people have habit of pulling leg of person who is trying to go beyond the wall and criticize when he falls back. nsg nuclear order will collapse if india joins nsg: pakistan efforts against india on nsg proved that both pak & ind must solve kashmir issue to move forward kashmirday its not all about india or nsg, but freedom of navigation in sth china sea is crucial, human rights in tibet, xinjiang is a question (1/3)" rt & switzerland sleeps with china in the nsg bedroom..., to back-stab india ! rt can we have mass movement for boycottmadeinchina, with no govt involvement?? nsg nsgmembership nsgmeet" rt congress spokespersons have 2 tweets saved in draft folder china okays: pichle sarkaar ki mehnat ka fal china rejects: fek..." rt india's nsg bid: most countries have expressed support, claims mea aaptards celebrating india failing to make it to nsg only confirms that they are traitors who can stoop to any level to berate modi china scuttles india's nsg bid rt nsg was an excuse for world tour by our travelling salesman of a pm. rt all that unsolicited hugging& hand squeezing& jhoola rocking & nagada bajoing & baracking& sleepless travelling & business pro... why is nsg membership important for india? rt diplomatic team india fighting hard. a battle may be lost but the war will be won. nsg the way u seems to be happy abt nsg it's a shame that you have an indian citizenship. you are the ramsey of delhi brexit rt india ought not try for annual tamasha for nsg entry..it is so demeaning,humiliating & demoralising,slap on face.shown doo.." at nsg today india didnt lost anything ..but now whole world knows specially we indians knows who are our haters and jealousies! unmasked ! rt every true indian now must boycottchineseproducts also these are 3rd quality products too! ban them like they do with ... rt i find it amazing that there are indian parties & amp; commentators smarting at india not getting the nsg membership..ridiculous s... rt a very bitter only love is for \$\$, scams & power. who cares about india right. if pm did not fight sti..." the unfortunate issue is many an erstwhile top politician now strewn by wayside on modi's wake wud rather see pak get an nsg nsg nsgmembership china can misguide but can't stop to us. we should try attacking policy to create pressure nsg time to think why we lost rt meanwhile, brexit drowns the nsg fiasco" nuclear suppliers group nsg meeting ends: no decision on india's entry modi china instead of condemning china-pak bloody-mindedness over india's nsg bid, opposition & msm will gloat over modi's ""failure"" to pin down xi" switzerland takes u-turn on its support to india's nsg bid unsc nuclear as a payback for nsg backstab, modi should now visit all countries that opposed india's entry" for congis rejoicing india not getting entry in nsg - were it not for nehru, we wud hav been global power already!

and secondly, signing npt for nsg will be huge blow for us, so modiji right in sticking for nsg without npt nsg"

mr. jha i think u don't qualify for nsg talk . you must have a better event management for rahul gandhi
*one who can't take care of his own nest is demanding clarification on nsg !!!

Fig. 4.2 Pre-processed Tweets

4.1.3 Feature Vector

List of unique vocabulary is generated.

blow	belve	fade
tirade	depth	weeks
except	summit	mtng
bigger	requires	weakness
hind	offensiveness	break
reformed	gv	shameful
real	ashamed	payback
aspects	gd	bank
rules	stops	govts
delhi	issues	mohrd
admitting	concerned	pakistanis
period	whatisnsg	dumps
spokespersons	citing	victory
culprits	hinduism	faileddiplomacy
using	friendly	modigovt
accepted	xinhua	luck
disappointed	asume	obdurate
dare	continues	manmohan
nsoj	facebook	signing
kennedy	telling	venue
suppliers	exits	principles
uthestory	shock	chutiya
laughing	underscores	celebrating

Fig. 4.3 Feature Vector

4.1.4 Stop Words

The words which doesn't have any contribute to Sentiment analysis.

Fig. 4.4 Stop Words

4.1.5 Input Vector

Input compatible to classifier to prepared.

-	-																		
BA	BB	BC	BD	BE	BF	BG	BH	BI	BJ	BK	BL	BM	BN	BO	BP	BQ	BR	BS	BT
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
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Fig 4.5 Input Vector

4.1.6 **Optimization algorithm**

This algorithm gives best smoothing parameter value as an output.



Fig. 4.6 Smoothing Parameter

4.1.7 Output of PNN classifier

This gives Sentiment Analysis of testing dataset for PNN classifier.

Single smoothing parameter for whole network:

```
Run 🦆 pnns
                                                                                                              ∯+ ≟.
neutral
     in positive
2.33974985831857e-823
|| 🛒 1.0
in negative
,c'
  🖶 In neutral
     1.0
  â
X
     result is ::
     2.33974985831857e-823
?
     positive
     in positive
     2.42351119848309e-823
     1.0
     in negative
     1.0
     In neutral
     1.0
     result is ::
     2.42351119848309e-823
     positive
     final result
     Process finished with exit code 0
• •
                                                                                                996:4 CRLF‡ UTF-8‡ 🚡 🌐 💵
```

Fig. 4.7 Output of PNNS Model of Testing Dataset

Different smoothing parameter for different class:



Fig. 4.8 Output of PNNC Model of Testing Dataset

The Sentiment Analysis of some tweets given by PNN classifier is given below.

Tweets	Classifier	Actual
	Sentiment	Sentiment
	Analysis	Analysis
don't lt down the spirit. regret those who r concerned with	1	1
pol.vendetta not the gain/loss of nation nsg		
rt whether succeeds in his effort or not nsg ; we must appreciate	1	1
him for this		
rt boycott chinese products india for nsg	0	1
china opposes to india's bid 4 nsg is coz of ""nehru"" who	1	1
rejected a unsc seat offered to india & amp; gave it on platter to		
china"		

nsg altho extra effort shown 2 get membership but actually it	0	0
seems not interested as now we r strong enuf 2 get all wout		
membership also ?		
world saw pm make a spectacle of himself & amp; india. now	-1	-1
india faces embarrasment unnecessarily: anand sharma on nsg		
@mahcongress: #SwitzerlandShocker : Even this handshake	-1	-1
failed. After promising support, Switzerland reneged on India's		
#NSG bid		
Nuclear Suppliers Group #NSG Meeting Ends: No Decision on	0	0
India's Entry #Modi #China		
RT @AnupamkPandey: @narendramodi Proud of you Sir !!	1	1
We will surly get into #NSG ; Bigger than that is, "You won		
the hearts of Many Leaders		
RT @vidyarthee: So much hoopla for #NSG. But #ModiGovt	-1	-1
gets blocked by China wall and the 'U-turn' by Switzerland.		
Failed diplomacy!		

4.2 Accuracy:

Accuracy of a Sentiment Analysis classifier is total no of correct output by a classifier divide by total no of tweets.

Accuracy for PNN model which have single smoothing parameter for whole network is given as:

Accuracy (PNNS) =
$$92/100 = 92\%$$

Accuracy for PNN model which have different smoothing parameter for different class is given as:

CHAPTER 5 CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

Sentiment Analysis of tweets, which are collected for using Twitter API, is determined using the proposed classification model. Input vector compatible to classifier is prepared using the Bag of Word. Probabilistic Neural Network is selected for a classification model in this proposed approach. Training of data in PNN classifier has a simple and faster architecture than other because only feedforwarding is required in this model, there is no back propagation. PNN is Bayesian classifier which is implemented in parallel way so its training does not require iterations.

A Probabilistic Neural network with self-adaptive approach is proposed. In this approach a self-adaptive algorithm is used to compute the best value for smoothing parameter for Probabilistic Neural Network using some data of training and testing dataset of same domain so that algorithm gives best value of smoothing parameter according to that particular domain. Two type Probabilistic Neural Network models are implemented in the proposed approach. First model of PNN have single value of smoothing parameter for whole network which is called as PNNS model. Second model of have different value of smoothing parameter for each class which is known as PPNC model. Performance of both model PNNS and PNNC according to accuracy is compared.

5.2 Future Work

In this approach, two models of PNN, PNNS and PNNC, is implemented. Remaining two models of PNN, PNNV and PNNVC, could be used for classification operation. PNNV is a model which have a different smoothing parameter to each data attribute of input vector. In PNNVC model have different smoothing parameter to each class and each data attribute of that class. Some algorithm like Q(0)-learning algorithm or Particle Swarm Optimization algorithm could be used for adaptive choice and computation of smoothing parameter for PNNV and PNNVC model a batter performance.

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