AN APPLICATION METHOD OF LONG SHORT-TERM MEMORY NEURAL NETWORK IN CLASSIFYING ENGLISH AND TAGALOG-BASED CUSTOMER COMPLAINTS, FEEDBACKS, AND COMMENDATIONS

Ralph Sherwin A. Corpuz *

Technological University of the Philippines
Philippines

***** Corresponding Author, e-mail: ralphsherwin_corpuz@tup.edu.ph

Abstract: Classifying unstructured text data written in natural languages is a cumbersome task, and this is even worse in cases of vast datasets with multiple languages. In this paper, the author explored the utilization of Long Short-Term Neural Network (LSTM) in designing a classification model that can learn text patterns and classify English and Tagalog-based complaints, feedbacks and commendations of customers in the context of a state university in the Philippines. Results shown that the LSTM has its best training accuracy of 91.67% and elapsed time of 34s when it is tuned with 50 word embedding size and 50 hidden units. The study found that the lesser the number of hidden units in the network correlates to a higher classification accuracy and faster training time, but word embedding size has no correlation to the classification performance. Furthermore, results of actual testing proven that the proposed text classification model was able to predict 19 out of 20 test data correctly, hence, 95% classification accuracy. This means that the method conducted was effective in realizing the primary outcome of the study. This paper is part of a series of studies that employs machine and deep learning techniques toward the improvement of data analytics in a Quality Management System (QMS).

Key words: Long Short-Term Memory, Deep Learning, Neural Network, Text Classification, Natural Language Processing, Customer Satisfaction.

1. INTRODUCTION

In the era of the so-called *Fourth Industrial Revolution (4IR),* organizations are constantly challenged to remain relevant with their visions and missions, particularly in consistently delivering quality products and services. This challenge is likewise evident in the case of state universities, wherein the satisfaction of students, parents, research and industry partners, including the regulatory bodies are considered crucial toward effective management of their core and support processes and toward the identification of areas for improvements [1]. For this purpose, state universities deploy various methods to determine, monitor, and evaluate customer satisfaction (CS), such as paper-based or online customer surveys, group discussions, and face-to-face or telephone interviews [2]. Among these methods, the most-widely used are the CS surveys, which usually have a Likert scale with set of questionnaires and a section used to capture feedbacks, commendations, or complaints of customers. While the numerical data are easily interpretable as measure of CS, the texts written in natural languages by customers are meaningful since they give direct insights on customer preferences, emotions or extent of satisfaction or dissatisfaction on the quality of product of services they received or experienced [3].

On the other hand, however, these text data are unstructured and highly dimensional to be analyzed computationally. Hence, this is where natural language processing (NLP) techniques, such as text classification, are explored in order to automate text analysis and prediction [3, 4]. Text classification is a process of labelling texts according to learned combination of feature sets (inputs) and their corresponding classes (outputs) [5]. Initially, each input text is converted into numerical vectors in order to extract only the meaningful features. Afterwards, a feature engineering technique is used to manipulate the features while an algorithm is used to design, train, and validate a proposed text classification model. Consequently, the resulting model learns text patterns then classifies texts automatically. Through effective text classification models, CS reports can now be generated faster and more accurately due to lesser-to-no human errors. Hence, text classification is considered an indispensable NLP application due to its capability to optimize manpower efforts, time, costs, and operational resources, and it is even more useful in cases of multiple datasets and languages. [6, 7]. For state universities, these results equate to a timelier response to the needs and expectations of customers and faster decision-making of the administrators toward the continual improvement of its processes, services, and products – quality curricular programs, research and extension projects.

One of the most robust and popular algorithms used in multitude of classification applications is the Long Short-Term Memory Neural Network (LSTM), which is considered as the most popular type of Recurrent Neural Network (RNN). LSTM is capable of addressing vanishing gradients, which is the main problem of RNN and other neural networks. In this case, it works by learning long-term dependencies between time steps of sequence data through the use of memory cell that remembers certain information over random time intervals, and gates that regulate the flow of information into and out of the memory cell [8]. Shown on Fig. 1 is a sample architecture of an LSTM layer. The direction of the arrows illustrates how the time series "i" flow based on features "F" and length "S". In every time step "t", the values of "o_t" and "c_t" denote the output or *hidden state*, and the *cell state* of the LSTM layer, respectively.

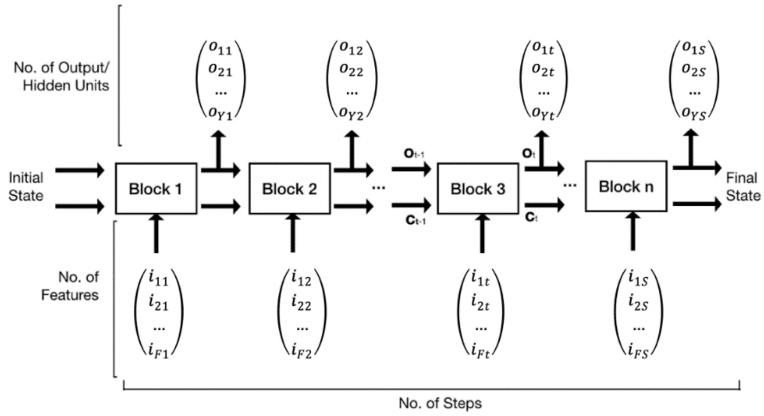


Figure 1. LSTM Layer Architecture

The basic unit of an LSTM layer is called a memory cell or a block. In block 1, for instance, the LSTM computes the first *hidden state* and updated *cell state* through its initial state and the first time step of the sequence. The LSTM then utilizes the current step of the network "c_{t-1} , o_{t-1}" and the next time step of the sequence in order to compute for the *hidden state* "o_t" and the updated *cell state* "c_t". Both the *hidden state* and *cell state* form-part of the LSTM layer state. The output of the LSTM layer is made-up of the *hidden state* for every particular time step "t". The information learned from the previous time steps are stored in the *cell state*. The LSTM layer then adds or removes information to and from the *cell state* in every time step, and controls this information through its gates. Illustrated further on Fig. 2 are the components of a sample LSTM block composed of 4 gates, namely: (1) *input gate "ig"* that controls the updates; (2) *forget gate "fg"* that resets the cell state; (3) *cell candidate "cc"* that adds information to the *cell state*; and (4) *output gate "og"* that controls the level of *cell state* as added to the *hidden state.*

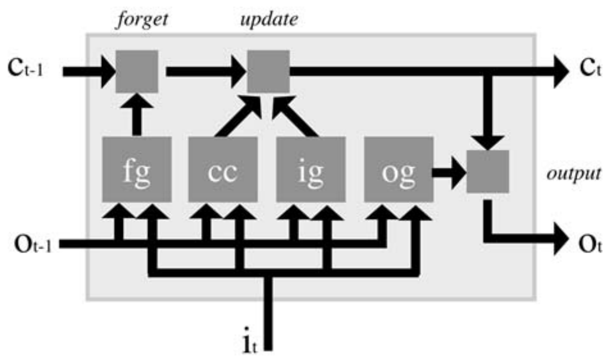


Figure 2. LSTM Block Components

Each gate of an LSTM layer learns information through its input weights “I_W”, recurrent weights “R_W”, and bias “b”, as expressed further in the following concatenated matrices:

$$I_w = \begin{pmatrix} I_{w_{ig}} \\ I_{w_{fg}} \\ I_{w_{cc}} \\ I_{w_{og}} \end{pmatrix}, R_w = \begin{pmatrix} R_{w_{ig}} \\ R_{w_{fg}} \\ R_{w_{cc}} \\ R_{w_{og}} \end{pmatrix}, b \begin{pmatrix} b_{ig} \\ b_{fg} \\ b_{cc} \\ b_{og} \end{pmatrix}, \qquad (1)$$

The *cell state* at time step “t” is expressed in the following formula. The symbols “⨀” is equivalent to the Hadamard product of vectors:

$$c_t = fg_t \odot c_{t-1} + ig_t \odot cc_t \qquad (2)$$

Meanwhile, the *hidden state* at time step “t” is determined by the following formula:

$$o_t = og_t \odot \sigma_c\,(c_t) \qquad (3)$$

where “σ_c” is the gate activation function computed by the sigmoid function:

$$\sigma\,(z) = (1 + e^{-z})^{-1} \qquad (4)$$

The following formulas are used to further describe the components of the time step “t” for each input gate, forget gate, cell candidate, and output gate, respectively:

$$ig_t = \sigma_{cc}\big(Iw_{ig}\, i_t + Rw_{ig}\, o_{t-1} + b_{ig}\big) \qquad (5)$$

$$fg_t = \sigma_{cc}\big(Iw_{fg}\, i_t + Rw_{fg}\, o_{t-1} + b_{fg}\big) \qquad (6)$$

$$cc_t = \sigma_c(Iw_{cc}\, i_t + Rw_{cc}\, o_{t-1} + b_{cc}) \qquad (7)$$

$$og_t = \sigma_{cc}\big(Iw_{og}\, i_t + Rw_{og}\, o_{t-1} + b_{og}\big) \qquad (8)$$

There is a wide-range of research papers related to the application of LSTM in text classification. LSTM has shown satisfactory performance in classifying patent documents [9], hotel sentiment analysis [10], settlement tweets [11], and healthcare documents [12]. As compared with other algorithms, LSTM has been found to have better accuracy than k-Nearest Neighbors (KNN), Naïve Bayes, Convolutional Neural Network (CNN), and other traditional training algorithms [9], [13], [14], [15]. However, there is a dearth of research studies related to the implementation of LSTM in classifying feedbacks, complaints, and commendations written in English and Tagalog languages. Specifically, the motivation of this paper focused in understanding the effects of manipulating hyper-parameters to enhance the learnability of a proposed text classification model. This study is one of its kind in the context of a state university in the Philippines. The resulting model is expected to be of help in automating classification of massive CS datasets, hence, expediting the generation of timely and accurate CS reports and related documents.

2. METHODOLOGY

2.1. Pre-processing

The author utilized the CS dataset from the Technological University of the Philippines – Manila, Philippines as of May 30, 2020. Illustrated on Fig. 3 is a screenshot of the 244 dataset composed of feedbacks (97), complaints (33), and commendations (114) written in English and Tagalog languages. In the dataset, the "text" were used as input and the "classification" as output. For the entire course of the study, the author employed MATLAB R2020a application in a 2.5 GHz, Intel Core i5 CPU with 8GB 1600 MHz DDR3 RAM.

Text	Categorical
Text	Classification
Answered all my queries in details	Commendation
The staff are very friendly and approachable.	Commendation
Keep up the good work!	Commendation
I would like to commend the CIE Dean's office for being very accommodating to the students.	Commendation
Too noisy, no discipline inside library, staff doesn't care if noisy, very disturbing,	Complaint
She's not doing her job. Give attention to her job, avoid using cellphone while she is on duty.	Complaint
Unfair treatment of faculty performance in research in the area of NBC 3.1.1.d on reseach results.	Complaint
Collect the trash more often	Feedback
Proper processing of papers should be observed. On schedule request should also be properly observed. ...	Feedback
They should propose standard index form for the university	Feedback
Masungit di ngumingiti. Student friendly dapat.	Complaint
Laging galit at mainit ang ulo. Give her 2 months vacation. I bet she needs it.	Complaint
Masungit, di ngumiti.	Complaint
Hindi sya nag eentertain at ang sungit ng apprach. kung kelan lang gusto dun sya mag tatrabaho. Sana sa...	Complaint
Gawin ng maayos ang trabaho at tama. Wag pong mainit ang ulo sa amin	Feedback
Sana po araw-araw malinis ang CR.	Feedback
Yung basurahan pakuha naman	Feedback
Magkaroon ng sipag sa trabaho	Feedback
I don't know in particular, but everyone that, talk to here everytime I visit is always pleasant, I guess, I co...	Commendation
Marami pong Salamat, Dr. Guevarra.. Taas kamay po ang pagsaludo ko sa inyo :)	Commendation

Figure 3. Sample Dataset Written in English and Tagalog-English Languages

The author then partitioned 90% of the total dataset for training and 10% for validation. Afterwards, the author pre-processed the dataset in order to extract only the most useful features. At this phase, the author converted the unstructured, raw texts into tokenized documents or string of words called tokens. The author then normalized, lemmatized the tokenized documents into their root forms; removed the stop words, punctuations, words with less than 2 or more than 15 characters, special characters, and HTML and XML tags. A sample result of preprocessing is reflected on Fig. 4a. As shown, an English commendation "*The staff are very friendly and approachable"* is trimmed down into *"staff friendly approachable"* with a total of 3 tokens. Another is a Tagalog feedback *"Yung basurahan pakuha naman"* ("kindly get the garbage") which is trimmed into *"yung basurahan pakuha naman"* with a total of 4 tokens. Meanwhile, Fig. 4b shows sample results of preprocessing of 5 English and 5 Tagalog datasets used during training and validation. It is noted that Tagalog texts generally has more tokenized words due to translation constraints of the function built-in the MATLAB.

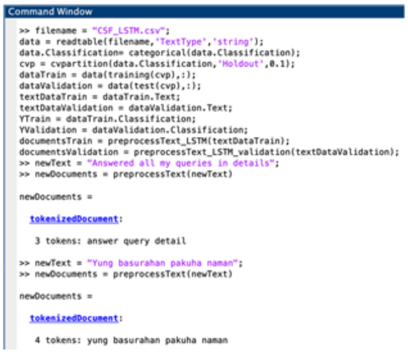


Figure 4a. Preprocessing function

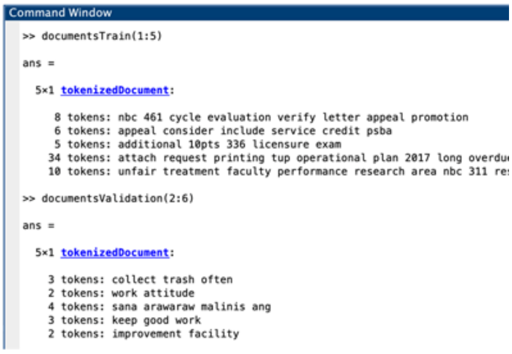
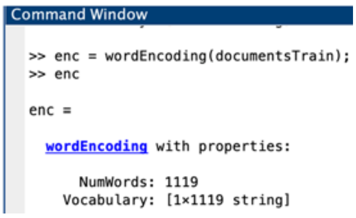


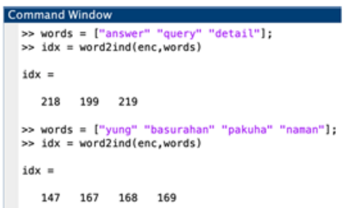
Figure 4b. Sample processing results

2.2. LSTM Text Classification Model Design

After pre-processing, the author then set the target length of each tokenized document into “60” since majority of the tokenized documents have 60 tokens. The author then left-padded those documents with lesser than 60 and truncated those with greater than it. This technique was employed in both training and validation datasets. Subsequently, the author utilized a feature engineering technique called *wordEncoding* (WE) in order to convert the tokenized documents into sequences of numeric indices. Shown on Fig. 5a is the WE function that generated a total of 1119 vocabularies called *NumWords*. In Fig. 5b, these *NumWords* are converted into their equivalent numerical indices, for instance “answer”, “query”, and “detail” are translated into 218, 199, and 219 indices; and then “yung (that)”, “basurahan (bin)”, “pakuha (get)”, and “naman (please)” are converted into 147, 167, 168, and 169 indices, respectively. Lastly, Fig. 5c shows the mapping of sample *NumWords* with sequence of indices from 147 to 169, and another from 199 to 220. These sequence of indices facilitates in resolving the vanishing gradient problems of text data, hence, they help improve the learning capabilities of the LSTM.



(a) 1119 NumWords

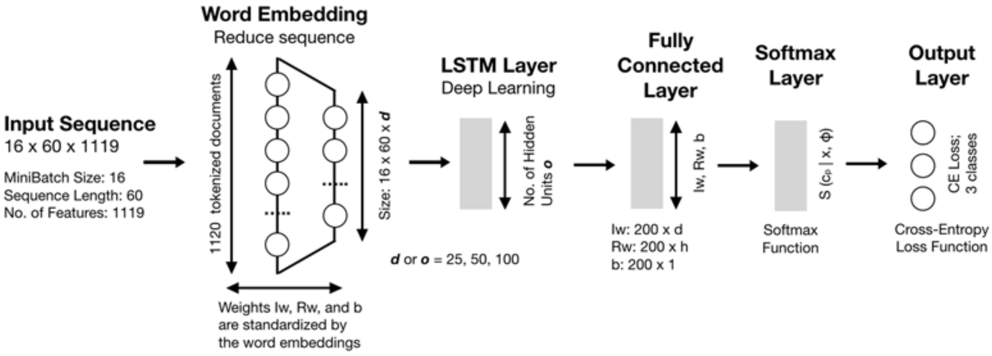


(b) Numerical indices

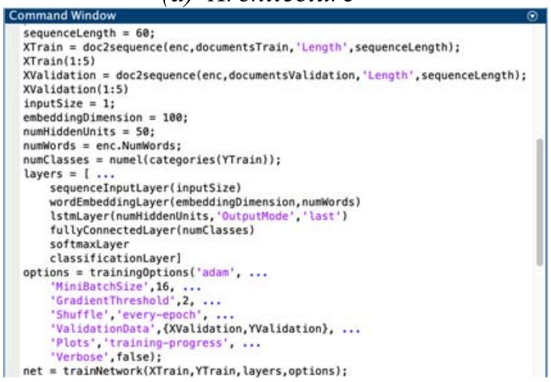
(c) Index sequences

Figure 5. Word Encoding function and results

Shown on Fig. 6a is the architecture of the proposed classification model composed of (1) an **input sequence** which has 1119 numeric indices as results of word encoding and preprocessing. Each input sequence has length size of 60 and mini batch size of 16; (2) a **WE layer** which sets the dimension size “d” to either 25, 50, 100 or 200; (3) a **LSTM layer** which controls the number of hidden units “o” to either 25, 50, 100 or 200; (4) a **fully connected layer**, which multiplies the input by a weight matrix and adds a bias vector; (5) a **softmax layer**, which uses the softmax function; and lastly, (5) a **classification output layer** which predicts the correct class of based in cross entropy loss for multi-classification. On the other hand, Fig. 6b shows the actual function used to implement the LSTM architecture in the MATLAB.



(a) Architecture



```
sequenceLength = 60;
XTrain = doc2sequence(enc,documentsTrain,'Length',sequenceLength);
XTrain(1:5)
XValidation = doc2sequence(enc,documentsValidation,'Length',sequenceLength);
XValidation(1:5)
inputSize = 1;
embeddingDimension = 100;
numHiddenUnits = 50;
numWords = enc.NumWords;
numClasses = numel(categories(YTrain));
layers = [ ...
    sequenceInputLayer(inputSize)
    wordEmbeddingLayer(embeddingDimension,numWords)
    lstmLayer(numHiddenUnits,'OutputMode','last')
    fullyConnectedLayer(numClasses)
    softmaxLayer
    classificationLayer]
options = trainingOptions('adam', ...
    'MiniBatchSize',16, ...
    'GradientThreshold',2, ...
    'Shuffle','every-epoch', ...
    'ValidationData',{XValidation,YValidation}, ...
    'Plots','training-progress', ...
    'Verbose',false);
net = trainNetwork(XTrain,YTrain,layers,options);
```

(b) Function

Figure 6. LSTM Text Classification Model Design

The softmax function of the classification model is expressed in the following formula [16]:

$$S\left(c_p \middle| x,\theta\right) = \frac{s\left(x,\theta \middle| c_p\right) s(c_p)}{\sum_{j=1}^{k} s\left(x,\theta \middle| c_j\right) s(c_j)} = \frac{\exp(a_p\,(x,\theta))}{\sum_{j=1}^{k}\exp(a_j(x,\theta))}, \tag{9}$$

where $0 \le S\,(c_p|x,\theta) \le 1$; $\sum_{j=1}^{k} S\,(c_j \mid x,\theta) = 1$; $a_p = \ln\,(S(x,\theta|cp)\ S(cp)$; $S(x,\theta|cp)$ is the conditional probability of the sample given class "p" and "$S(c_p)$" is the class prior probability. Meanwhile the cross-entropy loss function is expressed further as [16]:

$$CE\ loss = -\sum_{i=1}^{N}\sum_{j=1}^{K} t_{ij} \ln y_{ij}, \tag{10}$$

where "N" is the number of datasets, "K" is the number of classes, "t_{ij}" is the indicator that the "i_{th}" dataset belongs to the "j_{th}" class, and "y_{ij}" is the output for dataset "i" for class "j", which in this case, the value from the softmax function. After the design of the classification model, the author set the solver to Adaptive Moment Estimation (Adam) [17] then trained the LSTM for 30 epochs with gradient threshold of 1 and initial learning rate of 0.01.

2.3. Training and Testing

After the modelling, the author evaluated the performance of the text classification model in terms of training accuracy using the following formula [18], [19], [20]:

$$acc = \frac{(TP+TN)}{(TP+FP+FN+TN)} \tag{11}$$

where "acc" is the classification accuracy rating; "TP" is the number of true positive; "TN" is the number of true negative; "FP" is the number of false positive; and "FN" is the number of false negative. Afterwards, the results were further mapped out using confusion matrix through the MATLAB software. During training, the author tuned various hyper-parameters such as word embedding dimension size and number of hidden units in the LSTM layer in order to determine their correlations to the proposed model. After the training, the author then tested the model by using 20 randomly-selected commendations, complaints, and feedbacks written in either English or Tagalog. This was done to determine the level of effectiveness of the model based on actual implementation.

3. RESULTS AND DISCUSSION

Shown on Table 1 is the summary of performance of the LSTM during training, in consideration of the effects of the hyper-parameters manipulated. As such, the best performance of the LSTM model was recorded at 91.67% training accuracy with confusion error of 8.30% and elapsed time of 34s. This was made possible when the neural network was set with 50 word embedding dimensions and 50 hidden units.

Table 1. LSTM Training Performance Summary

Embedding Dimension	Hidden Units	Accuracy (%)	Confusion Error (%)	Elapsed Time (s)
25	25	70.83	29.17	28
25	50	75.00	25.00	22
25	100	79.20	20.80	39
25	200	66.67	33.30	60
50	25	70.83	29.17	19
50	50	91.67	8.30	34
50	100	66.67	33.30	37

50	200	62.50	37.50	58
100	25	75.00	25.00	20
100	50	83.33	16.67	26
100	100	79.17	20.8	47
100	200	66.67	33.33	86
200	25	83.33	16.67	26
200	50	79.17	20.83	35
200	100	75.00	25.00	51
200	200	66.67	33.33	83

Fig. 7 and 8 elucidate the best training progress and confusion matrix of the text classification model during training, respectively. As shown, it performed best with 390 iterations during training and 50 iterations during validation.

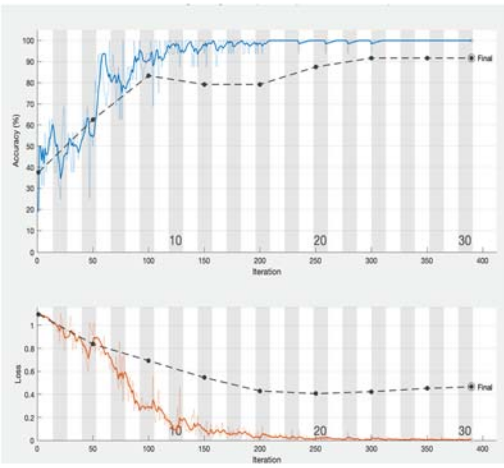


Figure 7. Best Training Progress

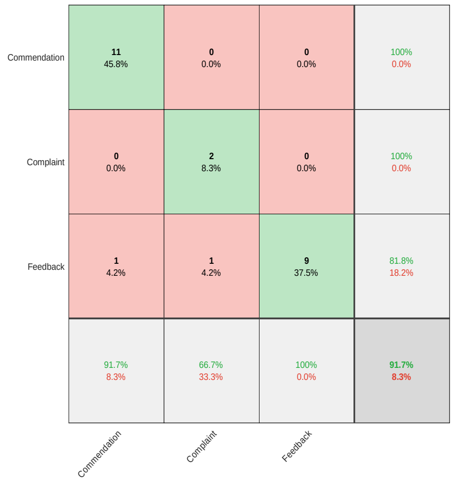


Figure 8. Best Confusion Matrix

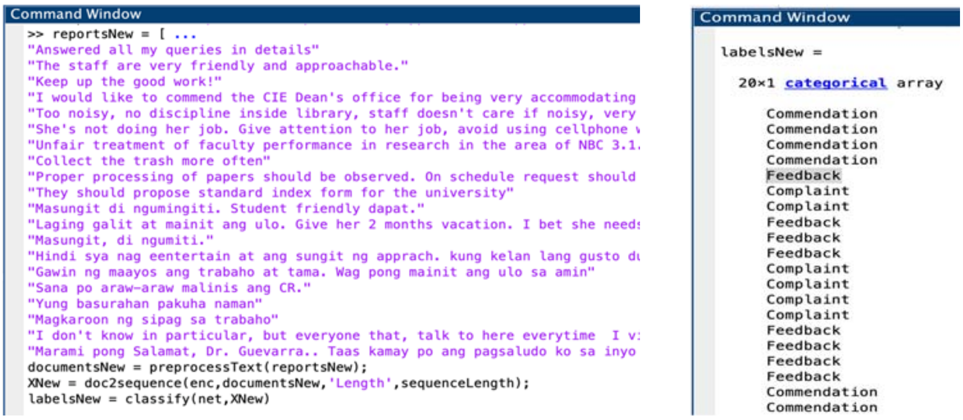
Moreover, the results of statistical analysis shown that there is strong, negative correlation between the number of hidden units and the classification accuracy, which is statistically significant at r = -.642, n=16, p=.007. This means that the lesser the number of hidden units are used, the higher is the training accuracy of the model. On the other hand, however, there is a strong, positive correlation between the number of hidden units and the elapsed time wherein r=.923, n=16, p=.000. This means that while the number of hidden units is increased, the training elapsed time is increased or the training time is slowed down. Interestingly, there is no significant correlation between the word embedding dimension and training classification accuracy or elapsed time.

Table 2. Pearson R Correlation Results

		Accuracy	Elapsed Time
Word Embedding Dimension	Pearson r	.171	.236
	Sig. (2-tailed)	.526	.380
	N	16	16
No. of Hidden Units	Pearson r	-.642**	.923**
	Sig. (2-tailed)	.007	.000
	N	16	16

Note: ** - correlation is significant at 0.01 level (2-tailed)

After training, the author then deployed the "best" LSTM text classification model into an actual implementation in order to validate its performance. Specifically, Fig. 9a shows the function used to classify the test dataset composed of 20-randomly selected commendations, feedbacks, and complaints written in English and Tagalog languages. The results of testing are shown on Fig. 9b. Out of 20 test data, the proposed model correctly classified 19/20 or equivalent to a 95% testing classification accuracy. The incorrect classification of a "feedback", which should have been a "complaint", is highlighted in gray. Nonetheless, all these results proved that the use of LSTM in the design of a proposed text classification model is effective in realizing the intended outcomes of the study.



(a) Function *(b) Results*

Figure 9. LSTM Text Classification Model Actual Testing

4. CONCLUSION

In the context of the study, LSTM was found to have its best training classification accuracy of 91.67%, confusion error of 8.30% and elapsed time of 34s. This was achieved when the hyper-parameters were tuned with 50 word embedding dimensions and 50 hidden units of the LSTM layer. Based on the results of Pearson r correlation, the study found that the number of hidden units has strong positive correlation with accuracy, and at the same time negative correlation with elapsed time during the training. This means that the lesser the hidden units are used in the design, the higher is the training classification accuracy and the faster is the elapsed time. On the other hand, the study found that tuning the word embedding size has no significant correlation with training accuracy and elapsed time. The proposed text classification model was found to be effective with 95% classification accuracy as implemented during testing. Future research should focus in adding more datasets to enhance its deep learning capabilities and to accurately determine the causal relationship between hyper-parameters and training performance. Moreover, future studies should compare the performance of the LSTM with other algorithms in the same context of application. Hence, in a subsequent study, the author compared the LSTM with another popular algorithm, the Support Vector Machine (SVM) [21].

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Information about the author:

Dr. Ralph Sherwin A. Corpuz currently serves as the Director of Quality Assurance and Associate Professor 3 of the Electronics Engineering Technology Department at the Technological University of the Philippines, Manila, Philippines. His research interests include applied artificial intelligence, robotics, embedded systems, technology management, and smart cities.

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