Original Article

Sentiment Analysis Of Student's Feedback Using Ai

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Abstract

Sentiment analysis the study of people's sentiments, views and emotions in the form of written language. In this project a tool is developed to perform analysis of the feedback/comments given by the students in sentential form and capture the overall sentiment distribution as happy, neutral, unhappy for five (5) most relevant courses of B. Tech syllabus namely Python, Data Structure, DBMS, Networking, and OS associated with mandatory lab sessions for the aspects: course expertise, course content, library facility and lab infrastructure. We were able to collect 1000 data from 200 students for 16 different features. After classical natural language preprocessing, we have used a hybrid deep learning based approach, test accuracy based weighted ensemble of five different Fine-Tuned BERT based models like Sequential, RNN, Stacked RNN, LSTM and BiLSTM. The overall maximum and minimum accuracy observed for by the weighted ensemble model is 99% and 78% respectively.

KEYWORDS Sentiment Analysis, LSTM, BERT, BiLSTM,RNN.

INTRODUCTION

Sentiment analysis is the process of determining the sentiment expressed in a piece of text such as data collected from surveys, various posts on social media like facebook ,twitter or news articles. Through sentiment analysis collected data or text is classified as positive, negative, or neutral based on the sentiment expressed. This classification is done by various natural language processing techniques, such as machine learning algorithms, lexicon-based methods, and rule- based methods. Sentiment analysis is widely used in business, marketing, and social media to gain insights into customer opinions and feedback, monitor brand reputation, and track public opinion on a particular issue. In Sentiment analysis we find the emotion presented in text form. We can use Sentiment analysis to analyze survey responses, customer opinions , product reviews and analysis of social media posts. Sentiment analysis has a variety of applications, including: Customer Sentiment Analysis, Marketing and Advertising, Social Media Monitoring, Political Sentiment Analysis, Sentiment Analysis in Finance, Healthcare Sentiment Analysis. Sentiment analysis has several benefits, including: Improved Customer Understanding, Better Decision Making, Real-time Insights, Increase Deficiency, Improved Customer Engagement, Enhanced Brand Reputation. There are various ways using which we can do sentiment analysis. Some of the ways are :use of methods based on rules, use of machine learning ,deep learning and hybrid models .

LITERATURE REVIEW

For sentiment analysis this paper[1] proposes an ensemble hybrid deep learning model. Three hybrid models namely RoBERTa, LSTM,GRU and BiLSTM were used in this model to project textual inputs into an embedding space and find long-range dependencies. The predictions of the models are used through averaging and majority voting to improve performance. Data augmentation with GloVe pre-trained word embeddings is used to address imbalanced dataset problems. The proposed model's performance is better than the existing state of the art methods with accuracy of 94.9%, 91.77%, and 89.81% on IMDb, Twitter US Airline Sentiment and Sentiment 140 datasets respectively.

This paper[2] examines the reliability of hybrid sentiment analysis techniques in social networks like linked in and Twitter. It focuses on hybrid models combining LSTM,SVM and CNN and compares them against models of SVM, LSTM, and CNN individually. The aim of this experiment is to check whether hybrid model's performance is better than single models on different types of datasets. The accuracy of hybrid models for sentiment analysis was better than the single models.

This paper[3] focuses on understanding the decisions made by methods that work on dataset such as pattern recognition and machine learning models. The increasing deployment of ML models in various businesses has raised concerns about their drawbacks, biases, and complexity. This paper studied literature to help data scientists and industry people to get knowledge of the field of machine learning and how they can apply the appropriate tool for accomplishment of their tasks. The paper explains approaches like transparent vs opaque model,model specific and model-agnostic explain approaches . The goal is to help organizations to learn why explainable ML and informed decisions making is important.

For sentiment analysis in low resource language , this paper[4] proposes a hybrid deep learning architecture.The approach uses a CNN to sentiment embedded vectors,These vectors are then combined with a set of optimized features selected through a MOO framework. The resulting combined optimized vector is used for training a SVM for sentiment classification. The approach was evaluated for sentence level and aspect level sentiment analysis on four Hindi datasets and two benchmark English datasets. Results show consistent performance across datasets and often outperformed state-of-the- art systems.

This paper[5] provides guidance for the area of explainable deep learning. It aims to help practitioners and researchers who are new to the field understand the methods and evaluations used in the area of explainable deep learning. The paper introduces three dimensions that define methods that contribute to explainable deep learning, discusses how we can evaluate model explanations, and places explain ability in the fields of other related deep learning research areas. The paper also covers user- oriented explanation design and potential future directions in explainable deep learning. The aim of this work is to provide a starting point for people who are just embarking on research in this field.

This paper[6] presents a systematic evaluation and classification of the various methods used in interpretability and explains the ability of deep learning models.methods and basic techniques of explaining ability are summarize through a classifier.Through the evaluation of classifier helps us to understand the challenges in developing unified deep learning framework [7][8][9].

PROBLEM & DATASET

PROBLEM DEFINITION

The goal is to develop a tool to perform analysis of the feedback/comments given by the students and capture their sentiments whether the students are happy, neutral, and unhappy with the particular course. The tool will also generate the dashboard where the detailed report for all the courses is displayed [10[11].

For each Course (Ci), given a Feedback Text (Tj) by a Student (Sj), against each Course Aspect Statements (CASk), determine the associated statistical distribution of each sentiment class (SCp), for each Aspect (APm) as a summary chart/graph [12[13].

where,

C={C1,C2,..,C5} and i=1 to 5

S={S1, S2, …, S200} and j=1 to 200

CAS={CAS1, CAS2, .., CAS16} and k= 1 to 16

SC={Happy, Not Happy, Neutral} and p=1 to 3
AP={Course Expertise, Course Content, Library Facility, Lab Infrastructure} and m=1 to 4

Input: A sentiment dataset (.csvfile)
Output: Sentiment distribution of each course for each aspect

DATASET ATTRIBUTES:

ASPECTS (AP)	ASPECT_ID	COURSE ASPECTSTATEMENTS (CAS)
Course Expertise (AP1)	CAS1	Teacher's Knowledge Base (As per received by you)
	CAS2	Ability to Explain the Subject (As per received by you)
	CAS3	Welcoming Questions
Course Content (AP2)	CAS4	Adequacy of Course Material
	CAS5	Quality of Course Material
	CAS6	Adequacy of Course Assignments
	CAS7	Quality of Course Assignments
	CAS8	Adequacy of Course Evaluation
	CAS9	Level of Course Evaluation
Library Facility (AP3)	CAS10	Availability of books related to Course
	CAS11	Availability of e-resources related to Course
	CAS12	Availability of previous course materials
Lab Infrastructure (AP4)	CAS13	Availability of S/W
	CAS14	Availability of H/W
	CAS15	Availability of Working Models
	CAS16	Availability of Lab Manuals

Table1: Course Aspect Details

A. **DATASET COLLECTION**
   Data was collected through circulation of Google Form for five (5) courses for four (4) aspects from 200 students. [14][15][16].
B. **DATASET ATTRIBUTES**
   We have considered sixteen (16) different aspect statements (features) CAS1 to CAS16 to cover the four (4) associated aspects AP1 to AP4.

C. **SAMPLE DATASET**

21	2022/12/0	ISHIRA GA	IT2022022	Python	TEACHER'S KNOWLEDGE BASE IS EXCELLENT.	H
22	2022/12/0	Biswadeep	CSE20221	Python	Very good	H
23	2022/12/0	Rohaan N.	IT2022111	Python	Pretty Good	N
24	2022/12/0	Biswadeep	CSE20221	Python	Good	N
25	2022/12/0	Biswadeep	CSE20221	Python	Good	H
26	2022/12/0	ISHIRA GA	IT2022022	Python	TEACHER'S KNOWLEDGE BASE IS EXCELLENT.	N
27	2022/12/0	Sohom Mi	CSE20220	Python	Good	N
28	2022/12/0	Sohom Mi	CSE20220	Python	GOOD	N
29	2022/12/0	Sohom Mi	CSE20220	Python	Good	H
30	2022/12/0	ISHIRA GA	IT2022022	Python	TEACHER'S KNOWLEDGE BASE IS EXCELLENT.	N
31	2022/12/0	Sohom Mi	CSE20220	Python	Good	N
32	2022/12/0	Sohom Mi	CSE20220	Python	Good	N
33	2022/12/0	Sohom Mi	CSE20220	Python	Good	H
34	2022/12/0	ISHIRA GA	IT2022022	Python	TEACHER'S KNOWLEDGE BASE IS EXCELLENT.	H
35	2022/12/0	ISHIRA GA	IT2022022	Python	TEACHER'S KNOWLEDGE BASE IS EXCELLENT.	H
36	2022/12/0	ISHIRA GA	IT2022022	Python	TEACHER'S KNOWLEDGE BASE IS EXCELLENT.	H

Table2: Sample Student Sentiment Data for Python Course

DESIGN AND IMPLEMENTATION OF FEEDBACK SYSTEM

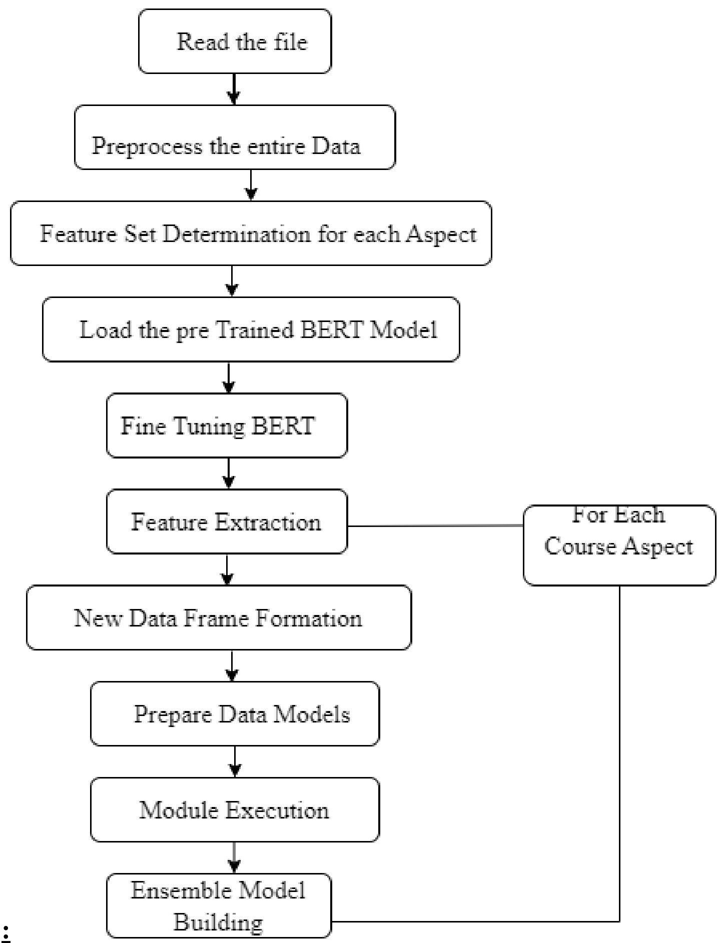


Fig 1: Proposed Project Workflow

1.Read Input File:Read input file in CSV format.

2.Preprocessing the entire data:Cleaned data using functions given below:
df=process.remove_null(df)
df=process.data_cleaning(df)

3.Feature Set Determination for each Aspect: Four feature sets for four aspects are extracted.

```
# Step-2: Feature Engineering

# Four Feature Sets for Four Aspects

fs1=df[['Select Course','CA1','CL1','CA2','CL2','CA3','CL3']]
fs2=df[['Select Course','CA4','CL4','CA5','CL5','CA6','CL6','CA7','CL7','CA8','CL8','CA9','CL9',]]
fs3=df[['Select Course','CA10','CL10', 'CA11','CL11','CA12','CL12']]
fs4=df[['Select Course','CA13','CL13','CA14','CL14','CA15','CL15','CA16','CL16']]
```

4.Load the PreTrained BERT Model:

```
# Loading PreTrained BERT Embedding
# import BERT-base pretrained model
bert = AutoModel.from_pretrained('bert-base-uncased')
# Load the BERT tokenizer
tokenizer = BertTokenizerFast.from_pretrained('bert-base-uncased')
```

1. **Class Preprocess**

Class Preprocess is responsible for cleaning the data and replacing the null values if any. In our case, if a null value exists in any aspect statement, then it will be replaced by a random value from the list of unique value set. Also, its corresponding label will be replaced by the associated random label value [17][18][19].

2. **Class FeatureEngineering**

Class Feature Engineering performs three basic functionalities like feature extraction, new data frame formation and class balancing of the newly created data frame. For a specific aspect, among the considered features, the feature with lowest occurrences of unique value is being eliminated with its label. We then merged the rest of the features and their associated labels to create the new data frame. To balance the new data frame with their class occurrences, the maximum class distribution samples are used for up sampling the other classes [20][21][22].

```
large=self.find_large(temp)

# Generating new samples according to the max sample
df_H_upsample=resample(df_H, n_samples=large, replace=True, random_state=123)
df_NH_upsample=resample(df_NH, n_samples=large, replace=True, random_state=123)
df_N_upsample=resample(df_N, n_samples=large, replace=True, random_state=123)

# Merge the new samples
dfn=pd.concat([df_H_upsample,df_NH_upsample,df_N_upsample], ignore_index=True)
```

3. **Class Prepare**

The two major functionalities of Prepare class are tokenization and Train-Valid-Test Split. We have used BERT tokenizer to tokenize the text in each aspect and 70:10:20 split.

4. **Class Execution**
   Class Execution performs the training, validation and testing of each model, followed by their performance analysis and ensemble model creation.

MODELS & SPECIFICATIONS

A. **BERT Embedding**
   The BERT (Bidirectional Encoder Representations from Transformers) model was developed by Google AI Language. It is a pre-trained language model for embedding semantic context of input text [23][24].
B. **Fine Tuning**
   Instead of building a model from scratch, it would be really time and cost optimization to have an already trained model for the similar kind of downstream task. Only need to make some modifications accordingly [25][26].
C. **Sequential Neural Network**
   A sequential model is a regular stacking of layers. Each layer has an input sensor and an output sensor [27].
D. **Recurrent Neural Network (RNN)**
   In a Recurrent neural network the output of the previous step is used as the input for the current step [28].
E. **Stacked Recurrent Neural Network (SRNN)**
   Stacked RNN is a stacked set of Recurrent Neural Network [29].

F. **Long Short-Term Memory (LSTM)**
   LSTM is a sequential network that allows information persistence. Use of LSTMs are to learn, process and classify sequential data because LSTMs identify and learn long -term dependencies between data time steps. LSTMs are able to handle the leakage gradient problem faced by RNNs [30].

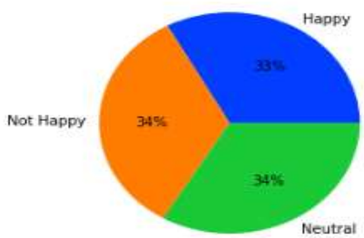
G. **Bidirectional -LSTM (BiLSTM)**
   BiLSTM is a RNN. It consists of two LSTMs It processes data in two directions due to two hidden layers.. BiLSTM has provided good results in natural language processing as compared to LSTMs [31].

H. **Weighted Ensemble Model**
   The mean ensemble or weighted mean ensemble models reduce the total error by combining the predictions of several different classifiers. We assume that different classifiers will make different errors in training and prediction. We generate a set of classifiers (with diversity) and then combine their outputs. After aggregating the outputs of several classifiers, a final prediction is made and the total error of the final prediction is reduced by the aggregation.

RESULTS & PERFORMANCE ANALYSIS

```
Step-3: Model Executions Completed
CourseName:Networking
```

```
STEP 4.1: GENERATING REPORT FOR COURSE EXPERTISE
```



	M1	M2	M3	M4	M5	**M6**
AP1	0.96	0.90	0.85	0.87	0.94	**0.85**
AP2	0.92	0.94	0.86	0.88	0.96	**0.98**
AP3	0.92	0.92	0.92	0.92	0.92	**0.97**
AP4	0.92	0.94	0.85	0.87	0.88	**0.96**

Table3 : Accuracy comparatives for all models of Networking

Note:

1. **Where M1= Sequential, M2=RNN, M3=SRNN, M4=LSTM, M5=BiLSTM, M6=Weighted Ensemble**
2. Green Code: Best Accuracy achieved by the model
3. Yellow Code: Worst Accuracy achieved by the model

Conclusion

The weighted ensemble of considered models with test accuracy and contextual embedding gives a satisfactory level of understanding of the collected student sentiment data with maximum accuracy of 98%. The hybrid deep learning approach as also suggested by the references holds good in our case too.

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