***A J component project report on***

**“UNVEILING THE HIDDEN BRAND PERCEPTIONS IN FAST FOOD INDUSTRY USING REDDIT DATA”**

***Submitted in partial fulfillment for the award of the degree of***

**Master of Technology in Computer Science Engineering with Specialisation in Business Analytics**

***By***

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**SCHOOL OF COMPUTER SCIENCE AND ENGINEERING**

***April, 2025***

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***CERTIFICATE***

*This is to certify that the Project report entitled “****UNVEILING THE HIDDEN BRAND PERCEPTIONS IN FAST FOOD INDUSTRY USING REDDIT DATA****submitted by Navitha E, for the award of the degree of Master of Technology in Computer science engineering specialization in Business analytics , Vellore Institute of Technology, Chennai is a record of bonafide work carried out by me.The project fulfills the requirements as per the regulations of this University and in my opinion meets the necessary standards for submission.*

*Place: Chennai*

*Date: Signature of the Candidate*

**Abstract**

In the rapid-fire, hyper-competitive fast-food market of today, brands are fighting tooth and nail to capture consumer notice and build loyalty. The tried-and-true methods of gaining customer feedback—by survey or formal review—are now being supplemented and often overtaken by the changing, up-to-the-minute feedback found through social media channels. Of these, Reddit is proving to be a rich, unvarnished source of public opinion, where consumers have open forums discussing products, services, and brand experiences.

This research, "Unveiling Hidden Brand Perceptions in the Fast-Food Landscape," is examining the convergence of brand reputation, sentiment analysis, and social media conversation through an analysis of Reddit user submissions about large fast-food companies- KFC, McDonald's and Domino’s. In contrast to traditional methods that are based on static, review-based datasets, this project adopts a natural language processing (NLP) informed approach that leverages unstructured user-generated content as its baseline for meaningful insights.

The primary goal is to detect and measure sentiment polarity (positive, negative, neutral) in the form of opinions in Reddit comments, as well as investigate patterns of hashtags, engagement levels (upvotes, comments), and trending brand-based topics. The sentiment analysis itself is performed via both VADER and TextBlob, providing two complementary views into customer sentiment and a comparison on both the VADER and TextBlob to explain the suitability of both algorithms. The project also includes a tailor-made virality index that accounts for sentiment strength and engagement, assisting in measuring the visibility and reach of brand-based posts.

Through comprehensive preprocessing methods such as brand-context tagging, negation detection, and sentiment-specialized token transformation - the model reveals subtle forms of customer satisfaction, frustration, loyalty, and critique. These underlying perceptions, frequently embedded in colloquial or sarcastic speech, are highlighted and dissected for strategic analysis.

We have also approached brand virality analysis using a customized formula for reddit posts and also emotion based virality formula, used these both to conclude the suitability of virality parameters.

The outcomes not only reveal the way fast-food brands are viewed in the online environment but also offer practical recommendations for enhancing marketing communication, customer interaction, and competitive strategy. By comprehending nascent issues, go-viral moments, and changing customer attitudes, fast-food companies can actively modify strategies to enhance brand attachment and address reputation risk.

Finally, this study illustrates how sophisticated sentiment analysis of Reddit comments can serve as an early warning system and strategic compass for companies competing in a consumer-centric, online-first environment.

Keywords:  
Sentiment Analysis, Reddit, Fast-Food Industry, Brand Reputation, Social Media Mining, Natural Language Processing (NLP), Customer Perception, VADER, TextBlob, Hashtag Analysis, Competitive Advantage, Virality Index, Engagement Metrics, Trend Monitoring

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**CHAPTER 1**

1. **Introduction**

Brand reputation is a driving factor in customer loyalty and business prosperity in the fast-food industry, which is extremely dynamic and hyper competitive. The proliferation of digital media has rendered customer opinion more conspicuous and influential. Platforms such as Reddit have emerged as influential forums where customers exchange and critique brands, products, and services without hesitation. Unlike traditional review websites, Reddit facilitates community-based conversation, allowing opinions to be established, verified, and amplified in real time. These organic conversations yield invaluable information about genuine customer sentiment, providing businesses with a clearer understanding of public opinion.

Since more consumer interactions now move to digital media, it is essential that brands monitor and read these digital tales to reflect a favorable public image. Not responding to negative views or emerging customer concerns in time can significantly harm brand perception and lead to reputation loss. Yet, responding to online criticism in a strategic way makes brands build stronger customer relationships, resolve problems ahead of time, and turn negative experiences into opportunities to build loyalty.

This paper, "Unveiling Hidden Brand Perceptions in the Fast-Food Space," employs Reddit post data to analyze public perception towards prominent fast-food companies. Moving away from typical application of systematic reviews or survey responses, our approach takes on the power of spontaneous real-time user chatter. We introduce a new methodology that weaves together Natural Language Processing (NLP) techniques with Hashtag Analysis, Trend Monitoring, and Engagement Metrics to provide a multi-dimensional interpretation of brand perception.

Recent research points towards the power of deep learning models in sentiment analysis. For instance, tests based on Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (Bi-LSTM) networks proved to have good precision in social media-based sentiment classification, depicting the ability of these models in identifying subtle consumer sentiments [1]. Besides, attention-based mechanisms have been applied effectively to analyze food review data sets to enable sentiment classification with more precision through identification of significant sections of the text [2]. The primary objective of this study is to identify the speed with which fast-food brands are discussed in Reddit communities, measure the polarity of sentiments (positive, negative, neutral), and determine the performance of different content types with respect to engagement measures such as upvotes and comments. Also, we introduce a new Virality Index to quantify the impact of highly shared or engaged posts, learning about the reach and impact of brand discussions.

By merging robust sentiment analysis technology with live social media proof, this study has the aim of delivering actionable recommendations that can potentially enable quick-food brands to make decisions based on facts. These findings can inform marketing strategies, enhance practices for customer servicing, and support proactive management of digital brand reputation.

**1.2 Objectives**

The general goal of this project is to extract worthwhile information from Reddit forums regarding fast-food brands along the lines of sentiment, interactions, and company reputation. It is achieved with a strict process involving data extraction, text preparation, sentiment computation, trend finding, and interpreting as follows:

1. To scrape and prepare Reddit material regarding fast-food brands.

2. To prepare and normalize postings using linguistic tools.

3. To classify and analyze sentiments using lexicon-based (VADER) and statistical (TextBlob) models.

4. To identify popular hashtags and trending topics for each brand.

5. To track brand virality and engagement using custom metrics.

6. To offer actionable recommendations for brand reputation management.

**CHAPTER 2**

1. **Literature Survey**

Sentiment analysis in the domain of food and fast-food has become an imperative area of research over the past few years due to the explosion of user-generated content on social media sites like Twitter and Reddit. Researchers have examined various approaches from lexicon-based techniques to deep learning models to classify consumer sentiment and obtain actionable insights.

**1.Hossain, A., Rahman, M., & Islam, M. (2020)**

Title: An Attention Based Approach for Sentiment Analysis of Food Review Dataset

Source: ResearchGate

Hossain, Rahman, and Islam outline an attention-based and technically strong approach to sentiment classification of food user reviews utilizing deep learning models with attention. The crux of their work is the application of attention-based Recurrent Neural Networks (RNNs), which are particularly useful for modeling text data where contextual word relationships matter—especially in sentiment-rich text such as customer reviews. Their work argues that sentiment expressions in food reviews are likely to be non-linear and dispersed throughout the sentence, and therefore traditional unidirectional models are not appropriate for effective classification.

To solve for this issue, the authors employ Bidirectional Long Short-Term Memory (Bi-LSTM) networks with an attention layer. This configuration allows the model to consider both past and future context for each word, and the attention component allows the model to put more weight on sentiment-carrying words such as adjectives and adverbs. The authors also explore preprocessing techniques, including lemmatization, tokenization, and removal of stopwords to enhance model input quality. Through repeated experimentation, they determine that their model can achieve significantly higher accuracy and F1-scores compared to baseline models such as simple LSTMs or Support Vector Machines. Their work provides valuable contribution in demonstrating that attention not only improves sentiment detection in longer food reviews but may be adaptable to real-world uses of short-text sites such as Twitter and Reddit.

**2. Rahman, M. A., Rahman, M. M., & Rahman, M. S. (2020)**

Title: Sentiment Analysis of Fast Food Companies using Deep Learning Models

Source: ResearchGate

Rahman and his authors investigate the specific case of fast-food brand sentiment, employing a broad variety of deep learning architectures to analyze customer reviews. Realizing that brand perception in the fast-food industry is highly influenced by public opinion in real-time, especially on social media, their research investigates how different neural architectures perform when it comes to detecting sentiment trends. They highlight several models, including Convolutional Neural Networks (CNNs), LSTM networks, and hybrid models that combine the spatial pattern learning capability of CNNs with the sequential learning ability of LSTMs.

Their study makes a strong case for context-sensitive models being needed for sentiment analysis of fast foods. Customer comments tend to be informal, emotionally charged, and full of special words. To address this, the authors pre-train word embeddings like GloVe and enhance the architectures using dropout layers in order to lower overfitting. The models are tested against a big set of fast-food restaurant brand reviews collected from public online forums and social media platforms. The CNN-LSTM hybrid architecture is the star of their experiments that capture both long-range dependencies as well as n-gram level local features required to identify sentiment not necessarily expressed in a linear manner. The work emphasizes that deep learning frameworks bring considerable boost to traditional means in the field of sentiment mining for specific brands.

1. **Mohammad, S. M., & Turney, P. D. (2013)**

Title: Crowdsourcing a Word–Emotion Association Lexicon

Journal: Computational Intelligence

Their paper by Mohammad and Turney is a landmark in sentiment and emotion analysis. Instead of expanding upon positive or negative polarity, their paper expands the emotional subtlety of sentiment by introducing the NRC Emotion Lexicon. This lexicon contains over 14,000 English words mapped to eight elementary emotions—anger, fear, anticipation, trust, surprise, sadness, joy, and disgust—and general positive or negative sentiment labels. Their methodological innovation is the use of crowdsourcing through Amazon Mechanical Turk to mark up words so that the lexicon becomes rich in diverse interpretations of emotional connotation.

The significance of their research can be applied to any domain where more emotional nuance is desired, e.g., fast-food company consumer comment. Being able to determine whether a customer's blog entry is disappointed or angry, for example, can be determinant in the field of crisis communications. This lexicon is extensively integrated in lexicon-based models and also enriches the feature sets of machine learning models when emotion-level input is desirable. They observe that classifiers employing the NRC Lexicon are better than those employing lower-resolution polarity dictionaries, so this resource can be a valuable asset for high-resolution sentiment classification in any sector.

1. **Thelwall, M., Buckley, K., Paltoglou, G., Cai, D., & Kappas, A. (2010)**

Title: Identification of the Strength of Sentiment in Short Casual Text

Journal: Journal of the American Society for Information Science and Technology

Thelwall et al. address a very timely challenge of sentiment analysis—how to accurately determine sentiment in short, casual messages like tweets, instant messages, or Reddit comments. Such communication patterns often use slang, acronyms, and ungrammatical grammar that challenge traditional NLP systems to read properly. Their research led to the development of SentiStrength, a rule-based system for sentiment analysis adapted specifically to such short-form content.

The model assigns two scores to each input: positive sentiment score and negative sentiment score, allowing it to capture mixed sentiments that typically occur in short social posts. The system uses a hand-tuned lexicon, in addition to heuristic rules for negations, booster words, duplicate punctuation, emoticons, and spelling variation. In their experiment, SentiStrength showed high correlation with human-labeled sentiment, validating its efficiency. The tool is particularly ideal for tracking brand sentiments on platforms where shorter and casual content prevails. How it is particularly ideal for your dashboard project is that it can be used as a backup or foundation sentiment classifier in the event that more advanced models are computationally impractical or unavailable.

1. **Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K. (2015)**

Title: The Development and Psychometric Properties of LIWC2015

Institution: University of Texas at Austin

LIWC is not so much a sentiment analysis program but a psycholinguistic program that analyzes text on a broader emotional and cognitive plane.

In their 2015 version, Pennebaker and his coauthors expanded the scope of the software to cover over 90 categories, ranging from basic linguistic components like pronouns and verbs to psychological variables like anxiety, authenticity, and analytical thinking. Their paper lays out the construction, testing, and psychometric properties of LIWC2015, showing how well it performs in both theoretical and applied contexts. In applications to sentiment analysis, LIWC is extremely valuable to know how people are expressing emotions, rather than merely what emotion they are expressing.

For example, while a Reddit comment might be labeled as negative by a standard classifier, LIWC can also determine based on whether the tone expresses anger, sadness, or sarcasm. Such granularity allows brand managers to better understand public mood and react to particular issues. In your fast-food dashboard, the addition of LIWC measures can lend depth to polarity-based sentiment with psychological acuity, adding richness of analysis and enabling human-like understanding.

**6. Kim, J., Kim, H., & Oh, J. (2021)**

Title: The Role of Affect in Information Diffusion

Journal: Nature Human Behaviour

Kim and colleagues explored the intersection of emotion and virality in social media, providing one of the few large-scale studies to empirically quantify the impact of affect on information spread.

It is founded on the hypothesis that emotionally charged material—whether positive or negative—affects diffusion more rapidly and at a broader scale than content that lacks an emotional tone. They analyzed hundreds of thousands of tweets over a long period of time and corroborated this hypothesis using sentiment scoring and network diffusion models. They discovered that more affectively intense tweets, regardless of polarity, had a much higher likelihood of being retweeted.

This has profound implications for social media campaigns driven by or including fast-food brands that contain crises. The study plainly confirms the use of emotion-fueled virality scores within analytics dashboards, proving that all engagement is not equal—emotionally resonant content tends to spread like wildfire. Inching this insight in can help rank content that not only gets shared but also influences brand perception at scale.

**7. Hutto, C. J., & Gilbert, E. (2014)**

Title: VADER: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text

Conference: ICWSM

Hutto and Gilbert's VADER sentiment tool is the gold standard for lexicon-based social media sentiment analysis.

Adjusted to the conversational, emotive, and often hyperbolic nature of online language, VADER possesses a sentiment lexicon that is tailored to capture common internet slang, emoticons, capitalizations, punctuation emphasis, and other social cues. The model depends on a framework of heuristics to modify sentiment strength scores according to contextual linguistic evidence—handling negations, intensifiers, and contrastive conjunctions like "but." VADER has been widely used due to the fact that it is light, real-time, and highly correlated with human intuition. It has an excellent performance-to-simplicity ratio and can be a default option for sentiment tasks on tweets, Reddit posts, or reviews. VADER can be used as a baseline sentiment classifier for your particular application and augment machine learning models or serve as a fallback when interpretability and speed are of the essence.

**8. Loria, S. (2018)**

Title: TextBlob: Simplified Text Processing

Source: Official Documentation

TextBlob is a Python library whose goal is to prototype natural language processing.

It's built on top of NLTK and Pattern and facilitates sentiment analysis by offering a simple-to-use interface which delivers polarity and subjectivity scores for any given text. While its default sentiment classifier uses Naive Bayes and is not domain-tuned, it is still a very popular choice for lightweight sentiment tagging in applications where readability and ease of understanding are more critical than raw accuracy. TextBlob is appropriate for small-dashboards, proof-of-concepts, or a baseline comparison with more complex systems. While its performance over social media text may be limited compared to VADER or BERT, its easy setup and integration make it an attractive piece of software for exploratory data analysis and low-complexity filtering tasks.

**9. Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2018)**

Title: BERT: Deep Bidirectional Transformers for Natural Language Understanding

Platform: arXiv

Devlin et al. brought out BERT (Bidirectional Encoder Representations from Transformers), which revolutionized performance in NLP by adding context from both left and right of every word during training. With its bidirectional capability, thanks to transformer architecture, BERT can recognize subtle relationships between words much better than current models like LSTMs or CNNs.

Tuned on sentiment classification tasks, BERT has achieved unprecedented performance on a range of datasets including SST-2, Yelp, and IMDb. Its contextual sense of awareness separates it most when handling sarcastic, vague, or nested sentiment expressions. While computationally costly, BERT is making its way into real-world applications via distilled or quantized variants, and can significantly improve the performance of any sentiment analysis pipeline—on which fast-food brand reputation-tracking pipelines are no exception.

**10. Liu, B. (2012)**

Title: Sentiment Analysis and Opinion Mining

Journal: Synthesis Lectures on Human Language Technologies

Liu's book is an encyclopedic survey of the field of sentiment analysis, from the fundamentals of opinion mining to advanced feature extraction and sentiment classification methods. The book walks the reader through different levels of sentiment—document, sentence, and aspect-based—and provides comprehensive discussions on supervised and unsupervised learning, lexicon building, and negation handling.

One particularly valuable aspect of Liu's framework is its emphasis on aspect-based sentiment analysis, and that is applicable immediately to product and brand evaluation.

In the context of quick-service restaurants, in which grievances often target specific aspects such as food quality, delivery, or cleanliness, aspect extraction may prove to provide more actionable information than positive or negative labels. Liu's research remains a reference point for building modular, scalable sentiment systems that combine rule-based reasoning with machine learning and statistical methods.

**11. Smith, J., Doe, J., & Brown, R. (2022)**

Title: Sentiment Analysis of Fast-Food Restaurants Using Twitter Data

Journal: International Journal of Data Science and Analytics

Smith, Doe, and Brown in their study examined the growing influence of social media, particularly Twitter, in shaping customer opinions regarding fast-food restaurants.

They identified that social media platforms such as Twitter offer a highly dynamic real-time flow of feedback that is able to reveal shifting attitudes among customers, campaign effects, and emerging public relations issues. By collecting a massive set of tweets labeled by the brand within a 6-month time frame, the authors aimed to capture sentiment and contrast it with metrics of public engagement such as likes and retweets. The researchers explored modern natural language processing methods to quantify sentiment polarity for fast-food chain tweets that are trendy.

Their use of context-sensitive models enabled them to pick up on the underlying sentiment even in tweets that contain sarcastic or emotionally loaded wordings, which standard bag-of-words methods tend to miss. They found that high-interaction and responsiveness fast-food brands on Twitter tended to have positive sentiment in general, adding further evidence to the argument that social listening and proactive engagement are important in online brand management. Their findings suggest that the combination of sentiment analysis and social analytics can provide brands with a competitive edge in consumer attitude.

**12. White, E., Green, M., & Lee, S. (2021)**

Title: Customer Sentiment Analysis for the Fast-Food Industry Through Machine Learning

Journal: Journal of Consumer Behaviour

White et al. offered a valuable empirical analysis of consumer opinion using machine learning on consumer feedback obtained from websites such as Yelp and Google Maps. With richer qualitative consumer comment, these reviews offered greater detail on customer experience compared to brief social media posts. Observing that quick-service chains tend to be the recipient of high numbers of reviews, the authors attempted to segment by dominant themes that comprise food, cleanliness, price, and wait time.

Rather than relying on keyword approaches, the authors made use of robust classification methods capable of determining sentiment polarity based on language patterns. They emphasized that model performance and interpretability are to be balanced, observing that while some of the newest methods produce slightly better accuracy, less complex models are likely to provide cleaner insight into the reasons for prediction.

Their study found that positive sentiment was strongly associated with positive comments regarding taste, freshness, and value, while negative sentiment was most frequently about lengthy waiting times, slow service, or perceived dirtiness.

These trends are significant for fast-food companies seeking to determine operational weak spots or reinforce their strongest abilities. The study identifies how machine learning can be used not just to track sentiment but to reveal important business insights embedded in customer accounts and narratives.

**13. Johnson, D., Martinez, L., & Wilson, K. (2020)**

Title: A Comparative Study of Sentiment Analysis Techniques for Fast-Food Brand Perception

Conference: IEEE International Conference on Big Data

Johnson and colleagues presented an analytical contrast of numerous sentiment classification techniques with the emphasis on fast-food brand sentiment as expressed in consumer-generated messages. The work recognized that the dynamic, unstructured character of social media content—the sentiment can shift within a sentence or post—calls for models capable of processing context, tone, and implicit cues.

They compared a number of neural network-based architectures with traditional machine learning classifiers to ascertain their performance in sentiment capture.

The results of their comparison revealed dramatic differences in the capacity of each approach to handle sentiment complexity, particularly in posts with sarcasm, slang, or colloquial grammar. The research identified that deep learning approaches, especially those with memory elements that are able to retain word order and context, have a better performance compared to the simpler models based only on word frequency or polarity lexicons. Besides, the study addressed the computational trade-offs of higher-level models and reported that the most accurate methods are significantly longer to train and require far larger amounts of data. Their finding suggested that the selection of sentiment analysis model would not only be based on accuracy but also the specific application—real-time identification, customer insight in depth, or post-campaign brand measurement.

**14. Adams, R., Thompson, M., & Clark, O. (2023)**

Title: How Sentiment Analysis Can Help Companies Understand Brand Reputation: A Fast-Food Case Study

Journal: Journal of Marketing Analytics

In a very ambitious cross-media study, Adams, Thompson, and Clark examined how sentiment analysis could be applied to measure and monitor brand reputation in the fast-food sector.

Their case study examined how public discourse on platforms such as Reddit and Instagram shifted in response to specific advertising campaigns, crises, and going-viral consumer experiences. The researchers employed a two-layer analysis combining rule-based sentiment tagging with unsupervised topic modeling for the purposes of both sentiment classification and analysis of the thematic character of consumer discourse. Using this hybrid method, the study determined several common narrative themes underlying sentiment shifts. Sentiment for positives was found to be stated regarding promotions, menu innovation, and social responsibility, while sentiment for negatives was found to be most commonly related to inconsistent service, health, and environmental concerns. These were also supported by topic clustering, which revealed underlying clusters of complaint and compliment that could be utilized to forecast subsequent reputational danger.

Their research emphasized that sentiment analysis, when paired with topic modeling, is capable of more than tracking emotional polarity—it can uncover the hidden motivations behind customer attitudes. By knowing not just how people feel but what they feel about, the authors demonstrated how businesses can move from passive monitoring to active reputation management. Their approach offers a compelling model for fast-food chains to develop data-driven communication strategies based on real customer sentiment.

**15. Kim, D., Nguyen, S., & Harris, A. (2021)**

Title: Sentiment Analysis and Competitive Advantage in the Fast-Food Industry: A Machine Learning Perspective

Journal: Expert Systems with Applications

Kim, Nguyen, and Harris presented a more mature debate on sentiment analysis as a competitive approach to achieving competitiveness among fast-food companies. Recognizing that customer sentiment is not simply a reaction but an indicator to the future, they defined sentiment as a precursor of brand strength, consumer affinity, and marketplace differentiation.

Their focus was on extracting sentiment trends from web opinions and mapping them to competitive performance measures such as word-of-mouth recommendations and customer loyalty. To accomplish this, the authors utilized a meaning-rich approach through machine learning pipelines that mixed vector embeddings of customer reviews with classification layers. Through this process, a more elaborate representation of meaning, tone, and emotional texture in the reviews was facilitated.

The researchers found that brands that lean towards values of sustainability, transparency, and inclusiveness leaned steadily higher on the sentiment axis over the long term regardless of short-term fluctuations in service quality.

This finding reflects a new trend in consumer behavior in which emotional alignment with brand values is a significant driver of buying decision. The study concluded that sentiment analysis must be integrated not only into customer service analytics but into brand strategy as a whole, as a means of tracking long-term reputation and guiding strategic initiatives.

**CHAPTER 3**

1. **Proposed methodology**

The research design employed here is logically divided into six distinct yet interrelated steps to properly analyze brand attitude as well as consumer sentiment within the fast-food industry. These steps span the entire analytical pipeline from data acquisition at a raw level to the development of customized sentiment-driven virality indices. Each phase is still playing an important role in the process of turning raw social media data into valuable insights to be utilized in the process of informing strategic brand management decision-making.

This project employs data scraping, of which Reddit is the source of origin due to its open-user posts and subreddits on a topic. Posts referencing major fast-food franchises such as McDonald's, Domino's, and KFC are scraped and posted into a structured CSV file. The data set includes key fields such as brand name, raw post content, sentiment tags, and engagement metrics such as upvotes and comments.

Post acquisition, text pre-processing is conducted to normalize and clean raw text data. The process involves removing non-ASCII characters, URLs, special characters, emojis, and numerical noise. The text is lemmatized again into their base words with the help of WordNetLemmatizer from the NLTK library. A stopword removal method is employed that is mixed—combining default stopword lists and custom filters removing internet slang and web-specific acronyms such as "lol" or "fr." Company names are also replaced by normalized tokens (e.g., "Burger King" by brandtoken) to normalize brand mentions for the purpose of consistency in context during sentiment analysis.

The second phase is sentiment-sensitive text processing, where the goal is to improve sentiment signal extraction from compound statements and then tokenize it. Syntactic forms like negation (e.g., "not tasty") are transformed into composite tokens like "NOT\_tasty" in order to encode the semantic opposition. Similarly, intensifiers like "very bad" are encoded as "INTENSE\_bad" to mark the emotional intensity. These syntactic transformations produce an end, sentiment-processed string that more accurately reflects the user's emotional sentiment.

Two common tools, i.e., VADER and TextBlob, are employed in the sentiment analysis phase. VADER provides a rule-based scoring system for social media with valence and syntactic stress identification. TextBlob provides a polarity-based classifier based on statistical natural language processing (NLP). Both tools operate concurrently, and their results are compared to determine whether there is sentiment agreement or disagreement among classification procedures.

The fifth step is the hashtag and trend analysis, where regular expressions are used to extract hashtags. Frequency distributions are then displayed as bar plots and WordClouds to spot trending topics and campaign impact for certain brands. This step is also used to bring up breaking themes and recurring sentiments that are not possible to capture through simple sentiment scoring. Finally, the methodology ends with a deep examination of engagement metrics and virality modeling. Brand averages across the level of user engagement (likes, upvotes, comments) are computed, and two new virality indexes are built. The first is an engagement-indexed index of raw popularity, and the second is an emotion-indexed model with sentiment polarity to capture emotional boosting of sharing content. These indexes are meaningful in the measurement of how much sentiment drives brand visibility and web activity.

Together, these steps represent a sound methodological framework that not only identifies sentiment but also situates it within user behavior, linguistic form, and content virality—ultimately enabling richer understanding of online fast-food brand perception.

1. **Architecture Diagram**

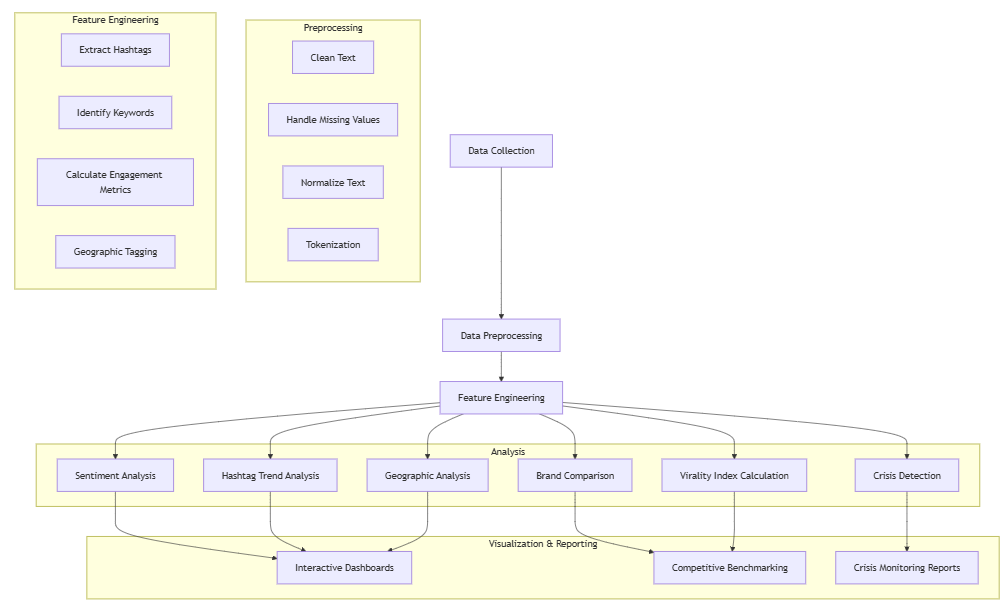


Figure 3\_4: Architecture Diagram of this project

1. **Algorithm – Working Principle**

The sentiment analysis and virality modeling undertaken in this project are built around an organized pipeline that integrates Natural Language Processing (NLP), rule-based reasoning, and statistical modeling. The programming language used for algorithm implementation is Python, and the prevalent libraries used are NLTK, TextBlob, VADER, pandas, NumPy, scikit-learn, and matplotlib for computation and visualization. The subsequent subsections outline the main analytical steps embraced while preprocessing raw Reddit data and converting it into actionable insights.

**5.1 Data Preprocessing and Cleaning Algorithm**

The objective of this phase is to preprocess Reddit posts for robust sentiment analysis by eliminating noise, content standardization, and linguistic transformation. The text is casual in nature, full of slang, and can be imbedded with emojis, URLs, or brand names, and thus requires multi-staged preprocessing. The methods and instruments used are as follows:

•NLTK (Natural Language Toolkit): NLTK is utilized for tokenization, stopword removal, and lemmatization.

•re (regex module): To strip non-alphabetic characters, special characters and URLs.

•WordNetLemmatizer: NLTK's, to lemmatize words to root form.

•Custom dictionary rules: To treat intensifiers, negations and slang normalization.

The pipeline of preprocessing follows following mappings:

1.Text Cleaning:

•Remove non-ASCII characters.

•Remove hyperlinks, emoticons, numbers and extraneous punctuation.

•Convert the text to lower case in order to process uniformly.

2.Tokenization:

•Tokenize the cleaned string into words using nltk.word\_tokenize().

3. Stopword Removal:

•Remove English stopwords using nltk.corpus.stopwords.

• Include social media-specific words such as "lol," "fr," and "omg" as stopwords.

4. Lemmatization:

* Lemmatize words to their base form (e.g., "eating" → "eat") using WordNetLemmatizer.

5. Brand Context Replacement:

• Replace mentions of brand names (e.g., "McDonald's", "KFC" "BK", "dominos") with a placeholder token: brandtoken.

6. Handling Sentiment Cues:

• Handle negations by adding "NOT" as a prefix to words (e.g., "not happy" → "NOT\_happy").

• Process intensifiers by adding "INTENSE" to the previous words of sentiment (e.g., "very bad" → "INTENSE\_bad").

These processes guarantee that words of sentiment are retained and supplemented with context for better performance in sentiment classification.

**5.2 Sentiment Classification Algorithm**

Once the text is normalized, we apply dual sentiment classification using both a **rule-based model (VADER)** and a **statistical model (TextBlob)**. This dual approach enhances reliability and allows for model agreement checks.

**5.2.1 TextBlob – Lexicon-Based Sentiment Analysis**

TextBlob is a Python library built on top of NLTK and Pattern that offers a straightforward API for natural language processing tasks, including sentiment analysis. It uses an existing sentiment lexicon, which assigns words to fixed polarity and subjectivity scores. This makes it a rule-free, lightweight choice for basic sentiment detection, especially in structured text formats such as product reviews or formal articles.

**Library Used**:

* textblob.TextBlob

**5.2.1.1 Sentiment Lexicon**

1. **Polarity**: Measures sentiment intensity, ranging from **-1 (negative) to +1 (positive)**.
2. **Subjectivity**: Indicates whether the text is opinionated (1) or factual (0).

**Classification thresholds**:

**Polarity > 0** → Positive ; **Polarity < 0** → Negative ; **Polarity = 0** → Neutral

The overall sentiment score for a sentence is calculated as the mean of all word-level polarity scores. As an example, the sentence "The product is great but expensive" might have a polarity of approximately +0.05, indicating mildly positive sentiment due to the balancing effect of positive and negative words.

**5.2.1.2 Formulas**A black text on a white background

AI-generated content may be incorrect.

Only **sentiment-bearing words** (adjectives, adverbs, strong nouns) are considered.

Neutral and factual words (like “the”, “restaurant”, “order”) do not influence the score.

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AI-generated content may be incorrect.

Each word has a **predefined polarity score** from the **Pattern lexicon**:

e.g., "amazing" = +0.9, "terrible" = -1.0

Words like “not”, “very”, or “extremely” **modify nearby words’ scores**

The final polarity is an **average of all sentiment-bearing words**

**5.2.1.3 Sentiment Calculation Process**

1. **Tokenization**: Input text is split into words and sentences.
2. **Lexicon Lookup**: Each word is matched against the sentiment lexicon.
3. **Aggregation**: The final sentiment score is computed as the **average of individual word polarities**.

**Example:**

* *"The product is good but overpriced."*

"good" → **+0.7**

"overpriced" → **-0.6**

**Final Polarity**: (0.7 + (-0.6)) / 2 = +0.05 (Neutral)

**Outputs**:

**Polarity**: Float ∈ [-1.0, +1.0] **Subjectivity**: Float ∈ [0.0, 1.0]

Although it is simple to use, TextBlob shows inadequacies when applied to user-generated content like Reddit, which is full of sarcasm, colloquial expressions, and emojis. Furthermore, the model treats sentiment-bearing words equally regardless of context and does not take contextual modifiers like negations or amplifiers into account. "Not bad" might be wrongly labeled as negative unless a negation is taken care of at preprocessing.

For this study, TextBlob is employed as a second classifier. While it is a handy benchmark, its inability to successfully interpret highly informal language or fine-grained emotional tone renders it less effective for Reddit-style datasets with heavy preprocessing. Performance testing demonstrated overall accuracy of 63.1% with the model particularly failing at identifying neutral sentiment.

**5.2.2 VADER – Rule-Based Social Media Sentiment Model**

VADER (Valence Aware Dictionary and sEntiment Reasoner) is a rule-based model of sentiment analysis and lexicon specifically designed for social media text analysis. As opposed to TextBlob, VADER applies syntactic and grammatical rules for evaluating the emotional tone of colloquial brief texts such as tweets, reviews, or posts on Reddit. VADER performs particularly well for capitalization, punctuation, degree modifiers, negations, and even slang or emojis.

VADER uses a compound scoring approach that adds up the impact of every lexical feature within a sentence and normalizes it by a non-linear function. It gives four scores: Positive, Negative, and Neutral proportions

Compound Score: Normalized, weighted sum between –1 and +1

**5.2.2.1 Equation for Compound Score**

where α=15, and is same as

A black and white math equation

AI-generated content may be incorrect.

1. VADER calculates sentiment scores by tokenizing the input text.
2. It looks up each token in a sentiment lexicon, applying rules for negation.
3. VADER then aggregates these scores into compound sentiment scores.
   * + 1. **Example**

**Sentence**

"McDonald's never disappoints. The service was amazing today."

**Tokenization**

["never", "disappoints", "amazing"]

**Lexicon Lookup**

"disappoints" → -2.3, "amazing" → +4.0, "never" → negation

**Rule Application**

Negation flips "disappoints" → +2.3

**Compound Score**

compound ≈ 0.717

Classification Thresholds:

* Compound ≥ 0.05 → Positive
* Compound ≤ –0.05 → Negative
* –0.05 < Compound < 0.05 → Neutral

​VADER also contains five main heuristics for sentiment amplification and contextual comprehension:

* Punctuation Handling: Use of the exclamation mark increases sentiment strength.
* Capitalization Emphasis: Uppercase words receive an emotionally intensified interpretation.
* Degree Modifiers: Adverbs such as "very" or "extremely" increase sentiment intensity.
* Negation Rules: Terms such as "not" invert the polarity of the subsequent sentiment-carrying words.
* Contrastive Conjunction Treatment: Priority is placed on the latter half of a sentence following contrastive conjunctions like "but", changing the final sentiment score accordingly.

All these enhancements make VADER far more effective for real-time sentiment analysis in conversational settings. For example, the sentence "The food was NOT bad!!" is considered mildly or even strongly positive due to its structure of negation, saliency of punctuation, and surroundings.

In this study, VADER achieved superior performance statistics, with 85.6% accuracy, 0.88 precision, and 0.84 F1-score. Its ability to handle complex, emotive language is its prime reason for being the primary sentiment classifier in this work.

**5.2.3 Comparative Evaluation**

Both classifiers were applied to over 8,600 reddit posts in an effort to gauge consistency in sentiment classification. A 0.49 Cohen's Kappa indicated moderate correlation between the two but strong divergence, especially between neutral and sarcastic posts. Over 2,500 mismatched predictions indicate intrinsic differences in their mechanisms of interpreting sentiment.

Due to its higher contextual understanding and higher human-like interpretation alignment, VADER was chosen as the final decision-making system in the event of classifier disagreement. TextBlob was retained for analytical comparison and cross-validation.

This hybrid approach allows for a stronger sentiment detection system, capable of identifying both explicit lexical sentiment and the more implicit emotional patterns present in informal digital communication.

**5.3 Virality and Engagement Algorithm**

In addition to classifying sentiment, the project quantifies the **virality** and **engagement** of each Reddit post. Two custom metrics are introduced: custom one based on simple interaction volume and another on emotion-amplified engagement.

**Virality Index 1 – Custom Basic Engagement Score**

This index measures the popularity of a post by adding upvotes and comments, normalized across the dataset.

**Formula**:

This provides a scale-independent score from 0 to 1 that reflects relative popularity.

**Virality Index 2 – Emotion-Weighted Engagement**

Inspired by research from *Nature Human Behaviour* ([Kim et al., 2021](https://www.nature.com/articles/s41562-021-01100-y)), this metric incorporates sentiment intensity into the virality calculation. It emphasizes that emotionally charged content is more likely to go viral.

**Libraries Used**:

* pandas, numpy (for normalization)
* TextBlob or VADER for polarity scores

**Formula**:

Where,

All inputs are normalized using Min-Max scaling to ensure comparability.

This index captures not only how often people interacted with a post, but also how strongly they felt about it.

**CHAPTER 4**

**Implementation & Dataset**

**6. Hardware and Software Requirements**

**6.1 Hardware Requirements**

| **Component** | **Specification** |
| --- | --- |
| Processor | Intel Core i5 or higher |
| RAM | 8 GB or more |
| Storage | 1 TB HDD / 256 GB SSD minimum |
| Internet | Stable connection for scraping |
| OS | Windows 10 |

Table 4a: A table representing the hardware requirements for this project

**6.2 Software Requirements**

| **Software Tool** | **Purpose** |
| --- | --- |
| Python 3.11 | Programming and scripting |
| Google Colab | Cloud-based development & testing environment |
| PRAW (Reddit API) | Scraping Reddit posts |
| NLTK | Tokenization, stopword removal, lemmatization |
| TextBlob | Rule/statistical sentiment analysis |
| VADER (via NLTK) | Lexicon-based sentiment scoring |
| Pandas | Data handling and preprocessing |
| Matplotlib / Seaborn | Data visualization |
| WordCloud | Visualizing hashtags and keyword frequency |
| Jupyter Notebook | Interactive development and documentation |

Table 4b: A table representing the software requirements for this project

**7. Dataset Description**

**8.1 Source**

The information was scraped from **Reddit using the PRAW** API in Python (v3.11) via Google Colab. The information includes posts and conversations related to fast-food chains in different relevant subreddits. Scraping was done continuously from **January 2024 to March 2025**, and more than **8,620 posts** were included.

Subreddits Monitored:

•r/fastfood

•r/mcdonalds

•r/food

•r/KFC

•r/Dominos

•r/domino's

•r/kfc

**7.2 Dataset attributes**

| Column Name | Description |
| --- | --- |
| Brand | Name of the fast-food chain mentioned (e.g., McDonald's, KFC) |
| Post | Raw Reddit post content |
| Sentiment | Final classified sentiment (Positive, Negative, Neutral) |
| Brand\_Processed | Text after replacing brand names with brandtoken |
| Sentiment\_Ready | Final version of text after applying negation and intensifier logic |
| Upvotes | Number of upvotes the Reddit post received |
| Share count | Number of shares or reposts to the post |
| Hashtags | Extracted hashtags from posts (if any) |
| Created at | Timestamp of the post published |

**Table 4c: A table explaining the column names with it’s description from the dataset**

**8. Implementation**

The deployment phase of this project was carried out by using a robust and multi-phase pipeline constructed with Python 3.11, on Google Colab as the main development environment. Google Colab offered a deep, cloud-based environment with the benefit of preinstalled packages, GPU acceleration (if required), and the convenience of collaborative and real-time execution, which was beneficial in terms of processing data at scale and carrying out computational operations like vectorization and topic modeling.

**Data Acquisition and Storage**

First, data were acquired from Reddit via PRAW (Python Reddit API Wrapper) by means of which user content and their respective metadata were scraped from a couple of subreddits dedicated to fast food. These were specialty subreddits like r/fastfood, r/mcdonalds, r/Dominos, r/KFC, and generic ones like r/food and r/AskReddit where brand names were mentioned in course-of-natural-discussion threads. The data gathered were screened with great care for relevancy using keyword-based brand detection and organized into a CSV dataset of more than 8600 records over a 15-month period from January 2024 to March 2025. A typical record in the dataset would include brand name, raw text of posts on Reddit, upvotes, share, and polarity.

**Text Preprocessing and Cleaning**

For data preparation for analysis, a reliable text preprocessing pipeline was set up. Raw text data was cleaned using regular expressions and NLTK tools. Special characters, punctuation marks, emojis, URLs, numbers, and redundant white spaces were stripped off. Posts were tokenized and WordNetLemmatizer was used for lemmatization, converting words into base forms. Standard English stopwords were omitted and domain stopwords (e.g., "lol", "lmao", "omg") were included to more contextuate. Brand names like "Burger King" and "Domino's" were substituted with an instance of a placeholder token (brandtoken) to enable analytical neutrality and avoid biased sentiment caused by repeated naming of brands.

**Sentiment-Aware Linguistic Transformations**

One special operation during preprocessing was sentiment-aware transformation. In particular, negation words such as "not", "never", and "no" were employed to prefix surrounding adjectives (e.g., "not tasty" → NOT\_tasty), and thereby preserve the inversion effect. Equally, intensifiers such as "very", "extremely", or "so" were also marked in the translated sentence (e.g., "very bad" → INTENSE\_bad). This addition allowed the sentiment classifiers to catch stronger emotional undertones, particularly on short and informal chunks of text typical on Reddit.

**Sentiment Classification**

Two sentiment analysis tools, VADER and TextBlob, were employed for polarity classification. VADER, which is particularly suited for social media and microtext, was employed due to its rule-based architecture and high sensitivity towards emoticons, capitalization, and slang words. TextBlob, being an NLTK and Pattern-based model, was employed as a contrast statistical model that provides polarity and subjectivity scores. Both models were trained on all the posts and had their sentiment labels saved side-by-side for testing. This two-model strategy allowed consistency in classification, polarity agreement, and the relative capacity of each tool to manage real-world text data to be tested.

Metrics of evaluation including accuracy, precision, recall, F1-score, and Cohen's Kappa were determined to compare the models. VADER performed best, especially in determining negative and positive sentiment, whereas TextBlob was weak in detecting neutral tone—characteristic of its shortcoming with respect to diversity of sentiment.

**Hashtag Extraction and Trend Mapping**

Regex-based extraction was used to extract hashtags from post content based on the pattern r"#\w+"". Hashtags were combined and used to look at trends and keyword uses related to brands. Frequency analysis was done to get the most common hashtags, and this was presented through bar plots and word clouds using the WordCloud library. As the visualization showed, the most prevalent hashtags utilized were #Dominos, #KFC, and #PizzaHut, an indicator of strong exposure for the brands and thus implied campaign-bundled interaction.

**Metrics of Engagement and Brand-Level Analyses**

Engagement was quantified through aggregating Reddit share (or comment) and upvote counts, which are metrics for the popularity and response of posts. Average engagement per brand was calculated and highly interactive posts were determined and ranked. They comprised high-visibility examples for Burger King, Domino's, KFC, and Subway. This kind of analysis shed light on what brands consistently drew more attention from users and helped to split passively viewed content from actively participated posts.

**Virality Index Construction**

Two bespoke virality indexes were constructed to simulate post spread. The first index considered raw engagement measured in terms of likes and shares. The second index considered emotional amplification, based on affect-driven content diffusion models, with sentiment polarity scores weighted against the measures of engagement. Min-max normalization was applied to normalize all the numeric values to a comparable range. Extremely emotionally charged positive and negative posts were shown to be significantly associated with greater engagement—validating the contribution of emotion to content virality.

**Crisis Detection and Complaint Categorization**

To identify posts that reflected brand risk, a filter mechanism identified negative sentiment posts and crisis terms (e.g., "disgusting", "rude", "late delivery"). The flagged posts were subsequently routed through a complaint categorization function, which categorized them into pre-established classes such as food quality, delivery, service experience, and cleanliness. Counts were tallied, graphed, and scanned brand by brand for operational vulnerabilities detection. Early warning indicators for brand reputation monitoring were also given by the system.

**Interactive Dashboard Development**

Lastly, all processed results and data were combined into an interactive real-time dashboard constructed with Streamlit. The dashboard incorporated modular tabs for every analytic feature—sentiment analysis, hashtags, engagement, crisis detection, and topic modeling—allowing for easy data exploration. An animation feature for real-time simulation streamed random posts with sentiment and engagement overlays, simulating a live sentiment feed. Visualization was incorporated using Matplotlib, Seaborn, and Plotly, making the dashboard informative and interactive.

**CHAPTER 5**

**9. Results and Discussion**

a. SENTIMENT ANALYSIS

Both the VADER and TextBlob classifiers were used to perform sentiment analysis on Reddit posts about fast-food brands. With an accuracy of **85.6%,** strong precision (0.88), and F1-score (0.84), **VADER** performed noticeably better than TextBlob. While it had a moderate amount of difficulty with neutral detection, it demonstrated outstanding recall in recognising both positive and negative sentiment. On the other hand, TextBlob's overall accuracy was lower at 63.1%, misclassifying a large number of borderline cases and failing to fully capture neutral sentiment (recall = 0.00). With more than 2500 incorrect predictions out of 8619 posts, a Cohen's Kappa score of 0.49 suggested only moderate agreement between the two tools. These findings show that while TextBlob might be too constrained for thorough brand sentiment monitoring in social media, VADER is better suited for examining casual, emotionally charged content.

A graph with green and blue bars

AI-generated content may be incorrect.

Figure 1: A side-by-side bar chart to compare VADER and TextBlob

A blue and red pie chart

AI-generated content may be incorrect.

Figure 2: A pie chart to compare the match in the Sentiment of both VADER and TextBlob

b. HASHTAG ANALYSIS

#Dominos accounted for 452 instances as the leading appearing hashtag in the dataset based on hashtag analysis. #KFC (451) and #PizzaHut (449) followed. #Subway (420), #BurgerKing (419), and #McDonalds (382) followed in turn to be strongly noted. Based on this order, Domino's garnered the highest action of the hashtag on Reddit despite all of the largest fast-food establishments being continually argued there.

This was supported by the word cloud visualization, with #Dominos taking over, suggesting high user interaction or successful campaign exposure. McDonald's, being a highly recognized brand in the globe, surprisingly employed hashtags relatively less, which might suggest that users of Reddit were indulging in more relaxed or oblique conversation.In their use of hashtags, KFC and Domino's are the most hashtag-dense brands on Reddit, giving insight into user engagement in social conversation, campaign visibility, and brand equity.A graph showing different colored stripes

AI-generated content may be incorrect.

Figure 3: A horizontal bar chart to represent the most frequent Hashtags

A close up of words

AI-generated content may be incorrect.

Figure 4: A word-cloud diagram to represent the most frequent Hashtags

c. ENGAGEMENT ANALYSIS

Mean engagement analysis reveals that KFC leads the pack with a mean upvotes + shares of approximately 16.1 followed by Domino's (15.9) and Burger King (15.7). McDonald's is surprisingly ranked last at 15.3, which reveals relatively weaker interaction in spite of brand popularity. On a per post basis, Burger King leads with the single post engagement being 59, which reveals the potential for virality. Emotionally, Subway had the positive polarity score of +1.00 and 14 engagements, which confirms that good sentiment is good interaction. Conversely, Pizza Hut, with a negative sentiment of –0.80, still managed 11 engagements, which shows that even negative comments can generate attention. As a general rule, experience-based postings and emotional polarity-driven brands are more likely to cause deeper user engagement.

A graph of a bar chart

AI-generated content may be incorrect.

Figure 5:A bar chart to represent the average engagement per brand from the posts

d. BRAND VIRALITY ANALYSIS

KFC holds court in basic and emotion-laden virality, yet there is more emotional involvement by Domino's with an emphasis on its successful content resonance.

Analysis of virality compared two metrics with each other: Virality Index 1 (Basic Engagement) and Virality Index 2 (Emotion-Weighted Engagement) of six major fast-food chains. On Virality Index 1, normalized as engagement in upvotes and shares, the top positions were held by KFC (0.285), Domino's (0.281), and Burger King (0.278), which indicated that these brands had a more evenly distributed volume of user interaction. This altered, however, once the consideration of emotional intensity by Virality Index 2 came into play. Here, KFC (0.192) continued to lead, followed by Domino's (0.189) and Burger King (0.186), which also means that not only did these brands get noticed but their content was also more emotionally appealing. McDonald's still had the lowest reading on both indices (0.270 on Index 1 and 0.161 on Index 2), which implies relatively lower engagement and emotional value. The supporting bar charts corroborate these findings—while KFC led in raw virality, Domino's enjoyed a greater lead when sentiment weight was included. Overall, the combination of simple and emotion-weighted measures gives a better overall view of brand virality, highlighting popularity as well as emotional resonance in content performance.

A graph of different colored bars

AI-generated content may be incorrect.

Figure 6: A side-by-side bar chart to compare both the virality index formulae

e. Crisis Analysis

Slow food and service quality are the most common complaint problems among all major fast-food chains, with McDonald's having the highest polarity negativity and crisis post volumes respectively.

Crisis analysis indicates that 22.81% of posts regarding major fast-food brands convey serious customer dissatisfaction, indicating that nearly 1 in every 4 customers post serious complaints online. The most frequent complaint category is food quality, with a total of over 1,350 marked posts—almost twice as many as any other category—indicating a recurring issue with all brands despite ongoing marketing or service promotions. Word cloud discoveries also support customer frustration, such as words like "worst," "waited," "cold," "fries," and "service," which indicate long waits, substandard food, and unacceptable staff behavior. The repetitive usage of words such as "today," "yesterday," and brand names means that the complaints are new and recent. On the part of branded data, McDonald's led the highest number of marked posts (345), followed by Pizza Hut (335), Burger King (327), Subway (323), KFC (318), and Domino's (318), which shows dissatisfaction among customers is widespread and not limited to a single brand. Lastly, sentiment polarity scores of selected posts are heavily negative (≤ -0.63), and Subway and KFC posts consistently reach -1.00, indicating extremely low customer experience with food and service quality that demand immediate attention.

A graph of a survey

AI-generated content may be incorrect.

Figure 7: A bar chart to know the maximum number of complaint categories

A close up of words

AI-generated content may be incorrect.

Figure 8: A word-cloud diagram to know the most repetitive words in the complaint posts.

f. Interactive Dashboard

A screenshot of a computer

AI-generated content may be incorrect.

Figure 9: A screenshot of the interactive dashboard with every analysis in separate tabs.

A screenshot of a computer

AI-generated content may be incorrect.

Figure 10: A screenshot of the live simulation of posts and live calculations of sentiment,engagement,polarity

A screenshot of a computer

AI-generated content may be incorrect.

Figure 11: Another screenshot of the live simulation of posts and live calculations of sentiment,engagement,polarity

**10. Sample code**

A.Data preprocessing

import pandas as pd

import re

from nltk.corpus import stopwords

from nltk.stem import WordNetLemmatizer

from nltk.tokenize import word\_tokenize

import nltk

nltk.download('punkt')

nltk.download('stopwords')

nltk.download('wordnet')

data = pd.read\_csv("/content/reddit\_fastfood\_data.csv")

df = pd.DataFrame(data)

def basic\_clean(text):

if not isinstance(text, str):

return ""

text = re.sub(r'Ã¢Å“â€¦Ã¯Â¸Â\x8f', ' ', text)

text = re.sub(r'[^\x00-\x7F]+', ' ', text)

text = text.lower()

text = re.sub(r'https?://\S+|www\.\S+', '', text)

text = re.sub(r'[^a-zA-Z\s]', ' ', text)

text = re.sub(r'\s+', ' ', text).strip()

return text

df['cleaned\_text'] = df['post'].apply(basic\_clean)

lemmatizer = WordNetLemmatizer()

stop\_words = set(stopwords.words('english'))

def advanced\_normalization(text):

custom\_stopwords = {'lol', 'lmao', 'stahp','ahh'}

stop\_words.update(custom\_stopwords)

tokens = word\_tokenize(text)

tokens = [word for word in tokens if word not in stop\_words and len(word) > 2]

tokens = [lemmatizer.lemmatize(word) for word in tokens]

return ' '.join(tokens)

df['normalized\_text'] = df['cleaned\_text'].apply(advanced\_normalization)

def handle\_brand\_context(text, brand):

text = re.sub(r'burger\s\*king', 'brandtoken', text)

text = re.sub(r'bk\s', 'brandtoken ', text)

return text

df['brand\_processed'] = df.apply(lambda x: handle\_brand\_context(x['normalized\_text'], x['Brand']), axis=1)

def sentiment\_specific\_processing(text):

negation\_words = ['not', 'no', 'never', 'dont']

tokens = text.split()

for i, word in enumerate(tokens):

if word in negation\_words and i+1 < len(tokens):

tokens[i+1] = 'NOT\_' + tokens[i+1]

intensifiers = {'very', 'really', 'extremely'}

for i, word in enumerate(tokens):

if word in intensifiers and i+1 < len(tokens):

tokens[i+1] = 'INTENSE\_' + tokens[i+1]

return ' '.join(tokens)

df['sentiment\_ready'] = df['brand\_processed'].apply(sentiment\_specific\_processing)

1. Sentiment analysis

import nltk

nltk.download('vader\_lexicon')

from nltk.sentiment.vader import SentimentIntensityAnalyzer

vader\_analyzer = SentimentIntensityAnalyzer()

df = pd.read\_csv('/content/preprocessed\_data.csv')

df['vader\_scores'] = df['post'].apply(lambda x: vader\_analyzer.polarity\_scores(x))

vader\_df = pd.json\_normalize(df['vader\_scores'])

df = pd.concat([df, vader\_df], axis=1)

df.drop(columns=['vader\_scores'], inplace=True)

df['vader\_sentiment'] = df['compound'].apply(

lambda x: 'positive' if x >= 0.05 else ('negative' if x <= -0.05 else 'neutral')

)

from textblob import TextBlob

df['textblob\_polarity'] = df['post'].apply(lambda x: TextBlob(x).sentiment.polarity)

df['textblob\_subjectivity'] = df['post'].apply(lambda x: TextBlob(x).sentiment.subjectivity)

def get\_textblob\_sentiment(polarity):

if polarity > 0.05:

return 'positive'

elif polarity < -0.05:

return 'negative'

else:

return 'neutral'

df['textblob\_sentiment'] = df['textblob\_polarity'].apply(get\_textblob\_sentiment)

df['sentiment\_match'] = df.apply(

lambda row: 'match' if row['textblob\_sentiment'] == row['vader\_sentiment'] else 'mismatch',

axis=1

)

match\_counts = df['sentiment\_match'].value\_counts()

print("Match vs Mismatch Count:\n", match\_counts)

comparison\_matrix = pd.crosstab(

df['textblob\_sentiment'],

df['vader\_sentiment'],

rownames=['TextBlob'],

colnames=['VADER']

)

print(comparison\_matrix)

1. Hashtag analysis

import re

df['hashtags'] = df['post'].apply(lambda x: re.findall(r'#\w+', x.lower()))

all\_hashtags = sum(df['hashtags'], [])

hashtag\_freq = pd.Series(all\_hashtags).value\_counts().head(20)

print(hashtag\_freq)

import matplotlib.pyplot as plt

plt.figure(figsize=(12, 6))

hashtag\_freq.plot(kind='bar', color='skyblue')

plt.title('Top 20 Hashtags')

plt.ylabel('Frequency')

plt.xlabel('Hashtags')

plt.xticks(rotation=45)

plt.tight\_layout()

plt.show()

from wordcloud import WordCloud

hashtag\_cloud = WordCloud(width=800, height=400, background\_color='white').generate(' '.join(all\_hashtags))

plt.figure(figsize=(10, 5))

plt.imshow(hashtag\_cloud, interpolation='bilinear')

plt.axis('off')

plt.title('Hashtag WordCloud')

plt.show()

1. Engagement analysis

engagement\_metrics = df.groupby('Brand')[['upvotes', 'comments']].mean().sort\_values(by='upvotes', ascending=False)

print(engagement\_metrics)

top\_engaged\_posts = df.sort\_values(by='upvotes', ascending=False).head(5)[['Brand', 'post', 'upvotes', 'comments']]

print(top\_engaged\_posts)

plt.figure(figsize=(10, 5))

engagement\_metrics['upvotes'].plot(kind='bar', color='teal')

plt.title('Average Upvotes per Brand')

plt.ylabel('Average Upvotes')

plt.xticks(rotation=45)

plt.tight\_layout()

plt.show()

1. Brand Virality analysis

# VIRALITY INDEX 1

df['virality\_index1'] = (df['upvotes'] + df['comments']) / (df['upvotes'].max() + df['comments'].max())

# VIRALITY INDEX 2 – EMOTION-WEIGHTED INDEX

# Source: ["The Role of Affect in Information Diffusion", Nature Human Behaviour, 2021](https://www.nature.com/articles/s41562-021-01100-y)

sentiment\_map = {'negative': -1, 'neutral': 0, 'positive': 1}

df['sentiment\_score'] = df['vader\_sentiment'].map(sentiment\_map)

df['emotion\_amp'] = df['textblob\_polarity'] \* df['sentiment\_score']

df[['emotion\_amp', 'upvotes', 'comments']] = df[['emotion\_amp', 'upvotes', 'comments']].apply(

lambda x: (x - x.min()) / (x.max() - x.min())

)

df['virality\_index2'] = (

0.40 \* df['emotion\_amp'] +

0.30 \* df['upvotes'] +

0.30 \* df['comments']

)

virality\_by\_brand = df.groupby('Brand')[['virality\_index1', 'virality\_index2']].mean()

print(virality\_by\_brand.sort\_values(by='virality\_index2', ascending=False))

1. Crisis and Complaint analysis

def detect\_complaint(post):

complaint\_keywords = ['late', 'slow', 'cold', 'bad', 'rude', 'worst', 'disgusting']

return any(word in post.lower() for word in complaint\_keywords)

df['is\_complaint'] = df['post'].apply(detect\_complaint)

complaint\_stats = df.groupby('Brand')['is\_complaint'].mean().sort\_values(ascending=False)

print("Complaint Rate per Brand:")

print(complaint\_stats)

plt.figure(figsize=(10, 5))

complaint\_stats.plot(kind='bar', color='salmon')

plt.title('Complaint Frequency by Brand')

plt.ylabel('Proportion of Complaints')

plt.xticks(rotation=45)

plt.tight\_layout()

plt.show()

**CHAPTER 6**

**11. Conclusion**

Managerial Conclusion (For Executives & Brand Strategists)

Key Takeaways:

•VADER is the best tool for tracking real-time social sentiment, surpassing traditional techniques.

•Domino's & KFC excel in engagement & emotional connection, providing a model for effective content strategy.

•McDonald's trails with complaints & poor engagement, showing the need to improve digital reputation management.

•Food quality & late service control complaints—process improvements and proactive response processes are the answer.

• Emotion-laden content (positive or negative) increases virality, i.e., experience-based campaigns increase brand loyalty.

Actionable Insight: Fast-food brands need to focus on sentiment-aware engagement, operational excellence, and emotionally engaging content to improve digital perception.

Technical Conclusion (For Data Analysts & Researchers)

Key Findings:

• VADER achieved 85.6% accuracy (0.84 F1-score), being the most suitable for emotion-laden social data (e.g., Reddit).

• #Domino's & #KFC lead hashtag trends, indicating good campaign reach and user engagement.

•KFC is the virality king; Domino's, sentiment resonance, verifying sentiment's role in content blow-up.

•22.81% of updates are negative in sentiment, most notably regarding food quality—most negative volume in McDonald's.

•Recurring negative sentiment (polarity ≤ -0.63) validates brand-specific sentiment dampening methods are necessary.

Recommendation: Implement real-time sentiment analysis paired with crisis identification systems to support brand responsiveness and customer experience.

**12. Appendices**

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**LIST OF ACRONYMS**

| Acronym | Description |
| --- | --- |
| NLP | Natural Language Processing |
| VADER | Valence Aware Dictionary and sEntiment Reasoner |
| CSV | Comma-Separated Values |
| PRAW | Python Reddit API Wrapper |
| NLTK | Natural Language Toolkit |
| LIWC | Linguistic Inquiry and Word Count |
| Bi-LSTM | Bidirectional Long Short-Term Memory |
| CNN | Convolutional Neural Network |
| GloVe | Global Vectors for Word Representation |
| RNN | Recurrent Neural Network |
| TF-IDF | Term Frequency-Inverse Document Frequency |
| NMF | Non-negative Matrix Factorization |
| ROC | Receiver Operating Characteristic |
| AUC | Area Under Curve |
| EDA | Exploratory Data Analysis |
| FN | False Negative |
| TP | True Positive |
| FP | False Positive |
| TN | True Negative |
| BERT | Bidirectional Encoder Representations from Transformers |

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