REVIEW RATING USING TRIP ADVISOR

A Project Report in partial fulfillment of the degree

Bachelor of Technology

in

Computer Science & Engineering & Engineering/ Electronics & Communication Engineering/ Electrical & Electronics Engineering

By

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CERTIFICATE

This is to certify that the Project Report entitled "Review rating using trip advisor" is a record of bonafide work carried out by the students A.Saivardhan reddy, S.Ramyateja, G.Varshini , Roll No(s) 19K41A04F0, 19K41A04H5, 19K41A05F5 during the academic year 2021-22 in partial fulfillment of the award of the degree of ***Bachelor of Technology*** in **Computer Science & Engineering/Electronics & Communication Engineering/Electrical & Electronics Engineering** by the Jawaharlal Nehru Technological University, Hyderabad.

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ABSTRACT

Sentiment or opinion analysis employs natural language processing to extract a significant pattern of knowledge from a large amount of textual data. Sentiment analysis is a natural language processing tool that is useful for monitoring applications, as it can reveal public opinion about numerous issues without requiring satisfaction inquiries. The availability of a huge volume of reviews makes it troublesome for service executives to know the percentage of reviews that affect their services. Thus, developing a sentiment assessment technique concerning hotel reviews is essential, particularly in Indonesia. This research uses the Long-Short Term Memory (LSTM) and Word2Vec models. The integration of Word2Vec and LSTM variables used in this research are Word2Vec architecture, Word2Vec vector dimension, Word2Vec evaluation method, pooling technique, dropout value, and learning rate. On the basis of experimental research performed through 555500 review texts as a dataset, the best performance was obtained and had an accuracy of 85.96%. The parameter combinations for Word2Vec are Skip-gram as architecture, Hierarchical SoftMax as an evaluation method, and 300 as vector dimension. Whereas the parameter combinations for LSTM are a dropout value is 0.2, pooling type average pooling, and a learning rate is 0.001.

Keywords: Service Executive, Word2Vec, lstm, Skip-gram

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1. INTRODUCTION

Sentiment analysis (also referred to as subjectivity analysis or opinion mining or emotion artificial intelligence) is a natural language processing (NLP) technique that identifies important patterns of information and features from a large text corpus. It examines comments, opinions, emotions, beliefs, views, questions, preferences, attitudes, and requests communicated by the writer in a string of text. It extracts the writer's feelings in the form of subjectivity (objective and subjective), polarity (negative, positive, and neutral), and emotions (angry, happy, surprised, sad, jealous, and mixed). It analyzes thoughts, attitudes, views, opinions, beliefs, comments, requests, questions, and preferences expressed by an author based on emotion rather than a reason in the form of text towards entities like services, issues, individuals, products, events, topics, organizations, and their attributes. It finds the author's overall emotion for a text where text can be blog posts, product reviews, online forums, speech, database sources, social media data, and documents. It usually consists of three elements depending on the context:

1. Opinions or emotions: An opinion is also referred to as polarity, whereas emotions can be qualitative such as sad, joy, anger, surprise, disgust, or happiness, or quantitative such as rating a movie on a scale of one to ten
2. Subject: It refers to the subject of the discussion where one opinion can discuss more than one aspect of the same subject, for instance, the camera of the phone is great, but the battery life is disappointing.
3. Opinion holder: It refers to the author/person who expresses the opinion.

Natural Language Processing (NLP) is a field of computer science and linguistics concerned with the interactions between computers and human (natural) languages.

The main objective of this study is to classify customer reviews into positive or negative sentiments, to measure the intensity of the sentiments generated by the customer, to analyze the association between customer reviews concerning different attractions in the city.

2. LITERATURE SURVEY

1.Tourist Place Reviews Sentiment Classification Using Machine Learning Techniques proposed by Shraddha S. Suratkar, and Apeksha Arun Wadhe, in this paper sentiment analysis has been implemented using a machine learning approach. The Dataset has been collected from various tourism review websites. performed comparative study of feature extraction algorithms i.e. Count Vectorization, and TF IDF Vectorization. Along with classification algorithms Naive Bayes (NB), Support Vector Machine (SVM), and Random Forest (RF). The performance of algorithms has been compared using various parameters like accuracy, recall, precision, and f1-score. Experiments found that the TF IDF Vectorization feature extraction algorithm has improved accuracy of the classification algorithm as compared to Count Vectorization for a given review dataset. In sentiment classification of tourist place reviews, TF IDF Vectorization with RF has given the highest accuracy 86% for a research dataset used.

2. Deep Learning-based Sentiment Analysis and Topic Modeling on Tourism During Covid-19 Pandemic proposed by J. Angel Arul Jothi, Ram Krishn Mishra, and Urolagin, the research looks at the data collected from the micro-blogging site Twitter for the tourism sector, emphasizing sub-domains hospitality and healthcare. The sentiment of approximately 20,000 tweets have been calculated using Valence Aware Dictionary for Sentiment Reasoning (VADER) model. Furthermore, topic modeling was used to reveal certain hidden themes and determine the narrative and direction of the topics related to tourism healthcare, and hospitality. Finally, a cutting-edge deep learning classification model was used with different epoch sizes of the dataset to anticipate and classify people's feelings. The deep learning model has been tested with multiple parameters such as training set accuracy, test set accuracy, validation loss, validation accuracy, etc., and resulted in more than a 90% in training set accuracy tourism hospitality and healthcare reported 80.9 and 78.7% respectively on test set accuracy.

3.VADER: A Parsimonious Rule-Based Model for Sentiment Analysis of Social Media Text proposed by Eric Gilbert, C. Hutto, VADER: a simple rule-based model for general sentiment analysis, and compare its effectiveness to eleven typical state-of-practice benchmarks including LIWC, ANEW, the General Inquirer, SentiWordNet, and machine learning oriented techniques relying on Naive Bayes, Maximum Entropy, and Support Vector Machine (SVM) algorithms, combining lexical features with consideration for five general rules that embody grammatical and syntactical conventions for expressing and emphasizing sentiment intensity. Interestingly, using our parsimonious rule-based model to assess the sentiment of tweets, we find that VADER outperforms individual human raters (F1 Classification Accuracy = 0.96 and 0.84, respectively), and generalizes more favorably across contexts.

4.Word2Vec on Sentiment Analysis with Synthetic Minority Oversampling Technique and Boosting Algorithm proposed by Erwin Budi Setiawan, Rayhan Rahman. In this research, aspect-based sentiment analysis was conducted on Telkomsel users on Twitter. The data used is 16,992 tweets from users who discuss several aspects such as Telkomsel's services and signals on Twitter. In this research, Word2Vec was used for feature expansion to minimize vocabulary mismatch caused by limited words in tweets. The results showed that Word2Vec, Synthetic Minority Oversampling Technique (SMOTE), and Boosting algorithm combination with Logistic Regression classifier achieve the highest accuracy of 95.10% for signal aspect and using hyperparameters makes the service aspect get the highest accuracy of 93.34%.

5.Travel time prediction with Lstm neural network proposed by Fei-Yue Wang, Lv Yisheng, and Yanjie Duan. In this paper, a deep learning model, the LSTM neural network model, for travel time prediction. Employing the travel time data constructed 66 series prediction LSTM neural networks for the 66 links in the data set. Through model training and validation, obtained the optimal structure within the setting range for each link. Then predict multi-step ahead travel times for each link on the test set. Evaluation results show that the 1-step ahead travel time prediction error is relatively small, the median of mean relative error for the 66 links in the experiments is 7.0% on the test set. Deep learning models considering sequence relation are promising in traffic series data prediction.

6.Sentiment Analysis with KNN Algorithm proposed by Hyunwoo Max Ch. A machine learning model that can predict if the person thinks positively or negatively about the movie based on the movie review data. To this end, the given data were first preprocessed to turn them into a dataset suitable for training. Then, the machine learning model using the KNN algorithm was trained and the model was able to predict peoples' sentiments with 82.5% accuracy. Since the above program uses the KNN algorithm, it does not need to know how negative or positive the word.

7. Sentiment Analysis Approach Based on N-gram and KNN Classifier proposed by Sumandeep kaur, Geetha. The proposed approach is a combination of feature extraction and classification techniques. The N-gram algorithm is applied for the feature extraction and KNN classifier is applied to classify input data into positive, negative, and neutral classes. To validate the proposed system, performance is analyzed in terms of precision, recall, and accuracy. The results of the experiment of the proposed system show that it performs well compared to the existing system which is based on an SVM classifier.

8. Opinion analysis of travelers based on tourism site review using sentimental analysis introduced by Siti Azza Amira, Mohammad Isa Irwan*. The support vector machine method combined with TF-IDF can solve problems in sentiment classification. This is evidenced by the ability of the TF-IDF method to give a weight value to a word and the ability of the Support vector machine method to provide labels in each review, which are positive reviews and negative reviews. With this value of accuracy, it means the classifier used has worked well in classifying reviews.

9.Sentimental analysis using word2vec and lstm for Indonesian hotel reviews. word2Vec and LSTM variables used in this research are Word2Vec architecture, Word2Vec vector dimension, Word2Vec evaluation method, pooling technique, dropout value, and learning rate. On the basis of experimental research performed through 2500 review texts as a dataset, the best performance was obtained and had an accuracy of 85.96%. The parameter combinations for Word2Vec are Skip-gram as architecture, Hierarchical Softmax as an evaluation method, and 300 as vector dimension. Whereas the parameter combinations for LSTM are a dropout value is 0.2, pooling type is average pooling, and a learning rate is 0.001

10.The influence of TripAdvisor application usage towards hotel occupancy rate in Solo proposed by D Sumarsono1,2,3*, B Sudardi1, Warto1, W Abdullah. Tripadvisor also plays the role as a reference of the world tourism industry in raising the rating of the hotel. Trip advisor plays the role as a reference of the worlds tourism industry in raising the rating of the hotel.

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2.2 Flowchart

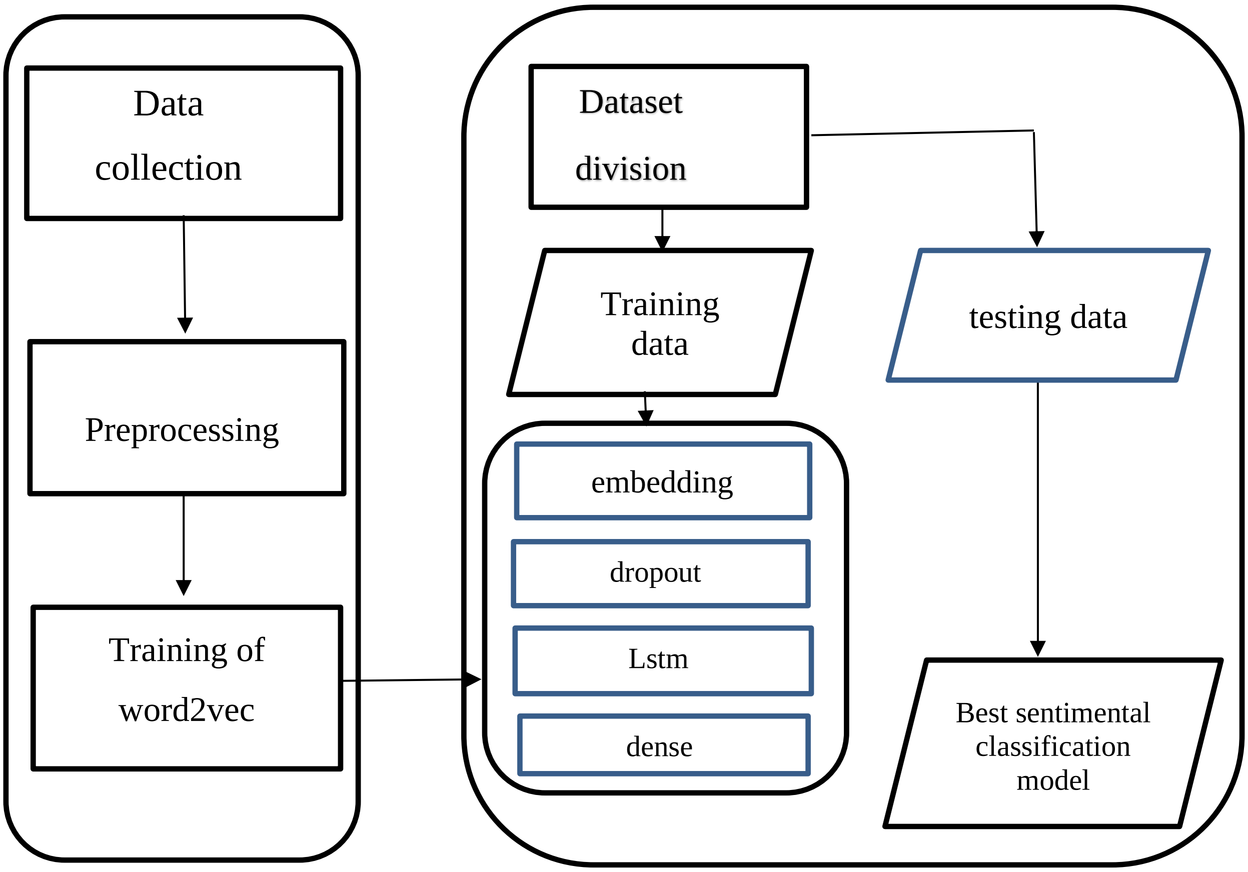

Fig.1: block diagram

Here we are collected the data set from Kaggle and uploaded that dataset in to google colab with the help of google drive. The data thus obtained is preprocessed using some techniques like tokenization, stemming etc., then the data is trained using word2vec model followed by layers such as embedding, dropout, lstm and dense. Finally, the data is tested and the accuracy obtained is 86 percent.

3. DATASET:

Address na	Additional_	Review_Da	Average_S	Hotel_Nar	Reviewer_	Negative_	Review_Tc	Total_Nun	Positive_R	Review_Tc	Total_Nun	Reviewer_	Tags	days_since	lat	lng
s Gravesa	194	########	7.7	Hotel Aren	Ireland	No Negati	0	1403	No real cc	105	7	7.5	[' Leisure t	0 days	52.36058	4.915968
s Gravesa	194	########	7.7	Hotel Aren	Italy	No Negati	0	1403	This hotel	59	6	9.2	[' Business	30 days	52.36058	4.915968
s Gravesa	194	########	7.7	Hotel Aren	Italy	No Negati	0	1403	This hotel	82	26	10	[' Leisure t	31 days	52.36058	4.915968
s Gravesa	194	6/29/2017	7.7	Hotel Aren	Netherlan	No Negati	0	1403	Public are	33	4	7.1	[' Business	35 days	52.36058	4.915968
s Gravesa	194	3/22/2017	7.7	Hotel Aren	United Kir	No Negati	0	1403	The qualit	77	3	10	[' Leisure t	134 day	52.36058	4.915968
s Gravesa	194	3/16/2017	7.7	Hotel Aren	United Kir	No Negati	0	1403	Beautiful	49	4	10	[' Leisure t	140 day	52.36058	4.915968
s Gravesa	194	2/20/2017	7.7	Hotel Aren	United Kir	No Negati	0	1403	The hotel	76	2	10	[' Leisure t	164 day	52.36058	4.915968
s Gravesa	194	########	7.7	Hotel Aren	Switzerlar	No Negati	0	1403	Basically e	84	16	9.6	[' Leisure t	175 day	52.36058	4.915968
s Gravesa	194	12/13/201	7.7	Hotel Aren	United Kir	No Negati	0	1403	The whole	56	1	10	[' Leisure t	233 day	52.36058	4.915968
s Gravesa	194	########	7.7	Hotel Aren	United Kir	No Negati	0	1403	Hotel was	68	1	9.2	[' Leisure t	236 day	52.36058	4.915968
s Gravesa	194	9/27/2016		Hotel Aren	United Kir	No Negati	0	1403	We upgra	38	1	10	[' Leisure t	310 day	52.36058	4.915968
s Gravesa	194	########	7.7	Hotel Aren	United Kir	No Negati	0	1403	Architectu	115	4	10	[' Leisure t	394 day	52.36058	4.915968
s Gravesa	194	########	7.7	Hotel Aren	United Kir	No Negati	0	1403	Breakfast	34	1	9.6	[' Leisure t	397 day	52.36058	4.915968
s Gravesa	194	########	7.7	Hotel Aren	United Kir	No Negati	0	1403	This hotel	78	1	8.8	[' Leisure t	397 day	52.36058	4.915968
s Gravesa	194	4/22/2016	7.7	Hotel Aren	United Kir	No Negati	0	1403	Beautiful	40	2	10	[' Leisure t	468 day	52.36058	4.915968
s Gravesa	194	3/17/2016	7.7	Hotel Aren	Ireland	No Negati	0	1403	Bar and re	33	1	6.7	[' Leisure t	504 day	52.36058	4.915968
s Gravesa	194	########	7.7	Hotel Aren	United Kir	No Negati	0	1403	The staff	35	1	10	[' Leisure t	542 day	52.36058	4.915968
s Gravesa	194	########	7.7	Hotel Aren	United Kir	No Negati	0	1403	The hotel	66	11	10	[' Leisure t	548 day	52.36058	4.915968
s Gravesa	194	1/23/2016	7.7	Hotel Aren	Ireland	No Negati	0	1403	Stayed in	78	1	10	[' Leisure t	558 day	52.36058	4.915968
s Gravesa	194	11/15/201	7.7	Hotel Aren	United Kir	No Negati	0	1403	Staff were	37	1	9.2	[' Leisure t	627 day	52.36058	4.915968
s Gravesa	194	########	7.7	Hotel Aren	United Kir	No Negati	0	1403	Staff were	47	3	9.2	[' Leisure t	631 day	52.36058	4.915968
s Gravesa	194	########	7.7	Hotel Aren	Australia	No Negati	0	1403	Good loca	37	17	10	[' Leisure t	641 day	52.36058	4.915968
s Gravesa	194	10/29/201	7.7	Hotel Aren	United Kir	No Negati	0	1403	Hotel and	67	5	9.2	[' Leisure t	644 day	52.36058	4.915968
s Gravesa	194	10/22/201	7.7	Hotel Aren	Ireland	No Negati	0	1403	This was c	31	2	10	[' Leisure t	651 day	52.36058	4.915968
s Gravesa	194	10/17/201	7.7	Hotel Aren	Canada	No Negati	0	1403	It was a w	35	1	10	[' Leisure t	656 day	52.36058	4.915968
s Gravesa	194	9/29/2015	7.7	Hotel Aren	Spain	No Negati	0	1403	I loved the	67	1	9.6	[' Business	674 day	52.36058	4.915968

Figure 2: Visualizing attributes of dataset

1. We have collected this dataset from the internet Kaggle, it consists of address name, an additional number of scorings, review date, average score, hotel name, reviewer nationality, negative review, review total negative word count, a total number of reviews, positive review, review total negative word count, a total number of reviews reviewer has given, reviewer score, tags, days since the review, lat(longitude) and lng(longitude). The dataset has 17 columns along with 515739 rows.
2. Of this data, we have removed some rows and columns and made the number of rows finally 399336 and the number of columns 4. The number of rows is decreased so that the processing of data takes less time compared with huge amounts of data and data can be accurately predicted.
3. The output feature predicts which trip is best for the customer.

4. DATA PREPROCESSING:

Dataset is a collection of data or related information that is composed of separate elements. A collection of dataset for positive and negative reviews. Dataset (rows X columns) 399336*4.

1.Data pre-processing is essential while working on large datasets because algorithms could only be applied to vectorized text. Data pre-processing thereby aims at covering text in a vectorized simple form which means tokenizing. Tokenizing means dividing the text into units of words or sentences. Tokenizing is the fundamental step for stemming and lemmatization.

Tokenization: Tokenization is the first step in any NLP pipeline. A tokenizer breaks unstructured data and natural language text into chunks of information that can be considered as discrete elements. The token occurrences in a document can be used directly as a vector representing that document. This immediately turns an unstructured string (text document) into a numerical data structure suitable for machine learning.

2. We have eliminated stop words from the dataset as they have no significance in deciding the meaning of the text. Stop words are the most common words in any language. By removing these words, we remove the low-level information from our text in order to give more focus to the important information, and reduces training time. Stemming has been applied to correlate the words belonging to the same root. Stemming is the process of reducing a word to its word stem that affixes to suffixes and prefixes or to the roots of words known as a lemma.

3. Then we would proceed with label encoding, the label encoding is to signify the categorical data for the semi-structured or unstructured data. Label encoding means giving the labels for the data in numerical. Next, stemming is done to produce morphological variants of a root/base word.

4. Stemming programs are commonly referred to as stemming algorithms or stemmers. These algorithms are used to give the domain vocabularies in domain analysis.

5.Neural networks require to have input of the same size. Therefore, sentence inputs are added with 0's after defining the max length and words are dropped and added accordingly.

5. METHODOLOGY:

This section talks about the algorithms used for the project. We used Word to Vector and LSTM(Long Short Term Memory)

5.1 WORD TO VECTOR

Word2Vec model is used for Word representations in Vector Space which is founded by Tomas Mikolov and a group of research teams from Google in 2013. It is a neural network model that attempts to explain word embeddings based on a text corpus.

Word2vec is a two-layer neural network that processes text by "vectorizing" words. Its input is a text corpus, and its output is a set of vectors. Feature vectors that represent words in that corpus. Once trained, such a model can detect synonymous words or suggest additional words for a partial sentence. As the name implies, word2vec represents each distinct word with a particular list of numbers called a vector. The vectors are chosen carefully such that a simple mathematical function (the cosine similarity between the vectors) indicates the level of semantic similarity between the words represented by those vectors.

The General Flow of the Algorithm

- Step-1: Initially, we will assign a vector of random numbers to each word in the corpus.
- Step-2: Then, we will iterate through each word of the document and grab the vectors of the nearest n-words on either side of our target word, concatenate all these vectors, and then forward propagate these concatenated vectors through a linear layer + SoftMax function, and try to predict what our target word was.
- Step-3: In this step, we will compute the error between our estimate and the actual target word and then backpropagate the error, and then modifies not only the weights of the linear layer but also the vectors or embeddings of our neighbor's words.
- Step-4: Finally, we will extract the weights from the hidden layer and by using these weights encode the meaning of words in the vocabulary.
- Word2Vec model is not a single algorithm but is composed of the following two pre-processing modules or techniques:

Continuous Bag of Words (CBOW) model:

The aim of the CBOW model is to predict a target word in its neighborhood, using all words. To predict the target word, this model uses the sum of the background vectors. For this, we use the pre-defined window size surrounding the target word to define the neighbouring terms that are taken into account.

Advantages of CBOW:

1. Generally, it is supposed to perform superior to deterministic methods due to its probabilistic nature. It does not need to have huge RAM requirements. So, it is low on memory.

Disadvantages of CBOW:

1. CBOW takes the average of the context of a word. **For Example,** consider the word apple that can be both a fruit and a company but CBOW takes an average of both the contexts and places it in between a cluster for fruits and companies.

2. If we want to train a CBOW model from scratch, then it can take forever if we not properly optimized it.

Skip Gram:

The continuous skip-gram model learns by predicting the surrounding words given a current word. The Skip-Gram model is trained on n-gram pairs of (target word, context word) with a token as 1 and 0. The token specifies whether the context words are from the same window or generated randomly. The pair with token 0 is neglected. the skip-gram model is the exact opposite of the CBOW model.

Code Implementation of Skip-Gram Model. Steps to be followed:

1.Build the corpus vocabulary

2.Build a skip-gram [(target, context), relevancy] generator

3. Build skip-gram model architecture

4. the Model

5. Word Embeddings

Advantages of Skip-Gram Model

1. The Skip-gram model can capture two semantics for a single word. i.e., two vector representations for the word Apple. One for the company and the other for the fruit.

2. Generally, Skip-gram with negative sub-sampling performs well then, every other method.

5.2 LSTM(LONG SHORT TERM MEMORY)

Deep learning model based LSTM(Long short term memory) method for review rating for trip advisor.

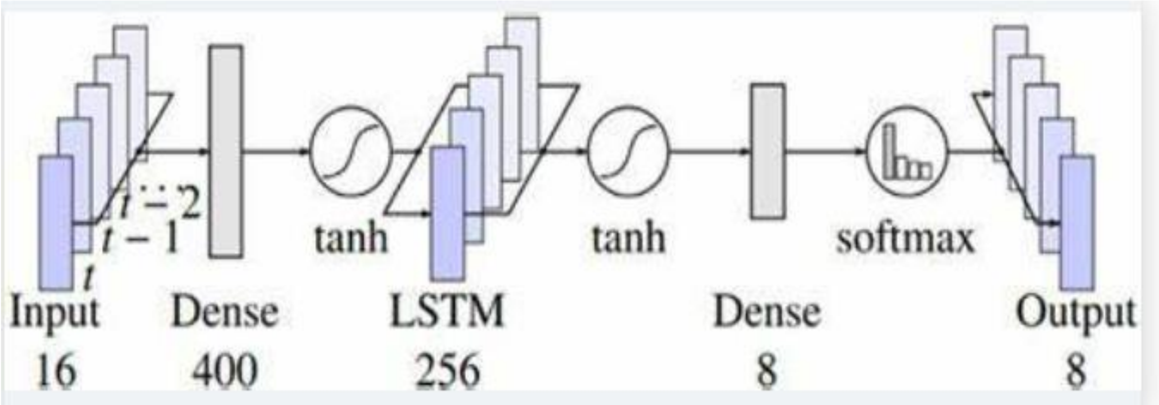

Fig 4: LSTM Model

LSTMs have three types of gates they are:

Input gates, forget gates, and output gates control the flow of information. The hidden layer output of LSTM includes the hidden state and the memory cell. Only the hidden state is passed into the output layer. The memory cell is entirely internal.

All recurrent neural networks have the form of a chain of repeating modules of neural networks. In standard RNNs, this repeating module will have a very simple structure, such as a single tanh layer.

LSTMs also have this chain-like structure, but the repeating module has a different structure. Instead of having a single neural network layer, there are four, interacting in a very special way.

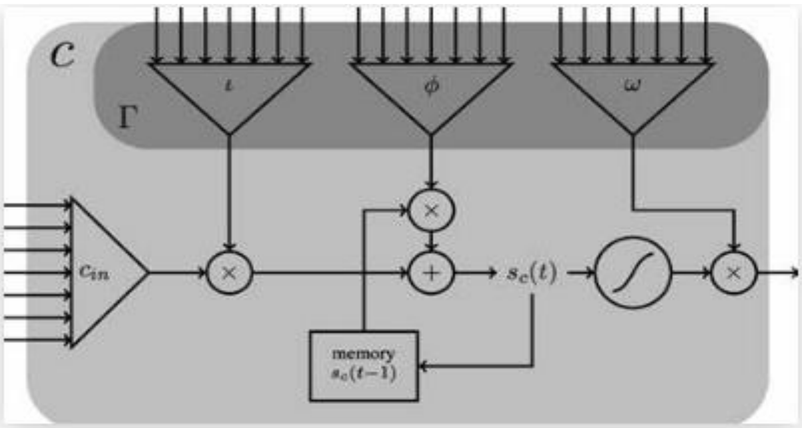

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Fig.5: gated memory cell in lstm

6. RESULTS:

```
score = model.evaluate(x_test, yval, batch_size=32)
print()
print("ACCURACY:",score[1])
print("LOSS:",score[0])
```

```
35/35 [==============================] - 4s 101ms/step - loss: 0.0727 - accuracy: 0.9812

ACCURACY: 0.9811659455299377
LOSS: 0.07265845686197281
```

Figure 8. Result of various models with the proposed model

The neural network deep learning algorithms that we used is LSTM(long-short term memory). This algorithms worked well on trip advising. We got 98% accuracy folds. LSTM has four layers 1)LSTM layer-1 2)LSTM layer-2 3)drop out layer 4)dense layer.

8. CONCLUSION:

The previous or existing trip advising systems used traditional text-based machine learning models. The results highly rely on the crafted extracted features. The performances are unstable when advising trips.

So, we propose a deep learning model based on the LSTM(Long short-term memory) method of trip advising systems. The neural network deep learning algorithm that we used is LSTM(long-short-term memory). This algorithm worked well on trip advising systems. We got 98% accuracy.

During the computation of long text emails which are far away, it is impossible to store which causes tvanishing of the gradient. In order to maintain we use LSTM(Long Short-Term Memory Network)

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