



Sentiment Analysis of User Reviews for Swiggy and Zomato Using MHA-BiRCNN Model

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Abstract. The online food ordering industry in India has shown growth at an impeccable pace, led by platforms like Swiggy and Zomato, that let users explore multiple restaurants, order their desired dishes, and have them delivered to their homes. Users can also post ratings and detailed comments about their experiences on the Google Play Store. The present research investigates the sentiment reflected in these user-generated reviews to uncover insights that may help improve service quality and customer satisfaction. Such opinions provide valuable understanding of consumer preferences and expectations, supporting data-driven decision-making for business growth. For this study, approximately 500,000 reviews from each application were gathered, resulting in a dataset comprising 11 distinct attributes for every review record. The data was preprocessed and analyzed with the help of MHA-BiRCNN (Multi-Head Attention – Bidirectional Recurrent Convolutional Neural Networks) model. The study showed an analysis for performance of the model and found an insight that its accuracy for Swiggy was 94.57% and Zomato was 95.35%.

Keywords: Online food delivery services, Zomato, Swiggy, User Reviews, Google Play Store, Sentiment Analysis, Neural Network

1 INTRODUCTION

In recent years, ordering meals online has grown into one of India's fastest-moving industries [1]. Modern technology has overhauled how people buy food, with apps on phones making it simple to select and modify orders [1]. Shoppers can look through many dining places, try new types of food, see full menus, and get their meal sent over right away. This has made the entire process smoother for the customer [2]. Because these services save valuable time and reduce work, more people are deciding to use them [3].

Phone applications have shifted the way ordinary jobs are done [4]. Today, apps handle everything from booking tickets [5] and sending messages [6] to watching movies [7], purchasing items on the web [8], and moving money between accounts. Knowing what shoppers think and feel is necessary for anyone's development and for a company to do well [1]. It enables businesses to study customer preferences, what they are liking and what they actually need [9]. Platforms for food delivery focus on delivering these hopes, which builds customer engagement [10]. Services like Swiggy and Zomato bring in enhanced user experience to make the application more intriguing and simpler to use [2].

Upgrades often include better ways to arrange customer opinions, screens that filter by scores, and sections for giving full comments [11]. These parts offer helpful clues for the people who build the apps, study the data, and design the look by pointing out troubles, extra features users ask for, and how the app is used day to day [12][13]. Reviews written by buyers are a clear picture of their thoughts and feelings about what they received [14]. They come in all shapes and sizes and there are so many that reading them one by one is not possible [15]. Studying sentiments gives an organized path to take out emotions, points of view, and habits from written words [16]. Feedback is most often sorted into good, bad, or in-between groups. People doing research apply sentiment study methods to pull useful ideas from what users say [12]. The job means looking at writing full of feeling, using fixed language rules or computer programs [17]. Important ways to do this are methods based on word lists and set rules [18], older styles of machine teaching [19][20], and newer deep thinking models [21]. Older machine teaching pays attention to how sentences are built and the situation around the words [22]. Deep thinking models, on the other hand, train themselves to see complicated signs through networks that act like a brain [23].

Swiggy first opened in 2013 in Bengaluru. It was started by Nandan Reddy, Sriharsha Majety, and Rahul Jaimini under the first name Bundl Technologies. The company originally worked in shipping and moving goods before

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turning toward bringing meals to people in 2014 and taking the name Swiggy. It placed itself as a bridge between those wanting food and the places that cook it, using a system built on technology. Swiggy's launch included 25 partner restaurants and a little team of delivery workers in Bengaluru. Only a few years later, it spread to main cities like Chennai, Delhi NCR, Hyderabad, Kolkata, Mumbai, and Pune, creating a wide web for moving orders. The business follows a mixed plan, serving both regular shoppers and other companies. After collecting large amounts of money from investors such as Naspers and DST Global, Swiggy reached unicorn level in 2018 and is counted among India's most quickly rising new companies [24][25][26].

Zomato was set up in 2008 by Pankaj Chaddah and Deepinder Goyal, first going by the name Foodiebay [27]. It began as an internet listing for restaurants in Delhi and quickly caught on in other big Indian cities, including Mumbai, Bengaluru, Kolkata, and Pune. In 2010, the company changed its title to Zomato as it planned to grow beyond the country's borders. Over the years, it stepped into markets like Qatar, the Philippines, South Africa, Sri Lanka, the UAE, and the UK. By 2013, it had moved into Turkey, Brazil, and New Zealand. In 2015, Zomato bought several overseas platforms, including Gastronautai in Poland and NexTable and Urbanspoon in the United States. But some steps into new nations led to money troubles, making it leave a number of countries. After changing its plan and putting fresh focus on the shopper's experience and how things are run, Zomato found steady ground again and hit unicorn status in 2018. Now, the app works in more than 24 nations, helping millions of people who use it each month across thousands of towns and cities around the world.

The contribution of our paper includes:

- This paper collected user reviews from the Google App Store for Swiggy and Zomato applications.
- This paper proposed a model for Swiggy and Zomato for sentiment analysis.
- This paper focused on LSTM-CNN with multi-head attention for text analysis of the collected reviews.

2 RELATED WORK

The limitations of lexicon-based sentiment methods occupied the attention of Wilson, Wiebe, and Hoffmann during their 2005 research. Traditional approaches typically attached fixed polarities to words irrespective of their usage patterns in real text. Their proposed framework operated at the phrase level while integrating contextual information into the decision process. Experiments conducted on the MPQA corpus demonstrated 70.2% classification accuracy, confirming that context-sensitive methodologies surpass rigid lexicon-dependent systems by significant edge [28].

Online investment communities provided the practical setting for Das and Chen's 2007 research. These digital spaces produce discussion in domain-specific vocabulary, unusual grammar, and sarcastic elements that regularly stuns usual analysis techniques. Their methodological innovation combined multiple classifiers, allowing their joint decisions to determine whether postings communicated optimistic, pessimistic, or directionally neutral market views. Investigation finds approximately 1.5 million messages extracted from Yahoo! Finance and Raging Bull revealed their integrated system correctly categorized 82.3% of manually labeled posts, exceeding the individual accuracy rates of all component classifiers [29].

Cross-language sentiment adaptation occupied Manurung's 2008 investigation, which tested whether English resources could support Indonesian analysis through translation. Because Indonesian lacks abundant labeled datasets, the researcher converted English film reviews into Indonesian via automated translation software and used this material for model training. The resulting Naive Bayes classifiers reached 78.82% accuracy, slightly behind the 80.09% figure obtained from English-trained models. These results suggest translation tools proposed practical alternatives for language communities with limited local resources [30].

Processing Chinese text motivated Liu, Xiong, and Song's 2010 contribution, which confronted the language's characteristic absence of word delimiters and context-dependent semantic fluctuations. Their methodological innovation combined a flexible sentiment lexicon with grammatical structure examination to fine-tune term orientations as per sentential context. Evaluation using Chinese consumer feedback documents produces 90.1% correct classification, surpassing the 86.4% benchmark established through conventional SVM implementations [31].

Sentence-level meaning extraction combined with traditional machine learning in Khan and associates' 2011 proposal. Their multi-phase procedure concludes semantic orientations for individual statements before passing these enhanced representations to classifiers for final categorization. Assessment against widely referenced film review collections produced 92.3% accuracy when utilizing Support Vector Machines, providing strong evidence that semantic preprocessing before algorithmic training delivers considerable performance gains [32].

Expanding sentiment caliber to Bangla motivated Tuhin and coauthors' 2019 research, which systematically analyzed multiple supervised techniques. The researchers collected a corpus of Bangla text comments and trained SVM, Naive Bayes, and Maximum Entropy models for comparative evaluation. Linear kernel SVM finds as the lead performer, achieving 83.02% correct categorization across test samples and establishing performance standards for related Bangla sentiment research [33].

YouTube movie trailer reactions became the focus of Novendri and colleagues' 2020 inquiry, which calculated viewer sentiment using comment analysis. The team delivered Naive Bayes classification on user responses to two notable film previews, grouping opinions into positive, negative, and neutral classes. The methodology remained consistent 75.35% average accuracy throughout both datasets, showing its reliability for extracting audience reviews from social media commentary [34].

3 METHODOLOGY

3.1 Data Collection

The dataset used for sentiment analysis is extracted from the Google Play Store's Reviews of the two popular online food delivery service applications i.e. Swiggy and Zomato. The nature of the dataset is structured and stored in csv format. Refer to Table 1 Unprocessed data for both platforms. The dataset gathered has 5 lakhs rows for both Swiggy and Zomato each with multifaceted features. The features of the dataset hereby reviewId, userName, userImage(link), content(user's reviews), score(rating), thumbsUpCount(likes at reviews), reviewCreatedVersion(user's reviews version), at(reviews posted date and time), replyContent(organization's reply to user), repliedAt (replied date and time) and appVersion(application version). Refer to Fig. 1 defines food platform based rating percentage. Refer Fig. 2 for sentiment percentage of platform reviews.

Table 1: Sample of Unprocessed Data

Platform	Content	Score
zomato	Good	5
zomato	Fast and furious delivery	4
swiggy	Good	5
swiggy	Fast and reliable	5
swiggy	I don't have cash on delivery please help	5
zomato	Nice	5
swiggy	Not delivered at my location	1
swiggy	What's with the moral policing making eggs	1
swiggy	My order was delivered with 2 missing pieces	1
swiggy	Nice	4

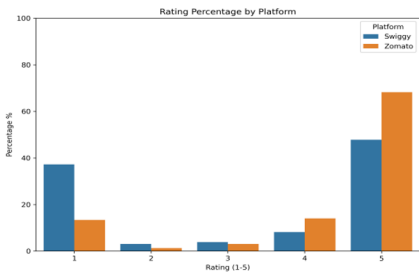


Fig. 1: Overall Platform Score

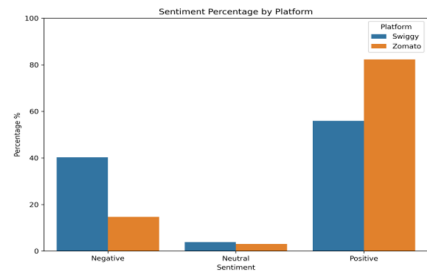


Fig. 2: Sentiment of Platform Reviews

3.2 Data Preprocessing

The two gathered dataset combined with incorporating a new column 'platform' having values swiggy or zomato. Considering the relevant features for further processing, another new column 'sentiment' is incorporated with fabrication by referring to the existing column named 'score' that ranges from 1 to 5 having values positive or negative. The dataset is refined with text preprocessing steps. Firstly, converting text to lowercase such that to prevent the same word in different cases from being treated as distinct, removal of URLs as they don't help in sentiment analysis, removal of non-alphanumeric characters (removing punctuation, numbers and special symbols) to get meaningful text and removal of emojis as it is complex than text and not contribute in sentiment analysis and trimming extra whitespaces (removing multiple spaces, tabs and newlines) as it does not affect the text also ensures clean and uniform text input. Labeling the sentiment feature into numeric value for smooth computation and applied class balancing to remove bias. Refer to Table 2 for sample data after preprocessing.

Table 2: Sample of Processed Dataset

Platform	Content	Sentiment	Label
zomato	good	Positive	1
zomato	fast and furious delivery	Positive	1
swiggy	good	Positive	1
swiggy	fast and reliable	Positive	1
swiggy	i dont have cash on delivery please help	Positive	1
zomato	nice	Positive	1
swiggy	not delivered at my location	Negative	0
swiggy	whats with the moral policing making eggs	Negative	0
swiggy	my order was delivered with missing piece	Negative	0
swiggy	nice	Positive	1

3.3 Feature Extraction

After preprocessing, tokenization technique is used to transform the cleaned text into a numerical representation. A tokenizer is initialized with a fixed vocabulary size limit of 30,000 words and an out-of-vocabulary token to handle unseen or rare words. After building the vocabulary, each review is converted into a sequence of numerical indices corresponding to the words in the tokenizer's word index. These sequences are then adjusted to a fixed length of 100 tokens using padding and truncation. Padding with zeros applied over short reviews whereas truncation was applied to longer reviews to maintain consistent input dimensions.

3.4 Proposed Model

This work proposes the building of a new, unified neural system made to detect opinion within text-based customer comments. The design works using two independent computational lanes that function concurrently.

The initial lane deciphers the order and relationship between words. The complementary lane finds recurring clusters of neighboring terms. The outputs from both processing streams are subsequently clubbed to formulate a final decision.

The process starts by transforming each word into a 128-number code. Then a technique known as dropout is applied. Each training iteration temporarily eradicates 30% of these numerical encodings. This method assists the model to prevent fixating on minor details present only in the training data.

The contextual lane is built upon a Bidirectional Long Short-Term Memory network. This element processes language in both its natural order and in reverse also. It contains two stacked layers. The first layer maintains 64 storage cells for forward reading and 64 for backward reading. The following layer maintains 32 cells per direction. Within these layers, during training, 30% of the pathways that carry information from one step to the another are deactivated randomly. The complete outcome from this network is directed to a focus module with eight independent calculation units. This module examines and assigns a significance weight to each word regarding its emotional content. The product of this focusing step is combined with the initial LSTM output through a direct additive link. This merged data is then standardized and reduced to a singular, representative vector through an averaging process.

Operating in collaboration, the pattern-detection lane applies convolutional operations. Three different analytical windows are used. The first reviews sequences of three consecutive words. The second reviews four words. The third reviews five words. Each window employs 100 unique feature identifiers. From the output generated by each identifier, two summary statistics are retained: the peak value observed (termed global max-pooling) and the mean of all observed values (termed global average-pooling). This procedure produces six compact data summaries that encapsulate characteristic expressions.

The representative vector from the contextual lane and the six data summaries from the pattern-detection lane are linked end-to-end. This unified data block is processed by interconnected decision units. The first cluster contains 256 units utilizing the ReLU activation function, after which a 50% dropout is imposed. The signals then move forward into another set of 128 processing nodes that use the ReLU function with a random 30% of the connections from these nodes are deactivated during the training phase. Ultimately, the information is channeled to a final, solitary unit with a sigmoid function. This unit computes a score from zero to one, implying the estimated likelihood of a favorable opinion.

The model learns by iteratively refining its internal arguments to reduce prediction errors, using the Adam optimization strategy at a constant adjustment rate. Error is quantified with the binary cross-entropy calculation. Refer to Fig 3 for model architecture diagram.

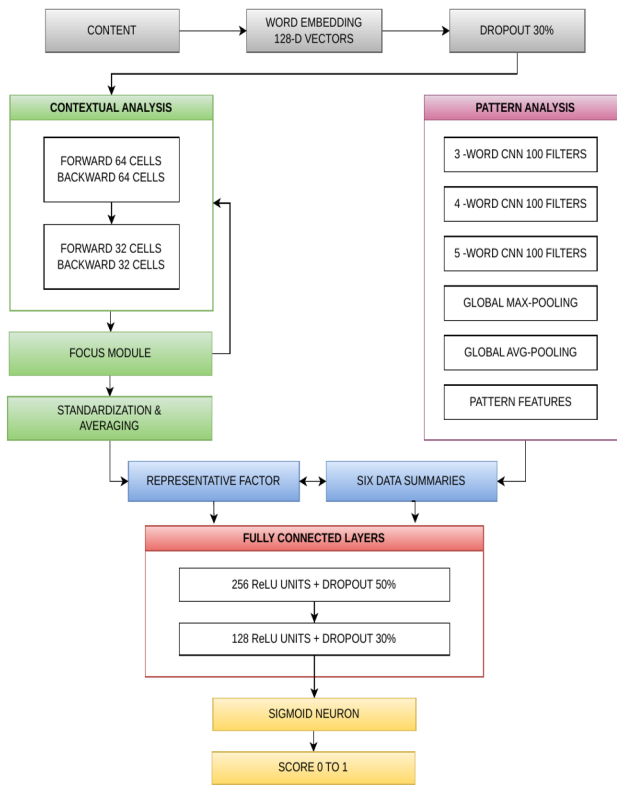


Fig. 3: Model Architecture Diagram

3.5 Evaluation Metrics

Accuracy measures the overall fraction of correct predictions made by a model across all classes. It is calculated as the total number of correct predictions divided by the total number of predictions [35].

$$\text{Accuracy} = (T_P + T_N) / (T_P + T_N + F_P + F_N)$$

Precision calculated the accuracy of a model when it identifies positive instances. It shows the proportion of correctly points out positive instance out of all instances in the model labeled as positive [35].

$$\text{Precision (PPV)} = T_P / (T_P + F_P)$$

Recall weigh a model's correctness in identifying all existing positive examples. It is the count of actual positives that are correctly identified as positive [35].

$$\text{Recall (TPR)} = T_P / (T_P + F_N)$$

The F1-Score is a unified performance measure that harmonizes precision or Positive Predicted Value (PPV) and recall or True Positive Rate (TPR) into a single metric. Calculated as their harmonic mean, it balances the trade-off between false positives and false negatives [35].

$$\text{F1-Score} = 2 \times (PPV \times TPR) / (PPV + TPR)$$

Where:

- T_P (True Positive): The positive instances that were correctly graded by the model

- T_N (True Negative): The negative instances that were correctly graded by the model
- F_P (False Positive): Cases that are actually negative but which the model incorrectly classified as positive
- F_N (False Negative): Cases that are actually positive but which the model incorrectly classified as negative

4. EXPERIMENT AND RESULTS

The empirical study was conducted over the 10 lakhs rows dataset that was collected from Google Play Store of online food delivery applications for Swiggy and Zomato. The study is focused on the text of the dataset used for sentiment analysis. Data cleaning is applied over the extracted dataset to remove inconsistencies, incorrect format. Removal of URLs, non-alphanumeric characters, blank whitespaces and emojis. The sentiment label was converted into a numeric format to facilitate mathematical processing. Class balancing techniques were then applied to the dataset to mitigate predictive bias. The study used tokenization and padding for word sequencing and embedding layer for mapping the word sequencing to dense vectors. The dataset then split into training and testing dataset for deep learning neural network techniques. Multi-Head Attention – Bidirectional Recurrent Convolutional Neural Networks have been used to train the model, the results can be observed in Table 3. Different models performance can be observed in Table 4 with proposed model [35]. Other metrics like training vs validation and confusion matrix are also considered, refer to Fig 4, 5, 6 and 7.

Table 3: Platform Based Model Performance

Platform	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Swiggy	0.9457	0.9495	0.9494	0.9492	0.9752
Zomato	0.9535	0.9701	0.9689	0.9693	0.9795

Table 4: Performance Comparison of Different Models for Swiggy and Zomato

Platform	Metric	RNN	BiRNN	LSTM	BiLSTM	GRU	BiGRU	Proposed
Swiggy	Accuracy	0.7780	0.8580	0.5590	0.8420	0.5590	0.8540	0.9457
	Precision	0.8810	0.8920	0.3120	0.8970	0.3120	0.8960	0.9495
	Recall	0.7780	0.8580	0.5590	0.8420	0.5590	0.8540	0.9494
	F1-Score	0.8100	0.8730	0.4000	0.8650	0.4000	0.8720	0.9492
Zomato	Accuracy	0.8720	0.9000	0.8230	0.8880	0.8230	0.8970	0.9535
	Precision	0.9180	0.9250	0.6780	0.9280	0.6780	0.9280	0.9701
	Recall	0.8720	0.9000	0.8230	0.8880	0.8230	0.8970	0.9689
	F1-Score	0.8890	0.9110	0.7440	0.9060	0.7440	0.9110	0.9693

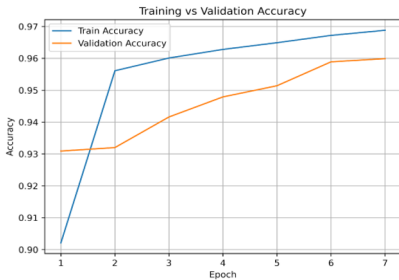


Fig. 4: Training vs Validation Accuracy

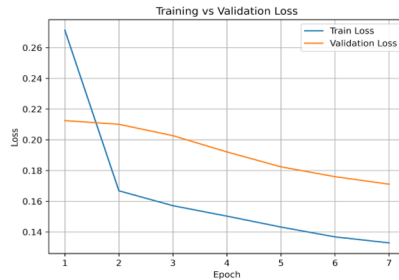


Fig. 5: Training vs Validation Loss

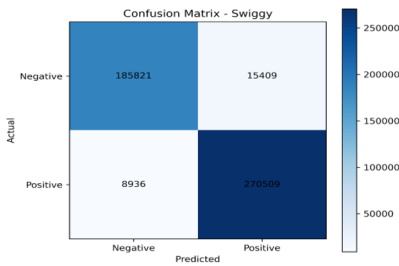


Fig. 6: Swiggy Confusion Matrix

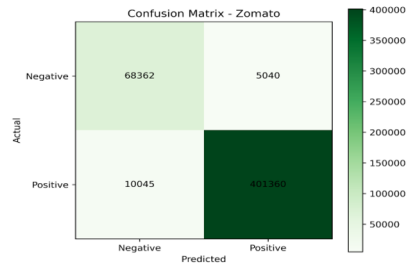


Fig. 7: Zomato Confusion Matrix

5. CONCLUSION AND FUTURE WORK

The results from testing show the new MHA-BiRCNN combined model works very well for sorting opinions in text. On Swiggy's data, it correctly classified 94.57% of reviews. On Zomato's data, it did even better, reaching 95.35%. For Zomato, its rate for correct positive guesses was 97.01%, and it found 96.89% of all real positives, giving a strong combined score of 96.93%. For Swiggy, its rate for correct positive guesses was 94.95%, and it found 94.94% of all real positives. This harmony yields a unified performance score of 94.92%. The framework's roc-auc value for swiggy and zomato was 0.9752 and 0.9795 respectively. The two-leveled, bidirectional memory circuit operates using its internal regulatory gates to conserve a review's narrative consistency throughout its entire length and maintains the strength of the instructional signal throughout the training cycle. At the same time, three different scanning filters, searching at windows of 3, 4, and 5 words, to select repeating local phrases. The multi-focus attention layer, runs on eight calculations in parallel, assess and enhance the signal for words that conveys strong emotions. The understanding of sentence flow, detection of common phrases, and emphasis on keywords creates a better and more data representation than simple models can generate. This is the primary reason the model achieves higher and synchronized scores for both finding positives and avoiding false alarms.

Future research can tackle the drawbacks of the current study's dataset, which is limited in scale as well as static. Second, the scope of the text analysis was limited to English language and future studies should inculcate multilingual support to increase the model's strength. Finally, a more meticulous assessment of platform responsiveness can be achieved by computing the difference of time between submission of reviews and its corresponding response.

REFERENCES

- [1] Vidani, Jignesh N. "The study of pestle analysis in Kerala state." ZENITH International Journal of Multidisciplinary Research, 5(12), 2015, pp. 33-50.
- [2] Solanki, H. V., & Vidani, J. N. "A new era of e-vyapar in 21st century: A review approach." International Journal of Multidisciplinary Education Research, 5(11(2)), 2016, pp. 61-77.
- [3] Pradhan, U., Tshogay, C., & Vidani, J. N. "Short Messages: Its Effect on Teenager's Literacy and Communication." International Journal for Innovative Research in Multidisciplinary Field, 2(7), 2016, pp. 115-120.
- [4] Al-Subaihini, Afnan, et al. "App store mining and analysis." Proceedings of the 3rd International Workshop on Software Development Lifecycle for Mobile, 2015.
- [5] Blanco-Fernandez, Yolanda, et al. "Exploiting digital TV users' preferences in a tourism recommender system based on semantic reasoning." IEEE Transactions on Consumer Electronics, 56(2), 2010, pp. 904-912.
- [6] Adinolfi, Paola, et al. "Sentiment analysis to evaluate teaching performance." International Journal of Knowledge Society Research (IJKSR), 7(4), 2016, pp. 86-107.
- [7] Onalaja, Samuel, Eric Romero, and Bosang Yun. "Aspect-based sentiment analysis of movie reviews." SMU Data Science Review, 5(3), 2021, p. 10.
- [8] Cui, Hang, Vibhu Mittal, and Mayur Datar. "Comparative experiments on sentiment classification for online product reviews." AAAI, vol. 6, 2006, pp. 1265-1270.

- [9] Vidani, J., & Solanki, N. K. "Consumer behavior in online versus offline shopping of electronic products in Ahmedabad city." *International Journal of Finance and Business Management*, 2(6), 2015, pp. 813–834.
- [10] Prajogo, D. I., & Sohal, A. S. "The integration of TQM and technology/R&D management in determining quality and innovation performance." *Omega*, 34(3), 2006, pp. 296–312.
- [11] Seyff, Norbert, Florian Graf, and Neil Maiden. "Using mobile re tools to give end-users their own voice." 2010 18th IEEE International Requirements Engineering Conference, IEEE, 2010.
- [12] Carreño, Laura V. Galvis, and Kristina Winbladh. "Analysis of user comments: an approach for software requirements evolution." 2013 35th International Conference on Software Engineering (ICSE), IEEE, 2013.
- [13] Prasetyo, Budi Eko, Divi Galih Prasetyo Putri, and Endang Wahyu Pamungkas. "Aspect extraction using informative data from mobile app data review." *International Journal of Computer Applications*, 975, 2017, p. 8887.
- [14] Ma, Haoxiang, Jong Min Kim, and Eunkyung Lee. "Analyzing dynamic review manipulation and its impact on movie box office revenue." *Electronic Commerce Research and Applications*, 35, 2019, p. 100840.
- [15] Larasati, Ukhti Ikhsani, et al. "Improve the accuracy of support vector machine using chi square statistic and term frequency inverse document frequency on movie review sentiment analysis." *Scientific Journal of Informatics*, 6(1), 2019, pp. 138-149.
- [16] Liu, Bing, and Lei Zhang. "A survey of opinion mining and sentiment analysis." *Mining text data*. Boston, MA: Springer US, 2012, pp. 415-463.
- [17] Yadav, Ashima, and Dinesh Kumar Vishwakarma. "Sentiment analysis using deep learning architectures: a review." *Artificial Intelligence Review*, 53(6), 2020, pp. 4335-4385.
- [18] Xu, Guixian, et al. "Chinese text sentiment analysis based on extended sentiment dictionary." *IEEE Access*, 7, 2019, pp. 43749-43762.
- [19] Cheng, Baoquan, et al. "Comprehensive assessment of embodied environmental impacts of buildings using normalized environmental impact factors." *Journal of Cleaner Production*, 334, 2022, p. 130083.
- [20] Cheng, Baoquan, et al. "Improving contractors' participation of resource utilization in construction and demolition waste through government incentives and punishments." *Environmental Management*, 70(4), 2022, pp. 666-680.
- [21] Gan, Mingxin, and Hongfei Cui. "Exploring user movie interest space: A deep learning based dynamic recommendation model." *Expert Systems with Applications*, 173, 2021, p. 114695.
- [22] Qian, Yingmiao, et al. "A Decision-Making Model Using Machine Learning for Improving Dispatching Efficiency in Chengdu Shuangliu Airport." *Complexity*, 2020(1), 2020, p. 6626937.
- [23] Da'u, Aminu, and Naomie Salim. "Recommendation system based on deep learning methods: a systematic review and new directions." *Artificial Intelligence Review*, 53(4), 2020, pp. 2709-2748.
- [24] Sen, A. "How Swiggy became India's fastest unicorn."
- [25] "Swiggy vs Zomato - Who does it better? [Case Study]." <https://gryffindoracademy.com/swiggy-vs-zomato-case-study/>
- [26] Khola, A. "Case study: Swiggy or Zomato?"
- [27] Gupta, Mitali. "A Study on Impact of Online Food delivery app on Restaurant Business special reference to zomato and swiggy." *International Journal of Research and Analytical Reviews*, 6(1), 2019, pp. 889-893.
- [28] Theresa Wilson, Janyce Wiebe, and Paul Hoffmann. 2005. Recognizing Contextual Polarity in Phrase-Level Sentiment Analysis. In *Proceedings of Human Language Technology Conference and Conference on Empirical Methods in Natural Language Processing*, pages 347–354.
- [29] Das, Sanjiv R., and Mike Y. Chen. "Yahoo! For Amazon: Sentiment Extraction from Small Talk on the Web." *Management Science*, vol. 53, no. 9, 2007, pp. 1375–88.
- [30] Manurung, Ruli. (2008). *Machine Learning-based Sentiment Analysis of Automatic Indonesian Translations of English Movie Reviews*.
- [31] R. Liu, R. Xiong and L. Song, "A sentiment classification method for Chinese document," 2010 5th International Conference on Computer Science & Education, Hefei, China, 2010, pp. 918-922.
- [32] Khan, Aurangzeb & Baharudin, Baharum & Khan, Khairullah. (2011). Sentiment Classification Using Sentence-level Lexical Based Semantic Orientation of Online Reviews. *Trends in Applied Sciences Research*. 6. 1141-1157.
- [33] R. A. Tuhin, et al. "An Automated System of Sentiment Analysis from Bangla Text using Supervised Learning Techniques," 2019 IEEE 4th International Conference on Computer and Communication Systems (ICCCS), Singapore, 2019, pp. 360-364.

- [34] Novendri, Risky & Callista, Annisa & Pratama, Danny & Puspita, Chika. (2020). Sentiment Analysis of YouTube Movie Trailer Comments Using Naïve Bayes. *Bulletin of Computer Science and Electrical Engineering*. 1. 26-32.
- [35] Y. Agrawal, V. Sharma and G. Sikka, "Comparative Study of Sequential Deep Learning Models for Sentiment Analysis of Swiggy and Zomato Reviews," 2025 Second International Conference on Pioneering Developments in Computer Science & Digital Technologies (IC2SDT), Delhi, India, 2025, pp. 76-81.

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