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A Bayesian Deep Learning Model for Sentiment Analysis Based Product Review Prediction

Nikita Sharma[1], Prof. C.K. Tiwari[2], Mr. Devkinandan Nagar[2]
M.Tech Scholar, Patel College of Science and Technology, Indore[1]
Associate Professor, Patel College of Science and Technology, Indore[2]
Assistant Professor, Patel College of Science and Technology, Indore[3]

Abstract Identifying the nature and polarity of customer reviews is critically important for businesses, typically based on opinion mining and sentiment analysis. It has a wide range of applications in information systems, including classifying reviews, summarizing review and other real time applications. There are promising possibilities to use sentiment analysis in real time business models. This work analyses the use of sentiment analysis for analysing customer reviews. Customer reviews are a valuable source of feedback for businesses. In this approach, the customer review dataset from Amazon reviews has been analyzed. Pre-processing of raw data has been done prior to using it to train a neural network. The regularization based Bayes Optimized Deep Neural Network has been used for sentiment classification from social media dataset. To compare the performance of the proposed system against existing research in the domain, the predication error metric has been computed. From the performance of the proposed system, it can be observed that the proposed system clearly outperforms the existing approaches in terms of prediction error and accuracy.

Keywords: Machine Learning, Sentiment Analysis, Deep Neural Networks, Regulrization, Mean Absolute Error, Accuracy.

1. Introduction

Customer sentiment analysis relies heavily on machine learning, which gives companies an effective tool for understanding and reacting to customer feedback. In a day of digital communication and information overload, it is critical to comprehend the feelings that customers are expressing. This paper examines the several factors that make machine learning essential for efficient customer sentiment analysis [1].
The sentiment extraction of users from large and complex data sets is however daunting. This is to be ensured that the context (semantics) is to be taken into account prior to reaching conclusions and implicit meaning has to be inferred correctly. Moreover accurate data pre-processing needs to be imposed in order to segregate the useful information from the raw data. Since user sentiments have a critical impact on several parameters and domains, hence sentiment analysis is critically important [2]. While several data sources are available on the internet to be mined, yet a judicious use of web mining is to be done prior to any system design model is to be used [3]. The critical factor is also the feature selection from the raw data to be included in the analysis of the data as a whole. Machine learning's ability to manage enormous amounts of consumer input is one of the main reasons it is crucial for sentiment analysis. Businesses now receive a dizzying amount of data from a variety of sources, including surveys, emails, social media, and online reviews. This scale is beyond the capabilities of traditional methodologies; in contrast, machine learning models process massive datasets effectively, allowing organisations to analyse feelings more broadly [4].

Sentiment analysis, also known as opinion mining, refers to the computational study of people's opinions, sentiments, emotions, and attitudes expressed in written language [5]. Sentiment analysis, also known as opinion mining, is a natural language processing (NLP) technique used to determine the sentiment expressed in a piece of text [6]. It involves identifying emotions, attitudes, and opinions in customer reviews and classifying them into predefined sentiment categories. Traditional sentiment analysis relied on rule-based approaches and lexicon-based methods, which involved predefined word lists and sentiment scores [7]. However, these methods lacked adaptability to complex language structures and contextual variations. Machine learning-based approaches have emerged as a more effective alternative, providing higher accuracy and better generalization [8].

Despite its advantages, sentiment analysis faces challenges such as:

1. Sarcasm and Contextual Understanding: Machine learning models struggle to detect sarcasm, irony, and implicit meanings in reviews.
2. Data Imbalance: Sentiment datasets often contain an uneven distribution of positive, negative, and neutral reviews, affecting model performance.

Evolving Language: Slang, emojis, and evolving customer expressions require continuous updates in sentiment analysis models

II. Existing Models

Sentiment analysis, also known as opinion mining, is a vital task in natural language processing (NLP) that aims to determine the emotional tone behind a body of text [9]. It is widely used in applications such as product reviews, social media monitoring, and customer feedback analysis. Over the years, sentiment analysis techniques have evolved from simple rule-based approaches to sophisticated machine learning (ML) and deep learning (DL) models. These models can process large-scale, unstructured data with improved accuracy and contextual understanding [10].

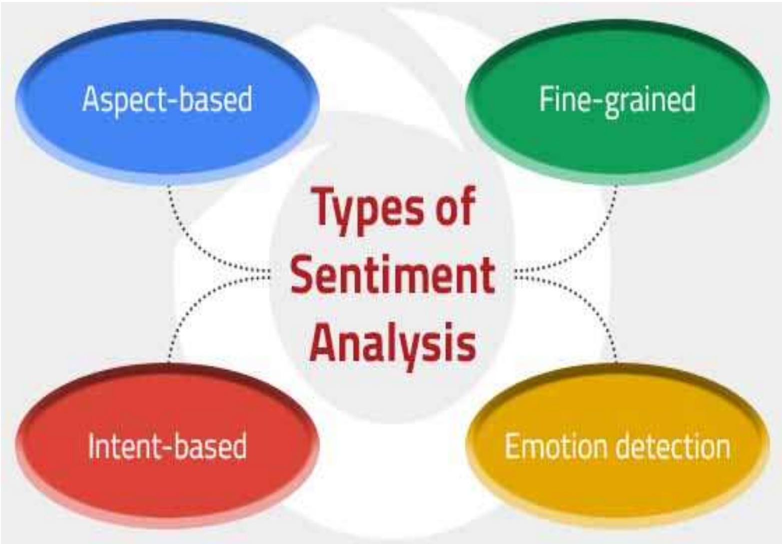

Fig.1. Sentiment Classification

Figure 1 depicts the categories of sentiment analysis. Traditional ML models laid the foundation for automated sentiment analysis. Algorithms like Naive Bayes, Support Vector Machines (SVM), Logistic Regression, and Decision Trees were commonly used. These models rely heavily on feature engineering, where input text is converted into numerical representations using techniques such as Bag of Words (BoW) or TF-IDF (Term Frequency-Inverse Document Frequency) [11]-[12]. For example, an SVM classifier trained on TF-IDF vectors has shown good performance for binary sentiment classification tasks. However, these models often fail to capture the semantics and context of language, especially in complex or nuanced statements [13].

Deep Learning Models for Sentiment Analysis
With the advent of deep learning, models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory networks (LSTMs) became popular for sentiment analysis. These models can automatically learn features from raw text data, reducing the need for manual feature engineering. LSTMs, in particular, have proven effective in capturing long-term dependencies in text, making them suitable for analyzing sentiments in longer sentences or documents. CNNs, originally designed for image processing, have also been applied to sentiment analysis by capturing local patterns in word sequences [14].

Despite the progress, sentiment analysis still faces challenges such as handling sarcasm, idioms, multilingual content, and domain adaptation. Deep learning models are data-hungry and computationally expensive, which can be a limitation in resource-constrained environments. Moreover, the interpretability of models remains a concern, especially in applications where transparency is crucial [15]

Bayesian Approach
While traditional DNNs perform well on large-scale sentiment data, they produce point estimates without indicating the confidence of predictions. This can lead to overconfident incorrect predictions, especially when encountering noisy or out-of-distribution data. Bayesian Deep Neural Networks (BDNNs) address this limitation by integrating Bayesian inference into deep learning [16]. In BDNNs, model parameters are treated as probability distributions rather than fixed values. This probabilistic framework allows BDNNs to express uncertainty in their predictions, making them more reliable and robust, particularly in high-stakes applications like healthcare sentiment analysis or financial sentiment forecasting [17]. In BDNNs, instead of learning fixed weights, the model learns a distribution over weights, typically using variational inference or Monte Carlo dropout methods. During inference, multiple samples from the weight distributions are used to make predictions, resulting in a distribution over the output sentiment classes. This allows the model not only to provide the most likely sentiment but also to quantify the confidence or uncertainty associated with that prediction. In sentiment analysis tasks, this helps distinguish between confidently positive reviews and ambiguous or borderline texts, improving trustworthiness and interpretability [18].
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Proposed Algorithm
As the customer review texts may have overlapping tags or tokens, hence a probabilistic Bayes Classifier has been proposed. The machine learning algorithm is the Deep Bayes Net which works on the principle of Bayes Theorem of conditional probability. The weights of the network are updated such that the condition for maximization is satisfied of a new sample bearing a conditional probability defined as [19]:

$$P\left(\frac{X}{X_i, k_1, k_2, M}\right) = \frac{P\left(\frac{X_i}{X, k_2, M}\right) P\left(\frac{X_i}{k_1, M}\right)}{P\left(\frac{X}{k_1, k_2, M}\right)} \quad (1)$$

Here,

P denotes the probability of occurrence of an event.
X_i denotes the vector corresponding to the bias and weight values of the network.
X denotes the training data set
M denotes the number of neurons and the hidden layers corresponding to the probabilistic network.
k_1 and k_2 denote the network regularization factor.
$\rho = \frac{k_1}{k_2}$ is termed as the network regularization factor corresponding to the cost function J for the network , whose primary goal is limiting the swing in the weight vector for the network [20]. The regularization based approach is more optimized in iterative training compared to forced truncation to achieve faster convergence as forced truncation doesn't allow the weight vector to attain final convergence, as opposed to limiting weights to attain faster convergence as in case of regularization. The training rule for the approach is based on the Bayes theorem of conditional probability which is effective for classifying overlapping feature vectors, based on a penalty $\boldsymbol{\rho} = \frac{\mu}{v}$. The weights are updated based on the modified regularized cost function [21]:

$$\boldsymbol{F(w) = \mu w^T w + v[\frac{1}{n}\sum_{i=1}^{n}(p_i - a_i)^2]} \quad \textbf{(2)}$$

If $(\pi \ll v)$: Network error are generally low.

else if $(\pi \geq v)$: Network errors tend to increase, in which case the weight magnitude should be reduced so as to limit errors (Penalty).

Start
{
Step.1 *Extract dataset.*

Step.2 *Divide the data into a ratio of 70:30 as training and testing data samples.*

Step.3 *Design a neural network with multiple hidden layers.*

Step.4 *Initialize training with random weights.*

Step.5 *Train models with training data and updated weights based on the back propagation rule as:*

$$\boldsymbol{w_{k+1} = w_k - \left[J_k J_k^T + \mu I\right]^{-1} J_k^T e_k} \quad \textbf{(3)}$$

Step.6 *Check for condition*

if (C_{cost} stabilizes or k==max.itr)
End training
else
{
Iterate over Step.5
}

Step.7 *Compute Classification Accuracy*
Stop
}

The performance parameters used for evaluation of the algorithm is the accuracy % which is computed as:

$$\boldsymbol{Accuracy\% = 100 - error\%} \quad \textbf{(4)}$$

IV Experimental Results

The experimental results have been presented next. The dataset has been taken from Kaggle, for Amazon Product Reviews. (https://www.kaggle.com/datasets/tarkkaanko/amazon?resource=download)
Out of the 4916 samples, the training and testing ratio has been selected as 70:30 making the testing samples as 1475 samples.

1		reviewerName	overall	reviewText	reviewTime	day_diff	helpful_ye	helpful_nc	total_vote	score_pos	score_ave	wilson_lower_bound
2	0		4	No issues.	23-07-2014	138	0	0	0	0	0	0
3	1	0mie	5	Purchased this for my device, it worked as	25-10-2013	409	0	0	0	0	0	0
4	2	1K3	4	it works as expected. I should have sprung	23-12-2012	715	0	0	0	0	0	0
5	3	1m2	5	This think has worked out great.Had a diff.	21-11-2013	382	0	0	0	0	0	0
6	4	2&1/2Men	5	Bought it with Retail Packaging, arrived leg	13-07-2013	513	0	0	0	0	0	0
7	5	2Cents!	5	It's mini storage. It doesn't do anything el	29-04-2013	588	0	0	0	0	0	0
8	6	2K1Toaster	5	I have it in my phone and it never skips a b	19-10-2013	415	0	0	0	0	0	0
9	7	35-year Technology (	5	It's hard to believe how affordable digital I	07-10-2014	62	0	0	0	0	0	0
10	8	4evryoung	5	Works in a HTC Rezound. Was running shc	24-03-2014	259	1	0	1	1	1	0.206549
11	9	53rdcard	5	in my galaxy s4, super fast card, and am to	10-11-2013	393	0	0	0	0	0	0
12	10	808TREX50	5	I like this SD Card because it can take musi	05-11-2013	398	0	0	0	0	0	0
13	11	98020	3	It works, but file writes are a bit slower tha	20-11-2013	383	0	0	0	0	0	0
14	12	9z4cda	5	THE NAME OF ITSELF SPEAKS OUT. GO SAN	07-04-2014	245	0	0	0	0	0	0
15	13	A4Q96 "Gadget Love	5	Solid SDHC card that is fast (at reading and	21-11-2013	382	0	0	0	0	0	0
16	14	Aaron "Aaron"	5	Heard that the card's write speed is insuffi	17-02-2014	294	0	0	0	0	0	0
17	15	Aaron "Aaron"	5	I bought this to use with my go pro hero 3	01-04-2013	616	0	0	0	0	0	0
18	16	Aaron Alvarez	5	got this because i had a 2 GB one that fille	03-02-2014	308	0	0	0	0	0	0
19	17	Aaron F. Virginie	5	Class 10 Speed Rating for Seamless Full HD	07-04-2013	610	0	1	1	-1	0	0
20	18	Aaron Graves	5	The read and write speeds are better than	05-02-2014	306	0	0	0	0	0	0
21	19	Aaron	5	This works with the NL1520. No video stu	01-07-2014	160	0	0	0	0	0	0
22	20	Aaron	5	Works as expected. High transfer speed. I	27-10-2013	407	0	0	0	0	0	0
23	21	Aaron	5	Works great in a Samsung Galaxy S3. Forn	29-12-2013	344	0	0	0	0	0	0
24	22	Aaron Madden	5	SanDisk never disappoints. As always SanD	11-05-2013	576	0	0	0	0	0	0
25	23	aaron mckaig	5	Good price, works flawless in my Samsung	04-04-2014	248	0	0	0	0	0	0
26	24	Aaron Nash	5	San disk is hard to beat. You will pay more	23-03-2014	260	0	0	0	0	0	0
27	25	Aaron Smith	5	Installed in my Blackberry Q10 SQN100-1 a	28-01-2014	314	0	0	0	0	0	0
28	26	Aaron T. Swain	5	I just received my card, it is the class 10 64	26-07-2012	865	1	1	2	0	0.5	0.094531

Figure.1 Raw Data.

The data is fetched and loaded to the MATLAB workspace, as a sequence of strings.

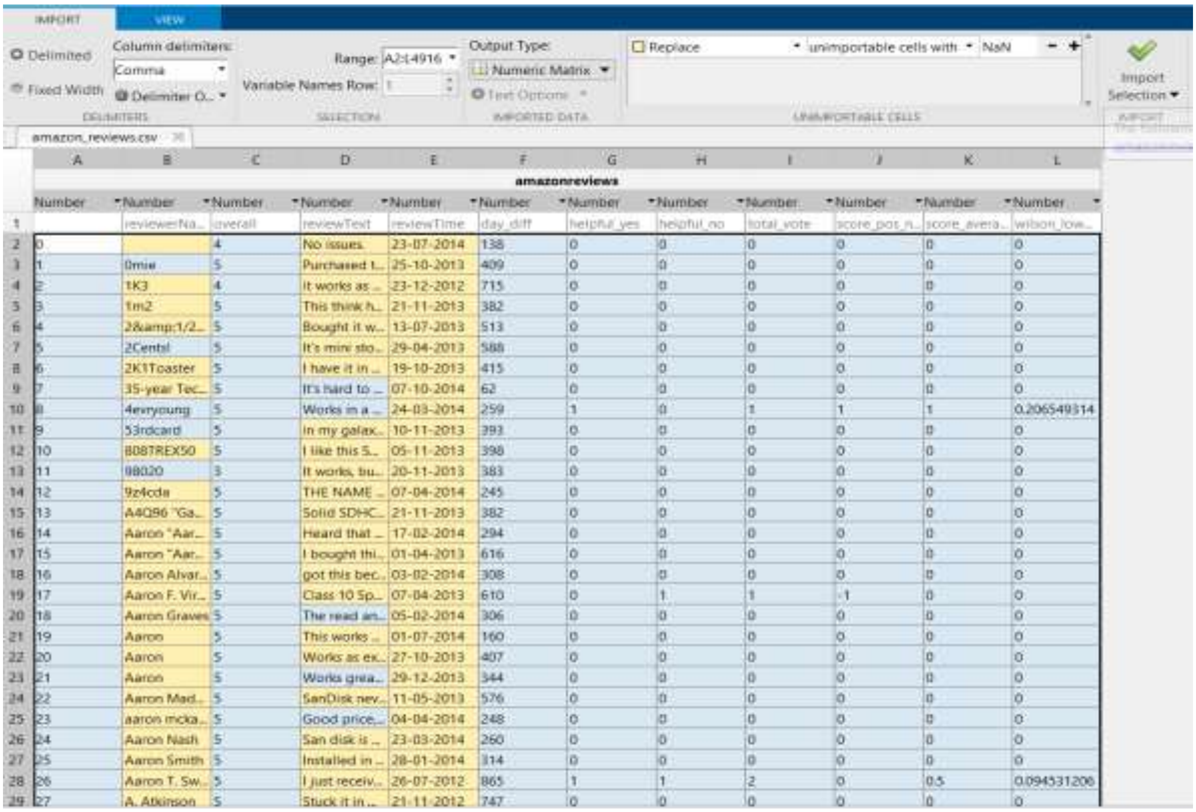

Figure.2 Imported Data to Workspace

Figure 2 shows the raw data being imported to the workspace.

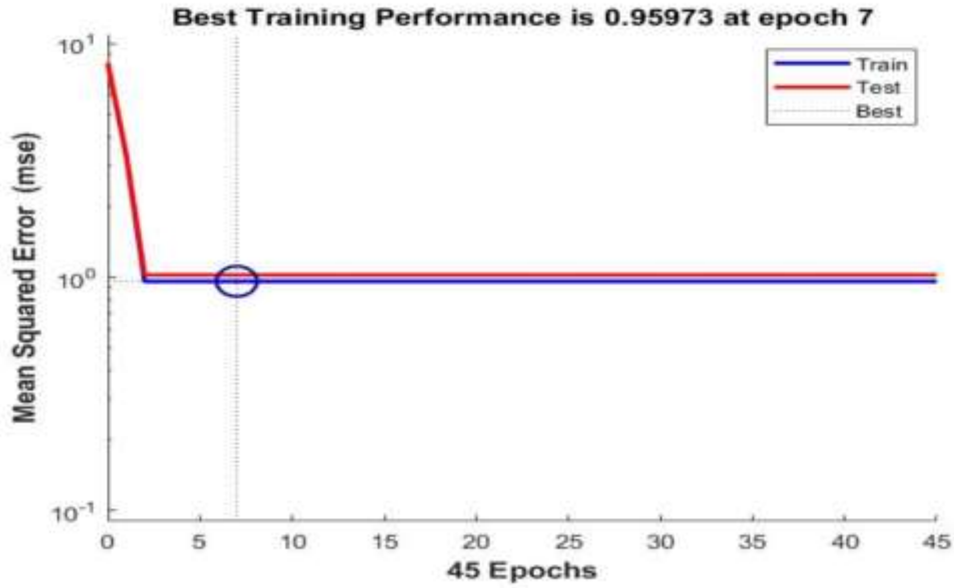

Figure.3 Convergence of algorithm w.r.t. iterations

Figure 3 shows convergence w.r.t. iterations.

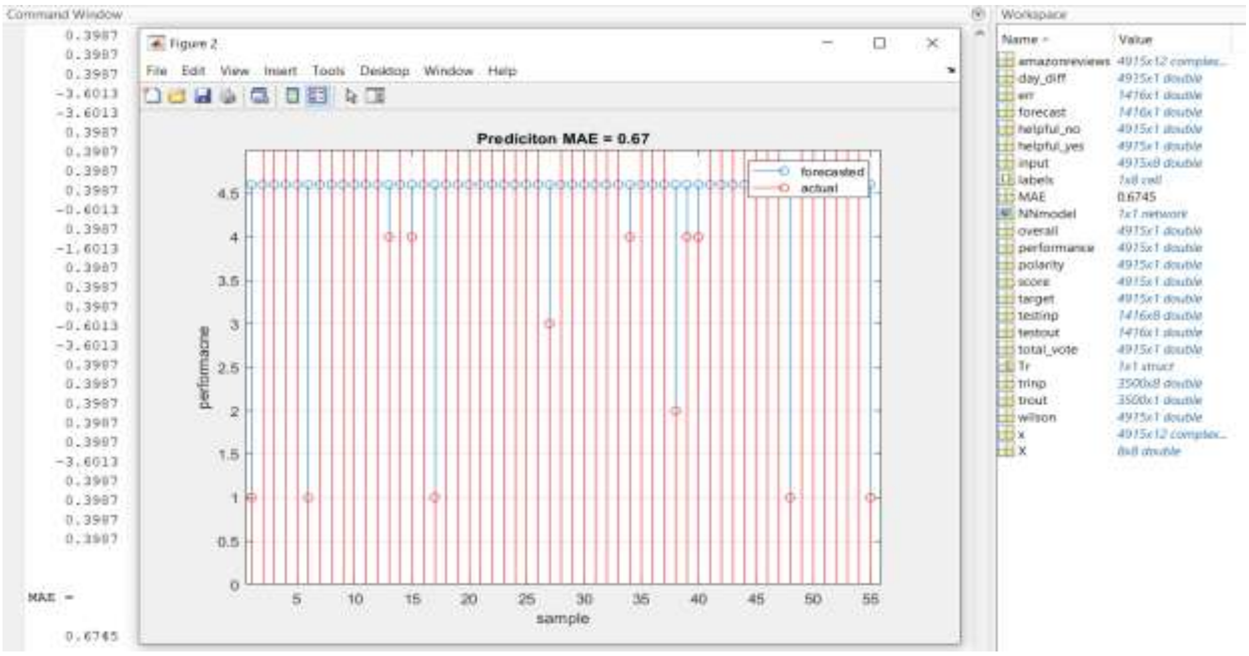

Fig.4 Command Line Screenshot

Figure 4 shows the command line screenshot for mean absolute error.
It can be observed that the mean absolute error (MAE) is 0.67% and the mean squared error (mse) is 0.95973 at the convergence of the algorithm at iteration 45.
Thus the accuracy of the algorithm in terms of accuracy is 100-0.67=99.34%.

The summary of results is presented in table 1

Table.1 Summary of Results

S.No	Parameter	Value
1	Dataset	Amazon Product Review Dataset
2	ML Category	Supervised
3	Algorithm	Bayesian Optimized Neural Network

4	Iterations to Convergence	45
6	Accuracy	99.3%
6	Obeidat et al.	93.5%
7	Zhao et al.	89%
8	Vohra et al.	92%

It comparative analysis with existing work clearly shows that the proposed work outperforms existing benchmark models is terms of classification accuracy

Conclusion:

In conclusion, Sentiment analysis has become a crucial tool for commercial purposes, offering valuable insights into user activities and choices. By employing sentiment analyzers, various methods and algorithms within Natural Language Processing (NLP) are utilized for a comprehensive understanding. This research conducts an extensive review of diverse datasets and research works employing different machine learning techniques for sentiment analysis. Sentiment analysis using machine learning has proven to be a powerful and versatile tool for extracting valuable insights from textual data. The reviewed studies showcased a diverse range of techniques, from traditional methods like Random Forest and Word2Vec to advanced approaches such as Recurrent Neural Networks (RNN). These techniques have demonstrated high accuracy in discerning sentiment across various domains. The future holds promise for continued advancements, particularly in the realm of video sentiment analysis, where the extraction of features from frames and the application of machine learning algorithms are poised to play a pivotal role. Overall, the research underscores the significance of machine learning in unraveling sentiment patterns, contributing to a deeper understanding of user sentiments in diverse applications and domains. The prediction results clearly indicate the improved performance of the proposed approach in comparison with existing research in the domain.

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