Software Engineering Comments Sentiment Analysis Using LSTM with Various Padding Sizes

Conference Paper · January 2023

DOI: 10.5220/0011845100003464

Sanidhya Vijayvargiya
BITS Pilani, Hyderabad

Lov Kumar
National Institute of Technology, Kurukshetra

Sanjay Misra
Institute for Energy Technology

Srinivas Padmanabhuni
Tarah Technologies

Software Engineering Comments Sentiment Analysis Using LSTM with Various Padding Sizes

Sanidhya Vijayvargiya[1], Lov Kumar[2], Lalita Bhanu Murthy[1], Sanjay Misra[3], Aneesh Krishna[4] and Srinivas Padmanabhuni[5]

[1]*BITS-Pilani Hyderabad, India*

[2]*NIT kurukshetra, India*

[3]*Østfold University College, Halden, Norway*

[4]*Curtin University, Australia*

[5]*Testaing.Com, India*

Keywords: Sentiment Analysis, Deep Learning, Data Imbalance Methods, Feature Selection, Classification Techniques, Word Embedding.

Abstract: Sentiment analysis for software engineering(SA4SE) is a research domain with huge potential, with applications ranging from monitoring the emotional state of developers throughout a project to deciphering user feedback. There exist two main approaches to sentiment analysis for this purpose: a lexicon-based approach and a machine learning-based approach. Extensive research has been conducted on the former; hence this work explores the efficacy of the ML-based approach through an LSTM model for classifying the sentiment of the text. Three different data sets, StackOverflow, JIRA, and AppReviews, have been used to ensure consistent performance across multiple applications of sentiment analysis. This work aims to analyze how LSTM models perform sentiment prediction across various kinds of textual content produced in the software engineering industry to improve the predictive ability of the existing state-of-the-art models.

1 INTRODUCTION

Technically, sentiment analysis (SA) is defined as the natural language processing (NLP) and opinion mining technique used in text analysis to understand if the given text portrays a positive, neutral, or adverse opinion. Off-the-shelf sentiment analysis tools struggle to perform efficiently and consistently because certain words in the text are technical and highly domain-specific. Sentiment prediction tools also occasionally fail to address the context-sensitive variations in the meanings of words, leading to worse performance. Another contributing factor is that the text often contains copy-pasted content, like code, which, when subject to sentiment analysis, can lead to misclassification of the overall sentiment of the text. Negations are challenging to deal with, proper nouns are misidentified, and the inability to handle irony and sarcasm are other issues that make sentiment analysis with high accuracy formidable.

In this research, we attempt to address the issues mentioned earlier by developing highly reliable sentiment analysis models that can be employed in the industry. The research questions (RQs) used to achieve the goals are listed below.

- RQ1: What is the optimal padding for the sentences in the text for which the RNN models yield the best performance?
- RQ2: What structure of LSTM models achieves the best results for sentiment analysis predictions?
- RQ3: How do the models' performance trained on class-balanced data using the different oversampling techniques compare with the versions of the models trained on the original data?

In this work, we investigate the sentiment prediction potential of various Long Short-Term Memory (LSTM) models. We provide an in-depth analysis of how different lengths of sentence padding affect performance to guarantee that each sentence has the same length as necessary for LSTM model inputs. Variations in the structure of the LSTM model are

Vijayvargiya, S., Kumar, L., Murthy, L., Misra, S., Krishna, A. and Padmanabhuni, S.
Software Engineering Comments Sentiment Analysis Using LSTM with Various Padding Sizes.
DOI: 10.5220/0011845100003464
In *Proceedings of the 18th International Conference on Evaluation of Novel Approaches to Software Engineering (ENASE 2023)*, pages 396-403
ISBN: 978-989-758-647-7; ISSN: 2184-4895

used to determine the best model for sentiment analysis as well as to improve the performance benchmarks. Previous works primarily focus on feeding numerical vectors from pre-trained word embeddings into the LSTM models. This work modifies the LSTM architecture to learn the numerical representations directly in the embedding layer. Unlike earlier research, in this study, we offer a full statistical analysis to back up the conclusions using statistical testing. The impact of class-balancing strategies on datasets to develop more accurate models is looked into, as well as which class-balancing methodology is best suited to software engineering. We have used Friedman test to confirm the observations drawn from the results of the different models trained. The objective is to prove which LSTM model is best suited to sentiment analysis of software engineering artifacts for research or use in industry.

Sections 2-5 of this work are organized as follows: A literature survey of several approaches to sentiment analysis for our desired applications is presented in Section 2. Section 3 describes the dataset, experimental setup, and study design, while section 4 makes a comparative analysis on the research outcome. The section compares the LSTM models with the RNN structures as well as class-balancing strategies. Finally, Section 5 summarizes the research findings and provides recommendations for further scope in this area.

2 RELATED WORK

2.1 Sentiment Analysis Techniques

Shen et al.(Shen et al., 2019) analyzed the various factors of the dataset and study design that contribute to the insufficient accuracy of sentiment prediction. The authors noted a jump in accuracy from 0.758 to 0.934 on the binary classification of emotions of comments from the StackOverflow dataset when the models were trained on a domain-specific dataset as compared to a non-tech dataset. According to the study, another contributing factor to sub-par results is the imbalance in the dataset used for training, and almost all previous evaluation works have suffered from this flaw.

The performances of four existing sentiment analysis tools are evaluated in the work done by Novielli et al. (Novielli et al., 2020). It was reported that retraining these four sentiment analysis tools did not produce laudable results when the sources from which the training and testing samples were retrieved varied. Hence, a lexicon-based technique is proposed as an alternative to retraining existing tools. Further, it was also concluded that upon training supervised tools with a small balanced training data set (of around one thousand documents), the models outperformed the lexicon-based tools. This was however true only if the training data had a high inter-rater agreement.

When the training and test sets come from multiple data sources, they discovered that retraining domain-specific sentiment analysis tools is not a sound approach. When retraining is not possible owing to the lack of a gold standard, they offer lexicon-based techniques, which they advocate anytime retraining is not feasible due to the lack of a gold standard. Further research suggested that when supervised tools are retrained with a small training dataset of roughly 1,000 documents, they perform better than lexicon-based tools, provided the training dataset is balanced and high inter-rater agreement is detected.

2.2 Lexicon-Based Methods V/S Machine Learning-Based

Jurado et al. analyzed the sentiment in commits of developers on GitHub using lexicon-based methods by first classifying whether the text was objective or subjective and then classifying the text as positive or negative sentiment (Jurado and Rodriguez, 2015). The authors used four different lexicons, ANEW, OpenFinder(OF), SentiStrength(SS), and WN-Affect(WA). NLTK was used for pre-processing, and SnowBall for the stemming process. For each issue, the number of words under the corresponding emotion (anger, disgust, fear, joy, sadness, and surprise) identified by WA were obtained, while the other lexicons provided a polarity analysis of the issue as negative or positive. It was worth noting that the positive and negative analyses for the polarity obtained with the appropriate lexicons had a positive association. This fact introduces undesired uncertainty and has an impact on the polarity's possible interpretations. The authors found that polarity analysis with the specified lexicons was unsuitable for their corpus but that it was effective for emotional analysis.

Calefato et al. (Calefato et al., 2018) developed the model Senti4SD, which was trained and tested on over 4000 posts manually tagged with emotion polarity from Stack Overflow.

Batra et al. (Batra et al., 2021) attempted to use transformer-based pre-trained models to achieve higher performance compared to that of the existing tools such as SentiCR, SentiStrength-SE, etc. The research proposed three distinct ways for analyzing BERT-based models: the first method fine-tunes the already existing pre-trained BERT-based models, the second approach uses an ensemble model using BERT variations, and the third approach employs a compressed model, also referred to as Distil BERT. The results showed that the models used by the authors were successful in outperforming the existing tools by 6-12% on F1 score for all three datasets. Data augmentation was performed using lexical substitution and back translation. The experimental results revealed that the methodologies utilized outperformed the existing tools, with f1-scores of 0.84 and 0.88 for the Jira, and the Stack Overflow datasets, respectively. In the GitHub dataset, the f1-score increased to 0.93 and 0.91 for positive and negative classes, respectively, with an overall f1-score of 0.92.

2.3 Word Embeddings for Sentiment Analysis

Qiu et al.(Qiu et al., 2020) classified the pre-trained models into two groups. The first one attempts to learn non-contextual word embeddings, as is the case with GLOVE, W2V, etc. As these embeddings are non-contextual, they fail to model polysemous words. The second generation has two families, one being LSTM-based, and the other being Transformer-based. Biswas et al.(Biswas et al., 2019) used an LSTM-based model for classification of the sentiment but used vectors obtained from pre-trained word embeddings such as W2V with Skip-gram. In this work, we obtain the embeddings using the Embedding layer in the LSTM model, which learns the embeddings jointly with the LSTM model. We do not use any pre-trained embeddings.

3 STUDY DESIGN

3.1 Handling Class Imbalance

As highlighted in Dataset section, class imbalance in the training dataset is a problem responsible for lower accuracies in previous research. We employ different variations of SMOTE to address this issue. The performance of the models built before and after accounting for class imbalance are compared. The various class balancing techniques used are Synthetic Minority Oversampling Technique (SMOTE), Support Vectors Synthetic Minority Oversampling Technique(SVM-SMOTE), and Borderline Synthetic Minority Oversampling Technique (Borderline-SMOTE). We have also compared the results of these techniques with original data

3.2 LSTM Model

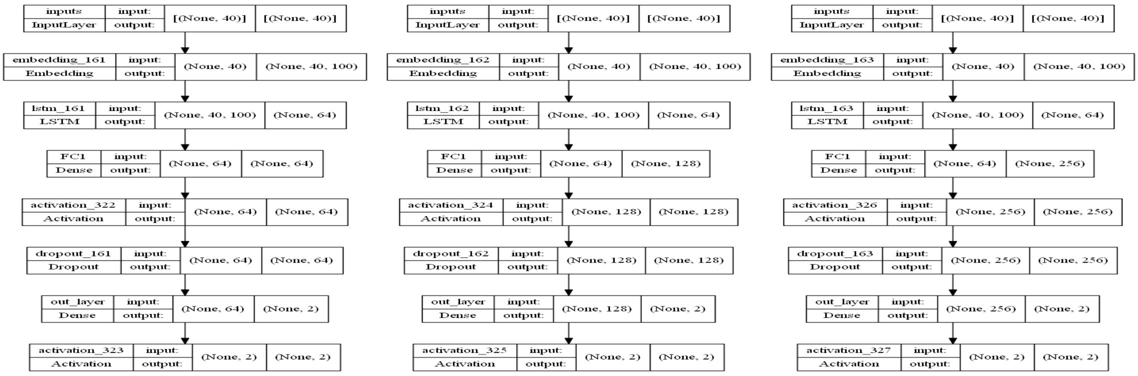
The sentiment of the text is predicted using three different LSTM models which have structures of the layers used. In the input, some texts are shorter, while others are longer. For inputting text to the LSTM model, all inputs need to be of the same length. This necessitates the use of padding. For each LSTM model, four different variations of text are inputted through the Input layer to initialize the Keras tensor. The variations in the input are due to the original text being subjected to different padding of 10, 20, 30, and 40 length. Both the padding and truncating occur at the end of the input.

Following the input layer in the LSTM model is the Embedding layer which is crucial to learning the domain-specific word embeddings along with the training of the sentiment prediction model. The dense vector returned by the Embedding layer uses 100 features to represent a word. This is then fed to the LSTM layer. The architecture of an LSTM differs from that of a traditional feedforward network because it includes a feedback loop. It also incorporates a memory cell, which stores past data for a longer period of time in order to make an accurate prediction. Traditional RNNs, which cannot forecast using such a long series of data and suffer from the problem of vanishing gradient, have been improved by LSTM with its memory cells.

The resulting data is fed into a Dense layer named FC1 as seen in Figure 1, which has a varying dimensionality of output space for each of the three LSTM models. This is followed by a Relu-based activation layer and a drop-out layer (working at a drop-out rate of 0.5) to curb overfitting. Finally, there is a Dense layer with an output space of dimensionality of two, followed by a sigmoid activation layer which gives the sentiment predictions.

3.3 Dataset

- The Jira dataset consists of 4,000 sentences and 2,000 issues comments from four open-source (OS) communities: CodeHaus, JBoss, Apache, and Spring. The contents of this dataset are categorized into six categories, namely, fear, surprise, joy, anger, sadness, and love. We re-categorized anger, sadness as negative, and joy, love as positive training examples. Surprise, being an ambiguous emotion was discarded, and along with fear, both emotions were rarely expressed.
- The StackOverflow dataset has over four thousand posts consisting of questions and answers, as well as the corresponding comments extracted



(a) LSTM-1 (b) LSTM-2 (c) LSTM-3

Figure 1: LSTM Different Models.

from StackOverflow. The different classes in the dataset are positive, negative, and neutral, and are all reasonably balanced. Both StackOverflow and Jira are considered the gold standard due to the well-defined guidelines followed during the labeling process.

- AppReviews is a dataset that contains around three hundred and fifty reviews chosen by Lin et al.(Lin et al., 2018) from 3,000 provided in (Villarroel et al., 2016), which are manually labeled. Four categories were considered here: suggestions, requests, bugs, and others.

4 EXPERIMENTAL RESULTS AND ANALYSIS

In total, 144[3 original datasets * 4(3 class-balanced + 1 imbalanced datasets) * 4 different paddings * 3 LSTM models] distinct sentiment prediction models were built. The performance of these models was compared using metrics such as accuracy, precision, recall, and Area under the ROC curve(AUC). For each performance parameter, statistics such as maximum, Q3, mean, Q1, and minimum were statistically examined using box plots for visual representation. Furthermore, the Friedman test was used to support any conclusions reached. Table 1 shows the predictive ability of the trained models, which are assessed using accuracy, precision, recall scores, as well as AUC values. The StackOverflow dataset has poorer performance metrics than the other two, indicating that sentiment analysis is a more difficult assignment on StackOverflow dataset. This is backed up by the fact that there was a difference of opinion in 18.6% of the classifications, even when done manually by people. To support the findings and draw conclusions, we have used box-plots for visual comparison of each performance metric and statistical analysis through the Friedman test for each ML technique used. The Friedman test either accepts the Null Hypothesis or rejects it and accepts the alternative hypothesis. The significance threshold for the Friedman test is 0.05 for all the comparisons made.

4.1 RQ1: What Is the Optimal Padding for the Best Performance of the LSTM Models?

Padding can significantly affect the accuracy of LSTM models. A padding length of 10 was found to be optimal across the three datasets, with a padding length of 20 providing competitive performance as seen in the box-plots in Figure 2, and their descriptive statistics are mentioned in Table 3. Meanwhile, the paddings of lengths 30 showed a higher variance in performance.

As the visual differences in box-plots of paddings of lengths 10 and 20 are indiscernible, we use the Friedman test to support the claim that padding of length 10 is the best, as seen in Table 2. The Friedman test is conducted on the AUC values with a null hypothesis stating, “the different padding lengths do not cause a significant difference in the performance of the sentiment analysis models.” Lower the mean rank from Table 2, better the performance. Thus, we can conclude that padding of length 10 is ideal with a mean rank of 1.76.

4.2 RQ2: What Structure of LSTM Models Achieves the Best Results for Sentiment Analysis Predictions?

The box-plots of the different structures of LSTM models, shown in Fig 3, show that there is not much

Table 1: Performance Parameters.

	Accuracy			Precision			Recall			AUC		
	LSTM-1	**LSTM-2**	**LSTM-3**	**LSTM-1**	**LSTM-2**	**LSTM-3**	**LSTM-1**	**LSTM-2**	**LSTM-3**	**LSTM-1**	**LSTM-2**	**LSTM-3**
All Metrics (OD): JIRA												
PAD-10	96.87	96.65	95.79	0.95	0.95	0.94	0.95	0.95	0.93	0.99	0.98	0.99
PAD-20	96.87	97.30	97.52	0.97	0.96	0.97	0.93	0.95	0.95	0.97	0.99	0.99
PAD-30	92.98	89.31	95.46	0.98	0.78	0.97	0.79	0.92	0.88	0.90	0.92	0.96
All Metrics (OD): AppReviews												
PAD-10	87.68	90.03	86.51	0.89	0.90	0.88	0.92	0.94	0.90	0.93	0.95	0.94
PAD-20	87.98	89.74	89.44	0.93	0.91	0.91	0.87	0.92	0.92	0.93	0.94	0.93
PAD-30	87.68	87.68	90.62	0.89	0.89	0.91	0.92	0.91	0.94	0.93	0.91	0.95
All Metrics (OD): StackOverflow												
PAD-10	92.07	90.73	91.60	0.94	0.95	0.94	0.97	0.95	0.96	0.88	0.86	0.85
PAD-20	91.20	93.00	91.87	0.95	0.95	0.95	0.95	0.97	0.96	0.88	0.91	0.89
PAD-30	92.13	92.33	91.00	0.94	0.93	0.93	0.97	0.99	0.97	0.77	0.83	0.77
SMOTE: JIRA												
PAD-10	90.25	90.17	90.17	0.90	0.89	0.89	0.91	0.91	0.92	0.96	0.96	0.96
PAD-20	91.19	89.86	90.64	0.93	0.90	0.90	0.89	0.90	0.91	0.96	0.96	0.95
PAD-30	89.31	62.03	88.92	0.94	0.57	0.86	0.84	0.98	0.93	0.94	0.58	0.93
SMOTE: AppReviews												
PAD-10	87.91	89.81	89.57	0.87	0.89	0.87	0.90	0.91	0.92	0.95	0.95	0.95
PAD-20	90.28	90.52	88.63	0.89	0.91	0.87	0.92	0.91	0.91	0.95	0.96	0.95
PAD-30	87.68	89.81	89.10	0.89	0.87	0.87	0.86	0.94	0.92	0.93	0.93	0.91
SMOTE: StackOverflow												
PAD-10	78.67	78.97	80.11	0.80	0.79	0.81	0.77	0.78	0.78	0.85	0.86	0.87
PAD-20	77.00	77.69	74.66	0.79	0.80	0.77	0.73	0.73	0.71	0.82	0.85	0.80
PAD-30	76.17	75.08	75.95	0.76	0.79	0.77	0.76	0.68	0.75	0.84	0.82	0.84
BSMOTE: JIRA												
PAD-10	90.64	90.02	90.49	0.90	0.90	0.91	0.91	0.90	0.90	0.96	0.95	0.96
PAD-20	88.99	88.84	88.68	0.89	0.89	0.88	0.89	0.88	0.90	0.94	0.94	0.95
PAD-30	80.27	87.74	85.53	0.84	0.90	0.84	0.75	0.85	0.87	0.87	0.90	0.91
BSMOTE: AppReviews												
PAD-10	88.39	87.68	87.20	0.91	0.87	0.87	0.85	0.88	0.88	0.94	0.94	0.93
PAD-20	88.39	90.28	87.68	0.89	0.88	0.86	0.88	0.93	0.90	0.94	0.93	0.94
PAD-30	87.68	89.34	90.28	0.85	0.89	0.93	0.91	0.90	0.87	0.92	0.95	0.95
BSMOTE: StackOverflow												
PAD-10	81.58	80.71	79.92	0.83	0.82	0.82	0.80	0.79	0.77	0.89	0.88	0.87
PAD-20	80.41	79.99	80.18	0.83	0.81	0.82	0.76	0.78	0.78	0.87	0.86	0.88
PAD-30	80.98	80.33	78.06	0.84	0.82	0.84	0.77	0.78	0.69	0.86	0.87	0.85
SVMSMOTE: JIRA												
PAD-10	88.99	88.52	87.74	0.88	0.88	0.85	0.91	0.89	0.91	0.95	0.95	0.95
PAD-20	88.99	89.39	87.74	0.87	0.89	0.85	0.92	0.90	0.92	0.94	0.95	0.93
PAD-30	87.58	89.70	82.15	0.86	0.88	0.77	0.90	0.92	0.93	0.95	0.94	0.84
SVMSMOTE: AppReviews												
PAD-10	85.55	86.73	87.91	0.84	0.86	0.88	0.87	0.88	0.87	0.93	0.94	0.94
PAD-20	89.34	86.97	88.15	0.88	0.86	0.87	0.91	0.89	0.89	0.96	0.94	0.95
PAD-30	88.39	87.68	91.94	0.85	0.90	0.94	0.93	0.85	0.90	0.93	0.94	0.95
SVMSMOTE: StackOverflow												
PAD-10	75.42	78.52	78.44	0.79	0.78	0.78	0.69	0.80	0.80	0.84	0.87	0.87
PAD-20	80.60	79.31	80.48	0.80	0.84	0.80	0.82	0.72	0.82	0.87	0.88	0.87
PAD-30	81.16	79.69	81.81	0.83	0.83	0.84	0.78	0.75	0.78	0.88	0.86	0.88

Table 2: AUC: Statistical and Friedman test results of Padding size.

	PAD-10	**PAD-20**	**PAD-30**	**PAD-40**	**Rank**
PAD-10	1.00	0.81	0.01	0.00	1.76
PAD-20	0.81	1.00	0.01	0.00	1.99
PAD-30	0.01	0.01	1.00	0.01	2.76
PAD-40	0.00	0.00	0.01	1.00	3.49

difference in the performance of the three, and they all offer high levels of accuracy. The descriptive statistics in Table 5, show that LSTM-3 seems to be the worst model of the three due to its high variability. For LSTM-2, the minimum AUC value is an outlier at 0.53, with the maximum being 0.99 and the mean AUC value being 0.89. The best visual indicator of the fact that LSTM-2 marginally outperformed the rest is the low variability.

The statistical analysis through the means of Friedman test, conducted on the AUC values, supports this claim, with the null hypothesis being that “the different structures of the LSTM models do not create a significant difference in the sentiment prediction performance.” The results of the Friedman test can be seen in Table 4. LSTM-2, with a mean rank of 1.94, marginally outperforms the rest. LSTM-1 and

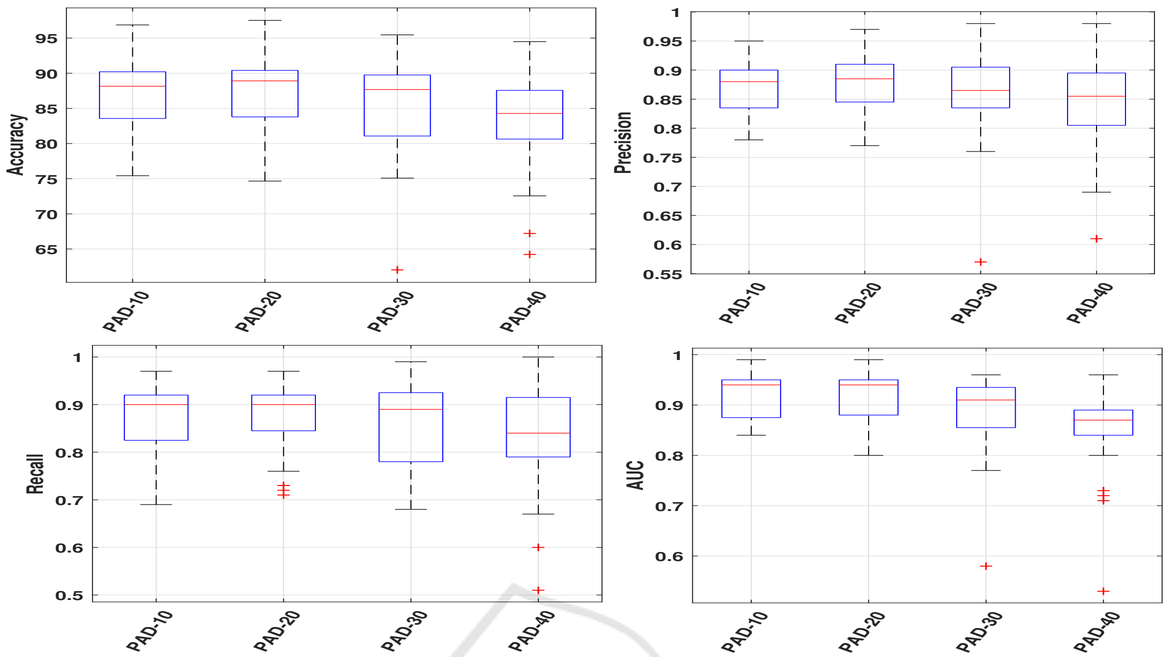


Figure 2: Performance Parameters Boxplots of Padding size.

Table 3: Descriptive Statistics: Precision, Recall, Accuracy, and AUC: Different Padding Length.

	Q1	Mean	Min	Median	Max	Q3
			Accuracy			
PAD-10	83.57	87.17	75.42	88.15	96.87	90.21
PAD-20	83.79	87.49	74.66	88.92	97.52	90.4
PAD-30	81.07	85.65	62.03	87.68	95.46	89.76
PAD-40	80.64	83.38	64.23	84.28	94.49	87.56
			Precision			
PAD-10	0.84	0.87	0.78	0.88	0.95	0.9
PAD-20	0.85	0.88	0.77	0.89	0.97	0.91
PAD-30	0.84	0.86	0.57	0.87	0.98	0.91
PAD-40	0.81	0.85	0.61	0.86	0.98	0.9
			Recall			
PAD-10	0.83	0.88	0.69	0.9	0.97	0.92
PAD-20	0.85	0.88	0.71	0.9	0.97	0.92
PAD-30	0.78	0.86	0.68	0.89	0.99	0.93
PAD-40	0.79	0.83	0.51	0.84	1	0.92
			AUC			
PAD-10	0.88	0.92	0.84	0.94	0.99	0.95
PAD-20	0.88	0.92	0.8	0.94	0.99	0.95
PAD-30	0.86	0.89	0.58	0.91	0.96	0.94
PAD-40	0.84	0.85	0.53	0.87	0.96	0.89

Table 4: AUC: Statistical and Friedman test results of LSTM Techniques.

	LSTM-1	LSTM-2	LSTM-3	Rank
LSTM-1	1.00	0.79	0.98	2.01
LSTM-2	0.79	1.00	0.85	1.94
LSTM-3	0.98	0.85	1.00	2.05

Table 5: Descriptive Statistics: Precision, Recall, Accuracy, and AUC: LSTM Models.

	Q1	Mean	Min	Median	Max	Q3
			Accuracy			
LSTM-1	81.37	86.23	75.42	87.68	96.87	89.8
LSTM-2	80.52	85.58	62.03	87.71	97.3	89.94
LSTM-3	81.12	85.96	67.21	87.74	97.52	90.23
			Precision			
LSTM-1	0.84	0.87	0.76	0.88	0.98	0.9
LSTM-2	0.82	0.86	0.57	0.89	0.98	0.9
LSTM-3	0.82	0.86	0.69	0.87	0.97	0.91
			Recall			
LSTM-1	0.8	0.86	0.69	0.89	0.97	0.92
LSTM-2	0.8	0.86	0.6	0.89	1	0.92
LSTM-3	0.81	0.86	0.51	0.9	0.97	0.92
			AUC			
LSTM-1	0.87	0.9	0.72	0.91	0.99	0.95
LSTM-2	0.86	0.89	0.53	0.91	0.99	0.94
LSTM-3	0.87	0.9	0.73	0.91	0.99	0.95

LSTM-3 had mean ranks equal to 2.01 and 2.05, respectively. Thus, the model with the dimensionality of output space of the FC1 layer as 128 performs better than the other two.

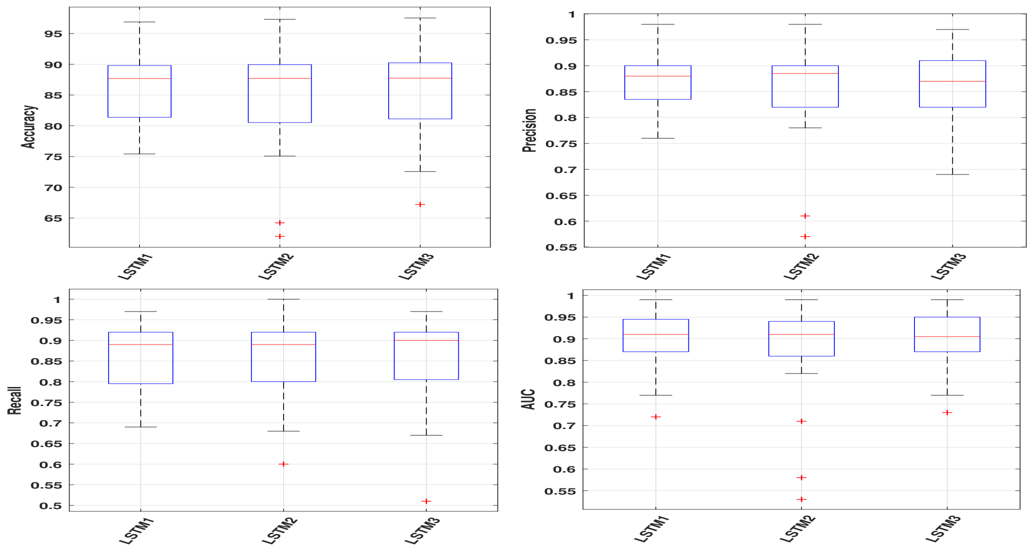


Figure 3: Performance Parameters Boxplots of LSTM Techniques.

4.3 RQ3: Does Class-Balancing Play a Significant Role in Improving the Performance of the Models? If so, Which Oversampling Technique Is the Best for SA-E Purposes?

The effect of class balancing can be seen through the box-plot in Figure 4. The descriptive statistics in term of Precision, Recall, Accuracy, and AUC, as mentioned in Table 6, shows that Class-balancing has regressed the performance of the models with the original dataset resulting in the highest accuracy. The models trained on the original dataset achieve a maximum AUC value of 0.99, with a mean of 0.9 AUC and a minimum of 0.53 AUC being an outlier.

The Friedman test has a null hypothesis that "there is not a significant difference between the performance of sentiment analysis models subjected to different class-balancing techniques." The degree of freedom for this test is three. The mean ranks, as seen in Table 7, show that while the original dataset, with a mean rank of 2.24 performs best, the difference in performance is marginal between the balanced and imbalanced datasets. SVM-SMOTE results in the best performance out of the various oversampling techniques, with a mean rank of 2.47. Thus, the oversampling techniques only regress the performance of the models, and the best performance is seen using the original dataset with imbalanced classes.

Table 6: Descriptive Statistics: Precision, Recall, Accuracy, and AUC: SMOTE.

	Q1	Mean	Min	Median	Max	Q3
Accuracy						
ORGD	88.72	91.25	82.27	91.1	97.52	93.37
SMOTE	77.35	83.07	62.03	85.55	91.19	89.81
BSMOTE	80.62	85.02	78.06	85.66	90.64	88.54
SVMSMOTE	80.68	84.35	64.23	86.85	91.94	88.27
Precision						
ORGD	0.89	0.92	0.78	0.93	0.98	0.95
SMOTE	0.79	0.84	0.57	0.87	0.98	0.89
BSMOTE	0.83	0.86	0.8	0.87	0.93	0.89
SVMSMOTE	0.81	0.84	0.61	0.85	0.94	0.88
Recall						
ORGD	0.92	0.93	0.79	0.93	1	0.95
SMOTE	0.76	0.83	0.51	0.88	0.98	0.92
BSMOTE	0.78	0.83	0.69	0.85	0.93	0.9
SVMSMOTE	0.81	0.85	0.67	0.87	0.93	0.91
AUC						
ORGD	0.88	0.9	0.53	0.93	0.99	0.95
SMOTE	0.84	0.88	0.58	0.87	0.96	0.95
BSMOTE	0.87	0.9	0.84	0.9	0.96	0.94
SVMSMOTE	0.87	0.9	0.71	0.92	0.96	0.95

Table 7: AUC: Statistical and Friedman test results of LSTM Techniques.

	ORGD	SMOTE	BSMOTE	SVMSMOTE	Rank
ORGD	1.00	0.18	0.31	0.59	2.24
SMOTE	0.18	1.00	0.29	0.29	2.78
BSMOTE	0.31	0.29	1.00	0.62	2.51
SVMSMOTE	0.59	0.29	0.62	1.00	2.47

5 CONCLUSION

In this study, we explored SA-E using an LSTM-based approach while testing various structural changes in the LSTM model itself. This approach to

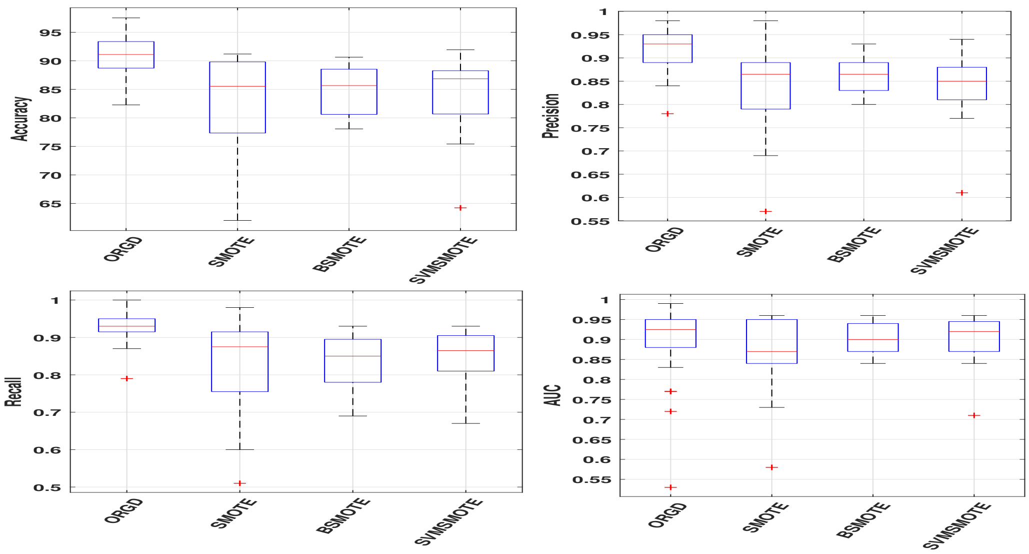


Figure 4: Performance Parameters Boxplots of Data Sampling Techniques.

SA-E has not been researched enough and thus necessitated this work. Future work can be focused on finding new applications of SA4SE, and more extensive datasets can be used. The key conclusions of this work are:

- The padding length of 10 was ideal for getting the best performance from the LSTM model. LSTM-2 had the best structure out of the three LSTM models and can be used for future work.
- Out of the various used oversampling techniques, SVM-SMOTE gave the best results.
- In case of LSTM-based approach, the imbalanced dataset yielded the best results, and performance was regressed upon balancing classes.

ACKNOWLEDGEMENTS

This research is funded by TestAIng Solutions Pvt. Ltd.

REFERENCES

Batra, H., Punn, N. S., Sonbhadra, S. K., and Agarwal, S. (2021). Bert-based sentiment analysis: A software engineering perspective. In Strauss, C., Kotsis, G., Tjoa, A. M., and Khalil, I., editors, *Database and Expert Systems Applications*, pages 138–148, Cham. Springer International Publishing.

Biswas, E., Vijay-Shanker, K., and Pollock, L. (2019). Exploring word embedding techniques to improve sentiment analysis of software engineering texts. In *2019 IEEE/ACM 16th International Conference on Mining Software Repositories (MSR)*, pages 68–78.

Calefato, F., Lanubile, F., Maiorano, F., and Novielli, N. (2018). Sentiment polarity detection for software development. *Empirical Software Engineering*, 23(3):1352–1382.

Jurado, F. and Rodriguez, P. (2015). Sentiment analysis in monitoring software development processes: An exploratory case study on github's project issues. *Journal of Systems and Software*, 104:82–89.

Lin, B., Zampetti, F., Bavota, G., Di Penta, M., Lanza, M., and Oliveto, R. (2018). Sentiment analysis for software engineering: How far can we go? In *Proceedings of the 40th international conference on software engineering*, pages 94–104.

Novielli, N., Calefato, F., Dongiovanni, D., Girardi, D., and Lanubile, F. (2020). *Can We Use SE-Specific Sentiment Analysis Tools in a Cross-Platform Setting?*, page 158–168. Association for Computing Machinery, New York, NY, USA.

Qiu, X., Sun, T., Xu, Y., Shao, Y., Dai, N., and Huang, X. (2020). Pre-trained models for natural language processing: A survey. *Science China Technological Sciences*, 63(10):1872–1897.

Shen, J., Baysal, O., and Shafiq, M. O. (2019). Evaluating the performance of machine learning sentiment analysis algorithms in software engineering. In *2019 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress (DASC/PiCom/CBDCom/CyberSciTech)*, pages 1023–1030.

Villarroel, L., Bavota, G., Russo, B., Oliveto, R., and Di Penta, M. (2016). Release planning of mobile apps based on user reviews. In *2016 IEEE/ACM 38th International Conference on Software Engineering (ICSE)*, pages 14–24. IEEE.