Decoding Emotions: Analyzing Amazon Pet Food Reviews through Advanced Recurrent Neural Network-based Sentiment Analysis

[1]B.Pujitha, [2]Dr. A. Mary Sowjanya,
[1]M.Tech, [2]Associate Professor,
[1]Department of CS&SE, College of Engineering, [2]Department of CS&SE, College of Engineering.
[1]Andhra University, Visakhapatnam, [2]Andhra University, Visakhapatnam

Abstract: Sentiment analysis, a transformative automated technique for discerning emotions within textual content, holds unparalleled significance across diverse domains. This study explores its multifaceted applications, including the analysis of sentiments within Amazon Pet Food Reviews. These reviews, integral to the e-commerce landscape, influence purchasing decisions and reflect public sentiment. Our investigation spans online commerce, academia, and social media, showcasing sentiment analysis's far-reaching implications. By harnessing cutting-edge learning techniques, sentiment analysis reshapes how we comprehend reviews, enriching decision-making processes with profound insights. The academic sphere witnesses the emergence of a pioneering sentiment analysis paradigm, amplifying precision in scholarly publications and rendering complex content accessible. This scholarly exploration delves into the orchestration of machine learning algorithms that categorize textual narratives, shedding light on the dynamics of classifier performance. Additionally, the research journey navigates the intricate landscape of advanced recurrent neural networks (RNN) and sophisticated natural language processing (NLP) methodologies. The integration of RNN models with advanced NLP techniques transcends traditional benchmarks, accentuating the depth and nuances of insights unveiled. Through this symbiotic interplay, sentiment analysis emerges as a discerning lens, unraveling layered contexts and sentiments, especially in the realm of Amazon Pet Food Reviews.

Keywords: Sentiment analysis, Amazon Pet Food Reviews, online commerce, Recurrent neural networks (RNN), natural language processing (NLP), Machine learning.

1. INTRODUCTION

In the digital era, where online platforms are teeming with freely flowing opinions, the skill to interpret emotions embedded within written content has gained unparalleled importance. Sentiment analysis, an automated technique, finds a unique role in assessing sentiments within reviews of Amazon Pet Food. These reviews, which are integral to the online shopping landscape, carry significant weight in purchase decisions and reflect public sentiments. Beyond just online shopping, sentiment analysis also plays a pivotal role in academia and social media, highlighting its transformative potential.

The progression of sentiment analysis surpasses the mere categorization of sentiments. It delves into the nuanced analysis of neutral, positive, and negative emotions, enhancing our grasp of human expressions. This evolution is made possible by the integration of advanced learning methods and sophisticated natural language processing techniques. As machine learning algorithms interweave with intricate classifier architectures, sentiment analysis not only uncovers sentiments but also reveals the intricacies that underlie model performance.

This research journey embarks on a meticulous exploration of sentiment analysis methodologies tailored to decipher sentiments within reviews of Amazon Pet Food. The expedition follows a systematic approach that encompasses data preparation, text cleaning, numerical representation, and the development of a central model—the Recurrent neural networks (RNN) model. This model stands as the cornerstone of our methodology, uniquely equipped to unlock sentiments with precision.

As we advance through the subsequent sections, we will delve into the intricacies of sentiment analysis and offer a comparative assessment of various models. Among these models, the RNN (Recurrent Neural

Network) model assumes a central role, providing an unparalleled understanding of complexities, autonomous feature learning, adaptability to diverse datasets, and the capability to capture non-linear relationships. Its effectiveness as a sentiment analysis tool serves as an exemplary illustration of the comprehensive methodology that steers our exploration, unveiling sentiments within Amazon Pet Food reviews and broadening its applicability to wider contexts.

2. LITERATURE SURVEY

Many researchers and students have written papers and theses to learn about sentiment analysis, how it works, and what techniques are used to prepare data and choose features. sentiment analysis of amazon food review data [1], Traditional machine learning methods for text classification, such as Naive Bayes [2], K-Nearest Neighbor (K-NN) [3], and the Support Vector Machine (SVM) [4], have found application in detecting fake reviews. These approaches typically rely on the bag-of-words model [5], which overlooks the inherent sequential structure and contextual nuances of the text. As a result, they struggle to adequately capture the contextual and semantic complexities of review text. Additionally, these conventional techniques require manual extraction of textual features, which are then input into the classifier. While features extracted manually can improve classification outcomes, they suffer from inefficiency and limited effectiveness in terms of model generalization [6]. The advancement of deep learning in Natural Language Processing (NLP) has spurred the adoption of various neural network-based methods for fake review detection. Convolutional Neural Networks (CNNs) [7] and Recurrent Neural Networks (RNNs) [8] stand out as frequently used models in this domain.[9] The focus of Chirath Kumarasiri and Cassim Faroo is on a Part-of-Speech (POS) Tagger based NLP technique for aspect identification from reviews. Subsequently, a Naïve Bayes (NB) Classifier is employed to categorize the identified aspects into meaningful categories. [10] I. K. C. U. Perera and H.A. Caldera have utilized data mining techniques such as Opinion Mining and Sentiment Analysis to automate the analysis and extraction of opinions from restaurant reviews. [11] Rrubaa Panchendrarajan, which identified rating values for different aspects of a restaurant through aspect-level sentiment analysis. This research introduced a novel taxonomy to the restaurant domain that captures hierarchical relationships among entities and aspects. [12] Neha Joshi provided insights into the consumer decision-making process, specifically for the Indian foodservice industry by conducting hypothesis testing using the chi-square test. [13] Bidisha Das Baksi, examined various attributes of existing restaurants and analyzed them to predict an appropriate location with a higher success rate for a new restaurant.

3. METHODOLOGY

In this section, we outline our comprehensive methodology for conducting sentiment analysis on textual data, elucidating crucial stages from data preparation to model preservation.

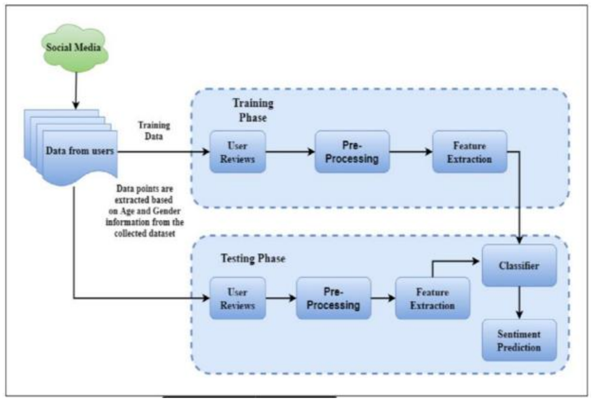


Figure 1: Methodology.

3.1 Data Pre-processing:

The first step involves meticulous data collection from Kaggle website, A Kaggle datasets/Kernels offer data for practicing problem-solving [14], pairing succinct opinions with corresponding ratings. Ratings are transformed into binary labels: '1' for positivity (ratings > 3) and '0' for negativity (ratings ≤ 3).

3.2 Text Cleansing:

To enhance data quality, we undertake thorough text cleansing by:

- Eliminating non-alphabetic characters and symbols for meaningful words.
- Ensuring uniform lowercase text.
- Segregating text into discrete words for intricate analysis.

- Discarding semantically trivial words using Standard English stop words.
- Employing stemming techniques to reduce words to foundational root forms.

3.3 Transformation to Numeric Representation:

For computational analysis, we convert textual expressions into numerical forms using CountVectorizer, an advanced tool with superior functionalities.

Step 3.3.1 Crafting the CountVectorizer Tool:

CountVectorizer empowers streamlined analysis by:

- Setting an upper bound on unique words for computational efficiency.
- Specifying a minimal word occurrence threshold to filter less significant terms.
- Handling intricate word associations to enrich contextual understanding.

Step 3.3.2 Encoding Text Numerically:

CountVectorizer seamlessly translates preprocessed text into numerical matrices. Opinions metamorphose into sequences of numbers, each signifying word occurrence frequencies.

3.4 Building the Recurrent Neural Network (RNN) Model:

In this phase, our journey entails the development of an intelligent program using Keras, a user-friendly neural network toolkit, for constructing the sentiment analysis model.

- Recurrent Neural Networks (RNNs) demonstrate exceptional proficiency in managing intricate data relationships, automating the discovery of essential features, adapting seamlessly to a wide spectrum of data types, and effortlessly scaling to accommodate diverse datasets. What sets RNNs apart is their unique capability to grasp and interpret intricate non-linear patterns. They excel in achieving high-performance levels through data-driven fine-tuning and prove especially effective in facilitating end-to-end learning from raw data. This highlights the versatility and effectiveness of RNNs, particularly in tasks characterized by intricate patterns.

Step 3.4.1 RNN Model Blueprint:

In our design plan, we have delineated distinct sections:

- Input segment ingesting numerical values from CountVectorizer.
- Two concealed layers extracting insights using RNN techniques.
- Output segment predicting sentiment.

Step 3.4.2 Model Construction:

Fusing input layers, concealed layers with 8 components, and an output layer using RNN architecture.

3.5 Training the RNN Program:

We embark on rigorous training for sentiment comprehension.

Step 3.5.1 Infusing Mathematical Sentiment Insight:

Mathematical techniques intertwine with sentiment, enhancing RNN understanding.

Step 3.5.2 Iterative Knowledge Refinement:

Diverse examples refine sentiment interpretation capacity.

3.6 Preserving the Trained RNN Program:

Proficiency achieved through training is preserved in 'model.h5', facilitating future application.

3.6.1 Comparison:

- RNN excels in capturing complex patterns, making it advantageous for intricate non-linear tasks.
- Unlike specialized models, RNN handles diverse data formats.
- RNN demands more resources but adapts to various data.
- RNN's performance relies on hyper parameter tuning.
- Its versatility suits different input types.

3.7 Performance Metrics Used:

Accuracy: The accuracy represents the ratio of accurately classified instances to the total number of instances. While this is a straightforward and commonly utilized metric, it can be deceptive when working with datasets that have imbalanced distributions.

$$Acc = \frac{TP+TN}{TP+FP+TN+FN} \qquad (Eq\text{-}1)$$

Precision: Also recognized as the positive predictive value, precision gauges the ratio of true positive predictions to all positive predictions. This metric proves valuable when the expense of false positives is significant.

$$P = \frac{TP}{TP+FP} \qquad (Eq\text{-}2)$$

Recall (Sensitivity or True Positive Rate): This measurement computes the ratio of true positive predictions among all the actual positive instances. Its significance becomes apparent when dealing with scenarios where the cost of false negatives is substantial.

$$S_n = \frac{TP}{TP+FN} \qquad (Eq\text{-}3)$$

F1-Score: The harmonic mean of precision and recall is encapsulated in this metric. Its value shines through when aiming to strike a balance between precision and recall, particularly in situations involving imbalanced datasets.

$$F1S = 2 * \frac{P * S_n}{P + S_n} \qquad (Eq\text{-}4)$$

Specificity (True Negative Rate):This metric quantifies the ratio of true negative predictions among all the actual negative instances. It complements the recall for the negative class.

$$S_p = \frac{TN}{TN+FP} \qquad (Eq\text{-}5)$$

4. EXPERIMENTAL RESULTS AND ANALYSIS

This model is run in Anaconda spyder python and saved. Once the model is built the review text can be given as input.

- Input Review Text 1: Perfect for our English Bulldog with Allergies
- Input Review Text 2: Natural Balance Lamb and Rice.
- Input Review Text 3: Don't Waste Your Money equality issues

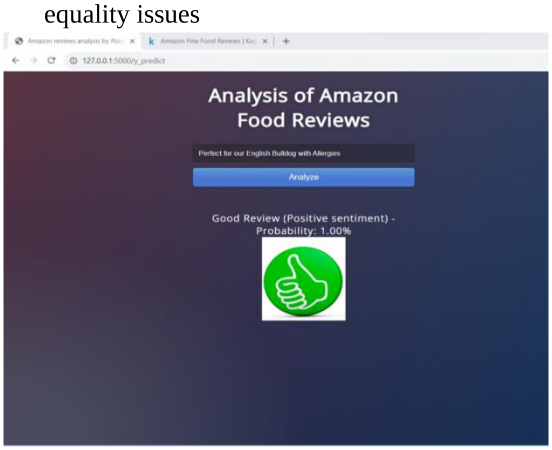


Figure 2.1: Shows the input Review Text 1 sentiment.

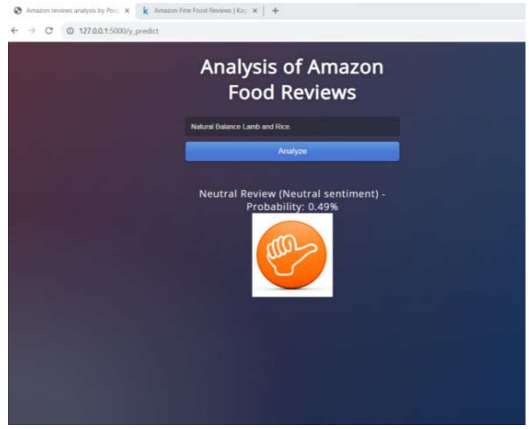


Figure 2.2: Shows the input Review Text 2 sentiment.

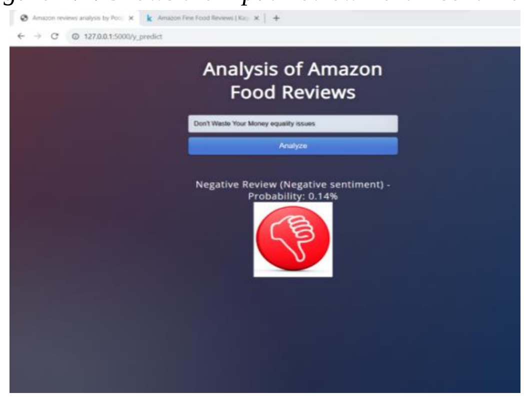
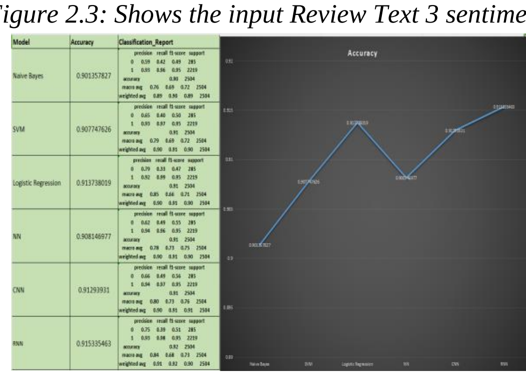


Figure 2.3: Shows the input Review Text 3 sentiment.



Model	Accuracy	Classification_Report	precision	recall	f1-score	support
Naive Bayes	0.901357827	0	0.59	0.42	0.49	285
		1	0.93	0.96	0.95	2219
		accuracy			0.90	2504
		macro avg	0.76	0.69	0.72	2504
		weighted avg	0.89	0.90	0.89	2504
SVM	0.907747626	0	0.65	0.40	0.50	285
		1	0.93	0.97	0.95	2219
		accuracy			0.91	2504
		macro avg	0.79	0.69	0.72	2504
		weighted avg	0.90	0.91	0.90	2504
Logistic Regression	0.913738019	0	0.79	0.33	0.47	285
		1	0.92	0.99	0.95	2219
		accuracy			0.91	2504
		macro avg	0.85	0.66	0.71	2504
		weighted avg	0.90	0.91	0.90	2504
NN	0.908146977	0	0.62	0.49	0.55	285
		1	0.94	0.96	0.95	2219
		accuracy			0.91	2504
		macro avg	0.78	0.73	0.75	2504
		weighted avg	0.90	0.91	0.90	2504
CNN	0.91293931	0	0.66	0.49	0.56	285
		1	0.94	0.97	0.95	2219
		accuracy			0.91	2504
		macro avg	0.80	0.73	0.76	2504
		weighted avg	0.90	0.91	0.91	2504
RNN	0.915335463	0	0.75	0.39	0.51	285
		1	0.93	0.98	0.95	2219
		accuracy			0.92	2504
		macro avg	0.84	0.68	0.73	2504
		weighted avg	0.91	0.92	0.90	2504

Figure 3: Accuracy for different classifiers.

5. CONCLUSION

In our project, we prefer to use Recurrent Neural Networks (RNNs). While other neural networks are good at different things like pictures, RNNs are excellent at understanding the feelings and opinions in text. We use RNNs to dive into reviews and learn more about what customers are saying. We mix various techniques like sentiment analysis and deep learning to figure out how users feel and the quality of products. Our RNN model keeps improving as it learns more, so it's a reliable tool for understanding feelings. In the online shopping world, where reviews can impact your decisions, RNNs are crucial for making informed choices. Additionally, we use Natural Language Processing (NLP) to make RNNs even better at understanding language and sentiments in reviews. This teamwork between NLP and RNNs gives us a deep understanding of what customers think, making RNNs the best choice for analyzing reviews in the online shopping world.

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[11] Rrubaa Panchendrarajan, Nazick Ahamed, Prakhash Sivakumar, Brunthavan Murugaiah, Surangika Ranathunga, and Akila Pemasiri composed a paper titled 'Eatery, a multi-aspect restaurant rating system,' which identifies rating values for different aspects of a restaurant through aspect-level sentiment analysis. This research introduced a novel taxonomy to the restaurant domain that captures hierarchical relationships among entities and aspects.

[12] In 2012, Neha Joshi authored a paper on 'A Study on Customer Preference and Satisfaction towards Restaurants in Dehradun City.' The paper aims to contribute to the limited research in this area and provide insights into the consumer decision-making process, specifically for the Indian foodservice industry. Neha Joshi conducted hypothesis testing using the chi-square test.

[13] Bidisha Das Baksi, Harrsha P, Medha, Mohinishree Asthana, and Dr. Anitha C co-authored a paper that examines various attributes of existing restaurants and analyzes them to predict an appropriate location with a higher success rate for a new restaurant.

[14] "Amazon_pet_food.csv", The dataset consists of reviews of fine foods from amazon. Source link is: https://www.kaggle.com/datasets/ snap/ amazon-fine-food-review