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An Efficient Review Classification Of National Eligibility Cum Entrance Test Using Attention Mechanism With Recurrent Neural Network And Maximum Entropy

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Abstract

Medical entrance examination system for students in India is suffering from various shortcomings at conceptual as well as implementation level. Indian students who are writing National Eligibility cum Entrance Test suffering from dress code restrictions,etc., which leads to stress and pressure. To address these issues, a comprehensive analysis of various associated factors is essential. To achieve good standards of medical education, our objective should be to re-evaluate each and every aspect as create an efficient accreditation system, to promote an equal distribution of resources, redesign curricula with stricter implementation and improved assessment methodologies; all of which will generate efficient medical graduates and resulting in desired change within the system.

This thesis presents a NEET exam review classification is useful function to analyzing student reviews and predicting sentiments with different categories (positive, negative and neutral). The objective of NEET review prediction is to accurately classify the target class for all case in the data. This research presents an Attention Mechanism with Recurrent Neural Network (AMRNN) technique with GloVe word embedding algorithm, a capable way that has improve the classification accuracy, unless the large amount of information on these platforms make them viable for use as data sources, in applications based on NEET review analysis.

According to the experimental results, the proposed algorithms mainly focused on NEET exam related students review classification prediction results using R 3.4.0 simulation tool. Based on these results the Central Government must analyses these review classes (positive, negative and neutral) and make the right decisions to make a favor for students future life.

Keywords: *NEET reviews,sentiment analysis*

1. Introduction

1.1 Medical Entrance Examination

National Eligibility and Entrance Test is the medical entrance examination which would be considered for filling the medical seats across the country. NEET was initially conceptualized with two main purposes. One was to remove the burden and stress of students writing entrance examinations for gaining admissions to medical colleges. The second was to reduce the financial inequalities that occurred during admissions in the private colleges. Due to regional diversities, there has been opposition to NEET in states such as Andhra Pradesh and Tamil Nadu, because during examination students suffered from several tortures such as removing headscarves, dress code restrictions.

NEET is formulated by CBSE. NEET currently appears to be disadvantageous to the rural and economically backward state board syllabus students, especially for students who study state syllabus of Kerala, Andhra Pradesh, and Tamil Nadu. However they cannot afford costly private tuitions to crack the examinations. Private tuitions are purposefully required to score high marks in this difficult examination. In addition, rich students who can afford high fees for availing private tuition for NEET examination are favored over backward, poor, and rural students who cannot afford

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the required special coaching. There are also complaints that NEET examination conducted in regional languages was comparatively tougher when compared to that of English.

NEET is mandatory for medical education, without considering the diversity between the states which likely leads to failure, imbalance, discrimination, and injustice to several students. NEET should be modified or exempted for medical admissions based on the prevailing current education system in a few states of India.

1.2 Data Mining

Data mining intends to discover useful outlines in data. A difficulty for several enterprises is the huge accessibility of prosperous data. Further, a detailed document extracts positive information from these huge quantities of data. Examining huge datasets and demanding to search inconsequential patterns associations is a challenge. By the rising quantity of data it is harder to regain knowledge from numerous datasets. Data mining can assist to search unsuspected associations among data. Data mining is also recognized as Knowledge Discovery from Data (KDD). Data mining is used to restore or improve human intelligence by examining the massive storehouses of data to determine meaningful original correlations.

1.3.Text Mining

Text mining uses the similar examination approach and methods as data mining. But data mining needs structured data, although text mining plans to determine patterns in unstructured data. For profitable use text mining will be the follow-up of data mining. With the rising amount of digitized documents and having huge text databases, text mining will become increasingly significant. Text mining can be an enormous benefit for searching appropriate and preferred text data from unstructured data sources.

Text mining employs unstructured documents as input data. In additional words, documents are difficult to understand in terms of significance. There are little companies functioning on advantageous submissions for text- mining. As of the challenges involved in functioning with text and the dissimilarities among languages it is a challenge to generate a common solution or application. The research area is presently “too young” to compact with all of the features of text and natural language processing and connecting information to all other.

A machine (text extracting algorithms) interprets a group of manifests and attempts to extract domain knowledge. This will be used to search a quantity out of a group of manifests. Extraction assignment can modify from an executing job to a controlling one. Designed for checking the result of text extraction algorithms and provide these algorithms comment, so in the prospect hidden data will be handled recovered. This is only the case in weakly-supervised learning, paragraph. A further approach can be that domain proficient only varies the result of domain knowledge gaining algorithm.

1.4 About the study

Huge datasets are available in on-line, they can be geometric or transcript file and they can be prearranged, semi-structured or non-structured. The techniques to be relevant and extract positive information from these data have been the key focuses of many researchers and practitioners recently. Several different information retrieval methods and tools have been proposed according to special data types. In addition to data and text mining, there has seen a rising interest in non-topical text examination in current years. Sentiment analysis, also recognized as opinion mining, is to recognize and extract subjective information in resource materials, which can be positive, neutral, or negative. With appropriate methods and techniques, this huge amount of data can be development into information to sustain operational, managerial, and considered decision making.

National Eligibility cum Entrance test student reviews dataset referred from https://www.youtube.com/results?search_query=neet+exam+2018+parents+reviews, https://www.youtube.com/results?search_query=students+and+parents+reviews+about+neet, https://www.google.co.in/search?q=neet+reviews+2018

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2 System Analysis and Design

2.1 Existing System

This chapter presents a system analysis study of existing and proposed framework. It covers the existing method of Hierarchical Deep Learning (HDL) algorithm and Supervised Word Embedding for Sentiment Analysis (SWESA) algorithm . In first, HDL is a hierarchical deep learning procedure which includes of dealing with attributes demonstrations resultant to the words and successive parses of the phrases and sentences. Second, SWESA used to learns word vector embeddings.

2.2 Hierarchical deep learning (HDL)

The basic scheme behind HDL approach is to discover representations for words (word vectors and matrices) which can clarify the aspect-sentiment labels at the phrase level. To categorize to resolve these issues, a hierarchical deep learning framework which includes of dealing with attributes demonstrations resultant to the words and successive parses of the phrases and sentences. These entire attribute representations finally contribute to an objective function that solve. To further leverage this objective function to come up with multiple formulations to solve the problem (*Himabindu Lakkaraju, Richard Socher* and *Chris Manning, 2014*) [5].

In this formulation, the feature extraction and sentiment extraction as two separate phases. To train two separate soft-max classifiers, each for attribute labels and sentiment label correspondingly. In this HDL process, an aspect label and a sentiment label are attained independently and the (feature, sentiment) pairs outcome from the concatenation of the two individual labels. Although this formulation is uncomplicated and simple to train, it has two foremost problems. Initially, as discussed in the beginning, the perception of joint modeling is not assisted by this formulation. Next, this formulation cannot switch the snippets with various (feature, sentiment) pairs as, although it is likely to attain an amount of aspect labels and another amount of sentiment labels (from two separate classifiers), there is no technique to associate them correctly due to the separate training of the two soft-max classifiers.

2.2.1 Merits of HDL

- To trains a single softmax classifier on the aspect-sentiment pairs.
- HDL can be achieved by allowing more than one element of the target distribution vector to be set to the value as 1.

2.2.2 Demerits of HDL

- The problem of aspect and sentiment detection as a multi-class soft-max classification problem in the context of deep learning.
- Feature prediction is very slow.

2.3. Supervised Word Embedding for Sentiment Analysis (SWESA)

Given a group of documents (d_1, d_2, …, d_N) with binary sentiments (y_1, y_2, …, y_N) correspondingly, the plan is to discover a classifier that when known a new, before unseen document d can correctly approximate the sentiment of the document. There could be class imbalance in the training data and so the algorithm must explicitly account for such a class inequality. SWESA concurrently learns word vector embeddings and a classifier, by creation use of document polarity/sentiment labels. Illustration of documents within SWESA is motivated by the information that in short texts like “I am sad”, “I am happy”, polarity of the sentence centers on the words “sad” and “happy”. For example, in the above instance, the distance among the vectors ($w_I + w_{am} + w_{sad}$) and ($w_I + w_{am} + w_{happy}$) would capture differences in sentiment of these two documents while at the similar time reflecting similarities in sentence structure (*Prathusha K Sarma and William A Sethares, 2018*) [11].

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2.3.1 Merits of SWESA Algorithm

- SWESA can able to do a good job discovering antonym pairs.
- The advantage of SWESA is principally towards exploiting strong polarity differences in words such as 'Excellent' and 'Poor', however not much success is noted towards less polarized synonyms such as 'Wet' and 'Dry.

2.3.2 Demerits of SWESA Algorithm

- The problem would be to use off-the-shelf word embeddings to learn document embeddings and then run a classification algorithm on the obtained embeddings.
- Bi-convex optimization problem.

2.4 Objective of the Thesis

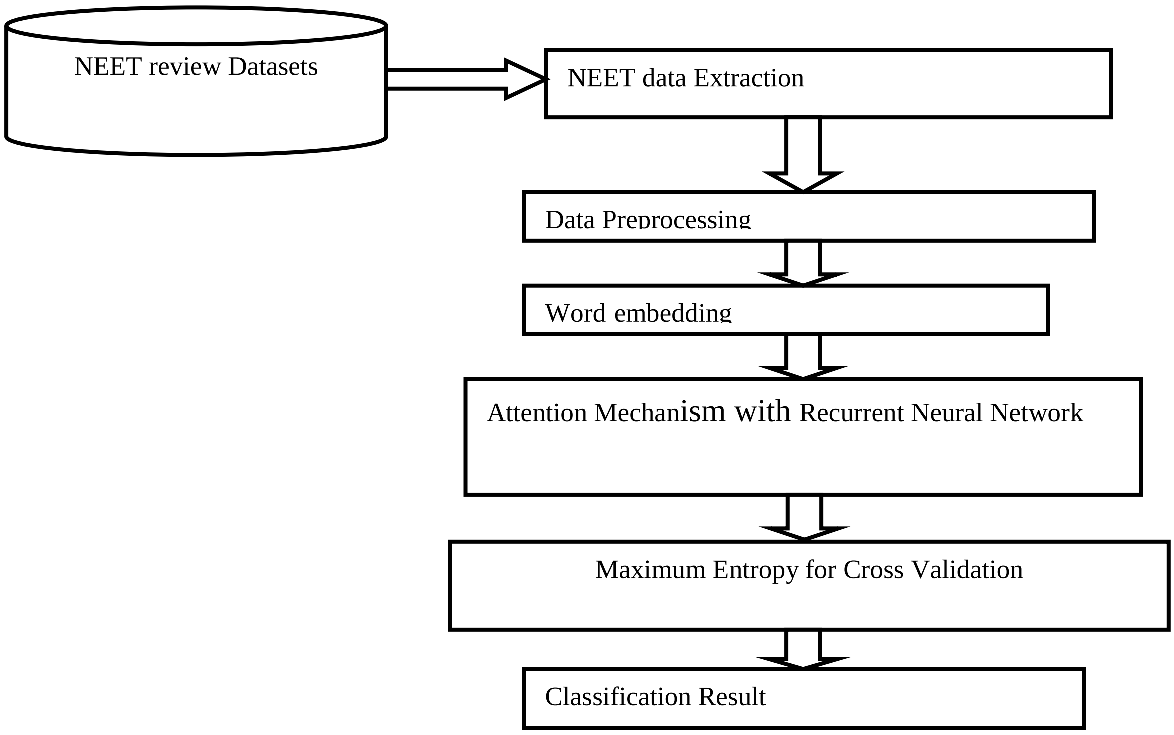
This thesis proposes a classification the sentiments using student reviews of NEET. The main objective of this thesis includes:

- The sentiment is extracted from the entire NEET review, and a whole opinion is classified based on the overall sentiment of the opinion holder. The goal is to classify a review as most positive, positive, most negative, negative, or neutral.
- The NEET review sentence presents some factual information, while a subjective sentence expresses personal feelings, views, emotions, or beliefs.
- Consumer sentiments are mainly expressed in an unstructured format. Text analysis involves taking unstructured data and finding ways to convert it into a more structured format that facilitates analysis of data and getting deeper insights into the sentiments.

2.5 Proposed System

This thesis proposed weakly-supervised deep embedding neural network process to learn the weak labels for NEET review sentiment analysis. The proposed method follows a well established word embedding technique for annotation makes level of underlying linguistic representation of text.

Figure.2.1: Flow diagram of Proposed System



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3 System Implementation

3.1 Data Preprocessing and Word Embedding

Data preprocessing method participate a very significant function in text mining techniques and applications. It is the initial step in the text mining process. NEET reviews are extracted and the extracted reviews irrelevant characters are removed by using the regular expression (filtering method).

Figure.3.1: Preprocessing the reviews

```
"Muslim boys, caps allowed",
"students.., were asked to remove their headscarves to seek entry into the exam halls",
"For NEET. the guys have to remove their shirts and then give their exams. And no jewellery is allowed for girls and inner wears are checked too.",
"NEET centre ...total torture to students..unjustifiable ..",
"Kindly change exam center....????? nearby district,exam time should be 11 am is okay 9 is too early",
```

Word embedding is a popular method for natural language processing (NLP) that intends to discover low-dimensional vector illustrations of words from NEET review documents. The proposed Supervised Word Embedding for Sentiment Analysis and GloVe for word embedding is one of the popular methods.

In figure 3.1 the reviews are preprocessed the irrelevant characters of the NEET reviews and the words are embedded which shows in the figure 3.2.

Figure.3.2:Embedding the reviews

```
[1] "Muslim boys caps allowed"

[2] "students were asked to remove their headscarves to seek entry into the exam halls"

[3] "For NEET the guys have to remove their shirts and then give their exams And no jewellery is allowed for girls and inner wears are checked too"

[4] "NEET centre total torture to studentsunjustifiable"

[5] "Kindly change exam center nearby districtexam time should be  am is okay  is too early"
```

3.2 GloVe Algorithm

Glove algorithm examines the words in the NEET reviews and calculates the weight for each word using predefined threshold values (default 0.5).

The proposed GloVe algorithm consists of following steps:

Step 1: Gather word co-occurrence statistics in a form of word co-occurrence matrix M. Every element M_{xy} of such matrix represents how often word x appears in context of word y. To scan the corpus in the following manner: for each term to look for context terms within some area defined by a window_size before the term and a window_size after the term. Additionally we give less weight for more far off words, normally utilizing this formula:

$$Separate = \frac{1}{thershold} \quad Eq.1$$

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Step 2: Define soft conditions for every word pair:

$w^{T}_{x} w_y + s_x + s_y = \log(M_{xy})$ Eq. 2

where, w_x - vector for the main word, w_y - vector for the context word, s_x, s_y are scalar unfairness for the main and context words.

Step 3: Define a cost function *Cf*

$$Cf = \sum_{x=1}^{V} \sum_{y=1}^{V} f(M_{xy})\left(w_x^T w_y + s_x + s_y - logM_{xy}\right)^2 \quad eq.3$$

Where, *f* is a weighting function which helps us to prevent learning only from extremely common word pairs.

3.3.Attention Mechanism with Recurrent Neural Network (AMRNN) Classification

- It works at the sentence level to give different words different emphasis in a sentence.
- It works second component works at the document level to give different sentences different emphasis in a document.

For a sentence $S_x = \{w_1, w_2, \ldots w_{y \ldots} w_{ly}\}$ with length l_y, every word w_y in S_x has a corresponding reading time t_{wx} . Let t_{Sy} denote the total reading time of S_y. Then,

$$t_{Sy} = \sum_{x=1, w_x \in S_y}^{l_y} t_{wx} \qquad eq.4$$

For sentence level attention, the *AMRNN* weight for w_x in S_y, denoted as $A_{Sy:wx}$, can be defined as:

$$A_{S_y:w_x} = \frac{t_{wx}}{t_{Sy}} \qquad eq.5$$

In figure 3.2 the reviews are embedded, and the embedded reviews are distinguished as emotions by representing the polarity as 0 and 1.

Figure.3.3: Analyzing the Sentiments

	anger	anticipation	disgust	fear	joy	sadness	surprise	trust	negative	positive
1	0	0	0	0	0	0	0	0	0	0
2	1	1	0	1	0	1	0	0	1	0
3	1	0	0	1	0	1	0	0	1	0
4	1	1	1	1	0	1	0	0	1	0
5	0	1	0	1	0	0	0	1	0	1

3.4 Maximum Entropy Classification

Maximum Entropy is an alternative technique of manipulating probability of class belonging. This classification method's fundamental principle is that distributions that are consistent should be preferred. Maximum Entropy performs the accuracy by 4 cross validating the matrices by using the sentiment and NLP function in R tool which provides high accuracy as 96% in NEET student reviews. This is more in line with intuition and MaxEnt has been shown to be effective in a number of different NLP applications.

The probability of data d belonging to class *c* is in a MaxEnt evaluation is as follows:

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$$P_{ME}(d) = \frac{1}{Z(d)} exp\left(\sum_{j=1} \lambda_{j,c} F_{j,c}(d,c)\right) \quad eq.6$$

where F_j, $c(d, c)$ is a feature function, $Z(d)$ is a normalization function and λ_j is the feature weight. A large λ_j shows that f_j is viewed as a strong indicator for class c. The parameter values are set to maximize the entropy of the distribution while still following the constraints set on the distribution by the training set.

4.Evaluation and Suggestion

4.1 Performance Evaluation

To the best of the information, there is no annotated dataset for opinion retrieval in NEET reviews. Consequently, a collected new NEET reviews dataset for this task is created. About the research collect NEET reviews are crawled and indexed using the Sentiment API. All NEET reviews are English. Using these NEET reviews a search engine is implemented. They were allowable to post any query. Particular students query from the google search engine would present a list of NEET exam related reviews ranked based on the Best Matching (BM25) score. Based on the opinion about the NEET reviews whether expresses opinion about a given review, people allocated a decision label to every review. Finally, more than 900 reviews are collected and those reviews are extracted and find out the polarity as positive, negative and neutral.

It suggests some social information can indeed help NEET reviews retrieval in facebook and some other web blogs. The URL feature is the most effective feature, perhaps because most textual content in these reviews are objective introductions. The effect of URL, statuses and followers features for web blogs ranking also supports our approach of using social information and structural information to generate “pseudo” objective reviews.

Figure.4.1: Sample datasets

	A
1	Muslim boys caps allowed
2	Students were asked to remove their headscarves to seek entry into the exam halls.
3	However, many feel these dress restrictions are fair. A number of professional IT certification course have similar restrictions such as no watches, no mobiles c shoes. So there is no harm in Neet following suit.
4	We don't have exam centres in my city and so, I need to travel some distance to the examination centre. We need to carry money and mobile phones. So they should at least allow us to carry these items.
5	One candidate was asked to remove her inner wear as its hook caused the metal detector to beep. Another reported that she had to remove her jeans because of the metal button. Some other candidates reportedly had to cut their full-sleeved tops as the code allows only half-sleeved clothes.

Dataset contains 1000 NEET reviews. In that reviews the proposed system performs the polarity of positive reviews as 472, negative reviews as 426 and neutral reviews as 73. By using the proposed method as AMRNN in R Tool to found out the reviews as positive, negative and neutral in students NEET reviews. Here, polarity counted by classifying the sentiments.

Figure.4.2: Results of Polarity

```
> table(polarity_senti)
polarity_senti
Negative  Neutral Positive
      24        5       26
>
```

55 Sample Data

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To find out the accuracy here Naïve Bayes, Decision Trees, Support Vector Machine, Random Forest and Maximum Entropy uses the NLP and sentiments function() are applied in R tool for NEET student reviews by cross validating the matrices. Different accuracies have found, we found that Maximum Entropy considered as the high accuracy by evaluating the cross validation among six methods.

Table.4.1: Shows comparison of classification algorithm

Methods	Accuracy
Naïve Bayes	0.6
Decision Trees	0.4625
Support Vector Machine	0.525
Random Forest	0.8666
Maximum Entropy	0.9642857

In a classification task, precision (Specificity) for a class is the number of true positives (i.e. the number of items correctly labeled as belonging to the positive class) divided by the total number of elements labeled as belonging to the positive class. Recall (Sensitivity) in this context is defined as the true positive and sum of the true positive and false negative.

A measure that combines precision and recall is the harmonic mean of precision and recall, the traditional *F*-measure or balanced F-score.

The choice of the dataset dimension on the performance of the system is also observed.

Sensitivity : 1.0000
Specificity : 0.5000

After found out the polarity, the values are applied for F measure

$F = \frac{precision \cdot recall}{Precision + recall} \quad eq.7$ $\qquad F = \frac{(0.50)(1.00)}{0.50 + 1.00}$

$$F = \frac{0.5}{1.5}$$

$$F = 0.3333$$

The value of F Measure is the average value of Precision and Recall of the NEET student reviews.To compare our adaptive algorithm Attention Mechanism with Recurrent Neural Network (AMRNN) technique with GloVe word embedding algorithm with four baseline algorithms, i.e., Naïve Bayes, Decision Tree (DT), Support Vector Machine (SVM), Random Forest (RF) and Maximum entropy (MAXENT)in figure 4.4.

Figure.4.3: Overall Classification Accuracy Results of NEET Review

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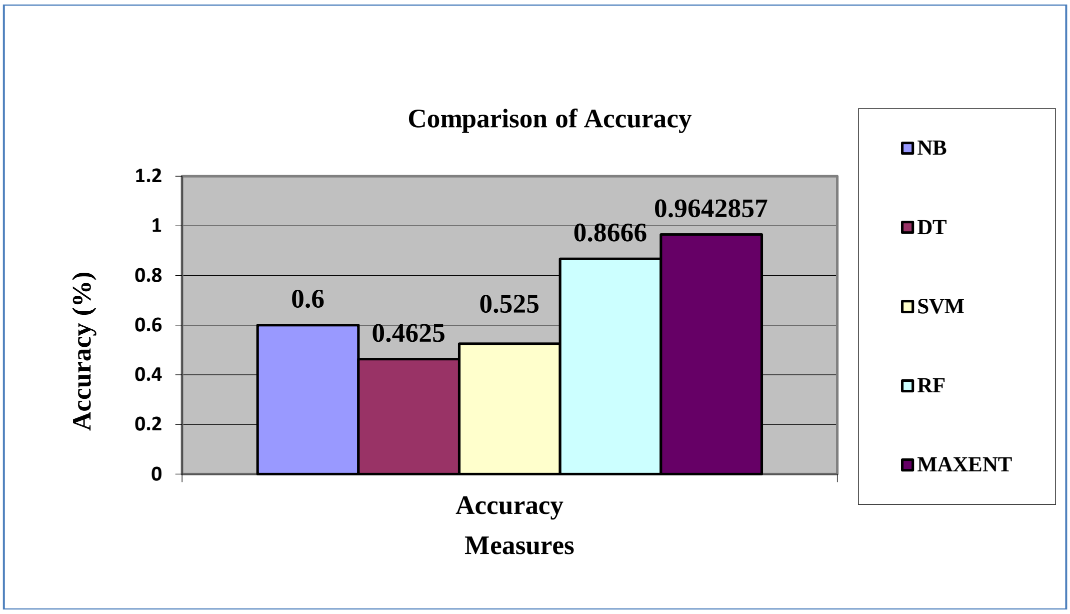
```
> confusionMatrix(xtab)
Confusion Matrix and Statistics

          predicted
           negative positive
  negative        1        2
  positive        0        2

               Accuracy : 0.6
                 95% CI : (0.1466, 0.9473)
    No Information Rate : 0.8
    P-Value [Acc > NIR] : 0.9421

                  Kappa : 0.2857
 Mcnemar's Test P-Value : 0.4795

            Sensitivity : 1.0000
            Specificity : 0.5000
         Pos Pred Value : 0.3333
         Neg Pred Value : 1.0000
             Prevalence : 0.2000
         Detection Rate : 0.2000
   Detection Prevalence : 0.6000
      Balanced Accuracy : 0.7500

       'Positive' Class : negative
```

```
> cross_validate(container, N, "MAXENT")
Fold 1 Out of Sample Accuracy = 1
Fold 2 Out of Sample Accuracy = 1
Fold 3 Out of Sample Accuracy = 0.8571429
Fold 4 Out of Sample Accuracy = 1
[[1]]
[1] 1.0000000 1.0000000 0.8571429 1.0000000

$meanAccuracy
[1] 0.9642857

> cross_validate(container, N, "TREE")
Fold 1 Out of Sample Accuracy = 0.3333333
Fold 2 Out of Sample Accuracy = 0.6666667
Fold 3 Out of Sample Accuracy = 0.25
Fold 4 Out of Sample Accuracy = 0.6
[[1]]
[1] 0.3333333 0.6666667 0.2500000 0.6000000

$meanAccuracy
[1] 0.4625

> cross_validate(container, N, "SVM")
Fold 1 Out of Sample Accuracy = 0.1666667
Fold 2 Out of Sample Accuracy = 0.6
Fold 3 Out of Sample Accuracy = 1
Fold 4 Out of Sample Accuracy = 0.3333333
[[1]]
[1] 0.1666667 0.6000000 1.0000000 0.3333333

$meanAccuracy
[1] 0.525

> cross_validate(container, N, "RF")
Fold 1 Out of Sample Accuracy = 1
Fold 2 Out of Sample Accuracy = 0.6666667
Fold 3 Out of Sample Accuracy = 0.8
Fold 4 Out of Sample Accuracy = 1
[[1]]
[1] 1.0000000 0.6666667 0.8000000 1.0000000

$meanAccuracy
[1] 0.8666667
```



4.2 Suggestion

- The prediction quality can be improved by using n-gram
- A subjectivity classification and sarcasm detection might also enhance the quality of SentiStorm.
- Extend the pattern-based model to cover more emotion categories.
- Generate more complex sentences with the pattern-based model using aggregation.
- Generate more texts that change from a current emotion into a different emotion. For example, an angry sentence becoming a happy sentence. Although the pattern-based model is capable of shifting valence, and also to explore other methods based on more comprehensive natural language generation technique.

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5.Conclusion

The research presented a novel approach with joined techniques from different fields and adapted to resolve the problem of NEET review classification selection. It has been observed that as the classification ratio and classification outcomes prevented the quality of the system.

The goal of this research is to show that AMRNN technique with GloVe word embedding algorithm is a capable way that has been proposed to improve the classification accuracy, unless the large amount of information on these platforms make them viable for use as data sources, in applications based on NEET review analysis. The system can easily analyze the sentiment word, classification information on the NEET reviews. Machine learning algorithms (Maximum entropy), can achieve high accuracy for classifying NEET sentiment when using this method. According to the experimental results the proposed algorithms mainly focused on NEET related students review classification prediction results using R 3.4.0 simulation tool. Based on these results, some of the suggestions given to the Central Government to not having over restrict of dress code by cutting sleeves. Provide free transport facilities and basic needs for parents. The State Government should make every effort to raise the current educational standards to the level of central syllabus, so that students are well prepared to face the examinations with confidence. The Central Government and the State Government after duly considering all the diverse factors should work out periodically to enforce a suitable formula that brightens the aspirations of students seeking for medical admissions. Entrance examinations and education systems should lighten up the future of students, cherish their dreams and reward their hard work. A single entrance examination like NEET in a stricter sense cannot truly reflect the attitude and intelligence of the students.

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