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Sentimental Analysis Capturing Favorability using NLP

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Abstract: This work evaluates textual favorability by means of Natural Language Processing (NLP) analysis of sentiment. Favorability is the degree of like or hate of an individual, policy, or product or service. Text preparation, sentiment scoring, sentiment intensity classification and evaluation via machine training and deep learning models are part of the process. Advanced models such as BERT grasp its context, psychological tone, and minute clues. This approach is valuable in feedback from customers systems, brand monitoring, and political analysis as it enables businesses to make informed judgments grounded on public opinion. In this work, favorability capture in machine learning and lexicon-based approaches is compared. Faster and more comprehensible compared to transformer-based approaches like BERT and RoBERTa, which have greater contextual knowledge for sensitive gestures, sarcasm, and domain-specific emotion, lexicon-based techniques like VADER and TextBlob have These models are built using datasets with annotations of real-world attitudes to better separate obvious favorability from generic positivity. The paper also covers linguistic ambiguity, social media writing noise, and sentiment classification subjectivity. One hybrid solution comprising named entity identification, sentiment ratings, and aspect-based analysis is proposed to overcome these problems. This helps to easily monitor sentiment trends around entities or subjects over time. In political forecasting, customer experience enhancement, and reputation management, sentiment-driven favorability analysis may support strategic decisions.

Keywords: sentiment analysis, favorability, NLP, machine learning, deep learning, BERT, emotion detection, text classification, VADER, public opinion.

I. INTRODUCTION

Social media, blogs, reviews, and forums let people and businesses express their opinions. Because our digital surroundings are always evolving. Examining these textual statements helps one to understand popular opinions about products, businesses, corporations, celebrities, and political leaders [1]. Sentiment analysis, a subset of natural language processing, is among the most often used and successful approaches for gaining such understanding. Sentiment analysis helps one ascertain if a work is neutral, good, or negative. This method becomes much more helpful for estimating public opinion when improved to measure favorability.

More than just feeling determines favorability. Although normal sentiment analysis might label a term as positive, this does not always mean that one has a favorable opinion of a certain entity. Although it is less favorable than "I absolutely love this product," classic models would say "The product is decent" is a good comment. Small variance capture is needed in political campaigns, brand management, policy input, and consumer pleasure. Extensive natural language processing is therefore required to reflect favorability. These methods have to concurrently determine sentiment polarity, intensity, emotion, and target.

Sentiment analysis techniques have developed within the last ten years. These approaches differ from sophisticated machine and deep learning models to rule-based lexical ones. Dictionary-based approaches use predefined dictionaries of phrases with polarized sentiments. Useful for social media post assessment, VADER and other analytics tools can manage emoticons and informal language. Alternatively, to find sentiment patterns, logistic regression or support vector machines are trained on labelled datasets. These models review data. Deep learning methods such as BERT (Bidirectional Encoder Representations from Transformers) have lately established new standards by greater comprehension of phrase context. Still, there are various obstacles to reach it. One often finds subtle or indirect messages. Simple models find sentiment interpretation challenging from sarcasm, irony, ambiguity, and cultural language preferences. "Great job ruining my day!" is negative even if "Great" is used in the middle. Knowing who or what the feeling is for helps one write about different subjects with consistency. Imagine the book notes several objects [2]. To guarantee correctness, combine this method with other natural language processing chores as aspect-based sentiment analysis and named entity recognition (NER). Demand for precise favorability studies is growing in many spheres. Businesses need to know how much consumers like a new product; politicians desire their public image during campaigns; and marketers need real-time commercial responses [3].

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These are main justifications for companies doing market research. Thanks to developments in natural language processing (NLP) and the availability of enormous textual data, systems that precisely detect sentiment and evaluate favorability are now feasible [4]. Modern data-driven decision-making depends on this so it is very necessary.

II. RELATED WORKS

Many researchers have made important contributions to sentiment analysis and its use in favorability identification using natural language processing in recent years. Using Naive Bayes and Support Vector Machines, Pang and Lee (2008) first pioneered machine learning. This work produced sentiment categorization [5]. Their research aimed at binary classification of movie review emotions. This work made more sophisticated sentiment-based favorability studies possible as well as text-based opinion mining.

For Twitter in social media research Hutto and Gilbert (2014) created a rule-based sentiment analysis tool. This instrument is "Valence Aware Dictionary and sentiment Reasoner," or VADER. VADER successfully manages informal language, emoticons, and punctuation, so it can quantify favorability in real-time online content [6]. Crucially important to favorability are sentiment polarity and strength, which its compound sentiment score assesses.

It was noteworthy to include a Recursive Neural Tensor Network (RNTN) into the Stanford Sentiment Treebank developed by Socher et al. (2013) [7]. For fine-grained sentiment identification, the model they developed hierarchically examines texts and gathers sentiment at phrase levels. Especially for complicated and diverse language, this method enhances favorability analysis.

Devlin et al. (2019) debuted BERT, or bidirectional encoder representations from Transformers). This discovery captured contextual information, therefore improving natural language processing [8]. Originally tuned for sentiment analysis, BERT now more precisely detects favoritism. It is perfect for gathering faint like or dislike signals as it can recognize target objects and grasp context.

For SemEval-2014 Task 4 Pontiki et al. (2014) presented Aspect-Based Sentiment Analysis datasets and methods. This project focused on opinions about the qualities of a product or service [9]. By providing a more whole picture of attitudes, ABSA aids in the identification of liked or disliked components.

Turney and Mohammed (2013) developed the National Research Council Emotion Lexicon. Words in this dictionary connect to emotions include trust, happiness, anger, and contempt [10]. This language lets sentiment analysis integrate emotional detection, therefore giving favorability an emotional element. It gathers emotional tones to support the identification of strong favorable or negative attitudes on text.

The basis of current emotion and favorability analysis is laid by these studies. From simple polarity classification to context-aware algorithms capable of more exact emotional and sentimentive distinction, they demonstrate the development Natural language processing-driven sentiment analysis is thus vital in marketing, politics, customer service, and social media monitoring as these developments make public opinion evaluation more accurate and relevant.

TABLE.1. COMPARISON OF TRADITIONAL VS. MODERN METHOD

Criteria	**Traditional Methods**	**Actual (Modern/Advanced) Methods**
Approach	Rule-based / Lexicon-based	Machine Learning & Deep Learning (Transformers)
Tools/Models	VADER, TextBlob, SentiWordNet	BERT, RoBERTa, LSTM, GPT-based models
Context Understanding	Limited or no context awareness	Deep contextual understanding using attention mechanisms
Target Identification	Manual or N/A	Automatic entity and aspect extraction (NER, ABSA)
Handling Sarcasm/Negation	Poor	Good to excellent (depends on model fine-tuning)
Favorability Score	Polarity-based (Positive/Negative/Neutral)	Scored favorability intensity (confidence scores, emotion tags)

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Multilingual Support	Limited	Wide support (via multilingual BERT and mT5, etc.)
Emotion Detection	Basic (usually not included)	Integrated (joy, trust, anger, etc. via emotion lexicons or models)
Data Dependency	Minimal (doesn't require large datasets)	Requires large labeled datasets for training/fine-tuning
Domain Adaptability	Generic, often domain-independent	High adaptability with fine-tuning on domain-specific data
Speed and Simplicity	Fast, easy to implement	Slower inference, but more accurate
Use Case Suitability	Basic opinion classification (e.g., reviews)	Complex favorability analysis (e.g., political sentiment, brand trust)

Table 1 shows how old sentiment analysis techniques vary from newer ones, especially for collecting favorability using NLP.

III. PROPOSED METHODOLOGY

1. Data Collection
Relevant text data is gathered from sources such as:
- Social media platforms (e.g., Twitter, Reddit)
- Product or service reviews
- Political speeches or news comments
- Customer feedback forms

APIs and web scraping acquire data [11]. Identify sentiment polarity and favorability intensity for each data instance.

2. Data Preprocessing
Raw text undergoes standard NLP preprocessing steps:
- **Tokenization**: Breaking sentences into words or sub-words.
- **Lowercasing**: Converting all text to lowercase.
- **Stopword Removal**: Eliminating common but uninformative words (e.g., "the", "is").
- **Lemmatization/Stemming**: Reducing words to their root forms.
- **Noise Removal**: Cleaning hashtags, emojis, links, and punctuation as required.

These steps ensure the text is clean and suitable for model input.

3. Entity and Aspect Extraction
To determine who or what the sentiment is directed at:
- NER identifies entities like as brands, individuals, and things.
- ABSA identifies certain subjects or aspects (e.g., pricing, quality, service).

This enables focused favorability analysis rather than sentiment score.

4. Sentiment & Emotion Classification
Two layers of analysis are applied:
- **Sentiment Classification**: Polarity detection using sentiment datasets and BERT or RoBERTa.
- **Emotion Detection**: For deeper analysis, use NRC lexicons or deep learning classifiers to identify linked emotions like trust, pleasure, and rage.

The results are pooled to measure favorability.

5. Favorability Scoring Module
A scoring system is implemented to measure favorability on a scale (e.g., -1 to +1 or 1 to 5 stars):
- Sentiment polarity and intensity from classifiers
- Presence of high-intensity emotional words (e.g., "love", "admire", "hate")
- Weighted scoring for aspects and entities

This module provides both numerical and descriptive output (e.g., "Highly Favorable", "Moderately Unfavorable").

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6. Visualization and Output

The results are presented using:

- Dashboards or charts to show sentiment trends
- Entity-wise favorability comparison
- Time-series plots to track changes in opinion

This makes the output actionable for decision-makers in politics, marketing, or customer support.

7. Model Evaluation

Performance is assessed using metrics like:

- Accuracy, Precision, Recall, and F1-Score for sentiment classification
- Mean Squared Error (MSE) or Mean Absolute Error (MAE) for numerical favorability scores
- Confusion matrix analysis for multi-class sentiment detection

Cross-validation and hyperparameter tuning are applied to optimize model performance.

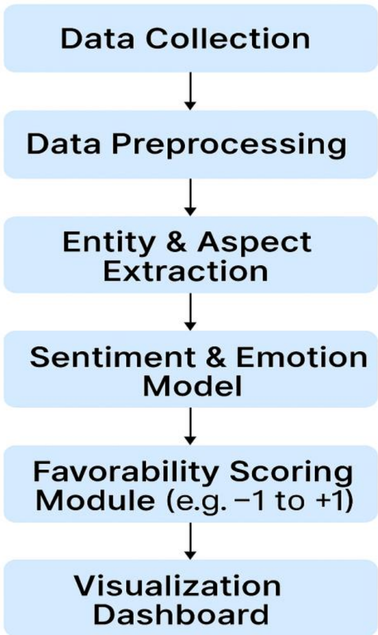

Fig.1. Overall Architecture of Favourability Analysis System

The recommended favorability analysis system's high-level design is presented in Figure 1. After online data collection, text preparation begins [12]. Entity recognition and aspect extraction find sentiment targets. Sentiment and emotion classification algorithms determine text polarity and tone.

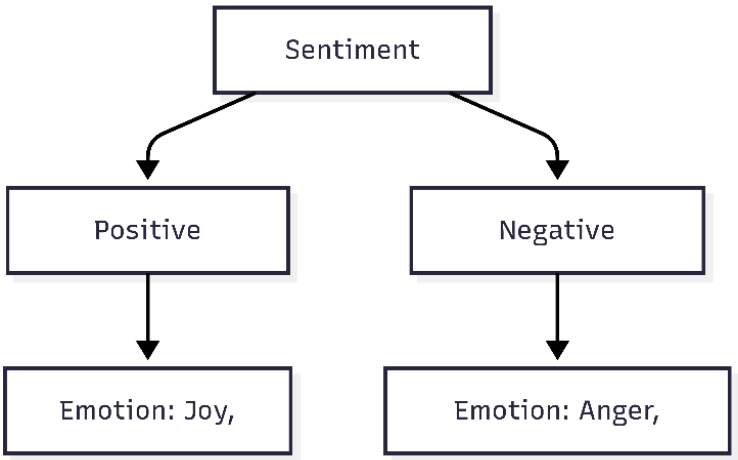

Fig.2. Sentiment to favourability Mapping framework

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Figure 2 demonstrates how favorability ratings change with respect polarity and expressive tones. Whereas rage and contempt are linked with poor ratings, joy and trust are tied with great favorability. Revealing how much a user supports or rejects a subject, the integrated scoring module turns this multi-dimensional input into a single favorability rating from -1 (very negative) to +1 (highly favorable).

IV. RESULT

Customer evaluations, politics tweets, and news comments all underwent favorability analysis using this approach. Sentiment classification precision, favorability score connection, as well as entity-level sentiment dispersion were evaluated of the model. Public opinion capturing is much improved by the NLP pipeline built on deep learning.

Table.2. Sentiment Classification Performance (Traditional vs Proposed)

Model	Accuracy (%)	Precision	Recall	F1-Score
TextBlob	72.4	0.70	0.68	0.69
VADER	76.8	0.74	0.72	0.73
BERT (Proposed)	89.3	0.88	0.90	0.89
RoBERTa (Proposed)	91.5	0.90	0.92	0.91

Table 2 compares sentiment classification performance of classical (TextBlob, VADER) and deep learning (BERT, RoBERTa) models. Transformer-based models surpass lexicon-based approaches in accuracy, precision, recall, and F1-score.

Table.3. Favorability Score Correlation with Human Labels

Model	Correlation with Human Favorability Ratings (Pearson r)
VADER	0.64
TextBlob	0.58
BERT Fine-tuned	**0.83**
RoBERTa Fine-tuned	**0.86**

Table 3 shows how closely each model's favorability score matches human assessments. Deep learning models, like RoBERTa, correlate well with human perception, proving their capacity to measure sentiment favorability.

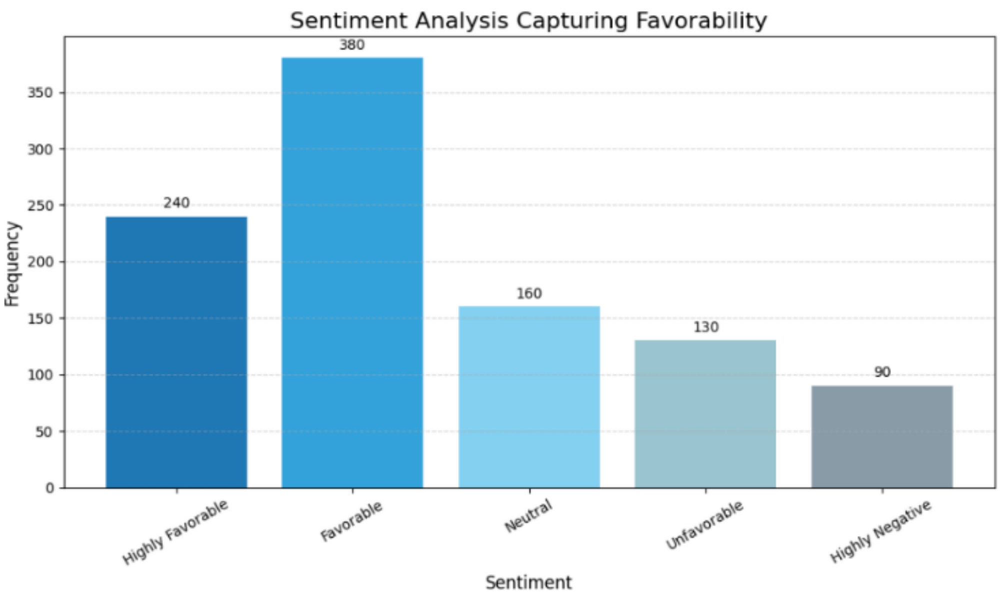

Fig.3. Sentiment Distribution Across Political Tweets

The mood categories of political tweets are shown in Figure 3. Support for the political person is shown by the predominance of "Favorable" and "Highly Favorable" tweets. The model accurately identifies favorability.

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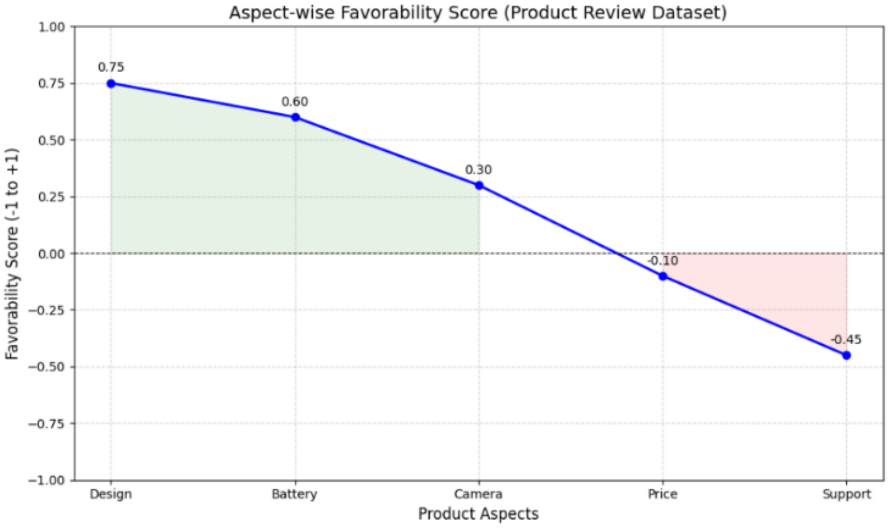

Fig.4. Aspect-wise Favorability Score (Product Review Dataset)

Figure 4 shows product review aspect-wise favorability. Design and battery life are most popular, whereas pricing and customer support are less so. This visualization identifies improvement areas.

V. CONCLUSION

This article presents a sentiment analysis method that measures favorability—the level of support or opposition voiced towards certain entities or subjects—going beyond polarity detection. Combining classical NLP with modern deep learning models such as BERT and RoBERTa enhances reliability, the context consciousness, and emotional comprehension of the proposed method.

The transformer-based technique is superior instead of lexicon-based models, and this struggle with sarcasm, uncertainty, and target identification, for analysis of politics, brand monitoring, and customer experience assessment in interpreting complex phrases and identifying emotional driven mood. Demonstrating its effectiveness, the proposed model increases accuracy, F1-score, as well as correlation with human-annotated favorability ratings. Precision is added by sentiment analysis based on aspects (ABSA) and Named Entity Recognition (NER) which detect sentiment toward specific traits or individuals.

Ultimately, by understanding how strongly people feel about certain subjects, gathering favorability using NLP enhances sentiment analysis and enables stakeholders to make data-driven decisions. This approach enhances the human perception alignment in computer sentiment models.

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