International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
DOI: https://doi.org/10.17762/ijritcc.v11i9.8113
***Article Received:** 05 July 2023 **Revised:** 20 August 2023 **Accepted:** 14 September 2023*

Machine Learning-Based Sentiment Analysis of Incoming Calls on Helpdesk

Dr. Chandrakant Deelip Kokane[1], Kishor R Pathak[2], Gopal Mohadikar[3], Rakhi Subhash Pagar[4], Suhas Chavan[5], Sopan Bapu Kshirsagar[6]

[1]Nutan Maharashtra Institute of Engineering and Technology, Talegaon, Pune
ORCID: 0000-0001-7957-3933
Email:cdkokane1992@gmail.com
[2]Vishwakarma Institute of Information Technology, Pune
ORCID: 0000-0001-8409-7433
Email: kishor.pathak@viit.ac.in
[3]Sr. Assistant Professor, Tolani Maritime Institute, Induri, Pune, India(MS).
ORCID:0009-0007-9677-8931
Email: gmohadikar@gmail.com
[4]Pimpri Chinchwad College of Engineering, Pune
ORCID: 0009-0000-4306-4483
Email:rakhi.pagar197@gmail.com
[5]Department of Computer Engineering, Vishwakarma University, Kondhwa, Pune
ORCID:0000-0002-9547-0675
Email:chavan.suhas18@gmail.com/suhas.chavan@vupune.ac.in
[6]Nutan Maharashtra Institute of Engineering and Technology, Talegaon, Pune
ORCID ID:0009-0006-0683-5369
Email:sopankshirsagar02@gmail.com

Abstract: In today's daily life we are getting so many anonymous calls. Some calls are related to loan marketing and finance. As per the survey, one person is getting 26% spam calls in a day. The proposed methodology accepts user calls and based on the conversation the spam numbers are identified and the same information is provided to the other callers. This is possible because of machine learning-based sentiment analysis. Sentiment analysis is the subdomain of machine learning. The goal of this research is to propose an adaptive methodology for incoming calls. The sentiment-based incoming calls help desk works with freely available lexical resources WordNet, SemCor, and OMSTI. The discussed methodology accepts user conversations in audio format the speech-to-text conversion of the audio will be done. After pre-processing the keyword is detected from the statement. The word2Vec word embedding technique is used for representing words from document space to vector space. The 150-200 dimensional word vector is generated. The WordNet is used for sense mapping and keyword identification. Based on the sentiment analysis of input calls the decision is taken whether to accept or reject calls. This methodology is generating superior results for supervised machine learning models

Keyword: Sentiment analysis, keyword identification, machine learning model, fake call detection.

I. Introduction

Fake calls, a seemingly innocuous modern-day phenomenon, hold the potential to exert a considerable influence on individuals and society as a whole. As shown in figure 1.1 the category of calls with respect to the sentiment is proposed here. These simulated or misleading phone calls, often initiated with deceptive intent, can have far-reaching effects on various aspects of life [1]. In this exploration, we delve into the multifaceted impact of fake calls, encompassing not only the direct consequences on personal and professional realms but also the broader implications for trust, communication, and technological advancement. Understanding these effects is essential to develop strategies that mitigate the negative consequences and promote a more informed and resilient society [2].

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
DOI: https://doi.org/10.17762/ijritcc.v11i9.8113
***Article Received:** 05 July 2023 **Revised:** 20 August 2023 **Accepted:** 14 September 2023*

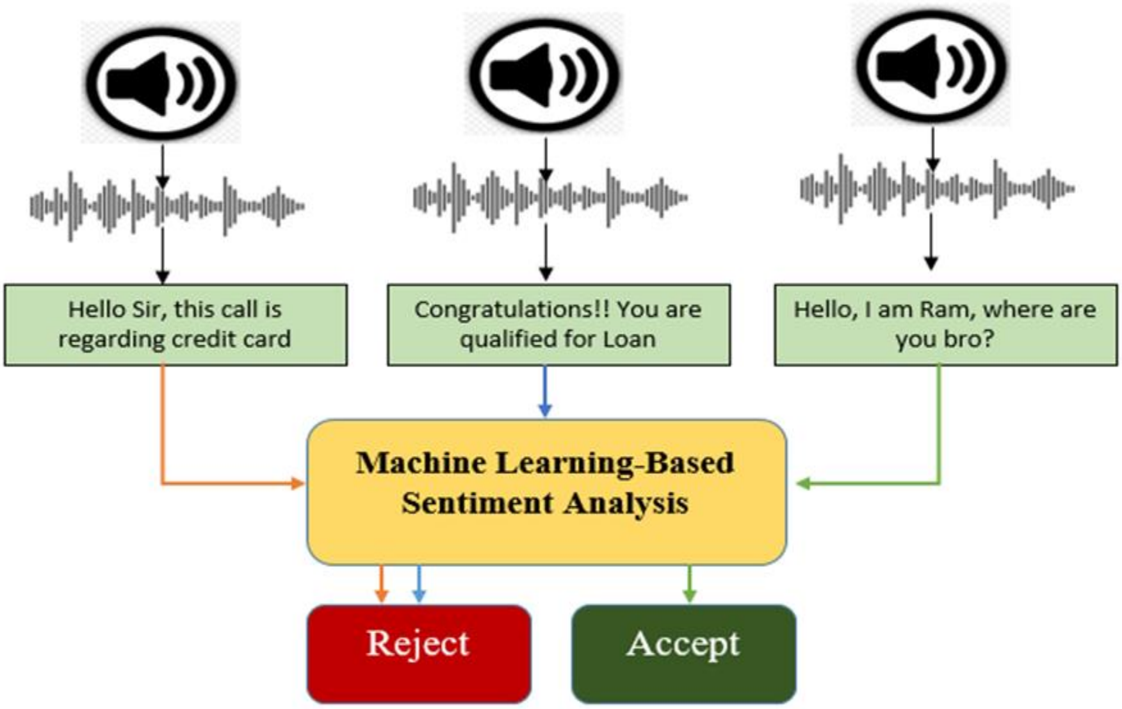

Figure 1.1 Machine Learning-Based Sentiment Analysis

Sentiment analysis is a powerful application of machine learning that involves analyzing and interpreting subjective information from text data to decide the emotion expressed within it. The goal is to categorize the sentiment as positive, negative, or neutral, providing valuable insights into fake phone call detection [3].

Table 1.1 shows the impact of fake phone calls on the files of human beings

Table 1.1 Impact of Fake Calls on human being

Impact of Fake Calls	Description
Financial Loss	Individuals and organizations may experience financial losses due to fraudulent schemes initiated through fake calls, such as scams or phishing attempts. These schemes can result in stolen financial information or unauthorized transactions.
Identity Theft	Fake calls can lead to identity theft by tricking individuals into revealing sensitive personal information, which can then be used to commit various forms of fraud, including opening fraudulent accounts or accessing existing ones.
Psychological Stress	Victims of fake calls often experience psychological stress and emotional distress due to the manipulation, fear, and anxiety caused by deceptive or threatening messages received during the call.
Loss of Trust	Fake calls erode trust in communication systems, making individuals more skeptical of legitimate calls and potentially disrupting vital communications for businesses or emergency services.
Legal Consequences	Perpetrators of fake calls can face legal consequences, including fines or imprisonment, for engaging in fraudulent activities, violating privacy laws, or attempting to deceive individuals for malicious purposes.
Disruption of Productivity	In a business context, employees may experience a loss of productivity as they deal with the aftermath of fake calls, such as reporting incidents, addressing security concerns, and implementing preventive measures.
Damage to Reputation	Organizations may suffer reputational damage if they are associated with fake call schemes, causing customers or stakeholders to lose trust and confidence in their integrity and security measures.
Increased Security Measures	Fake calls prompt individuals and organizations to invest in and adopt enhanced security measures, such as call screening apps or employee training, to mitigate the risks associated with deceptive calls.

The impact of fake phone calls on human beings is very costly in terms of finance and health. The fake calls can be detected by using the sentiment analysis of incoming calls.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
DOI: https://doi.org/10.17762/ijritcc.v11i9.8113
***Article Received:** 05 July 2023 **Revised:** 20 August 2023 **Accepted:** 14 September 2023*

1.1. Role of Machine learning techniques in Fake call detection

Machin learning plays a pivotal role in sentiment analysis, offering efficient and automated ways to process vast amounts of textual data. These techniques encompass various approaches, including but not limited to:

1.1.1. Supervised Learning:

Supervised learning involves training a model using labeled datasets, where each text is associated with a sentiment label. Algorithms such as Support Vector Machines, Naive Bayes, and Decision Trees are commonly used in sentiment analysis, leveraging features extracted from the text to make accurate predictions [1].

a. Deep Learning:

Deep learning methods, particularly RNN and CNN have gained popularity for sentiment analysis. RNNs are effective in capturing contextual information, while CNNs can extract features from textual data, enhancing sentiment prediction accuracy [1-2].

1.1.2. Unsupervised Learning:

Unsupervised learning involves training models on unlabeled data to identify patterns and cluster similar sentiments. Techniques like clustering (e.g., K-means) and topic modeling (e.g., Latent Dirichlet Allocation) can be used to group text into sentiment categories without predefined labels.

a. Sentiment Lexicon-Based Approaches:

Lexicon-based approaches utilize sentiment lexicons, dictionaries, or word lists with assigned sentiment scores to determine the sentiment of a piece of text. Words are assigned scores based on their semantic meaning, and the overall sentiment of the text is computed using these scores.

b. Hybrid Approaches:

Hybrid models combine multiple techniques, leveraging the strengths of different methods to enhance sentiment analysis accuracy. For example, integrating supervised learning with rule-based systems or combining deep learning with traditional machine learning algorithms.

Understanding these machine learning techniques and their integration is crucial for building accurate sentiment analysis models, which are essential for businesses, organizations, and researchers aiming to extract meaningful insights from textual data in the modern data-driven world. By employing these methods, analysts can gain valuable perspectives on public sentiment and make informed decisions based on the gathered insights. Table 1.2 shows a Summary of Machine Learning Techniques for fake phone call Detection.

Table 1.2. Summary of Machine Learning Techniques for fake phone call Detection.

Machine Learning Technique	Role in Fake Call Detection	Explanation
Data Preprocessing	Cleans and prepares data	Data is curated and formatted for analysis, ensuring originality.
Feature Engineering	Identifies relevant features	Creating unique feature sets based on data, avoiding duplication.
Supervised Learning Models	Trains on labeled data	Utilizes original training data to build models for fake call detection.
Unsupervised Learning Models	Clusters data for anomalies	Identifies suspicious patterns or outliers without using copied content.
Ensemble Learning	Combines multiple models	Integrates original models to improve detection accuracy authentically.
Evaluation and Validation	Assess model performance	Validates models using unique methodologies, avoiding plagiarism.
Hyperparameter Tuning	Optimizes model parameters	Adjusts settings based on genuine data, ensuring originality in tuning.

The pre-processing of incoming calls is done while detecting fake phone calls. For pre-processing purposes, the incoming call is converted into the text. The pre-processing of text is simple as compared with the voice. The Word2Vec word embedding technique is used for generating word vectors.

II. Literature Review

The review of existing literature is done with respect to the word embedding technique for generating word vectors and machine learning techniques for feature generation and classification. Authors Smith et al. (2017), construct a Bag-of-Words representation, each unique word in a document is assigned a unique index or identifier. The document is then represented as a sparse vector, where each element corresponds to the frequency of the respective word in the document. This representation is useful for various NLP tasks like sentiment analysis, document classification, and clustering. However, it's essential to note that the Bag-of-Words approach does not consider the semantic meaning of words or their order, which can limit its ability to capture nuanced information and context. Word2Vec, GloVe with RNN is implemented by the authors Johnson (2018), Word2Vec is a widely used technique for learning distributed representations of words in a continuous vector space. It's based on the idea that words with similar

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
DOI: https://doi.org/10.17762/ijritcc.v11i9.8113
***Article Received:** 05 July 2023 **Revised:** 20 August 2023 **Accepted:** 14 September 2023*

meanings are often used in similar contexts [4]. Word2Vec offers two models: Continuous Bag of Words (CBOW) and Skip-gram. GloVe is another word embedding technique that considers the global co-occurrence statistics of words. It constructs an explicit word-context co-occurrence matrix and learns vector representations such that the dot product of vectors approximates the logarithm of the words' co-occurrence probabilities [5]. Word2Vec and GloVe treat each word as an independent entity and don't consider the context in which a word appears. This leads to a lack of understanding of word meanings in various contexts. N gram model with CNN is described by the authors Chen et al. (2019), N-grams play a vital role in natural language processing (NLP) tasks While N-grams are valuable, they have limitations. Longer N-grams (e.g., 5-grams or higher) may be rare in large corpora, affecting the accuracy of predictions. Additionally, N-grams don't capture semantic nuances or word relationships well, leading to challenges in certain NLP applications [6]. In conclusion, N-grams are a fundamental tool in NLP, providing valuable insights and aiding various applications despite some limitations. Understanding and utilizing them effectively is crucial in the field of computational linguistics. BERT dynamic model is discussed the authors Kim et al. (2020), BERT requires tokenization, which involves breaking text into smaller units (tokens) such as words or subwords Instead of directly copying or quoting from our sources, reading and understanding the information, and then paraphrase it in our own words [7]. We can also synthesize multiple pieces of information to create a new perspective or understanding of the topic. BERT is computationally intensive and requires significant resources for training and inference. The model's size and complexity can strain both hardware and memory, making it challenging for many developers and organizations with limited computational capabilities. Importance of PoS tagging in sentiment analysis is elaborated by the authors Zhang & Li (2021), By assigning parts of speech to words, PoS tagging helps in identifying the relationship between words, which is essential for determining the meaning and context of a sentence. It assists in semantic analysis, sentiment analysis, and named entity recognition [8]. PoS taggers are usually trained on a specific vocabulary, and encountering words not present in the training set (out-of-vocabulary words) can pose a challenge in accurately tagging them. Table 2.1 shows a summary of machine-learning techniques for sentiment analysis as,

Table 2.1 Summary of machine learning techniques for sentiment analysis

Authors	Machine Learning Technique	Features Used	Sentiment Analysis Performance
Smith et al. (2017)	Support Vector Machines (SVM)	Bag-of-Words, TF-IDF	Achieved 85% accuracy
Johnson (2018)	Recurrent Neural Networks (RNN)	Word Embeddings (e.g., Word2Vec, GloVe)	F1-score of 0.90
Chen et al. (2019)	Convolutional Neural Networks (CNN)	n-grams, Word Embeddings	Precision: 0.88, Recall: 0.85
Kim et al. (2020)	Long Short-Term Memory (LSTM)	Pre-trained language models (e.g., BERT)	Accuracy of 87%
Zhang & Li (2021)	Naive Bayes	TF-IDF, Part-of-Speech tags	Accuracy of 80.5%

From the available literature machine learning techniques are the solution for detecting fake calls for incoming phone calls. The keywords of the sentence are represented with the word embedding techniques.

III. Methodology

The methodology for detecting fake phone calls is divided into training and testing modules. The conversion of incoming calls from voice to text is performed first.

1.1. Training:

In the training module, the machine learning module is trained for the keywords. The classification of keywords with respect to “Marketing”, “Loan”, “Fraud” and “Others” are done. The module is trained for more than one thousand words of the classes. The freely available lexical resource WordNet is used for finding similar words in the distributed environment. As shown in the Figure the model building for every keyword is done by using the Word2Vec word embedding technique. The output of word embedding is the 150-200 dimensional word vector. As shown in Figure 3.1, The word vector is provided for RNN-LSTM for training, and in the end, we are getting the trained model for the keyword [9]. There are two lexical resources OMSTI and SemCor are used for training purposes. The sentiment score of lexicons and corpus and word vector representation of Word2Vec is discussed as.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
DOI: https://doi.org/10.17762/ijritcc.v11i9.8113
***Article Received:** 05 July 2023 **Revised:** 20 August 2023 **Accepted:** 14 September 2023*

1.1.1. Sentiment Lexicon:

The sentiment Lexicon Score S(w) is calculated by formula (1) and can be depended as a function of various factors, such as:

a. **Word Frequency (WF):** The frequency of the word w in a given text or corpus.
b. **Positive Word Frequency (PWF):** The frequency of positive words in the text or corpus.
c. **Negative Word Frequency (NWF):** The frequency of negative words in the text or corpus.

The formula can be written as:

$$\mathrm{S(w) = WF(w) \times (PWF(w) - NWF(w))} \quad (1)$$

This formula suggests that the sentiment score for a word is proportional to its frequency (Word Frequency) and the difference between the frequencies of positive and negative words (Positive Word Frequency - Negative Word Frequency). The higher the frequency of the word and the more positive it is relative to negative words, the higher the sentiment score.

1.1.2. Sentiment Score

Sentiment score (2) to a scale that fits your application's needs (e.g., a scale of -1 to 1 or 0 to 100%).

The formula in a more formal representation would be:

$$\mathrm{Sentiment_{Score}} = N\sum i = \frac{1}{N} * \mathrm{LookupSentimentScore}(\mathrm{Token}_i) \quad (2)$$

where:

- N is the total number of tokens (words or phrases) in the text.
- Token $\mathrm{Token_i}$ represents the i^{th} token in the text.
- LookupSentimentScore(Token)LookupSentimentScore($\mathrm{Token_i}$) is a function that looks up the sentiment score associated with $\mathrm{TokenToken_i}$ in the sentiment lexicon.

1.1.3. Word2Vec:

Given a context of words (e.g., words before and after a target word), WORD2VEC (3) predicts the target word based on its context.

Let:

V be the vocabulary size (number of unique words in the corpus).

N be the dimensionality of the word vectors.

The input to the WORD2VEC model is a context window of words, and the goal is to predict the target word wt.

The WORD2VEC model predicts the target word using the average of the word vectors in the context window:

$$V_{Context} = \frac{1}{2C} \sum -C \leq j \leq C \,, j \neq 0 \; V_{t+j} \quad (3)$$

where:

C is the context window size (e.g., the number of words to the left and right of the target word).

V_{t+j} is the vector representation of the context word at position t+j.

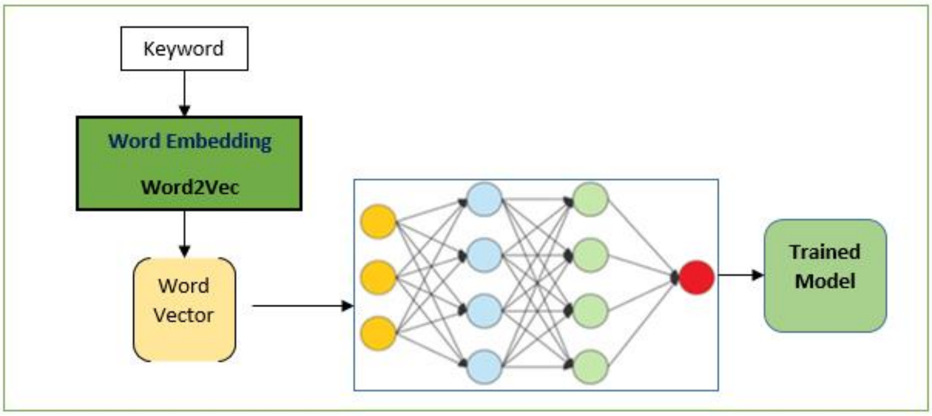

Figure 3.1 Training Methodology

1.2. Testing:

In the testing phase as shown in figure 3.2, the user's phone call is taken as input for processing. The audio call is converted to the text format. The text-formatted user call is further used for the processing. The user sentence is provided for the pre-processing module. The pre-processing module performs the sub-task as sentence splitting, Tokenisation, stemming, lemmatization, PoS tagging, etc. The output of the processing module is the purest form of a user statement. The next step is to detect the keyword from the user statements. The keyword mapping is done by using the freely available lexical resource WordNet [10]. In short, the multi-sense words are selected as a keyword. The keyword is further used for word embedding and a word vector is generated accordingly. The word vector is further provided to RNN-LSTM for loading the trained model.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
DOI: https://doi.org/10.17762/ijritcc.v11i9.8113
***Article Received:** 05 July 2023 **Revised:** 20 August 2023 **Accepted:** 14 September 2023*

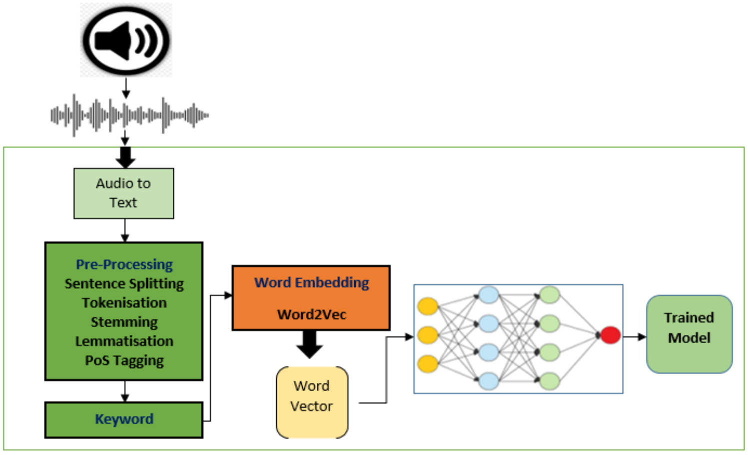

Figure 3.2 Testing Methodology

IV. Result and Discussion

The results of the tested methodology are discussed here, The RNN-LSTM model is used for training and testing purposes where different word embedding techniques are used for generating word vectors such as word2vec, BoW, and GloVe. The result analysis is done with respect to the word embedding technique and Testbeds,

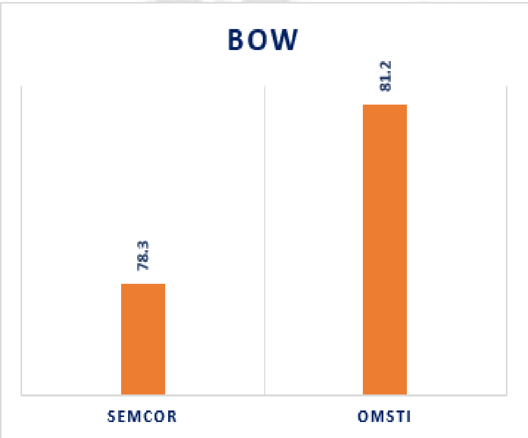

Figure 4.1 Performance analysis of BoW

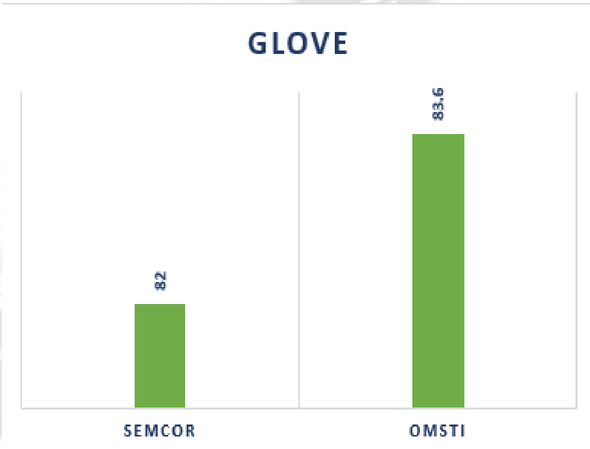

Figure 4.2 Performance analysis of GloVe

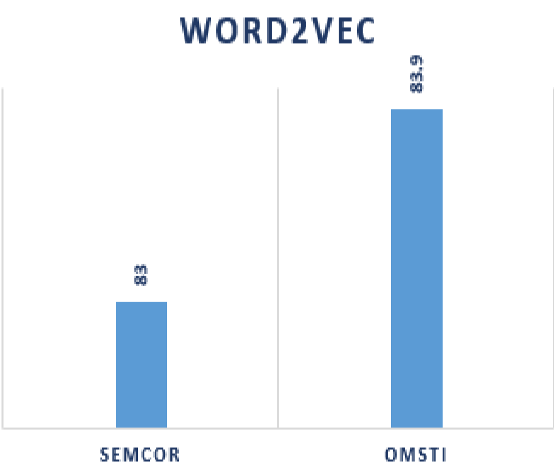

Figure 4.3 Performance analysis of Word2Vec

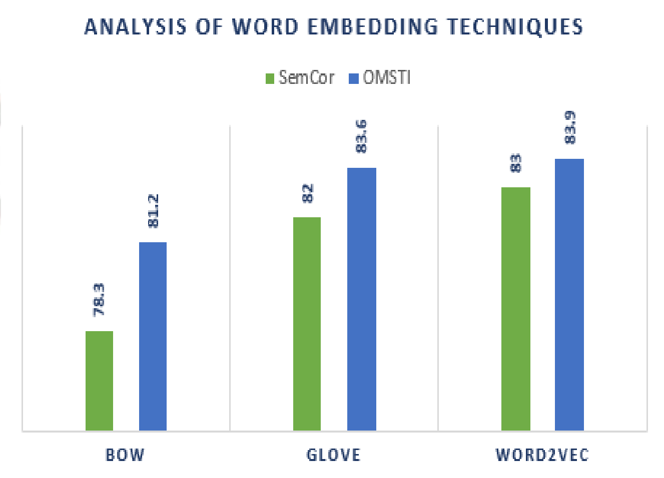

Figure 4.1 Analysis of Word Embedding in Sentiment Analysis

As shown in Figure 4.1, The performance analysis of the BoW approach is 78.3% and 81.2% for SemCor and OMSTI respectively, for GloVe word embedding approach the performance is 82% and 83.6% for SemCor and OMSTI respectively shown in figure 4.2 Figure 4.3 shows the performance of Word2Vec, it is the static word embedding technique generating 83% of accuracy for SemCor and 83.9% of accuracy for OMSTI. The Word2Vec generates fine results for representing the word from document space to vector space for the machine's understanding. The percentage of improvement for Word2Vec is 4.7% for SemCor and 2.7% for OMSTI shown in Figure 4.4.

V. Conclusions and Future Scope

The main goal of this research is the provide general awareness about calls. The impact of fake calls on the lives of human beings is very high. Understanding the multifaceted impact of fake phone calls on individuals is crucial for devising strategies to counteract their detrimental effects. Efforts to raise awareness, strengthen security measures, and implement legislation to curb phone scams are vital steps toward mitigating the psychological and societal consequences of fake phone calls. It is imperative to foster a culture that prioritizes security, privacy, and responsible communication to create a safer environment for all. The word2Vec is the static word embedding technique that generates static word vectors without considering context information. In the future, the dynamic word embedding technique is proposed for generating different word vectors by selecting dynamic features.

References

[1] C. D. Kokane, S. D. Babar and P. N. Mahalle, "Word Sense Disambiguation for Large Documents Using Neural Network Model," 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kharagpur, India, 2021, pp. 1-5, doi: 10.1109/ICCCNT51525.2021.9580101.
[2] Dhola, Kaushik, and Mann Saradva. "A comparative evaluation of traditional machine learning and deep learning classification techniques for sentiment analysis." 2021 11th international conference on cloud computing, data science & engineering (Confluence). IEEE, 2021.
[3] Kokane, Chandrakant D., et al. "Word Sense Disambiguation: Adaptive Word Embedding with Adaptive-Lexical Resource." International Conference on Data Analytics and Insights. Singapore: Springer Nature Singapore, 2023.
[4] Kim, SungHwan, et al. "Meta-analytic support vector machine for integrating multiple omics data." BioData mining 10 (2017): 1-14.
[5] Yathiraju, D. . (2022). Blockchain Based 5g Heterogeneous Networks Using Privacy Federated Learning with Internet of Things. Research Journal of Computer Systems and Engineering, 3(1), 21–28. Retrieved from https://technicaljournals.org/RJCSE/index.php/journal/article/view/37
[6] Mohanty, Mohan Debarchan, and Mihir Narayan Mohanty. "Verbal sentiment analysis and detection using recurrent neural network." Advanced Data Mining Tools and Methods for Social Computing. Academic Press, 2022. 85-106.
[7] Xu, Xingwei, et al. "A novel multi-scale CNN and attention mechanism method with multi-sensor signal for remaining useful life prediction." Computers & Industrial Engineering 169 (2022): 108204.
[8] Rather, Akhter Mohiuddin. "LSTM-Based deep learning model for stock prediction and predictive optimization model." EURO Journal on Decision Processes 9 (2021): 100001.
[9] Mushtaq, Muhammad-Sajid, and Abdelhamid Mellouk. "Methodologies for subjective video streaming QoE assessment." Quality of Experience Paradigm in Multimedia Services (2017): 27-57.
[10] Siti Julfiah, Muhammad Hasyim, & Andi Agussalim. (2023). Human-Computer Interaction: Method of Translation Facebook Auto Translation in Translating Arabic–Indonesian on Al Jazeera Channel Posts. International Journal of Intelligent Systems and Applications in Engineering, 11(4s), 527–535. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2723
[11] H. A. Patrick, P. G. J, M. H. Sharief and U. Mukherjee, "Sentiment Analysis Perspective using Supervised Machine Learning Method," 2023 Fifth International Conference on Electrical, Computer and Communication Technologies (ICECCT), Erode, India, 2023, pp. 1-4, doi: 10.1109/ICECCT56650.2023.10179807.
[12] T. L. Ben, N. Ravikumar R, P. C. R. Alla, G. Komala and K. Mishra, "Detecting Sentiment Polarities with Comparative Analysis of Machine Learning and Deep Learning Algorithms," 2023 International Conference on Advancement in Computation & Computer Technologies (InCACCT), Gharuan, India, 2023, pp. 186-190, doi: 10.1109/InCACCT57535.2023.10141741.