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E-Learning Based Sentiment Analysis Using Wisconsin High-Order Neural Network

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Abstract— Nowadays, when the world is still in the COVID-19 pandemic, many schools and universities have moved their education from physical classrooms to online platforms. E-learning systems are becoming more and more popular in educational institutions. Schools and universities investigate e-learning student feedback to gain valuable insights into the online teaching process. Sentiment Analysis (SA) is a method that helps extract information from large amounts of data. This helps the teachers understand the students' performance and conduct the lessons in a way that suits the students. However, manually processing student reviews is challenging, and processing large amounts of feedback from e-learning platforms is not feasible. The existing method provides low classification results and high time complexity during finding results. To resolve this problem, the proposed Wisconsin High Order Neural Network (WHONN) algorithm is used to classify the e-learning based student reviews. Initially, collecting an e-learning based student reviews dataset, the first step pre-processing process is used to remove unwanted noise and irrelevant data using Gaussian Iterable Filter (GIF) technique. After that, the Bag of Words Model (BOWM) is used to analyze the lexical term from texts. Then lexical representations are supplied into Automatic Class Relevance based Keyword Extraction Score Measurement (ACRKESM) algorithm to select the finest features of lexical terms, calculate review text weightages and analyze the sentiment score. Finally, weightage features trained into the WHONN algorithm is used to SA classification is helps to improve teaching quality and e-learning student performance. The proposed algorithm provides high classification accuracy performance compared to previous algorithms.

Keywords: Sentiment Analysis (SA), E-learning students, Gaussian Iterable Filter (GIF), sentiment score, classification, Bag of words model, reviews, lexical terms.

I. INTRODUCTION

Due to the COVID-19 pandemic, numerous schools and universities have switched from traditional face-to-face physics courses to online courses. In recent years, advances in science and technology have advanced online course technology, allowing more students in developing countries and remote areas to study courses from leading universities via computers and mobile phones. Many e-learning students rely primarily on online courses to improve their learning skills, meet new students, and identify specific topics, rather than relying mainly on them to complete the course.

Therefore, it is crucial for learning institutions to review student feedback regarding their experience using online learning platforms. It will help the professor understand what needs to be changed and improved. The student structure of feedback usually contains closed questions, but open questions allow e-learning students to express their thoughts on all aspects of education. It is essential to confirm the student's text sentiment on specific aspects of feedback because it's a widespread way to ask others for advice when making a decision.

Sentiment Analysis (SA) is a method that helps extract information from large amounts of data. It is considered one of the research fields of text mining, and its use in recommender systems and e-learning environments is essential. Aspect-based SA as a fine-grained sentiment classification task is gaining more and more attention. It aims to identify the sentiment polarity of the whole sentence. Typically, the amount of data from these student reviews is so large that it is impractical to process them manually and is a challenging task. The existing studies provide low accuracy performance based on e-learning students reviews.

To resolve this problem, the proposed Wisconsin High Order Neural Network (WHONN) algorithm is used for classification. The first step Gaussian Iterable Filter (GIF) approach removes noise and irrelevant data. The second step is Bag of words model techniques is used to calculate weightage then Automatic Class Relevance based Keyword Extraction Score Measurement (ACRKESM) technique is used to measure sentiment score of e-learning student reviews. Finally, the proposed WHONNN algorithm is used to classify whether positive, negative or neutral.

II. RELATED WORK

B. Liu et al. (2012), the author discusses Sentiment Analysis (SA) and Opinion Mining (OM) to analyze the e-learning student’s opinions. SA is a research field that analyzes e-learning students' opinions, emotions, evaluations, attitudes, and emotions from the written language. In that study investigated SA classification challenges and problems.

O. Araque et al. (2019), the author studied Vocabulary resources that are widespread and famous in Sentiment Analysis (SA) because vocabulary resources represent resources that directly encode sentiment knowledge. This study proposes a Sentiment Classification Model (SCM) based on semantics similarity measures. But in this method didn't work correctly during classification.

D. Meškelė et al. (2020), the author investigates the aspect-based SA allows the calculation of aspect sentiment in a specific context. The author suggests the A Lexicalized Domain Ontology and a Regularized Neural Attention model (ALDONAr) algorithm utilized for aspect based SA. A two-way contextual attention mechanism is introduced to measure the effect of each word in a particular sentence on the emotional value of the aspect. One of the problems with this analysis is that language can have different emotions differently. In addition, one aspect of sentiment can be significantly influenced by domain-specific knowledge.

W. Wei et al. (2019), the author presents microblog sentiment classification (MSC) based on a Dual Attention Mechanism (DAM), and Bidirectional Long-short Term Memory (BLSTM) was used to classify the sentiment terms of microblog. Similarly, S. M. Rezaeinia et al. (2019), the author presents that Improved Word Vectors (IWV) maximize the classification accuracy performance of microblogs. But these methods take much more time; this method produces the wrong classification results.

G. Zhai et al. (2020), the author studied the educational evaluation of SA helps educators discover the student's true feelings about the course in time, adjust the education plan in a timely and accurate manner, and improve education quality. They suggest the Multi-Attention Fusion Modeling (Multi-AFM) method is utilized for SA classification to improve accuracy performance. But that method didn't consider the similarity of words, producing high misclassification results.

S. Poria et al. (2016), the author, focuses on SA of aspect extraction using the Deep Convolutional Neural Network (DCNN) algorithm. Similarly, J. Zhou et al. (2019), the survey discusses aspect-based SA challenges using Deep Learning (DL) techniques for analysing sentiment word polarity.

O. Irsoy et al. (2014), the author introduces the deep Recurrent Neural Network (RNN) approach for extracting the opinion expression. Similarly, T. H. Nguyen et al. (2015) presents the Recursive Neural Network (RNN) approach utilized for aspect-based SA. But these methods provide high misclassification performance.

X. Yan et al. (2021), the author introduces the sentiment analysis knowledge graph (SAKG) approach used to classify the SA based on online reviews. But in that study didn't focus on Parts of Speech (POS) and Bag of Words (BOW).

Duy-Tin Vo et al. (2015), the author, focuses on extracting a rich set of automated features, can get competitive results without using grammar. In particular, it divides the tweet into factors and a proper context according to specific goals and uses distributed word representation and neural pool functions to extract features.

J. Wang et al. (2018), the author introduces the BLSTM approach for aspect based SA with word-level and Clause level networks. Similarly, D. Ma et al. (2017), the author introduces the Interactive Attention Networks (IAN) approaches to identify the sentiment polarity. But this method is a very challenging task during classification.

Z. Ren et al. (2020), the author proposes a lexicon-enhanced attention network (LEAN) and LSTM methods was used to classify the aspect based sentiment information. Likewise L. Bao et al. (2019), the author uses the LSTM approach for aspect based sentiment analysis to improve classification accuracy. But this suggested techniques didn't focus accurate sentiment words during classification.

B. Shin et al. (2016), the author presents CNN algorithm to classify the SA based on lexicon of words. To improve classification accuracy parameters such as F-measure, precision, and recall uses the Fuzzy sentiment analysis based on Feature Ensemble Model (FEM) techniques proposed by H. T. Phan et al. (2020). But these methods provide high false classification results of sentiment analysis.

C. R. Aydin et al. (2020), the author presents combination of Recursive and RNN algorithm is used to aspect based SA of words extract the corresponding information. F. Yin et al. (2020), the author presents Context-dependent POS chunks (CP-chunks) method uses to solve the lexical semantic classification problem. POS is analysis the text polarity and intensity then chunks analysis the text sentiment score. However, this method provide low accuracy performance and high false rate results.

III. PROPOSED METHODOLOGY

Sentiment Analysis (SA) is a method used to identify the emotions expressed in the text. The need for sentiment analysis of the text has gained more and more attention on the sentence's human situation. The comments collected from the online e-learning chat using the form are input data. Use the training data in which the system is trained. After receiving test samples, the trained classification system treats sentences as negative, neutral, and positive using a machine learning algorithm.

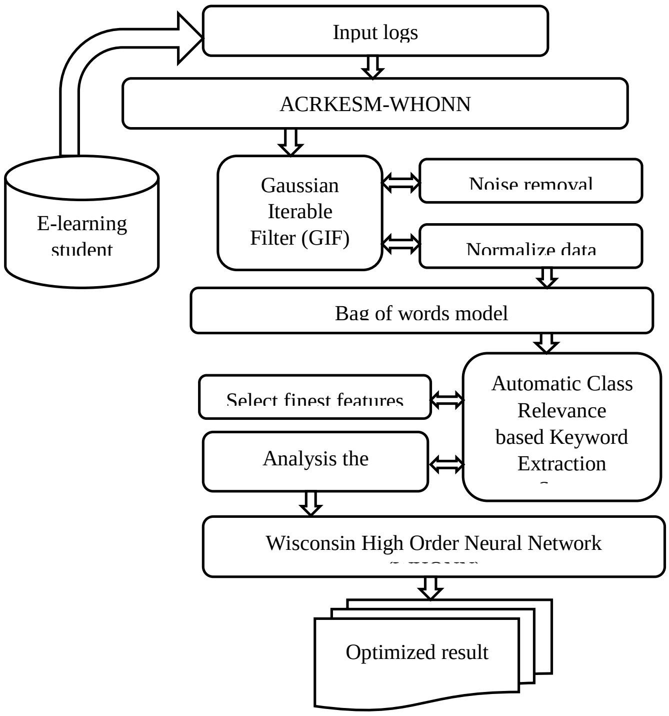

Fig. 1. Proposed architecture diagram

The proposed WHONN e-learning based sentiment analysis classification architecture diagram shown in figure 1. GIF techniques removes non-letter words such as numbers and symbols, removes stop words, and converts all comment sentences to lowercase. Then pre-processed data supplied into Bag of Words Model (BOWM) techniques is used to analysis the lexical terms from student review text dataset. After that lexical terms trained into ACRKESM approach is used to selecting finest terms of review text and calculate the lexical weightages. The proposed WHONN algorithm classify as positive, negative or neutral.

A. Gaussian Iterable Filter (GIF)

The original e-learning student review dataset is full of noise and misspelling and contains a lot of acronyms and slang. Such noisy features typically include the execution of sentiment analysis methods. This phase data pre-processing is done to remove white space, symbols, punctuation, and numbers using GIF technique.

Algorithm steps

Step1: initialize the datasetI_D. And the I_D is contain several e-learning chat review.

$$I_D = s_1, s_2, s_3, \ldots s_n$$

The number of $s_1, s_2, s_3, \ldots s_n$ sentences represented as s

Step2: remove the uninformative symbol(U_s).

s ←Remove the uninformative U_s from the sentence $s_1, s_2, s_3, \ldots s_n$

Step3: Tokenizing the sentences from the s.Tokenization is the process of separating the sentence into a smaller text.

Step 4: Stop-words removal: Gaussian Iterable Filter eliminates frequently used words that are meaningless and useless for text classification. This reduces the size of the corpus without losing important information

$for(i = 0; i < s.length; i + +)$

Sentence word =$w[i]$;

$if(!\, isEmpty(w))$

if(not.$equalsIgnoreCase(w)$&& $i + 1 < w.length$)

$I_D = w[+ + i] +$ "$\_not$");

s ← List the stop removal words$w$

The above algorithm steps provide is done removes non-letter words such as numbers and symbols, removes stop words, and converts all comment sentences to lowercase.

B. Bag of words Model

At this stage, the lexical terms of the pre-processed data are analyzed using the proposed BOWM. This model can characterize or calculate the document's features from term frequency and normalize the term frequency by the inverse of a document frequency. The proposed BOWM will reflect the importance of a word in the document. The main idea to convert the Term Frequency (TF) and Inverse Document Frequency (IDF) weighting is to transform the values into the Vector Space Model (VSM), which increases the performance of the classification systems.

Algorithm steps

Input: Given sentence S= $S_1, S_2, S_3, \ldots S_n$ comprising the w words and find the relations of words in each sentence.

Step1: Get the number of reviews from the given e-learning chat review sentence$s$.

Step2: The number of frequencies (events) must be calculated manually for each review given in this sentence. The given formula is used to declare the word frequencies from the sentence.

Word frequency = ${}^{ni,j}/_{\sum_k nk,j}$

Where $n\,i,j$ represents the number of occurrences of the review.

Step3: Create a vocabulary list

Vocabulary = $unique\ (T1 + T2)$

Step4: Filter the vocabulary list

Filtered_ vocabulary = [];

For s in vocabulary: // s denoted as any vocabulary represent the sentence

If s not in stop words

Filtered_ vocabulary. Append (w);

Step5: To calculate the TF formula

TF = $1 + \log({}^{N}/_{S})$

s ←TF-IDF

N=Total number of reviews represent the dataset, S- number of sentence represents the e-learning chat, W- number of words represents each sentence, T1+T2 = tokens.

The above algorithm steps provide analysis vocabulary (or) lexical terms form pre-processes dataset.

C. Automatic Class Relevance based Keyword Extraction Score Measurement

Analysis the lexical terms dataset fed into ACRKESM approach is used to select the finest features and calculate average weightages. This proposed feature selection has many types of class labels. ACRKESM treats vapid labels as a positive integer, starting with one. It can be identified by categories of labels such as negative, neutral, positive.

Algorithm steps

Step1: Extract the review label from the s sentence

Step2: The given sentence namespace n_s is used to get the feature id (anyone details such as name).

Step3: The sentence vocabulary word v and text have been extracting from the word. The text has split the Automatic Class Relevance based Keyword Extraction Score Measurement scheme to create a matrix from the vocabulary word v is assign to s.

$$score\ (F) = v + w/(s - 1) \quad (1)$$

The above algorithm steps successfully calculate text weightages.

D. Wisconsin High Order Neural Network

In this stage extract feature fed into the proposed WHONN algorithm for sentiment analysis classification. The proposed Input layer involves sequential input of the student e-learning review dataset; the hidden layer calculates text weights it represents the network's memory; finally, the output layer classifies the SA results.

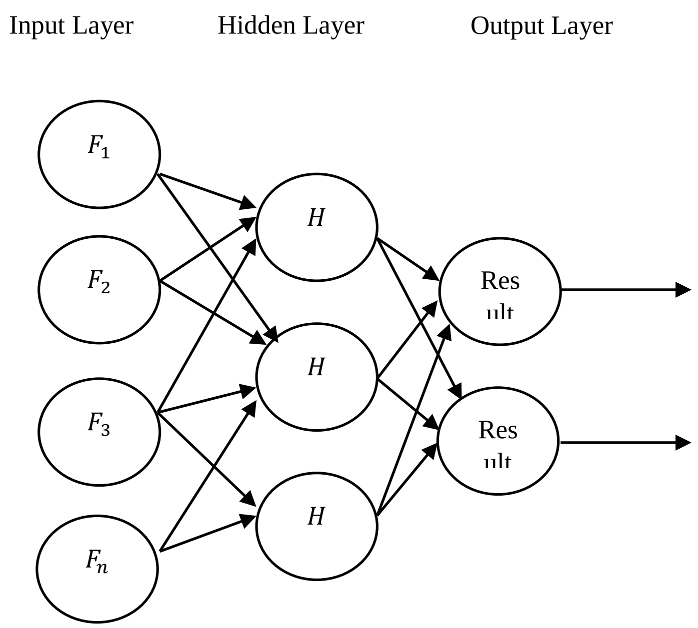

Fig. 2. General Architecture diagram for Wisconsin High Order Neural Network

Figure 2 describes the general architecture diagram for Wisconsin High Order Neural Network (WHONN) algorithm.

Algorithm steps

Input: Feature extraction dataset (F)

Output: Optimized results

Begin

Step 1: Import the feature selection dataset (F)

Step 2: Count total number of features

F←0

Step 3: Calculate hidden layer weightages (H)

$$H = (s + s(t-1))$$

Step 4: Computing each record for classification

C (o)= $\sigma(s * H(s))$

Step 5: If (C (o)>0) Then

Return←Positive

Else if (C (o) <0) Then

Return ←Negative

Else

Return ←Neutral

End if

Step 6: Obtained result

Stop

The above algorithm steps is done to classify the sentiment terms as positive, negative or neutral. Let assume H refers to hidden layer with time t, s represent to best features, σ activation function, C (o) refers to classification results.

IV. RESULT AND DISCUSSION

This section describes the proposed implementation result analysis parameters are sensitivity, specificity, classification accuracy performance, false rate analysis, and time complexity.

TABLE 1: SIMULATION PARAMETERS SETTINGS

Parameters	Values
Language	Python
Tool	Anaconda
Dataset name	E-learning student reactions
Number of data	4000
Training dataset	3500
Testing dataset	500

The proposed algorithm Simulation parameters settings present in table 1. The proposed Wisconsin High Order Neural Network (WHONN) algorithm compared to Recurrent Neural Network (RNN) and Perceptual Neural Boltzmann Machine (PNBM).

TABLE II. ANALYSIS OF CLASSIFICATION ACCURACY PERFORMANCE

No of data	RNN in %	PNBM in %	WHONN in %
400	32	44	48
800	48	59	64
1200	59	69	75
1600	64	87	92

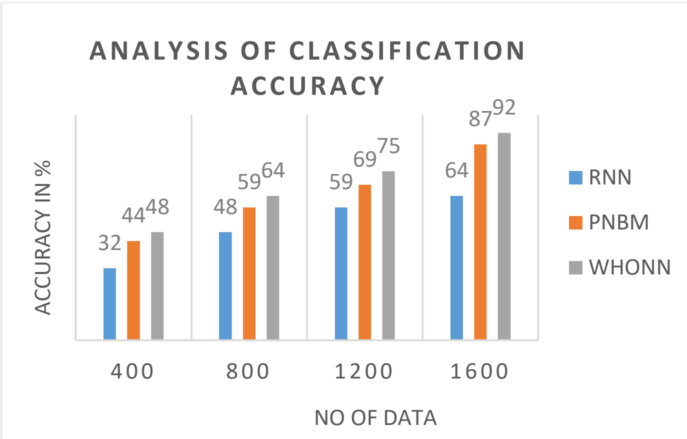

Fig. 3. Analysis of classification accuracy performance

The above Table 2 and figure 3 defines the classification of accuracy performance. The proposed WHONN algorithm provide 92% for 1600 data, similarly the existing study RNN algorithm has 64% and PNBM has 64 for 1600 data.

TABLE 3: ANALYSIS OF SENSITIVITY PERFORMANCE

No of data	RNN in %	PNBM in %	WHONN in %
400	52	56	65
800	58	62	71
1200	61	75	80
1600	65	85	89

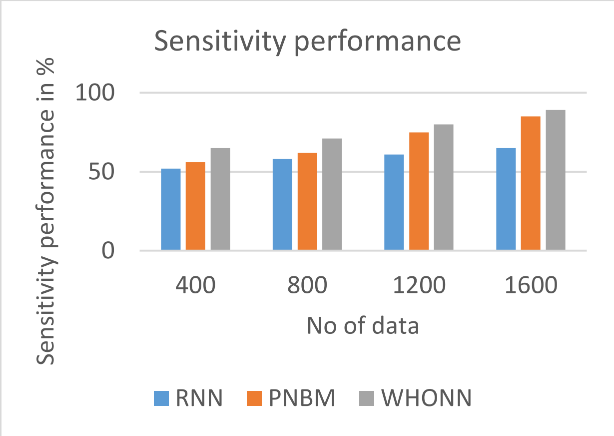

Fig. 4. Analysis of Sensitivity performance

The above figure 4 and table 3 defines the sensitivity performance graph comparison results. The proposed algorithm WHONN has 89% for 1600 data, similarly the exiting algorithm PNBM algorithm has 85%, and RNN algorithm has 66%.

TABLE IV. ANALYSIS OF SPECIFICITY PERFORMANCE

No of data	RNN in %	PNBM in %	WHONN in %
400	54	60	66
800	62	66	72
1200	70	74	78
1600	74	83	88

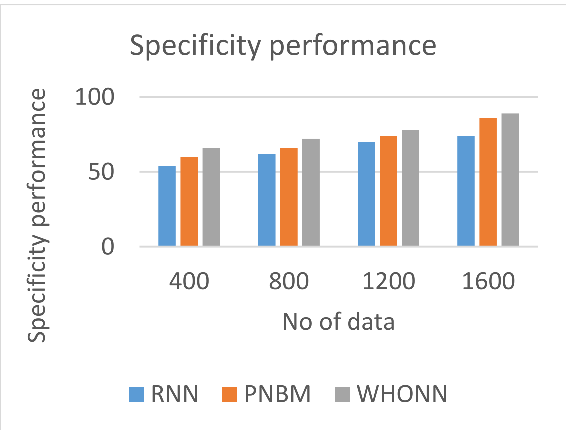

Fig. 5. Analysis of specificity performance

Figure 5 and table 4 represent the analysis of specificity performance graph comparison result. The proposed WHONN algorithm has 89% for 1600 data, similarly the existing algorithm PNBM algorithm has 86% and RNN algorithm has 74%.

TABLE V. ANALYSIS OF FALSE RATE PERFORMANCE

No of data	RNN in %	PNBM in %	WHONN in %
400	78	56	52
800	52	41	36
1200	41	31	25
1600	36	13	8

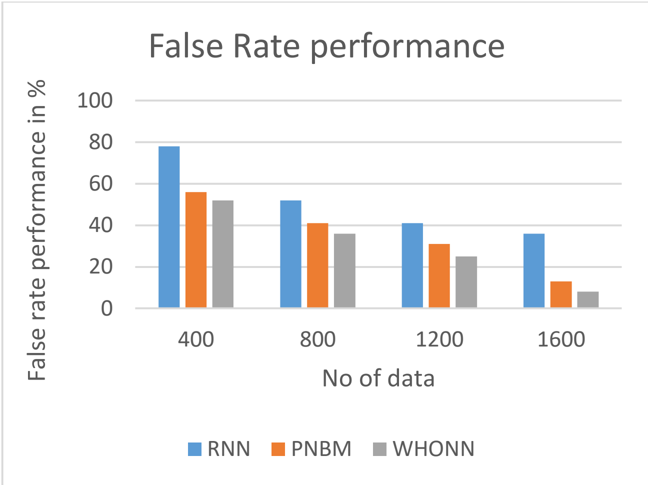

Fig. 6. Analysis of false rate performance

The above figure 6 and table 5 false rate performance comparison results. The proposed algorithm provide 8% for 1600 data likewise the existing algorithm PNBM algorithm has 13%, and RNN algorithm has 36% for 1600 data.

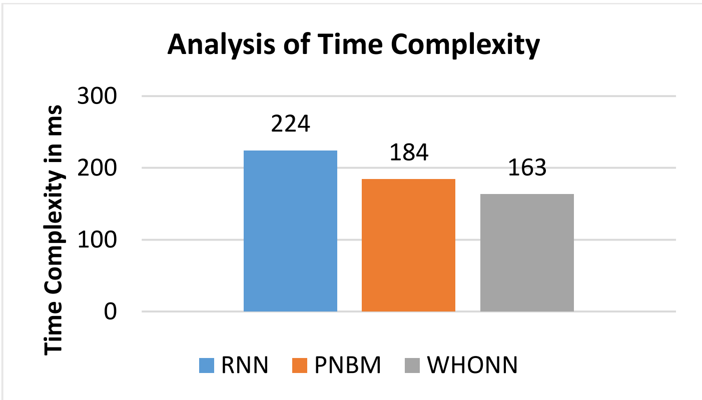

Fig. 7. Analysis of time complexity

Figure 7 defines the analysis of time complexity performance the proposed and existing algorithm comparison result. The proposed algorithm WHONN time complexity has 163ms, similarly the exiting algorithm PNBM has 184ms and RNN algorithm has 224ms.

5. Conclusion

To conclude this paper E-learning based Sentiment Analysis (SA) using Wisconsin High Order Neural Network (WHONN) algorithm. GIF techniques removes non-letter words such as numbers and symbols, removes stop words, and converts all comment sentences to lowercase. Then pre-processed data supplied into Bag of Words Model (BOWM) techniques is used to analysis the lexical terms from student review text dataset. After that lexical terms trained into ACRKESM approach is used to selecting finest terms of review text and calculate the lexical weightages. The proposed WHONN algorithm classify as positive, negative or neutral. The proposed algorithm gives results are Classification accuracy performance is 92%, sensitivity performance is 89%, specificity performance is 88%, false rate performance is 8%, and time complexity is 164ms.

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