Lecture Notes on Data Engineering
and Communications Technologies 55

P. Karuppusamy
Isidoros Perikos
Fuqian Shi
Tu N. Nguyen *Editors*

Sustainable Communication Networks and Application

Proceedings of ICSCN 2020

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P. Karuppusamy · Isidoros Perikos ·
Fuqian Shi · Tu N. Nguyen
Editors

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Editors
P. Karuppusamy
Department of EEE
Shree Venkateshwara Hi-Tech Engineering
Erode, Tamil Nadu, India

Fuqian Shi
College of Information and Engineering
Wenzhou Medical University
Wenzhou, China

Isidoros Perikos
Department of Computer Engineering
and Informatics
University of Patras
Patras, Greece

Tu N. Nguyen
Department of Computer Science
Purdue University Fort Wayne
Fort Wayne, IN, USA

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This book is gratefully dedicated to all the researchers and editors in the field of Sustainable Communication Networks and Applications.

Foreword

It is with deep satisfaction that I write this Foreword to the proceedings of the ICSCN 2020 held at Surya Engineering College (SEC), Erode, India, during 06–07 August 2020.

This conference brought together researchers, academics and professionals from all over the world, experts in sustainable networking technology, sustainable applications and sustainable computing and communication technologies.

This conference particularly encouraged the interaction of research students and developing academics with the more established academic community in an informal setting to present and to discuss new and current work. The papers contributed the most recent scientific knowledge known in the field of ultra-low-power sustainable system, sustainable vehicular ad hoc networks, Internet-enabled infrastructures for sustainability and sustainable mobility and vehicle management. Their contributions helped in making the conference as outstanding as it has been. The local organizing committee members and volunteers have put much effort ensuring the success of the day-to-day operation of the meeting.

We hope that this program will further stimulate research in sustainable big data frameworks, energy and power-constrained devices, low-power communication technologies, sustainable vehicular ad hoc networks, smart transport systems and smart data analytics techniques.

We thank all authors and participants for their contributions.

Dr. E. Baraneetharan
Conference Chair, ICSCN 2020
Associate Professor & Head
Department of EEE, Surya
Engineering College
Erode, India

Preface

This conference proceedings volume contains the written versions of most of the contributions presented during the conference of ICSCN 2020. The conference provided a setting for discussing recent developments in a wide variety of topics including communications, networks and sustainable applications. The conference has been a good opportunity for participants coming from various destinations to present and discuss topics in their respective research areas.

This conference tends to collect the latest research results and applications on intelligent data communication technologies and networks. It includes a selection of 53 papers from 293 papers submitted to the conference from universities and industries all over the world. All of the accepted papers were subjected to strict peer-reviewing by 2–4 expert referees. The papers have been selected for this volume because of quality and the relevance to the conference.

We would like to express our sincere appreciation to all authors for their contributions to this book. We would like to extend our thanks to the keynote speakers, all the referees for their constructive comments on all papers. Especially, we would

like to thank to the organizing committee for their hard work. Finally, we would like to thank Springer publications for producing this volume.

Dr. P. Karuppusamy
Shree Venkateshwara Hi-Tech Engineering College
Erode, India

Dr. Fuqian Shi
Rutgers Cancer Institute of New Jersey
New Jersey, USA

Dr. Isidoros Perikos
Professor
Department of Computer Engineering
and Informatics
University of Patras
Patras, Greece

Dr. Tu N. Nguyen
Professor
Director of Network Science
Department of Computer Science
Purdue University Fort Wayne
Fort Wayne, USA

Acknowledgements

ICSCN 2020 would like to acknowledge the excellent work of our conference organizing committee, keynote speakers for their presentation during 06–07 August 2020. The organizers also wish to acknowledge publicly the valuable services provided by the reviewers.

On behalf of the editors, organizers, authors and readers of this conference, we wish to thank the keynote speakers and the reviewers for their time, hard work and dedication to this conference. The organizers wish to acknowledge Thiru. Andavar. A. Ramasamy, Ln. K. Kalaiyarasan, Dr. S. Vijayan, Prof. E. Baraneetharan for the discussion, suggestion and cooperation to organize the keynote speakers of this conference. The organizers wish to acknowledge publicly the valuable services provided by the reviewers. Many thanks to all persons who helped and supported this conference. We would like to acknowledge the contribution made to the organization by its many volunteers. We would like to like to acknowledge the contribution made to the organization by its many volunteers and members contribute their time, energy and knowledge at a local, regional and international level.

We also thank all the chairpersons and conference committee members for their support.

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About the Editors

Dr. P. Karuppusamy is working as a Professor and Head in the Department of Electrical and Electronics Engineering at Shree Venkateshwara Hi-Tech Engineering College, Erode, India. In 2017, he had completed doctorate in Anna University, Chennai, and in 2007, he had completed his postgraduate Power Electronics and Drives in Government College of Technology, Coimbatore, India. He has more than 12 years of teaching experience. He has published more than 60 papers in national and international journals and conferences. He has acted as Conference Chair in IEEE and Springer international conferences and Guest Editor in reputed journals. His research area includes modeling of PV arrays and adaptive neuro-fuzzy model for grid connected photovoltaic system with multilevel inverter.

Dr. Isidoros Perikos received the Diploma of Computer Engineer in 2008, the M.Sc. and the Ph.D. on Computer Science from the Department of Computer Engineering and Informatics, University of Patras, in 2010 and 2016, respectively. He is currently an Assistant Professor (adjust) at the Computer Engineering and Informatics Department. His main research interests include artificial intelligence, machine learning, data mining and knowledge extraction, human–computer interaction, natural language processing, and affective computing. He has published over 80 papers in international conferences, journals, and workshops. He is a member of IEEE, ACM, and the Artificial Intelligence in Education Society.

Dr. Fuqian Shi is currently working as a Professor at Wenzhou Medical University, College of Information and Engineering, Prague. He had completed his Ph.D. in Computer Science and Application at Zhejiang University, P.R. China, and completed his M.S. in Control Theory and Engineering at Zhejiang University of Technology, P.R. China. He had published more than 100 papers in national and international journals. He is the reviewer and editorial board member in many reputed journals. His research interest includes computer networks, computer programming, computer graphics, image processing, data structure, operating system, and medical informatics.

Dr. Tu N. Nguyen (Senior Member, IEEE) received the Ph.D. degree in Electronic Engineering from the National Kaohsiung University of Science and Technology (formerly, National Kaohsiung University of Applied Sciences) in 2016. He was a Postdoctoral Associate with the Department of Computer Science & Engineering, University of Minnesota—Twin Cities in 2017. In 2016, he joined the Missouri University of Science and Technology as a Postdoctoral Researcher with the Intelligent Systems Center. He is currently an Assistant Professor with the Department of Computer Science, Purdue University Fort Wayne. His research interests include design and analysis of algorithms, network science, cyber-physical systems, and cybersecurity. He has served as the TPC Chair for the NICS 2019, SoftCOM (25th), and ICCASA 2017, the Publicity Chair for iCAST 2017 and BigDataSecurity 2017, and the Track Chair for ACT 2017. He has also served as a technical program committee member for more than 70 premium conferences in the areas of network and communication such as INFOCOM, Globecom, ICC, and RFID. He has been serving as an Associate Editor for the EURASIP Journal on Wireless Communications and Networking since 2017 and IEEE ACCESS since 2019. He has also been the Editorial Board of Cybersecurity journal, Internet Technology Letters since 2017, the International Journal of Vehicle Information and Communication Systems since 2017, the International Journal of Intelligent Systems Design and Computing since 2017, and IET Wireless Sensor Systems since 2017.

A Long Short-Term Memory (LSTM) Model for Business Sentiment Analysis Based on Recurrent Neural Network

Md. Jahidul Islam Razin, Md. Abdul Karim, M. F. Mridha, S. M. Rafiuddin Rifat, and Tahira Alam

Abstract Business sentiment analysis (BSA) is one of the significant and popular topics of natural language processing. It is one kind of sentiment analysis techniques for business purpose. Different categories of sentiment analysis techniques like lexicon-based techniques and different types of machine learning algorithms are applied for sentiment analysis on different languages like English, Hindi, Spanish, etc. In this paper, long short-term memory (LSTM) is applied for business sentiment analysis, where recurrent neural network is used. LSTM model is used in a modified approach to prevent the vanishing gradient problem rather than applying the conventional recurrent neural network (RNN). To apply the modified RNN model, product review dataset is used. In this experiment, 70% of the data is trained for the LSTM and the rest 30% of the data is used for testing. The result of this modified RNN model is compared with other conventional RNN models and a comparison is made among the results. It is noted that the proposed model performs better than the other conventional RNN models. Here, the proposed model, i.e., modified RNN model approach has achieved around 91.33% of accuracy. By applying this model, any business company or e-commerce business site can identify the feedback from their customers about different types of product that customers like or dislike. Based on the customer reviews, a business company or e-commerce platform can evaluate its marketing strategy.

Md. Jahidul Islam Razin · Md. Abdul Karim (✉) · S. M. Rafiuddin Rifat · T. Alam
Department of Computer Science and Engineering, University of Asia Pacific, 74/A Green Road, Dhaka, Bangladesh
e-mail: karim.cse007@gmail.com

Md. Jahidul Islam Razin
e-mail: razin.cse@gmail.com

S. M. Rafiuddin Rifat
e-mail: rifat.cse@uap-bd.edu

T. Alam
e-mail: tahira.cse@uap-bd.edu

M. F. Mridha
Bangladesh University of Business and Technology, Dhaka, Bangladesh
e-mail: firoz@bubt.edu.bd

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Keywords Business sentiment analysis · Product reviews · Recurrent neural network · LSTM

1 Introduction

Nowadays, the Internet is a fundamental part of our daily life. All fields of information are rising exponentially every moment, where it is easier to share our opinions on e-commerce websites, forums and media for various types of products and services. It provides essential information about some different number of domains and some social applications. It is difficult to handle these huge amounts of data manually. For this reason, business sentiment analysis (BSA) is very feasible, which also provides an idea on the requirements of people. It has become a popular research topic in natural language processing domain. Analysis of reviews can quickly extract information from a text and can also define the target and opinion polarity. Various types of social applications and websites can use BSA to forecast consumer patterns, economic policies and stock market forecasting.

Researchers perform business sentiment analysis using various machine learning (ML) techniques. ML's support learning models include support vector machines (SVM) [1], logistic regression [2], naive Bayes (NB) [3], random forests [4] and so on. Artificial neural network (ANN) is one of the areas of ML [5]. ANN also has various forms like recurrent neural network (RNN) [6] and convolution neural network (CNN) [7]. Artificial neural networks are mainly constructed using three layers. These are the input layer, hidden layer and output layer. This concept is extended in deep learning. Deep learning is constructed using more than two hidden layers. How much deeper the network is defined by the layers used in the hidden layer. Deep learning is a part of artificial neural network. Deep learning gives much better services than other ML techniques like SVM, NB, etc. These techniques are used in all natural language processing fields like all types of recognition (speech, entity, pattern) [8] and computer vision techniques. For its accuracy level, it has become very popular nowadays. Good accuracy can be achieved if the representation of data is perfect. Conventional ML algorithms are depending on handcrafted characteristics. But deep learning needs high computation ability and storage to increment the number of hidden layers as comparison to conventional ML algorithms and getting better performance. Deep learning technique can adapt more swiftly as it will get more and more training data. As business sentiment analysis needs to process a lot of data for the prediction, and this motivated us to apply deep learning technique for business sentiment analysis [9].

The importance of consumer views and the vast amounts of centric data are available to the public and the unpredictability of the market climate has led the organization to introduce monitoring and tracking measures such as sentiment analysis, which is mainly performed here as business sentiment analysis.

The principal contribution of the proposed research work can be summed up as follows. This paper presents the study of the business sentiment function by a list of product feedback. Using the proposed model, the reviews are divided into three categories, which are positive, neutral and negative. A well-defined text dataset is used to apply long short-term memory (LSTM) as a part of modified RNN model that gives better accuracy result in comparison to conventional RNN model. This is a different approach when compared to traditional feed-forward networks [10].

A feed-forward network takes a limited text for predicting the next word. Here, RNN can easily use previous words for prediction. An RNN model sees the text as a signal made up of terms, where it is presumed that recursive weights reflect short-term memory. LSTM is different, which is a part of the RNN structure in the ANN network. It is allowed for both long and short patterns and it sorts out the problem of vanishing gradient. So, LSTM is now approved in several numbers of applications and it is a promising practice for business sentiment analysis.

This article is structured as follows. Section 2 explains the related works and the motivation of this research. Section 3 discusses about the methodology. Section 4 discusses about implemented tools. Section 5 explains result and analysis. Section 6 concludes the paper.

2 Related Work

Several numbers of researches have been performed on sentiment analysis for different languages using different types of neural networks. Some of them are summarized as follows.

Xu et al. [11] applied supervised learning algorithms like the perceptron algorithm, naive Bayes and support vector machine to predict the reviewer's ratings. They used 70% data for training and 30% data for testing. They also determine the precision and recall values for the different classifiers.

Deep learning is very popular in this area of sentiment analysis. Sujata Rani, Parteek Kumar, applied convolution neural network for sentiment analysis [12]. After cross-validation, they have used 50% data as train data and 50% for test data.

Mikolov et al. [13] proposed a model applying recurrent neural network (RNN); it is used for processing sequential text data. An RNN model is depending on the input layer, hidden layers and output layer. When an RNN model is performed, the input layer is added with the hidden layer, which is arranged for a new input layer to calculate the hidden layers. This is working as a loop and it has been repeated after a limit of time '*t*.' All the information from the previous layer is successfully reversal using it. For this, the performance is increased and also helping to squint all words in sequential order. So, this model is beneficial for looping and sequencing facilities.

However, the RNN model covers the orderly structure of the text and it can fix a short-term dependence problem. But it is not possible to fix the long-term dependence problem using RNN, because it cannot gain any knowledge properly from the long term. If there is an interval between two relative texts and the current location is larger, then there will always be a problem in the RNN model. As there are many layers in the back-propagation through time optimization algorithm (BPTT), it is indicating the loss of information while training. So, long short-term memory (LSTM) is used for our business sentimental analysis, where it provides better results than the traditional RNN model.

3 Methodology

This section will describe our method for business sentiment analysis from reviewer's text data. For business sentiment analysis, long short-term memory (LSTM) is used. The LSTM model is designed for avoiding long-term dependency. Remembering that long-term dependency is the default behavior of LSTM. This model is most popular with researchers. Within this model, the RNN node is replaced by the LSTM cell, which can easily store previous knowledge. For this reason, business sentiment analysis using LSTM is better than other methods.

Our proposed method is divided into four phases:

3.1 Discussion about RNN and LSTM architecture.
3.2 Data processing.
3.3 Training the model.
3.4 Testing new data.

3.1 Discussion About RNN and LSTM Architecture

LSTM is a subsection of RNN and there are many similarities between them. This work has proposed some structural diagram and brief discussion about LSTM and RNN.

Figure 1 [14] provides an illustration of a traditional RNN model where $X(t)$ is input, $h(t)$ is output and A is the neural network that can gain knowledge from the previous. One output goes to another and passed the information easily.

Figure 2 [14] provides a clear knowledge of a single LSTM cell. LSTM model is kind of similar like standard RNN, except that the memory block is just replaced into the hidden layer, as in Fig. 4 [14]. The symbols in Fig. 3 [14] have the following meanings. X is using for scaling of information, σ means Sigmoid layer, '$\tan h$' means hyperbolic Tangent layer, $h(t-1)$ means sigmoid layer, '$\tan h$' means hyperbolic tangent layer, $h(t-1)$ means output of last LSTM unit, $c(t-1)$ means memory from last LSTM unit, $X(t)$ means current input, $c(t)$ means new updated memory,

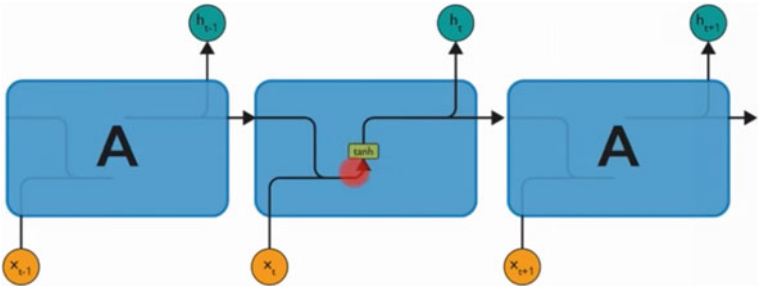

Fig. 1 The structural diagram of RNN model

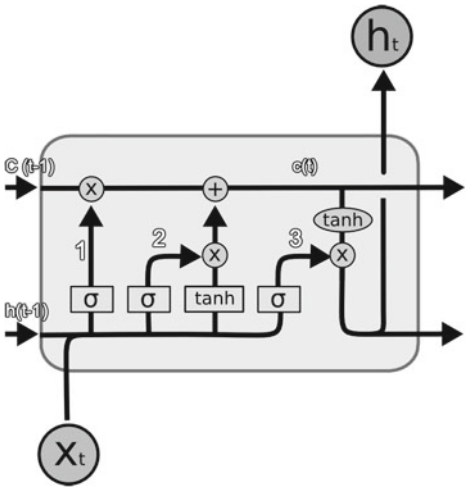

Fig. 2 Structural diagram of LSTM cell (a)

$h(t)$ means current output. In RNN, only the hyperbolic tangent layer is using to overcome the vanishing gradient problem [15]. The second derivative of the hyperbolic tangent function can solve the problem before going to zero. But it cannot forget or remember anything. That is why the sigmoid layer is also used in LSTM model with the hyperbolic tangent layer. Sigmoid can output 0 or 1, which is used to forget or remember the information.

The first step in the LSTM is to find the useless text which is not needed and also thrown away from the cell state. It is achieved by a sigmoid layer, called a forget layer. New pieces of information will be processed in the cell in the second level, which will be decided by a sigmoid layer called the gate layer of the data. In the third stage, the old cell state updates into the new cell satellite with the above-mentioned input gates and forgets gates information. The output gate essentially defines the output value, which is dependent on the cell state.

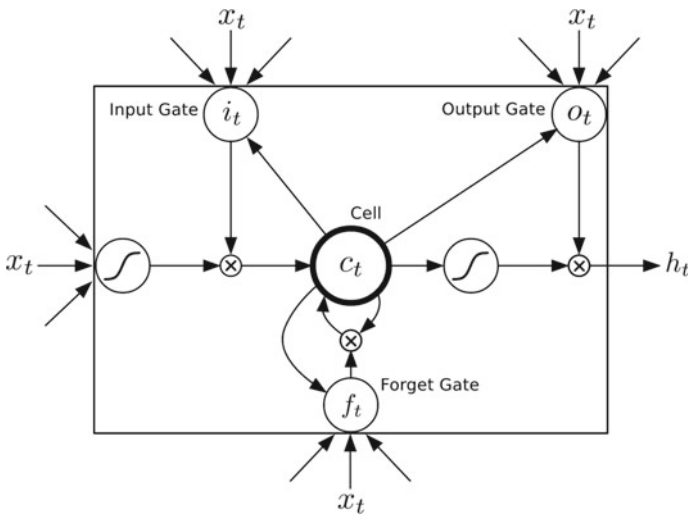

Fig. 3 Structural diagram of LSTM cell (b)

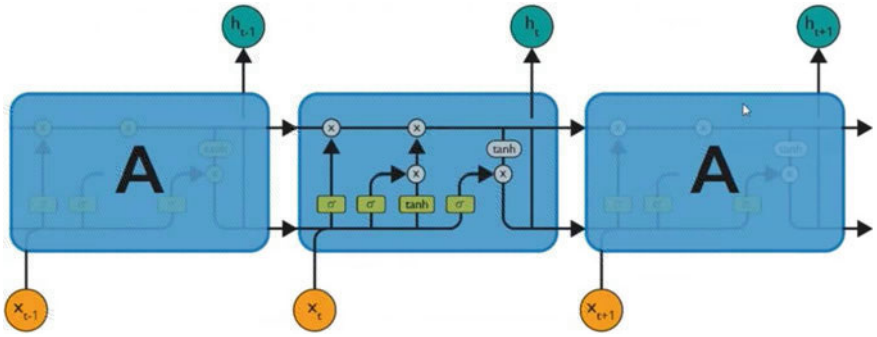

Fig. 4 LSTM architecture

Mainly, four steps of calculation process in LSTM.

- Initially calculates the forget gate values and input gate values.
- Update the cell stage of LSTM.
- Calculate output gate's value.
- Lastly update the cell state [16–19].

All equations are shown in below [14].
Input Gates:

$$i_t = \sigma(x_t U^i + h_{t-1} W^i) \tag{1}$$

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, None, 32)          640000
_________________________________________________________________
lstm_1 (LSTM)                (None, 100)               53200
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 101
=================================================================
Total params: 693,301
Trainable params: 693,301
Non-trainable params: 0
_________________________________________________________________
None
```

Fig. 5 LSTM network

Forget gates:

$$f_t = \sigma(x_t U^f + h_{t-1} W^f) \tag{2}$$

Cells:

$$\underline{C}_t = \tanh(x_t U^g + h_{t-1} W^g) \tag{3}$$

$$C_t = \sigma(f_t \times C_{t-1} + i_t \times \underline{C}_t) \tag{4}$$

Output gates:

$$O_t = \sigma(x_t U^o + h_{t-1} W^o) \tag{5}$$

Cell output:

$$h_t = \tanh(C_t) \times O_t \tag{6}$$

RNN and LSTM consider the problem of the vanishing gradient via a sequenced sentence of text. RNN model will display lower error rate. But when there is a long text argument, LSTM is more effective at overcoming the vanishing gradient problem. In our business sentiment analysis, the modified RNN-based LSTM model is applied. The proposed model is shown in Figs. 5 and 6.

3.2 Data Processing

To train the proposed model, a business review dataset is collected from amazon.com on product analysis. The dataset was created by Web scraping or APIs. Researchers

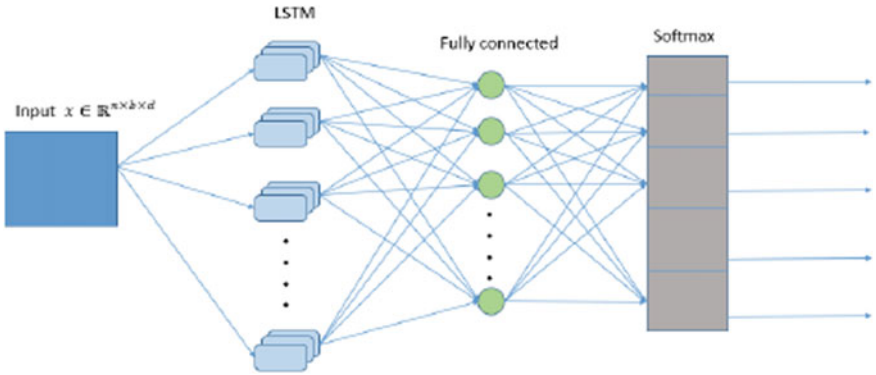

Fig. 6 LSTM architecture

compiled the information from Amazon Review Information (ARD) when it comes to Amazon datasets [20]. This dataset contained punctuation and HTML tags. In order to vanish these, a function is used for taking a text string as a parameter and then preprocess the string to remove punctuation and HTML tags from the given string. These punctuation and HTML tags are replaced with an empty space. All the single characters and multiple spaces are removed. At last for each term, the analysis text is naturally divided into emotions of the business class. Then, a tool is used for vector representation to transform every term into a vector using the vector equation:

$$v \in R_1 \times d \tag{7}$$

which is known as the word embedding. Here, word2vector tools are used. Then the cycle was followed by the natural order; the sentence of participles was traversed from left to right, which is the forward calculation of LSTM. The results of the production depended on the probabilities of the word at 't' time and also the sequence of vocabulary giving before 't' time. Finally, the error was determined by the likelihood of a common distribution of all the words in the sentences.

3.3 Training the Model

After preprocessing the data and splitting the dataset, LSTM model is used to train our model. LSTM layer is created with 100 neurons and also added a dense layer with sigmoid activation function.

The process is introduced as follows:

- Due to their emotional marks, all training data is divided into three groups, has positive, negative and neutral. The LSTM models are then trained in each data

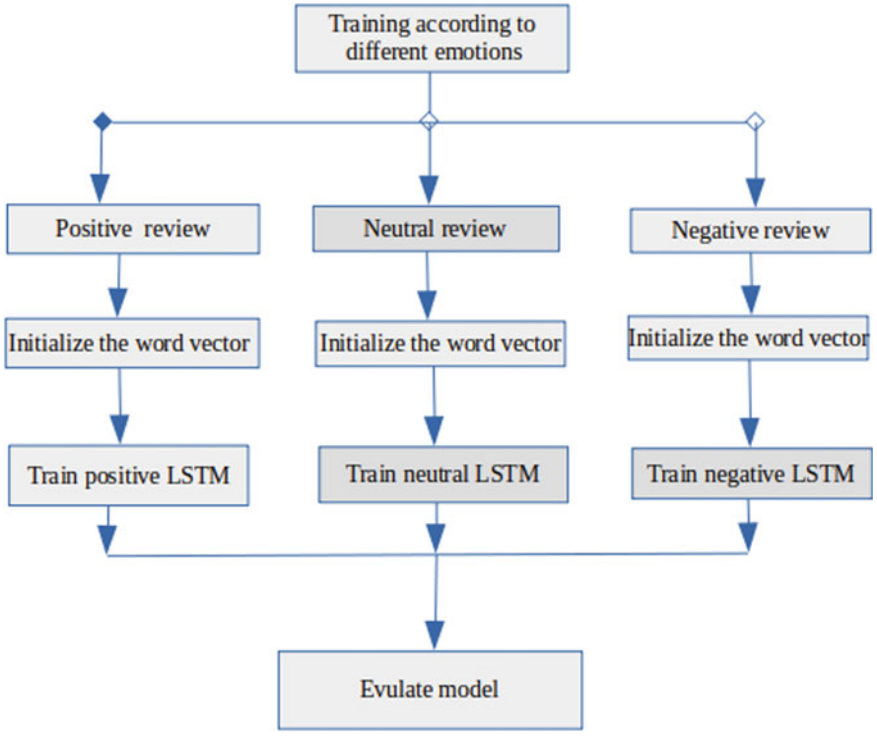

Fig. 7 Business sentimental emotion classification

category and with multiple LSTM models resulting in them as well. This is done for equal ratings.

- To get a new input review, the LSTM models are available in the training phase evaluated on the new input review. The model which is giving the smallest error value is assigned to the new input review.

Figure 7 is showing the structure of the processing of the training phase: This model could overcome the vanishing gradient problem completely than the conventional RNN model. It also better performs in many experiments, like as structure with conjunctions, such as, 'not only…but also…,' 'However,' 'in addition,' etc.

3.4 Testing the Model

After training the model, new text data is used for testing our model. When a new product review is coming, this model has classified the new review as negative, positive or neutral.

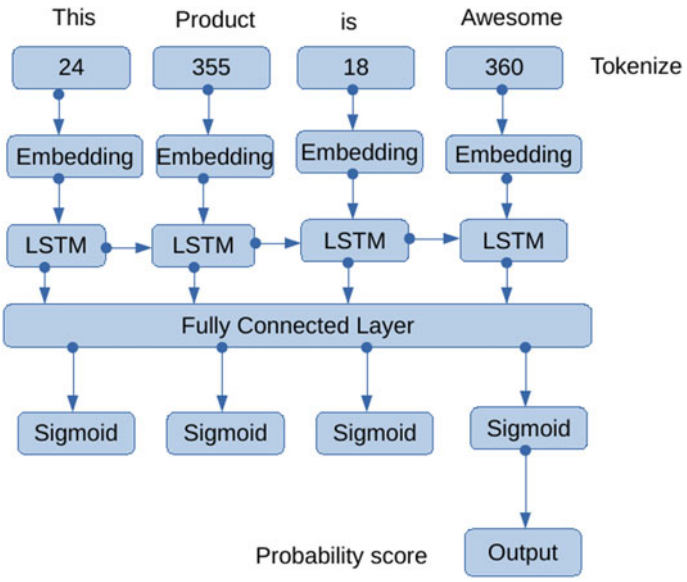

Fig. 8 RNN-LSTM working process in business sentiment analysis

Figure 8 described the working process of our RNN-LSTM model in business sentiment analysis.

4 Implementation Tools

The proposed work has used the Jupyter Notebook [21], which is an open-source Web platform. It has helped to develop an environment to perform our experiments and also creating and sharing all types of documents like code, text, equations and visualizations. The LSTM-RNN model is developed using TFLearn (deep learning library) Python packages, which are installed at the top of the TensorFlow [22]. The proposed work also uses Keras (NNs API) [23], which is written with Python and runs in TensorFlow.

5 Result and Analysis

The analysis of the outcome along with the result for the entire system is discussed in this section. The outcome is splitted into three parts. This is an experimental dataset (Sect. 5.1), Experiment Result Analysis (Sect.5.2) and Comparison (Sect.6).

Table 1 Accuracy of LSTM model

Epoch	Training accuracy	Testing accuracy
10	0.9504	0.8954
30	0.9551	0.9092
50	0.9623	0.9193

5.1 Experimental Dataset

Amazon Review Information Dataset (ARD) [20] contains 142.8 million ratings and a variety of metadata. This work has taken a selected amount of data from this dataset. After taking the data from dataset, all the data has been categorized into positive, neutral and negative. Then Word2Vec tools are used to create word embedding for our LSTM model. After that, it has been gone through the LSTM layer. There is a Dense() layer, which is the final layer of the model. It can crunch all the output that is coming from the LSTM layer and convert it as a single numeric value of 0.0 and 1.0.

Total of 25,000 product reviews, which are divided into a 70% items for the training set and a 30% items for the testing set. Then train and test have been performed by the proposed model. It achieved 95.04% (from Table 1) accuracy on the training data and 89.54% accuracy on the test data for 10 epochs. Then increasing the epoch size into 20, our accuracy for training data 95.51% and accuracy for test data 90.92%. Again, the epoch size is increased from 20 to 50, then the accuracy on training data will be 96.23% and accuracy on testing the data will be 91.33%. If epoch size is increased more than 50 iteration, the deference between training and test result is increased a lot and overfitted. That is why the epoch size is not increased more than 50. Figure 9 is showing the training and testing loss; after 20 iteration, here blue line are showing training loss and orange line are showing testing loss.

Figure 10 is showing the training and testing accuracy; here, blue line is indicating training accuracy and orange line is indicating testing accuracy. Our model test data accuracy is 91.33%.

5.2 Experiment Results Analysis

After training and testing this model, it can easily classify a new product review, which is previously unseen. Previously unseen product review of, ‘ The product was not so great.’ Here, the prediction probability value is around 0.1368. From Table 2: When the value is less than 0.30, the model predicts it as very bad. If the value is greater than 0.30, then it is predicted as bad. When the value is greater than 0.50, then it is positive. When the value is greater than 0.60, then it is predicted as good. When it is greater than 0.80, then it is predicted as excellent. For multi-valued analysis, it is required to encode as positive (0, 0, 1), neutral (0, 1, 0) and negative (1, 0, 0).

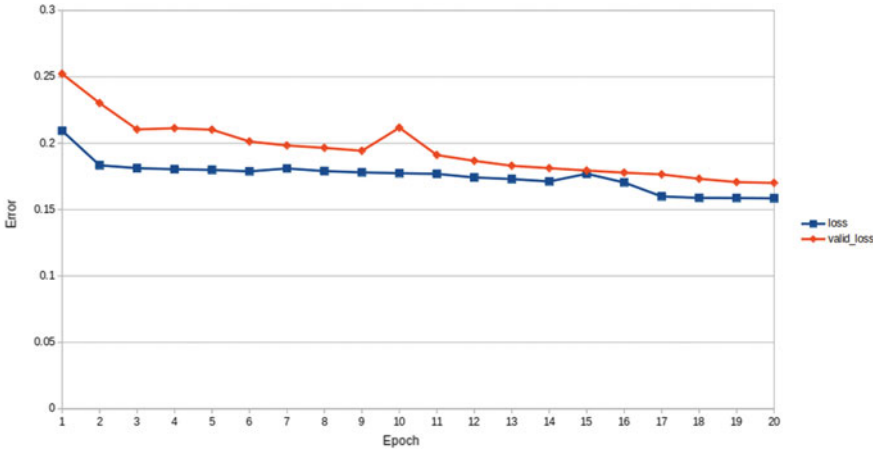

Fig. 9 Loss versus epoch graph

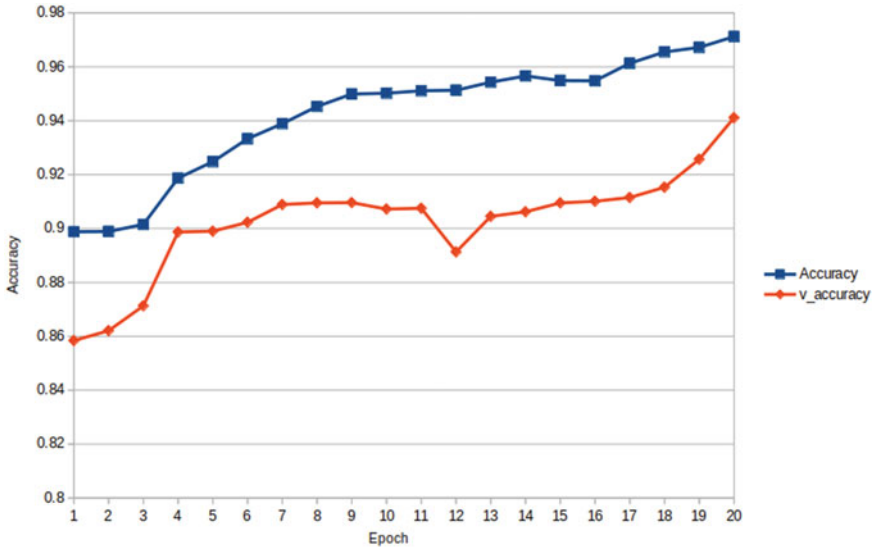

Fig. 10 Accuracy versus epoch graph

Table 2 Review type

Prediction	Result
Greater than 0. 80	Excellent
Greater than 0.60	Better
Greater than 0.50	Good
Less than 30	Very bad
Greater than 0.30	Bad

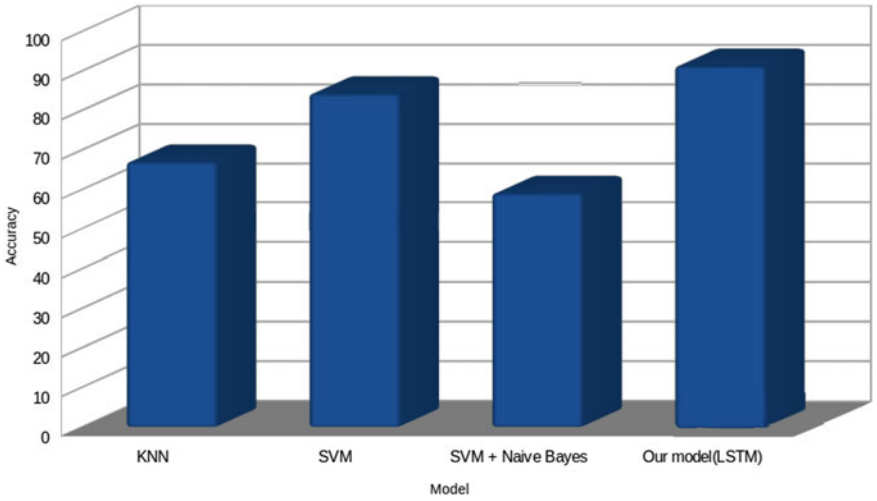

Fig. 11 Comparison with other models (Accuracy)

6 Comparison

Mohammad Rezwanul Huq and Ahmad Ali proposed a two model for sentiment classification [24]. Their model is based on k-nearest neighbor (KNN) and another model is based on a support vector machine (SVM). 84.32% accuracy is achieved based on KNN model and 67.03% accuracy is achieved based on SVM model. Xu et al. [11] applied SVM and naive Bayes model to predict the reviewer's rating. 88.8% accuracy is achieved on training data by this model and 59.1% accuracy is achieved on testing data. Figure 11 is showing a comparison graph between different models and their accuracy. Here, our model has been achieved 91.33% accuracy, which is better and maximum than other proposed models.

7 Conclusion

In this paper, an LSTM model based on RNN is used to evaluate the business sentiment. It covers all the sequences and performance of business sentiment analysis. This model is used for multi-classification in product reviews. This model can be used for any kind of product review datasets for different languages. In the future, it will be attempted to improve our algorithm for obtaining a better accuracy rate by preprocessing the dataset before feed into the model and by proper feature engineering and tuning. The dataset is required to adjust depending on our local market, which is more balanced than this one. Further, a Web tool will be developed for our local market in order to help the local businesses.