ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

TEXT CLASSIFICATION USING RECURRENT NEURAL NETWORK AND SUPPORT VECTOR MACHINE ON A CUSTOMER REVIEW DATASET

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ABSTRACT

Text is constantly generated from our day to day use of the internet, and these large amounts of data generated are mostly unfiltered. In most cases, unstructured data needs to be classified to improve the rate at which a given text is understood. Text classification is a branch of Natural Language Processing that is used to create a distinction in unstructured text data. Machine learning is widely used in the classification of textual data as a result of its ability to create complex prediction functions dynamically. Similarly, statistical models are commonly used to classify textual data because they can describe the relationship between two or more random variables. In an e-commerce environment, sentiment analysis is usually a challenging task. Machine learning techniques of Naïve Bayes and Decision Tree have limitations in sentiment analysis performance. In this study, a comparative study of Recurrent Neural Network (RNN) and Support Vector Machine (SVM) is done for classification of customer product review dataset on whether they have positive or negative comments. This study tends to enhance the traditional RNN with the use of Long Short Term Memory (LSTM) in order to achieve optimal result. The result of this work shows that RNN with an accuracy of 94.86% is better than the state of art SVM with an accuracy of 86.67%. The result of this work is not only better in terms of accuracy, also in other performance metrics measured.

Keywords: *Recurrent Neural Network; Support Vector Machine; Text Classification; Review*

1. INTRODUCTION

The problems of text classification have been widely researched and debated in many fields in recent years. In particular, with the advancement in text mining and natural language processing (NLP), many scholars are now able to create software that uses text classification techniques [1]. Sentiment Analysis is the job of evaluating the publics' feelings in text evidence such as product evaluations, film reviews, or tweets sentiment and extracting their polarity and perspective. The challenge may be either a multi-class or binary problem. Binary sentiment classification classifies datasets into negative and positive categories, while multi-class sentiment analysis classifies texts as fine-grained labels or multi-level durations [2]. NLP primarily deploys many machine learning models for the categorization of test results. However, classifiers such as Recurrent Neural Network and Support Vector Machine are popular and often favoured approach used for the classification of textual data.

Traditionally, text is understood as a piece of documented or spoken content in its natural form. Also, text can also be described as any kind of language that can be understood by a reader. It could be as simple as one or two words or as complex as sequence of sentences logically combined together. While classification, on the other hand, is a challenge of defining the groups in which new discovery is associated with, based on training collection of data comprising certain observation of which membership of the group is identified. Text classification is a semi-supervised system designed for learning tasks which assigns documents in an automatic way to a collection of categories which are defined on its text data including features that were extracted. It is an automatic process which places significant focus on content creation, spam filtering, product review analysis, sentiment analysis, product marking and so on.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

There are three major machine learning approach which includes the unsupervised, semi-supervised and supervised learning methods. The traditional supervised learning approach uses machine learning algorithms to obtain accurate regression and data classification analysis. In a Supervised machine learning algorithms, training a set of data is used for the implementation of an algorithm. In the unlabeled test dataset, the qualified algorithm in the supervised learning model is fed into categories of related classes [3]. For traditional SVM and RNN classification task, the class group is well noted and the models are properly trained to ensure data is properly allocated to the right class. Support Vector Machine can be employed for both nonlinear and linear classification [4].

Unsupervised learning are machine learning methods where interpretations is done from a text by clustering the text format into separate clusters without a labeled answer, which mean the output. On the contrary, the machine is not supplied with training data. Initially, it seems to be complicated, but as data increases in the framework, the model redefine itself for great performance. Self-organizing key component analysis and clustering maps are also used in unsupervised research. Clustering is about the same in many scenarios as unsupervised learning [5].

The machine learning method consists of two past procedures. Scholars have seen that there are few unlabeled details which may lead to the enhancement in accuracy, hence, the development of semi-supervised learning approaches [6]. The application field suffers from lack of availability of classified data, though unmarked dataset is readily available and cheap. It is very difficult to get labeled instances because seasoned programmer expected to label unidentified patterns of data. Semi Supervised Learning algorithm tackles the concern and serves as a halfway link between supervised and unsupervised learning [7]. Semi Supervised Learning has been suggested to solve these problems the testing group that can understand from a limited amount of training data can classify unknown test data. This can also be used in building a model with some trends classified as training data and the rest of the data patterns like the test results. The current concern in the assessment of SSL approaches criticizes the common trend of setting aside a small part of the training data as 'marked' and a significant part of the same training data as 'unlabeled.' This method of separating the data leads to a situation where all the texts in this sort of "unlabeled" set have the tacit promise that they are taken from the very same class distribution as the "marked" set. As a result, some SSL approaches are in-performing under a more practical situation where unlabeled samples do not have this assurance [8].

In this study, supervised learning approaches of Recurrent Neural Network and Support Vector Machine is designed and a comparison is done on which of the machine learning techniques performs better for a text classification task for a customer review dataset. The performance of both methods was measured in term of Accuracy, Recall, True positive rate, specificity, sensitivity, False-negative rate, and F-score. This study tends to enhance the traditional RNN with the use of Long Short Term Memory (LSTM) in order to achieve optimal result.

2. REVIEW OF LITERATURES

Shan et. al., [21] worked on SSL for sentiment classification using very small label data, trained a semi-supervised deep neural network to have different configuration and compared method output to the original, a supervised deep neural network trained with an equal amount of labelled results. The study used a labelled dataset which are separated into two sections; the trained and test data. The work achieved a decline in the performance of the classifier dataset as the labelled trained dataset reduces. Binary cross-entropy is used to calculate the reduction while the Adam process is used for optimization. The work obtained a planned result because the unmasked datasets are chosen at random. This study was limited to a label data which makes the classifier dataset to be declining, the work can be improved on by using unlabeled dataset.

Boiy & Moens, [22] worked on a machine learning approach to sentiment analysis in multilingual web text, they present machine learning experiments on peoples opinion in the review, blog, and groups text found on the internet and written in French, Dutch and English, They are drawn from a sample of statements and sentence that are distinguished manually into negative, neutral and positive, concerning a particular instance. The study was able to achieve 68% and 70% precision for French and Dutch texts respectively, while 83% precision for texts in English text. The study was limited to a selected languages.

Chauhan [23] worked on a comparative analysis of a supervised machine learning algorithm

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

using a fast miner. In their study, a comparative study of four supervised machine learning techniques Neural Network, Naive Bayes, Support Vector Machine and Decision Tree are used for analyzing emotions based on various output functionalities. The result of the study showed that the Support Vector Machine has more efficiency than the other three supervised machine learning techniques. Based on the study of the different findings for all emotion classification strategies, they concluded that Support Vector Machine has a high score of 68.29% compared to Decision Tree and Naïve Bay with 61.11% and 57.08% respectively. Though SVM performed better, however the accuracy based on percentage was low.

Kumar & Zymbler [24] worked on machine learning technique for research tweets to improve user service. Features were derived from tweets using the word embedding in the Glove dictionary framework and the n-gram technique. SVM, ANN and CNN were used to create a classification models which maps the tweets to pleasant and negative categories. Convolutional Neural Network has been seen to have outperformed variants of Support Vector Machine and Artificial Neural Network. It achieved an accuracy of 92.3 per cent after 2700 iterations on the validation range, a respectable score compared to the Artificial Neural Network model, which achieved an accuracy of 69.16 per cent. It is also clear that CNN is more efficient than the ANN and is capable of executing text data more precisely.

Yin-Wen et al, [25] in their work on document classification using support vector machine discussed in depth the implementation of the Support Vector Machine for the measurement of the word frequency of features used as Sports, Industry and Entertainment for categorization with the aid of a manual domain dictionary. They find out that it is comparatively less cumbersome to identify divisions that broadly characterize the knowledge stored in these sets. A package called LIBSVM was used in past literature to incorporate the SVM in their work.

Ghorbani et. al., [26] Worked on a deep learning approach to sentient research in cloud computing. The study suggested an optimized architecture of the Long Short Term Memory and Convolutional Neural Network network to classify the polarity of terms in Google Cloud and conduct computing on Google Collaboratory. In the experimentation of their work, a dataset of film reviews has been used, and it is a compilation of negative and positive film reviews where each review includes a phrase. The findings of the analysis reveal that the proposed model has an accuracy of 89.02 per cent better than existing methods.

Pengfei et al, [27] In their work on RNN for text categorization with multi-task learning used the multiple task learning, proposed three separate models of knowledge exchange with recurrent neural networks (RNN), relevant activities are merged into a single machine that is jointly qualified. The first model uses only one shared layer for all functions. The second model uses various layers for different activities, but each layer can read data from diverse layers.

Yennimar et. al., [28] worked on emotion analysis for the opinion IESM product using a recurrent neural network approach focused on long-term memory, they suggested the Long Short-Term Memory Recurrent Neural Network to identify the opinion IESM product as opposed to other models such as K-Nearest Neighbor, Naïve Bayes, artificial neural network, and Support Vector Machine, based on dataset outcome survey square with emphasis. Based on the experimental results of the dataset, the naive Bayes, the Support Vector Machine and the Artificial Neural Network with 75.23 per cent, 87.21 per cent and 63.56 per cent result is lower than the proposed approach which combines the power of the Recurrent Neural Network and the Long Short Term Memory Model, which is more reliable compared to the other model with 93.90 per cent for training and 91 per cent.

Fikri & Sarno, [29] worked on a comparative study of sentiment analysis using Support Vector Machine and SentiWord Net, and emotional recognition uses a rule-based approach using the SentiWordNet and Support Vector Machine (SVM) Term Frequency – Inverse Text Frequency (TF-IDF) technique as a feature extraction method. Data as a scenario for sentiment analysis is stated in Indonesian. While the number of sentences in the positive, negative and neutral classes is not balanced, the over-sampling technique is applied. The rule-based SentiWordNet and SVM algorithms achieve 56 per cent and 76 per cent accuracy for the extremely unbalanced data collection, respectively. However, for the balanced data collection, the rule-based SentiWordNet and SVM algorithms reach 52 per cent and 89 per cent accuracy, respectively.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

From the existing literatures, the research gap identified was based on two major factors which are Lack of sufficient dataset and Lack of applying the right method on text classification task for instance the using CNN for a classification task where methods such as statistical method such as Naïve Bayes, SVM and Deep Learning Techniques exist. [25], discovered that, it is relatively less cumbersome to define categories that broadly classify the information contained in the collections of data they used. Despite the improved performance of the novel approach of the multi-task learning model proposed by [27]. The result of the performance still doesn't measure up to the novel LSTM model with the highest performance when compared to MBOW, MV-RNN, RNTN,DCNN, and PV. Therefore, this study proposed a comparative analysis of two machine learning techniques (RNN and SVM) on large customers' review dataset, so as to determine which of the machine learning techniques perform better on text classification.

3. MATERIAL AND METHODS

The dataset in this experiment is the popular amazon product review for a customer. The dataset contains 3772 customer review where 70% was used for training and 30% for testing. The dataset is retrieved from a data hub repository and the comparative analysis using both the RNN and SVM is done on same datasets at different time to determine which one gives the best performance. Both models was trained and tested in a MATLAB environment

3.1 Overview of Research Method

The flow of the work in this study begins by loading our dataset into the development environment, after which it goes through a cleaning process. The data is partitioned into training and testing respectively. The design of each classifier is done and evaluation is done for the performance metrics of each model as described in figure 1.

3.2 Long Short Term Memory (LSTM)

The Long Short Time Memory is an artificial recurrent neural network architecture that has been developed to overcome the gradient problem of the conventional recurrent neural network. The Long Short Term Memory is the most common structure in the world and is intended to help catch long-term dependences. LSTM solves major issues with vanilla Recurrent Neural Networks by inserting a memory cell to recover values over arbitrary time spans and three gates that are entry gate, exit gate, forget gate to control information [30-34]. In this study, Long Short Term Memory (LSTM) will be added to the traditional Recurrent Neural Network so as to achieve an optimal result. The work flow of the Recurrent Neural Network (RNN) is described in the figure 2

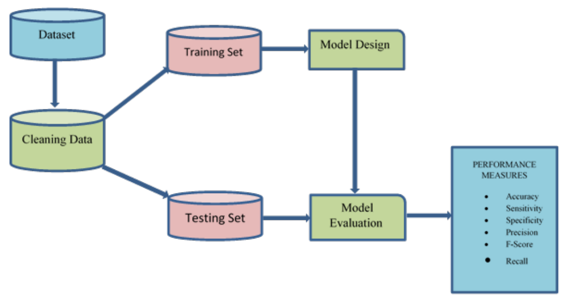

Figure 1: Workflow diagram

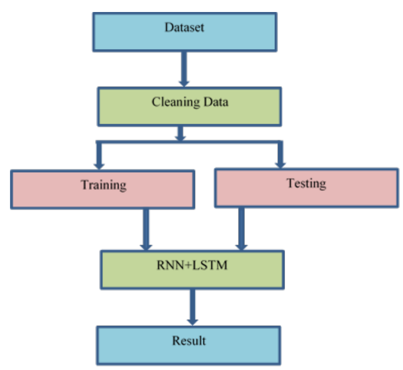

Figure 2 Flow Diagram for RNN model

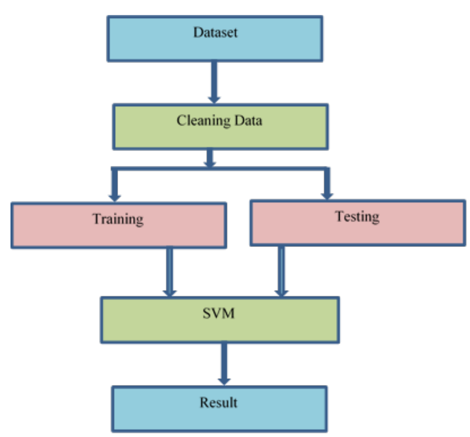

Figure 3: SVM flow diagram

3.3 Performance Evaluation Matrices

The performance evaluation metrics of the classifiers are evaluated in terms of accuracy, sensitivity, specificity, precision, f-score, true

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

positive rate and true negative rate. Assessing machine learning algorithms efficiency needs certain validation metrics. The confusion matrix is often used to evaluate four characteristics of the classification model; True negative (TN), True positive (TP), and False Negative (FN), False Positive (FP), It discovers the example categorized incorrectly and correctly from the data set sample given to test the model [35-38]. This is described below.

ACCURACY: This is the easiest measure to score. Explains the amount of correctly graded instances

Accuracy = ((True positive + True Negative))/(True Positive + True Negative + False Positive + False Negative)

SENSITIVITY: The Sensitivity Score, also referred to as Recall or True Positive, shows how likely the test will return positive to the sample.

Sensitivity= (True positive) / ((False Positive + False Negative))

SPECIFICITY: The precision also known as the true negative refers to the potential of the classifier to distinguish negative outcomes.

Specificity= (True Negative) / ((True Positive +True Negative))

PRECISION: This is a measure of retrieval instance that are relevant

precision = (True positive) / ((False Positive + False Negative))

F-SCORE: It is a way to measure a model accuracy based on recall and precision

F-score = (2×True positive) / ((2×True Positive + False Positive + False Negative))

FALSE POSITIVE RATE: it occurs when we accept a user which should be rejected.

False Positive Rate = (False Positive) / (True Negative + False Negative)

FALSE NEGATIVE RATE: This occurs when we reject a user to whom should be accepted.

False Negative Rate = (False Negative)/(True positive + False Negative)

4. IMPLEMENTATION AND RESULT

This section describes the implementation of both Recurrent Neural Network and Support Vector Machine for text classification task of a customer review of the popular amazon dataset in a MATLAB environment. The confusion matrix of each model is used to calculate the performance measure of the two models.

a. Recurrent Neural Network.

The RNN classification is performed using 9 input with 20 hidden layers and 2 output. The representation of the training performance in the classification of RNN is 0.137636 while the test performance is 0.204319 with a dataset that contains a total of 3772 features and 16 attributes. The features in the dataset are being partitioned into 70% for training and 30% for testing and this is done on the benchmark dataset to generate the best possible result. The architectural implementation of RNN using a feed-forward neural network for text classification configuration is as follow:

Type of network = feed-forward
Amount of Input =1
Amount of Output =1
Amount of neurons in input node= 9
Amount of neurons in output node = 2
Amount of Hidden node = 2
Amount of neurons in hidden node = 20
Maximum number of iteration = 20

Figure 4 shows the confusion matrix for the RNN model. The Confusion matrix of RNN is trained with the customer review dataset. With metrics True Negative (TN) = 47, False Negative (FN) = 7, False positive (FP) = 4 and True Positive (TP) = 156 to calculate the performance metrics.

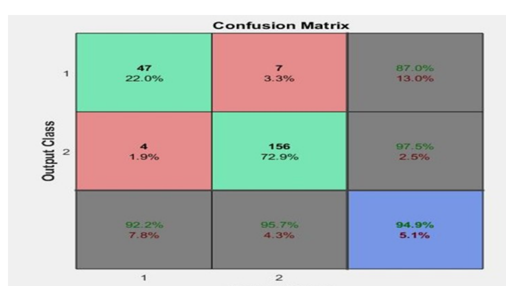

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Figure 4: Confusion matrix for RNN

By applying the formulas as discussed in the methodology, we can deduce the performance metrics of our mode as described in Table 1.

Table 1: Performance Metrics table

Performance Metrics	Results (%)
Accuracy	94.86
Specificity	87.04
Precision	95.71
False Positive Rate	12.96
False Negative Rate	0.25
Sensitivity	97.5
F1 score	96.59

The significant application of the data obtained from the amazon dataset for customer review on a text classification task is not consistent and to achieve such classification, a variety of parameter, a variety of algorithms have been proposed. These algorithms typically require optimization of parameters to get detailed results. It is very important to find an optimal collection of textual data that can be used in classification whether it is Negative or Positive.

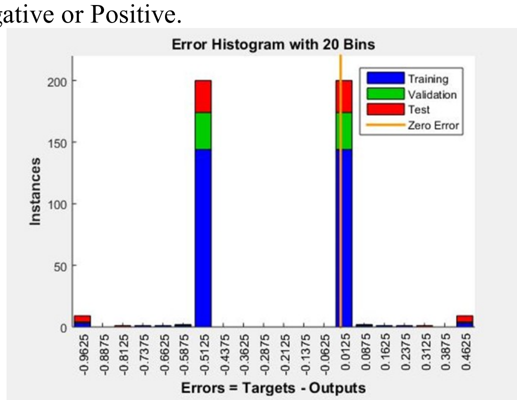

Figure 5: Error Histogram for RNN

Using RNN, for instances of about 200, there are 12 errors which are represented on the histogram with the highest recorded error at 0.0125. This is also the point at which there is no error recorded with over 200 instances of iteration. The RNN has been passed along with 20 histogram bins. For the estimation of the algorithm, both the short-and long-term dependencies resulting from the proposed recurrent neural network and the standard recurrent model are analyzed using an error histogram as seen in Figure 5. Based on the tendency and error frequency per bin histogram, the Recurrent Neural Network model achieves lower error rates relative to the state of the art. The error histogram also distinguishes between preparation, checking and validation, which ranges from 150 to 200 classification events. However, as a result of the proper partitioning of the training and testing of 70% and 30% respectively, we can achieve an equivalent result in areas where are there is the least possible error and in areas where there is the highest number of errors.

b. Support Vector Machine

Support Vector is implemented in this study and below is the result of the experimentation.

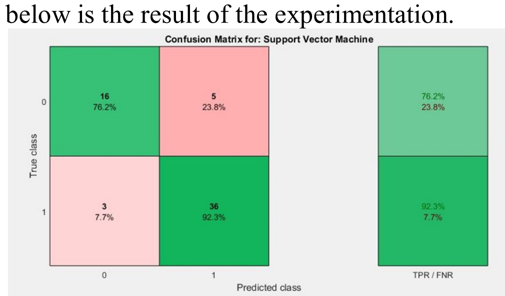

Figure 6: Confusion Matrix for SVM

Figure 6 shows the confusion matrix of the support vector machine (SVM) classifier trained with the amazon customer review dataset. With the confusion metrics True Negative (TN) = 16. False Negative (FN) = 3, False positive (FP) = 5 and True Positive (TP) = 36 to calculate the performance matrix in table 3, by applying the formulas for our performance measures as described in the methodology we have the following result for the implementation of Support Vector Machine.

Table 2: performance evaluation measures of Support Vector Machine

Performance Metrics	Results (%)
Accuracy	86.67
Specificity	76.19
Precision	87.8
False Positive Rate	23.81
False Negative Rate	0.76
Sensitivity	92.3
F1 score	90.11

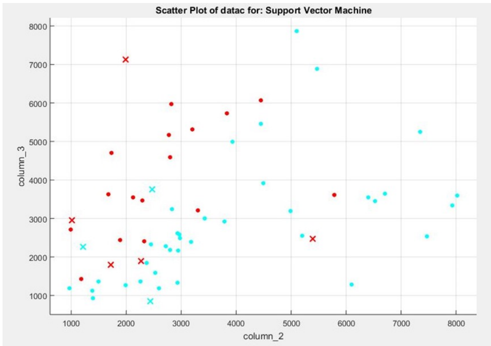

Figure 7: Scatter plot for SVM

The results of the classification show the difference between the similarities of each sample means of each class. The different colours on the graph as described in the graphs in figure 7 shows that there are clear distinctions between the positive and negative reviews. Therefore, classification using the amazon customer review dataset is done linearly, making it is easy to separate between the positive and negative sentiment in peoples review concerning a product.

c. Comparative analysis of Recurrent Neural Network and Support Vector Machine

The comparative analysis of Recurrent Neural Network and Support Vector Machine results are carried out and shown in table 3. However, the results of the experimentation indicate that Recurrent Neural Network (RNN) with an accuracy of 94.86% outperforms Support Vector Machine (SVM) with an accuracy of 86.67. Also, the result shows that the Recurrent Neural network is better than the Support Vector Machine in terms of Specificity, sensitivity, F1 score, and recall.

Table 3: Performance matrix table for RNN and SVM

Performance matrices	Result for RNN %	Result for SVM%
Sensitivity	97.5	92.3
Specificity	87.04	76.17
Precision	95.71	87.8
False-positive rate	12.96	23.81
False Negative rate	0.25	0.76
Accuracy	94.86	86.67
F1 Score	96.59	90.11

In this study, an experiment has been performed to classify a pre-processed dataset to know if a customer opinion is Positive or Negative. The classification techniques that were employed in this study is Recurrent Neural Network and Support Vector Machine, the Recurrent Neural Network with 94.86% outperforms the support Vector machine with 86.67% in term of accuracy.

d. Comparative Performance with other Techniques

The result of the experiment in this study is further compared with existing methods in literature and has proven to be an efficient method that can be adopted by researchers for further investigations and improvements. Table 4 shows the results of existing methods in the literature

Table 4: Comparison with existing literature

Authors	**Techniques**	**Accuracy %**
Pengfei, Xipeng, uanjing (2006)	Logistic Regression	86.2
Minaee (2020)	Character-level CNN	77.8
Boiy & Moens (2009)	BPL Neural Network	70.0
Schmidhuber (2015)	Naïve Bayes + word2Vec	62.30
Hartmann (2019)	Bi-LSTM	91.41
Brownlee (2020)	Multivariate Bernoulli NB	70.96
Wahdan et. al., (2020)	Naïve Bayes	87.45
Proposed model	RNN	94.86

5. CONCLUSION

In this study, a comparative study of Recurrent Neural Network and Support Vector Machine for text classification was done for customer review on an e-commerce benchmark dataset. The implementation of both recurrent neural network and support vector machine algorithm was done on the same dataset. The result was generated in terms of F -score, Accuracy, Specificity, Sensitivity, False Positive Rate, False Negative Rate and Precision. At the end of the experimentation, the Recurrent Neural Network performed better than the Support Vector Machine in term of accuracy. Hence in an e-commerce environment for a positive or negative

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

customer review, RNN will assist merchants in recognizing customer's opinion concerning a product, and informing other people's decision regarding a particular product. It is also noted that the two algorithms that were proposed in this study were far better than existing techniques in literature in terms of classification as captured in table 4.

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