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A PROBABILISTIC MACHINE LEARNING MODEL FOR SENTIMENT ANALYSIS OF SOCIAL MEDIA DATA

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ABSTRACT

Recently, big data and big data analytics have found applications in various fields. The realm of social media and related applications is a significant area of research where Artificial Intelligence has demonstrated remarkable influence. This paper proposes a mechanism for classifying text data into various sentiment categories. This scenario utilizes data in the form of tweets. The raw data has undergone pre-processing before being utilized to train a neural network. A Neural Network is subsequently trained utilizing the data categories, which consist of tweets reflecting the happy, neutral, and sad emotions of Twitter users. The Bayesian Regularization (BR) approach has been employed to train the artificial neural network. This proposed approach attains an accuracy of 98%.

Keywords- Artificial Neural Network (ANN), Text Mining, Bayesian Regularization, Mean Square Error (MSE).

1. INTRODUCTION

The advent of data analytics has been enormous and text mining and opinion mining has garnered huge importance because of its broad range of applications in a variety of domains like the social media, analytics of data, business applications etc [1]. Sentiment analysis can be defined as a study that is based on a computational analysis and determination of textual opinions, emotions, behaviour and the attitude exhibited towards any entity. [2] Sentiment analysis tries to find out the attitude or an opinion of the user based user's textual data. It also aids in making decisions. Sentiment Analysis helps in determining whether the piece of tweet or any piece of writing is positive, negative or neutral [3]-[4]. It analyses the sentiment behind the text of any user, hence it helps companies for product reviews and enhance business prospects [5]. It has got a broad range of applications today, especially in the areas where outcomes are dependent on human sentiments and opinions. It can also be considered as opinion mining [6]. To be able to analyse and implement such tasks, Artificial Intelligence is used. In this context, the concept of data mining is utilized which a knowledge based procedure which is based on extraction of skilled patterns and information [7]-[8]. The extracted data is then used in visualization of applications and creation of real time programs for the process of decision making. The applications can be diverse such as marketing and finance, advertising, opinion polls, social media, product reviews just to name a few. The following diagram illustrates the mechanism [9].

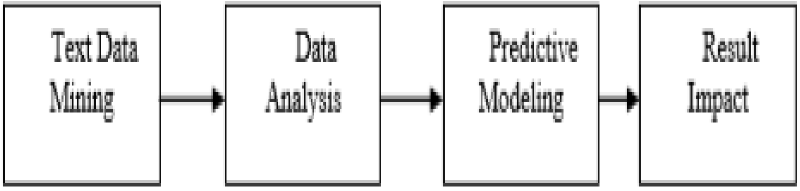


Fig.1 Text Mining model for sentiment analysis

While several data sources are available on the internet to be mined, yet a judicious use of web mining is to be done prior to any system design model is to be used [10]-[11]. The critical factor is also the feature selection from the raw data to be included in the analysis of the data as a whole. The unstructured text mining approach is often used and the text is to be replaced with suitable tokens or numerical counterparts prior to training any designed mechanism for the classification of the text data [12]. While data as a whole can consist of more than textual data, hence pre-processing of the data is of topmost priority [13]. The automated classification of sentiment based classification can be leveraged in several applications which need an automated mechanism for sentiment classification [14]-[15]. The major challenge in this section is the proper training of the automated system as the training accuracy would yield high classification accuracy later [16].

2. CONTEXTUAL ANALYSIS AND DEEP LEARNING

One of the major challenges in sentiment analysis is the contextual analysis of data. The different aspects are discussed subsequently [17].

2.1 Contextual Analysis- It is often difficult to estimate the context in which the statements are made. Words in textual data such as tweets can be used in different contexts leading to completely divergent meanings.

2.2 Frequency Analysis- Often words in textual data (for example tweets) are repeated such as ##I feel so so so happy today!!.

In this case, the repetition of the word is used to emphasize upon the importance of the word. In other words, it increases to its weight. However, such rules are not explicit and do not follow any regular mathematical formulation because of which it is often difficult to get to the actuality of the tweet [18].

2.3 Converting textual data into numerically weighted data- The biggest challenge in using an ANN based classifier is the fact that the any ANN structure with a training algorithm doesn't work upon textual data directly to find some pattern. It needs to be fed with numerical substitutes. Hence it becomes mandatory to replace the textual information with numerical information so as to facilitate the learning process of the neural network [19].

the machine or artificial intelligence system requires training for the given categories [8]. Subsequently, the neural network model needs to act as an effective classifier. The major challenges here the fact that sentiment relevant data vary significantly in their parameter values due to the fact that the parameters for each building is different and hence it becomes extremely difficult for the designed neural network to find a relation among such highly fluctuating parameters. Generally, the Artificial Neural Networks model's accuracy depends on the training phase to solve new problems, since the Artificial Neural Networks is an information processing paradigm that learns from its environment to adjust its weights through an iterative process [20].

Deep learning models do have the capability to extract meaning form large and verbose datasets by finding patterns between the inputs and targets. 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 deep learning structure is depicted in figure 2 [21].

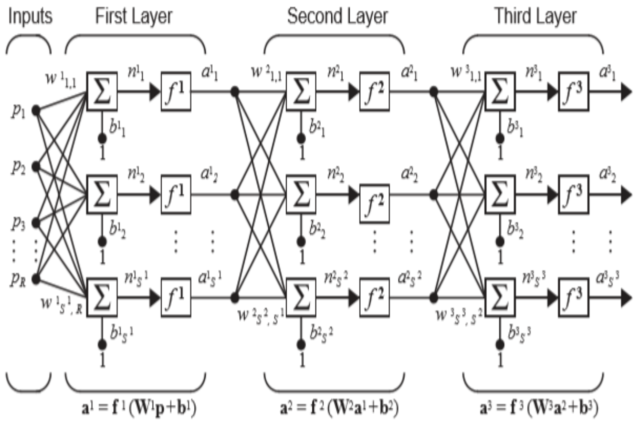

Inputs
First Layer
Second Layer
Third Layer
p_1
p_2
p_3
p_R
$w^1_{1,1}$
$w^1_{S^1,R}$
n^1_1
a^1_1
b^1_1
f^1
$w^2_{1,1}$
$w^2_{S^2,S^1}$
f^2
$w^3_{1,1}$
$w^3_{S^3,S^2}$
f^3
$a^3_{S^3}$
$\mathbf{a}^1 = \mathbf{f}^1(\mathbf{W}^1\mathbf{p}+\mathbf{b}^1)$
$\mathbf{a}^2 = \mathbf{f}^2(\mathbf{W}^2\mathbf{a}^1+\mathbf{b}^2)$
$\mathbf{a}^3 = \mathbf{f}^3(\mathbf{W}^3\mathbf{a}^2+\mathbf{b}^3)$

Fig.2 The deep learning structure

The deep learning structure is depicted in figure 2 and it is basically a cascade of stacked neural networks.

Multiple hidden layers facilitate the analysis of complex data. The cascading weight updating can be understood as:

$$\mathbf{a^n} = \boldsymbol{\varphi_n}(\boldsymbol{\varphi_{n-1}} \dots \dots . \boldsymbol{\varphi_1}\{\mathbf{wp} + \mathbf{b}\}) \qquad \textbf{(1)}$$

Here,

W is the weight

b is the bias

a is the input to the final nth layer

ϕ is the activation function

The output is given by:

$$y = f(\textstyle\sum_{i=1}^{n} x_i w_i + \theta) \qquad (2)$$

3. PROPOSED ALGORITHM

The proposed approach is mathematically modelled as:

Let the universal set of all data sample be represented by U. Thus any sample of the data class would be a subset of the universal set A given by:$\mathbf{A \epsilon U \nabla U}$ **(3)**

Here,

A is the data sample set

U is the universal set

The overlapping group classification occurs in case of the data sample belonging to both data categories of A and B with some overlapping attributes [22]. In such cases, the decision has to be made based on a probabilistic approach by the classifier and the classification is prone to errors. The decision becomes more complex with increasing number of attributes termed as features or parameters. The decision in such an overlapping attributed class can be done using the Bayes' theorem which is invoked by the Probabilistic Neural Network as:

$$\mathbf{P}\left(\frac{\mathbf{C1}}{\mathbf{C2}}\right)=\frac{\mathbf{P}\left(\frac{\mathbf{c2}}{\mathbf{c1}}\right)\mathbf{.P\,(C1)}}{\mathbf{P\,(C2)}} \qquad \textbf{(4)}$$

Here:

P $\left(\frac{\mathrm{C1}}{\mathrm{C2}}\right)$ represents the probability of occurrence of C1 given C2 is true

Prob $\left(\frac{\mathrm{N}}{\mathrm{M}}\right)$ represents the probability of occurrence of C2 given C1 is true

Prob (C1) represents the individual occurrence probability of the event C1

Prob (C2) represents the individual occurrence probability of the event C2

The weight updating strategy for the probabilistic classifier can follow the backpropagation based gradient descent approach given mathematically as:

$$\mathbf{W_{n+1}=W_n-\{(J_n^TJ_n+cI)^{-1}\}J_n^Te_n} \qquad \textbf{(5)}$$

Where,

$\mathrm{W_n}$ is weight of nth round or iteration of weight update for the network

$\mathrm{W_{n+1}}$ is weight of (n+1)st round or iteration of weight update for the network

$\mathrm{e_n}$ represents the error of the nth round or I represents an identity matrix

c represents the combination co-efficient given by $\mathrm{c=w_{n+1}-w_n}$, which gives the magnitude of weight change per iteration at any given iteration n

$\mathrm{J_n}$ is the Jacobian matrix given by [23]

$$\mathbf{J_n}=\begin{pmatrix}\frac{\partial^2\mathbf{e1}}{\partial\mathbf{w1}^2} & \cdots & \frac{\partial^2\mathbf{en}}{\partial\mathbf{w1}^2}\\ \vdots & \ddots & \vdots\\ \frac{\partial^2\mathbf{em}}{\partial\mathbf{wn}^2} & \cdots & \frac{\partial^2\mathbf{em}}{\partial\mathbf{wn}^2}\end{pmatrix} \qquad \textbf{(6)}$$

$\mathrm{J_n^T}$ is the transpose of the Jacobian Matrix.

The Jacobian matrix is essentially the second order rate of change of the errors of the network w.r.t. to the weights of the networks[24].

Typically, the classification is done based on the maximum posteriori probability of the data sample given by:

Let there be 'N' classes of data sets available in the sample space 'U'.

The conditional probabilities of N classes for the universal set U is given by:

$$\mathbf{P(\tfrac{A}{U}),\ P(\tfrac{B}{U}),\ \ldots\ldots..\ \ P(\tfrac{N}{U}).} \qquad \textbf{(7)}$$

The maximum magnitude of the probability of a particular class is found as:

$$\mathbf{P(max)}=\begin{matrix}\mathbf{P(\frac{A}{U})}\\ \mathbf{P(\frac{B}{U})}\\ \vdots\\ \vdots\\ \vdots\\ \vdots\\ \mathbf{P(\frac{N}{U})}\end{matrix} \qquad \textbf{(8)}$$

The maximum probability decides the class of the new data sample.

The final classification accuracy is computed as:

$$\mathbf{Ac}=\frac{\mathbf{TP+TN}}{\mathbf{TP+TN+FP+FN}} \qquad \textbf{(9)}$$

Here.

TP represents true positive

TN represents true negative

FP represents false positive

FN represents false negative

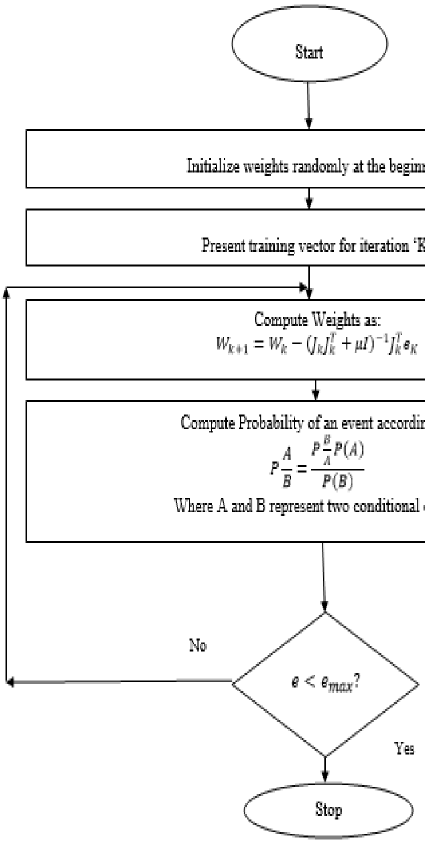
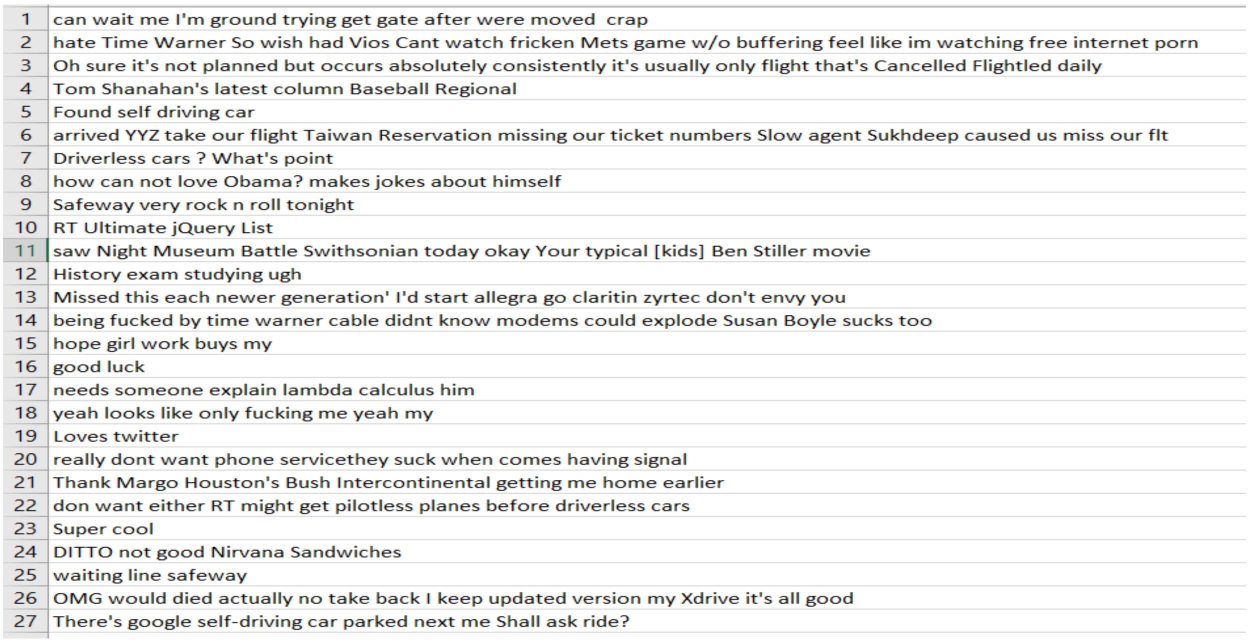

Start
Initialize weights randomly at the beginning
Present training vector for iteration 'K'
Compute Weights as:
$W_{k+1} = W_k - (J_k J_k^T + \mu I)^{-1} J_k^T e_K$
Compute Probability of an event according to:
$P\frac{A}{B} = \frac{P\frac{B}{A}P(A)}{P(B)}$
Where A and B represent two conditional events
No
$e < e_{max}$?
Yes
Stop

Fig.3 Flowchart for training

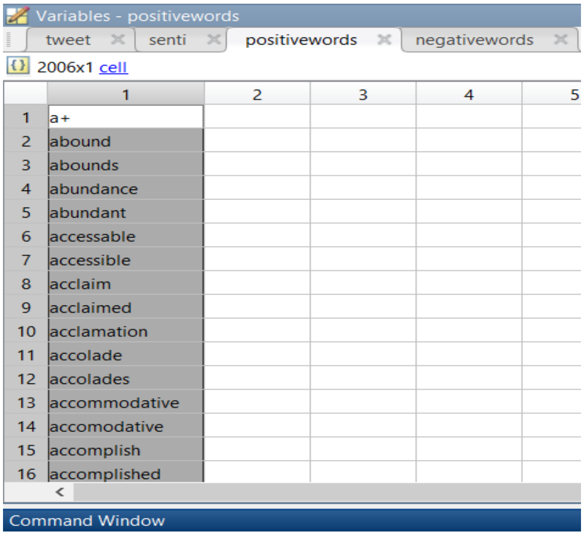
4. RESULTS

The proposed system utilizes the textual data in the form of tweets to be analyzed based on positive, negative and neutral tokens to be represented by -1, 0 and 1 respectively. Subsequently, the number of tokens with polarity is also fed to the neural network as a training parameter.



1	can wait me I'm ground trying get gate after were moved crap
2	hate Time Warner So wish had Vios Cant watch fricken Mets game w/o buffering feel like im watching free internet porn
3	Oh sure it's not planned but occurs absolutely consistently it's usually only flight that's Cancelled Flightled daily
4	Tom Shanahan's latest column Baseball Regional
5	Found self driving car
6	arrived YYZ take our flight Taiwan Reservation missing our ticket numbers Slow agent Sukhdeep caused us miss our flt
7	Driverless cars ? What's point
8	how can not love Obama? makes jokes about himself
9	Safeway very rock n roll tonight
10	RT Ultimate jQuery List
11	saw Night Museum Battle Swithsonian today okay Your typical [kids] Ben Stiller movie
12	History exam studying ugh
13	Missed this each newer generation' I'd start allegra go claritin zyrtec don't envy you
14	being fucked by time warner cable didnt know modems could explode Susan Boyle sucks too
15	hope girl work buys my
16	good luck
17	needs someone explain lambda calculus him
18	yeah looks like only fucking me yeah my
19	Loves twitter
20	really dont want phone servicethey suck when comes having signal
21	Thank Margo Houston's Bush Intercontinental getting me home earlier
22	don want either RT might get pilotless planes before driverless cars
23	Super cool
24	DITTO not good Nirvana Sandwiches
25	waiting line safeway
26	OMG would died actually no take back I keep updated version my Xdrive it's all good
27	There's google self-driving car parked next me Shall ask ride?

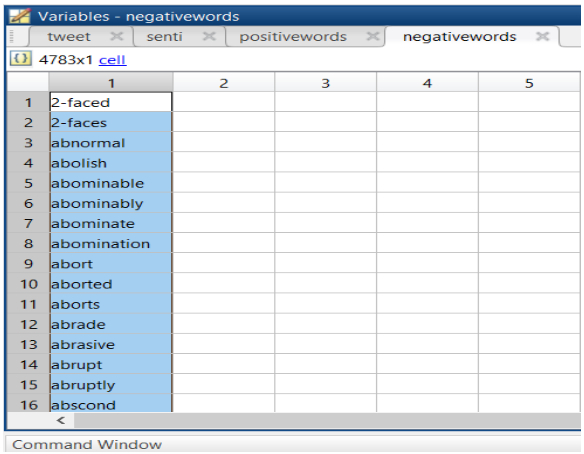
Fig.4 Sentiment Data



2006x1 cell

	1	2	3	4	5
1	a+				
2	abound				
3	abounds				
4	abundance				
5	abundant				
6	accessable				
7	accessible				
8	acclaim				
9	acclaimed				
10	acclamation				
11	accolade				
12	accolades				
13	accommodative				
14	accomodative				
15	accomplish				
16	accomplished				

Fig. 5 Positive Tokens



4783x1 cell

	1	2	3	4	5
1	2-faced				
2	2-faces				
3	abnormal				
4	abolish				
5	abominable				
6	abominably				
7	abominate				
8	abomination				
9	abort				
10	aborted				
11	aborts				
12	abrade				
13	abrasive				
14	abrupt				
15	abruptly				
16	abscond				

Fig. 6 Negative Tokens

The Deep Net with 5 hidden layers is designed. The number of layers in limited to five to reduce the time complexity.

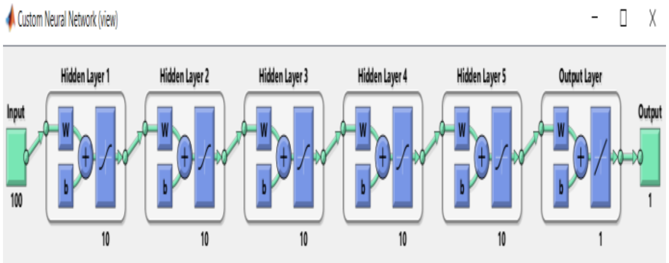
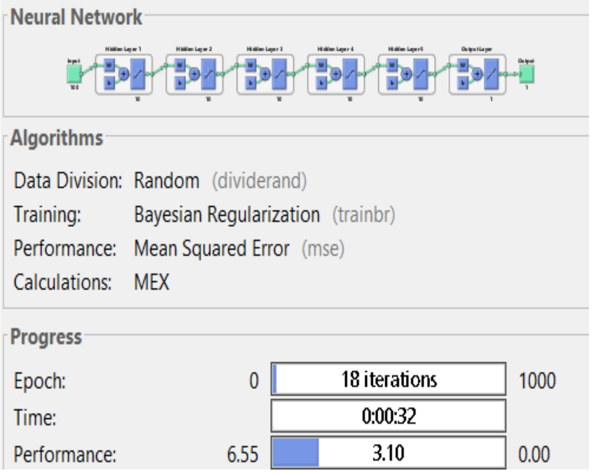


Fig. 7 Designed Deep Net



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

Epoch: 0 18 iterations 1000
Time: 0:00:32
Performance: 6.55 3.10 0.00

Fig.8 Deep Net Parameters

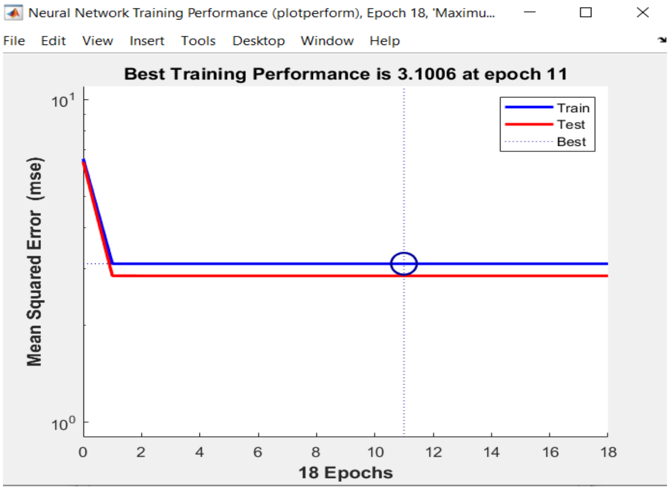
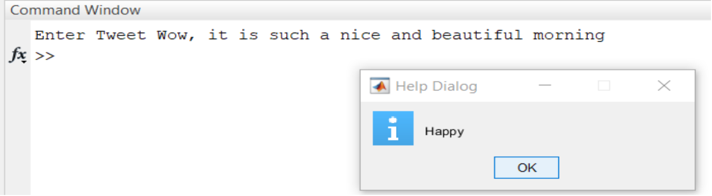
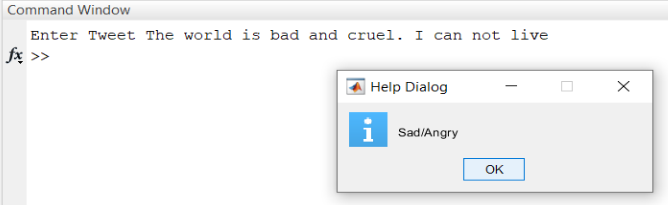


Fig.9 MSE Variation


Command Window

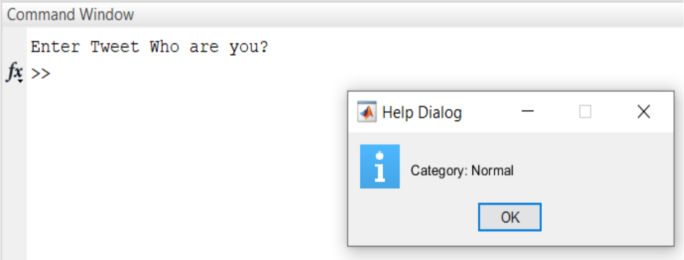
```
Enter Tweet Wow, it is such a nice and beautiful morning
>>
```

Fig.9 GUI for classification (happy)


Command Window

```
Enter Tweet The world is bad and cruel. I can not live
>>
```

Fig.9 GUI for classification (sad)


Command Window

```
Enter Tweet Who are you?
>>
```

Fig.9 GUI for classification (neutral/normal)

The proposed system parameters can be summarized in table 1.

Table 1. Summary of Results

Parameter	**Value**
ML category	Deep Supervised Learning
No. of hidden layers	5
Iterations	18
Error	2%
Accuracy (Proposed Work)	98%
Accuracy (Previous Work, [1])	91%

5. CONCLUSION

Sentiment analysis has diverse uses in information systems, encompassing the classification of reviews, summarization of reviews, and various real-time applications. There are potential opportunities to implement sentiment analysis in real-time business models. This study concentrates on sentiment analysis through the classification of tweets from social media (Twitter) data. A deep Bayesian network has been utilized for the training and subsequent evaluation of tweets. The Bayesian Regularization (BR) algorithm has been employed, and the resulting outputs exhibit variability due to its probabilistic classification. The suggested technique achieves a classification accuracy of 98%, far surpassing prior methods.

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