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Company Sentiment Analysis Using Machine Learning

Kashmira Jayakar¹, Akash Tale², Bhagwat Solunke³, Om Sore⁴, Shantanu Waghmare⁵

Department of Information Technology, RMD Sinhgad School of Engineering, Pune, India

Abstract: Sentiment analysis, which is also known as opinion mining and is a part of text mining where we mine data to extract their opinion. People provide their opinion, comments, feedbacks and these are very important indicators. From opinion mining a company may get a feedback for their products from their users, so that they can improve it further on the basis of feedbacks. Politicians can also use it to analyze sentiment about their policies or some other political issues. This paper presents various techniques used in the whole process of opinion mining and how it can help business to make better decisions and make better results. Here we will also see the problems that are still there in extracting the sentiment about a company.

I. INTRODUCTION

Sentiment analysis studies the sentiment of people towards certain entities like Companies or Product. There are millions of people on social networking sites expressing their opinions about various products and their features. On internet we find a large amount of data which can be very useful if we can simply extract opinions or emotions from it.

It can act as active feedback for the companies developing the products.

Sentiment analysis task is to retrieve opinion about certain product and features and to classify them as positive or negative. In the age of ubiquitous digital footprints, every click, review, and social media mention leaves a trail of valuable data. For companies navigating the dynamic landscape of public opinion, this online chatter presents a golden opportunity. Understanding what people are saying and feeling about their brand is no longer a luxury, but a necessity for strategic survival. This is where sentiment analysis, a powerful tool for extracting and analyzing emotions from text, becomes essential. This review paper embarks on a comprehensive exploration of company sentiment analysis, unravelling its potential to transform the way businesses listen to and engage with their audience.

These sentiments can be categorized as positive, negative or neutral; or into an n point scale and it can be like: -very good, good, satisfactory, bad, very bad. Unfortunately, the internet's open forum nature, a boon for free expression, also fosters obstacles for accurate sentiment analysis. Spammers and irrelevant comments, like digital weeds choking honest opinions can skew results and mislead. Deciphering these fake" whispers from genuine voices becomes a crucial challenge in navigating the online jungle of sentiment. Glassdoor like websites can be used to retrieve reviews for sentiment.

II. LITERATURE REVIEW

Hrithika Yadav, Karthik Dwivedi, G.Abirami,[1] Explores the valuable insights hidden within employee reviews of companies, particularly focusing on how online reviews can be harnessed for understanding employee perceptions. In today's digital age, employees and job seekers increasingly rely on online company reviews to assess their workplace experiences. Conversely, companies can utilize these reviews as a rich source of feedback. The study outlines a comprehensive methodology that involves pre-processing user reviews using various techniques, extracting key aspects of significance from these reviews, and ultimately classifying overall sentiment. The sentiment analysis is accomplished through a range of machine learning classifiers, including Multinomial Naive Bayes, Decision Trees, Support Vector Machines, and Random Forest.

G R Usha, L. Dharmanna, [2] delves into the field of Sentiment Analysis, also known as Opinion Mining, which involves the systematic analysis of emotions, opinions, and subjective content within text using natural language processing techniques. It has wide-ranging applications, from marketing and customer service to healthcare materials and social media. The primary goal of this study is to assess the accuracy and effectiveness of different sentiment analysis algorithms when applied to product reviews. The research collected a substantial dataset comprising 4,444 online product reviews sourced from online product reviews sourced from an e-commerce platform. By subjecting these reviews to a variety of sentiment analysis algorithms, the paper aims to provide insights into the performance of these techniques.

Andreea Salinca, [3] presents a sentiment analysis approach to classify business reviews using a large dataset from Yelp. The authors propose several approaches, using two feature extraction methods and four machine learning models. They also conduct a comparative study of the effectiveness of ensemble methods for reviews sentiment classification.

Saumya Chaturvedi, Vimal Mishra, Nitin Mishra, [4] investigates the use of machine learning for sentiment analysis of business reviews. The authors propose several approaches using two feature extraction methods and four machine learning models. They also conduct a comparative study of ensemble methods for reviews sentiment classification. The authors find that the ensemble methods outperform the individual machine learning models. They also find that the best feature extraction method depends on the machine learning model used.

Pothapragada Sri Krishna Chaitanya, Kaushik Kasoju, Sunil Bhutada, Bellamkonda Naga Udaya Chandrika, [5] This literature review dives into the world of ranking companies based on sentiment analysis, specifically focusing on the application of the Valence Aware Dictionary and Sentiment Reasoner (VADER) tool. VADER offers a unique approach to sentiment analysis by considering not just positive and negative words, but also nuances like context, sarcasm, and slang.

The review delves into:

(i) Existing methods for company ranking: Exploring traditional ranking methods like financial performance and customer satisfaction alongside newer sentiment-based approaches.

(ii) Strengths and limitations of VADER: Examining VADER's ability to handle complex language, its ease of use, and potential biases or limitations compared to other sentiment analysis tools.

Lei Zhang, Shuai Wang, Bing Liu, [6] presents provide an in-depth exploration of deep learning's applications in sentiment analysis. It begins with a comprehensive overview of deep learning fundamentals and then delves into the various deep learning techniques employed for sentiment analysis tasks. The paper meticulously details how deep learning has revolutionized sentiment analysis, enabling advancements in text classification, opinion mining, and sentiment prediction.

Victoria Ikoro, Maria Sharmina, Khaleel Malik, [7] Explores the challenges associated with sentiment analysis tools relying on general sentiment lexicons, specifically in the context of gauging public opinion on Twitter by UK energy consumers. The study addresses the limitation of fixed sentiment scores in general lexicons, emphasizing their domain insensitivity. The first lexicon is adept at extracting sentiment-bearing terms and negative sentiments, while the second lexicon is employed for classifying the remaining data.

G. Thamarai Kannan, M Gunasekar, [8]. introduces ABWE (Aspect-Based Word Embedding), a novel sequence labeling subtask for Aspect-Based Sentiment Analysis (ABSA). ABWE focuses on filtering sentiment words for aspect words, utilizing an aspect-fused and context-fused sequence labelling neural network model. The model effectively integrates aspect word information into context words using LSTM networks and generates a final word representation by merging global context information, aspect, and opinion details. The proposed approach holds promise for pair-wise opinion summarization and other downstream sentiment analysis tasks.

Andy Moniz and Franciska de Jong, [9] paper takes an innovative approach to measuring corporate reputation by diving into the previously overlooked perspective of employee sentiment. Instead of focusing on external sources like media and consumer opinions, it analyses online employee reviews to gauge internal satisfaction and its potential impact on financial performance. The research introduces a unique "joint aspect-polarity model". It first generates a dataset of review-based employee sentiment. Then, using Latent Dirichlet Allocation (LDA), it identifies key aspects like "firm outlook" in the reviews. Subsequently, it calculates the overall sentiment polarity of each company's aggregated reviews. Finally, by combining the identified aspect with overall sentiment, the paper defines a novel metric for employee satisfaction. The findings suggest that incorporating this employee satisfaction metric into financial forecasting models may benefit investors. This pioneering research opens up promising new avenues for understanding corporate reputation by valuing the voices of employees alongside traditional external sources.

Kashif Ali, Hai Dong, Athman Bouguettaya, Abdelkarim Erradi, Rachid Hadjidj, [10] This paper proposes a novel framework called "Sentiment Analysis as a Service" (SAaaS) for gleaning valuable insights from social media data. Unlike existing sentiment analysis tools, SAaaS takes a holistic approach, encompassing: Sentiment extraction: It pulls sentiment information from various social media services. Dynamic analysis: It adapts its analysis methods based on the specific social platform, ensuring optimal results. Quality assessment: It introduces a unique model to evaluate the reliability of the analyzed data. Motivated by public health surveillance, the paper demonstrates the potential of SAaaS to combat disease outbreaks. It highlights how SAaaS can analyse the spatial and temporal patterns of social media sentiment to identify potential outbreak hotspots. Real-world data experiments showcase the promising performance of this ground-breaking approach.

Xi Ouyang; Pan Zhou; Cheng Hua Li; Lijun Liu, [11] This paper focuses on applying deep learning for sentiment analysis, Specifically through a Word2vec + Convolutional Neural Network (CNN) framework. Motivated by the increasing need to extract meaningful information from social media "big data", the authors explore a novel approach for analysing textual sentiment. Paper presents a promising approach for sentiment analysis using deep learning, demonstrating the potential of Word2vec-based CNNs for extracting sentiment from textual data. It showcases the effectiveness of this method for tasks like analysing social media content and offers insights for further research in this area.

Hemanlatha S; Ramanthika Ramanthika, [12]. This paper investigates the sentiment of Yelp reviews for restaurants, focusing on identifying whether user's express positive, negative, or neutral opinions about food, service, price, and ambience. It aims to assign a probability score to each review reflecting its sentiment.

III. PROPOSED DESIGN

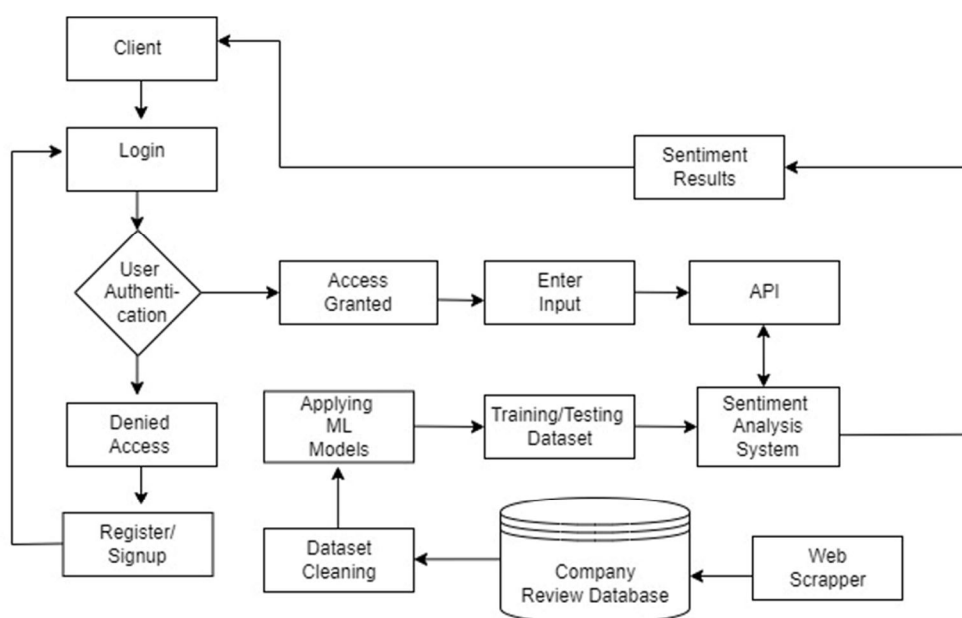


Figure 1: Proposed System Architecture

In the proposed system architecture, an authentication system plays a pivotal role in ensuring secure user interactions. Illustrated within the architecture is a mechanism for user registration. Upon submission of registration details, the system communicates with an authentication endpoint, typically residing on a server, to create user accounts. Subsequently, the system verifies the success of the registration process and generates an authentication token upon successful creation. This token, a crucial aspect of user authentication, is then securely stored within the client's browser using localStorage. Such an architecture not only facilitates user management but also enhances system security by ensuring that only authenticated users can access sensitive functionalities. By integrating robust authentication mechanisms, the proposed architecture fortifies the system against unauthorized access and elevates the overall user experience.

It is important that, in the proposed architecture of the system, the React JavaScript library is adopted as the front-end framework because it allows for designing dynamic and responsive user interfaces. Furthermore, the Flask Python micro-framework is considered for hosting the backend API that would ensure seamless intercommunication between the React frontend and the sentiment analysis system. With this approach, there will be uninterrupted information exchange from the user to the React frontend to the Flask API and back. At this stage, the Flask API processes input into meaningful data utilizing the sentiment analysis system.

Then, the data is sent back to the React frontend where it will be displayed to users after the completion of the analysis. By leveraging React for frontend development and Flask for backend API communication, the architecture not only ensures a smooth user experience but also fosters modularity and scalability. This amalgamation of technologies underscores a robust foundation for the proposed system, poised to deliver efficient sentiment analysis functionalities seamlessly integrated into the user interface. We also have used Web Scraper to Scrape data from different websites. We have used Machine Learning Models like Simple Neural Network, Convolutional Neural Network and Long Short Term Memory Network in Sentiment Analysis System.

So this is the overall summary of the Proposed System Architecture we have make sure that the system has prioritize the Security by using Login Authentication We have used the Machine Learning Models like SNN, CNN and ANN for Sentiment Analysis of the Textual data.

IV. METHODS/ALGORITHMS

We have used Various Machine Learning Algorithms for Sentiment Analysis of the textual data

A. Convolutional Neural Network

We present the use of Convolutional Neural Network (CNN) for sensitivity analysis. The CNN model was developed using Keras, with an architecture consisting of an embedding layer, a one-dimensional convolutional layer, a global max pooling layer, and a dense layer. The embedding layer uses pre-trained weights and is placed untrained. The convolutional layer uses a kernel size of 5 with 128 filters and a ReLU activation function. In addition to the convolutional layer, a global max pooling layer is used to reduce the spatial dimensions. The last layer is a dense layer with sigmoid activation function, which is used for binary classification.

The model is compiled using the ADAM optimizer and binary cross-entropy loss function. It is trained on a training data set with a batch size of 128 for 6 epochs, where 20% of the training data is used for validation. The performance of the model is evaluated on a test set, and both accuracy and loss over time are plotted for the training and validation set plots for a visual representation of the learning process and model performance. This one-dimensional CNN model convolution function is a powerful tool for extracting local features and understanding the spatial structure of texture data, making it highly efficient for sensitivity analysis tasks.

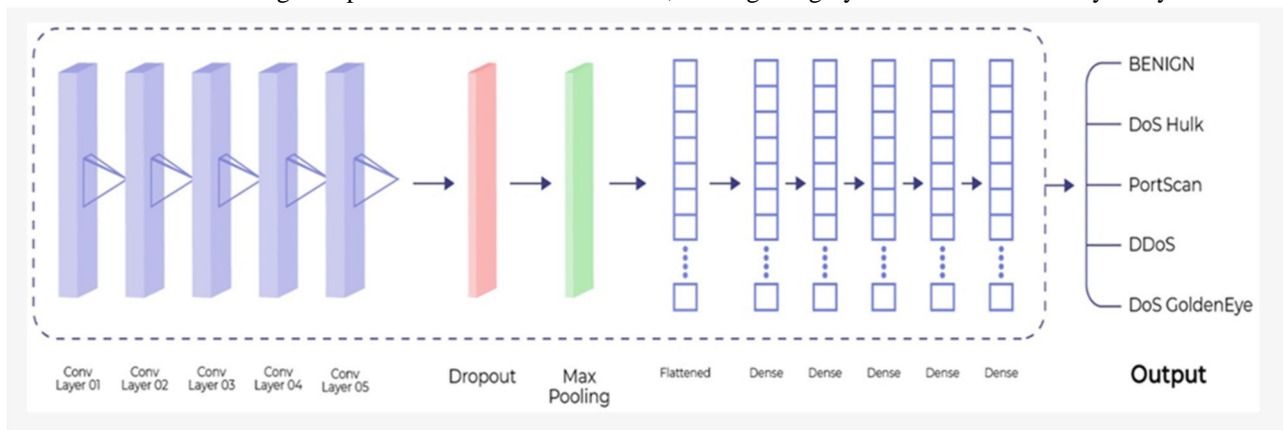


Figure 2: Architecture of CNN

B. Recurrent Neural Network (LSTM)

We introduce a Recurrent Neural Network (RNN) using long-term and short-term memory for sensory analysis. The LSTM model was created using Keras, including the embedding layer and the LSTM layer. The embedding layer uses pre-trained weights and is placed untrained. The LSTM layer has 128 units, which means it reads 128 attributes from the input sequence per time step.

The model also includes a dense layer with a sigmoid activation function, which is used for binary classification. The model is compiled using the ADAM optimizer and binary cross-entropy loss function. It is trained on a training data set with a batch size of 128 for 6 epochs, where 20% of the training data is used for validation. The performance of the model is evaluated on a test set, and both accuracy and loss over time are plotted for the training and validation set plots for a visual representation of the learning process and model performance. This LSTM algorithm with long-term dependent memory capabilities is a powerful tool for understanding sequential patterns in textual data, making it highly efficient for sentiment analysis tasks.

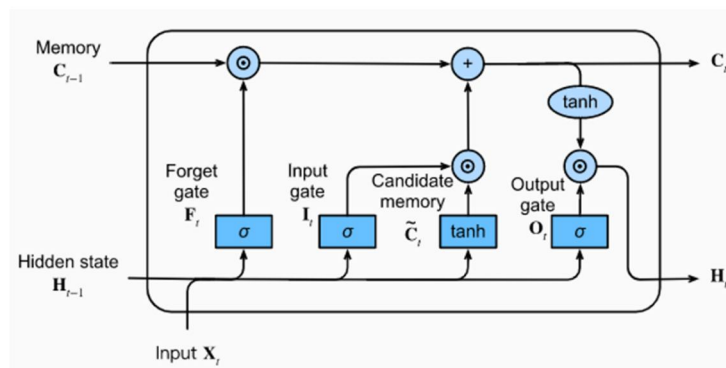


Figure 3: Architecture of LSTM

C. Transformer Based Network

In our Sentiment analysis application, we used a transformer-based neural network model, which is specifically optimized to process information and classify sentiments. The ideal architecture consists of several transformer encoder layers, each with self-attention mechanisms and position-wise feedforward neural networks. The input text is tokenized and embedded into dense representations, which are then enhanced with position codes to capture text quality a series of. move through layers, where auto-attentive mechanisms enable the model to focus on the right parts of the input sequence, and better capture remote dependence. The latter is a prediction of sensitivity for each input reading, obtained by linear layer with a sigmoid followed by a function.

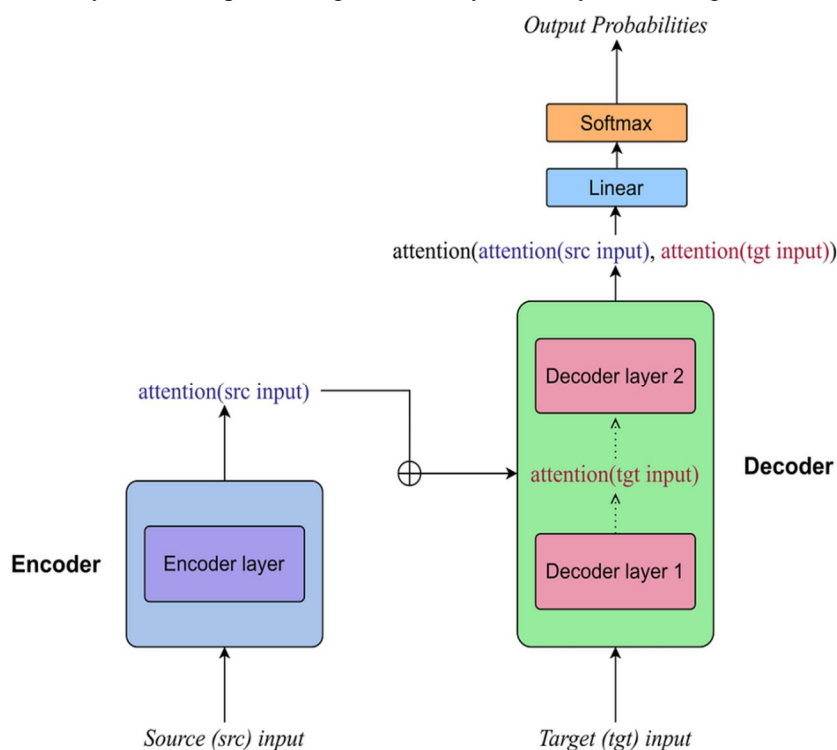


Figure 4: Transformer Based Network Architecture

Self attention Mechanism:

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}(\mathbf{Q}\mathbf{K}^T / \sqrt{d_k})\mathbf{V}$$

Position- wise feedforward neural network:

$$\text{FFN}(\mathbf{x}) = \max(0, \mathbf{x}\mathbf{W}_1 + \mathbf{b}_1)\mathbf{W}_2 + \mathbf{b}_2$$

V. APPLICATIONS

A. Brand Reputation Management

Brand Reputation Management is basically involves managing reputation of the brand of the company. Rating and opinions about the product from customers can enhance or degrade the reputation. So basically Sentiment Analysis helps in determining products a company's brands, which affects the reputation of the brand.

B. Customer and Product/Service Analysis

Analyse customer reviews and feedback to understand what you're doing well and where you can improve. Tailor your communication and offerings based on individual customer sentiment. Proactively address negative feedback and improve customer satisfaction. Use customer sentiment data to inform product development and service enhancements.

C. Market Research and Competitive Intelligence

Monitor public opinion on industry trends and identify emerging customer needs. Benchmark your brand against competitors and identify their strengths and weaknesses. Use customer sentiment data to identify unmet needs and potential growth opportunities. Analyse sentiment data to support strategic decision-making across various departments.

D. Employee Relations and Morale

Analyse internal communications and social media posts to understand employee morale and identify potential issues. Use sentiment data to inform initiatives that boost employee satisfaction and engagement. Analyse sentiment about your company as an employer to attract and retain skilled professionals. Gather feedback and understand employee perspectives to improve workplace culture and practices

VI. CONCLUSION

In conclusion, Sentiment analysis for corporates using machine learning is a powerful tool that can be used to improve customer satisfaction, employee engagement, and brand reputation. By understanding the sentiment of customers and employees, corporations can identify areas where they can improve and make better decisions. Corporations can use sentiment analysis to analyse a variety of different types of data, such as customer reviews, social media posts, and employee surveys. This data can be used to identify trends and patterns in sentiment over time, as well as to predict future sentiment. The applications of Machine Learning, including sentiment analysis, image classification, business analytics and many others things. The applications of ML can enhance the capability of analysing data and to do repetitive task.

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