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Aspect-Based Sentiment Analysis of Marathi Bank Sector Reviews Using Transformer-Based Models

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Abstract

Aspect-Based Sentiment Analysis (ABSA) has become an important method of fine-grained opinion mining, finding opinion targets and their sentiment polarity. Although much has been done regarding the use of ABSA in English and other high-resource languages, little has been focused on low-resource Indian languages like Marathi, especially in relation to domain-specific applications such as banking. This paper introduces an in-depth transformer-based ABSA of Marathi bank reviews with BERT and its multilingual counterparts. The proposed methodology is based on two steps: aspect term extraction as a sequence labelling task and aspect-level sentiment classification based on contextual sentence-aspect representations. In this work, the proposed aspect-based sentiment analysis system converted 1000 customer reviews into 3115 sentiment instances for each aspect and achieved high classification performance, with a total validation accuracy of 95.18%. Empirical evidence shows that integrating POS-based aspect extraction with transformer-based sentiment classification are effective in fine-grained banking review analysis under low-resource language conditions.

Keywords: Aspect-Based Sentiment Analysis, Marathi Language, Banking Reviews, BERT, IndicBERT, Low-Resource NLP

1. Introduction

The reviews left by the users are critical towards the formation of the general opinion and judgment in the banking industry. As the number of digital banking platforms being adopted in India rises, clients often give their feedbacks using their local languages, including Marathi. The use of such reviews is critical in helping banks to enhance the quality of services provided, customer satisfaction and efficiency [1]. The conventional sentiment analysis techniques are mainly centred on document or sentence level of document polarity, which does not reflect the opinion regarding particular elements of the service [2]. As an illustration one of the customers can be very positive with regards to customer service and negative with regards to processing of loans. Aspect-Based Sentiment Analysis (ABSA) deals with this drawback by recognizing the aspect terms and establishing the sentiment polarity of each aspect. Although it is

essential, ABSA research in Marathi has not been done extensively because of the presence of a few annotated datasets, the complexity of the language and the lack of computational resources. Current expansions in transformer-based models, particularly BERT have been amazingly successful in NLP tasks with deep contextual representation. This spurs the development of transformer-based strategies of Marathi ABSA[3, 4].

The aspect-based sentiment analysis system of Marathi banking reviews is executed in a pipeline which is organized in the form of data collection, pre-processing, aspect extraction and sentiment classification. First of all, a list of reviews of Marathi banking is gathered and purged with missing and duplicate data. Normalization of the text is then done using the Unicode and whitespace normalization methods to provide consistency. This is then followed by cleaning, then tokenization to divide the text into single words after which stop-word removal is done to remove most common yet meaningless words. This pre-processing phase makes the textual data ready to be analysed effectively by making noise reduction and enhancing the quality of features to be utilized in the next phase.

After pre-processing, aspect term extraction is performed based on a lexicon based method, i.e. domain specific banking words like service, charges, account, transactions and ATM are extracted out of the reviews. In each review, there can be several aspects and thus, the data is converted into an aspect-sentiment structured format with each row corresponding to a review, its aspect, and sentiment. The affinity of every facet is then categorized with the assistance of machine learning and profound learning models, including transformer-based ones such as IndicBERT, Multilingual BERT, and XLM-RoBERTa. The annotated data are used to train the models and performance measures of the models are evaluated on the basis of accuracy, precision, recall, and F1-score. The process is stepwise and will help the system to capture the fine-grained sentiments pertaining to various banking aspects with more insights on the customer opinions.

Contributions of this work

1. A domain-specific ABSA for Marathi bank reviews.
2. Creation of a manually annotated Marathi bank review dataset.
3. Development of ABSA using transformer-based Models

2. Literature Review

Work on aspect-based sentiment analysis (ABSA) and transformer architectures is mature for English and several low-resource languages, but Marathi, especially in the banking domain, remains largely unexplored.

ABSA in Low-Resource and Indic / Morphologically Rich Languages.

Some significant assets of Aspect Based Sentiment Analysis (ABSA) have been recently implemented in low-resource and morphologically rich languages, which was able to establish the necessary trend of data gaps, complex inflectional morphologies, and shortages of annotated corpora.

- Hindi ABSA: Multilingual Transformer-based models that combine rule-constrained linguistic aspects with fine-tuning of mBERT variants (that is, Hindi -based multilingual BERT (Hi -BERT)) and multilingual ensembles of fine-tuned mBERT variants also achieve good performance on movie review datasets [5, 6](Soni et al., 2025).
- Odia and Turkish ABSA: It has been recently shown that members of the deep-learning architecture and pre-trained Transformer-based models can successfully specialize to agglutinative and under-resourced languages. [5, 6](Soni et al., 2025; Bilgin and Turan, 2025).
- Bengali ABSA Bengali ABSA: transformer-based and hybrid BERT Random Forest (tRF-BERT): BERT and Random Forest models clearly outperform the traditional ML models on restaurant and cricket data [5, 7](Soni et al., 2025; Ahmed et al., 2024).
- Arabic ABSA: Arabic ABSA models (AraBERT, MARBERT) have very high F1 when detecting an aspect category and classifying sentiment [8](Almasaud and Al-Baity, 2024).

In banking, ABSA and transformers have already started to emerge primarily beyond the Marathi:

Sentiment analysis of bank customer reviews (document level) based on the BERT demonstrates that BERT is significantly more effective than LSTM in terms of polarity prediction but fails to predict aspect-level emotions [9](Siddique et al., 2025). The article Multilingual Banking ABSA: A framework of multilingual banking sentiment analysis uses XLMRoBERTa and BERT Transformer models to apply ABSA on code -mixed banking reviews written in English, Sinhala, and code-mixed languages[10] (Rizvi et al., 2025).

Marathi Sentiment Analysis and Transformers

Within the context of the Marathi language processing the available literature using the transformer models focused almost exclusively on the sentiment inference on a sentence or document scale, neglecting the aspect level granularity The empirical findings prove that the transformer model is more successful as compared to the baselines; however, the study does not address facet extraction, domain-specific discrimination, or reviews related to the banking industry[11] (Kakde & Padalikar, 2022). A different research question is focused on sentiment detection by using a transformer in transliterated Hindi and Marathi. The systems under analysis are MuRIL, XLM -RoBERTa, and IndicBERT, which are all improved with lexicon-based and graph-based auxiliary. Although such models have shown significant accuracy on artificially created data and comments found on Youtube, their sentiment has been assessed at the general sentence level rather than at the sentiment level at aspects or a domain scene like banking[12] (Sutar and Desai, 2025).

Framing of the Present Work

An original research input in the field would thus be one dealing with several combined directions as reflecting a literature contribution.

The first one would be the construction or adaptation of a Marathi banking reviews dataset towards Aspect-Based Sentiment Analysis (ABSA), including aspects categories (country-specific) like quality of the services, digital banking facilities, interest rates and service fee, employee conduct and loan or credit

processing. (Ahmed et al., 2024; Zhang et al., 2021)[7, 13]. Second, to apply either joint- or pipeline-based Aspect Term Extraction (ATE) or Aspect Polarity Classification (APC), the study would involve fine-tuning one or more Indic and multilingual Transformer architectures, such as MuRIL, XLM-RoBERTa, IndicBERT, and mBERT. More syntactic features or mechanisms of multi-granular attention could be added to models with the aim of enhancing the representation learning process with applications of contextual and aspect-level representation that utilize them, as in using architectures like SRE-BERT, T-MAGAN, and other models to improve context and aspect representation learning[12, 14-18](Mewada & Dewang, 2022; Sun et al., 2020; Huang et al., 2024; Zhao et al., 2023; Jayakody et al)

Third, the framework must clearly touch on linguistic complexities that exist in actual-life Marathi banking reviews such as Marathi code-mixing with English, spelling differences, transliteration, banking domain jargon among others.[10] [19] (Rizvi et al., 2025; Sutar and Desai, 2025). Lastly, the suggested system would strive to produce aspect-wise, explainable sentiment results, which would be banking-specific. The interpretability of the framework might be improved by introducing explainable AI—including SHAP, LIME and attention visualization—to facilitate greater trust and utility on decision support by adapting explainable Transformer-based ABSA models that have already been used on other linguistic and financial problems[9] [10](Siddique et al., 2025; Rizvi et al., 2025).

3. Methodology

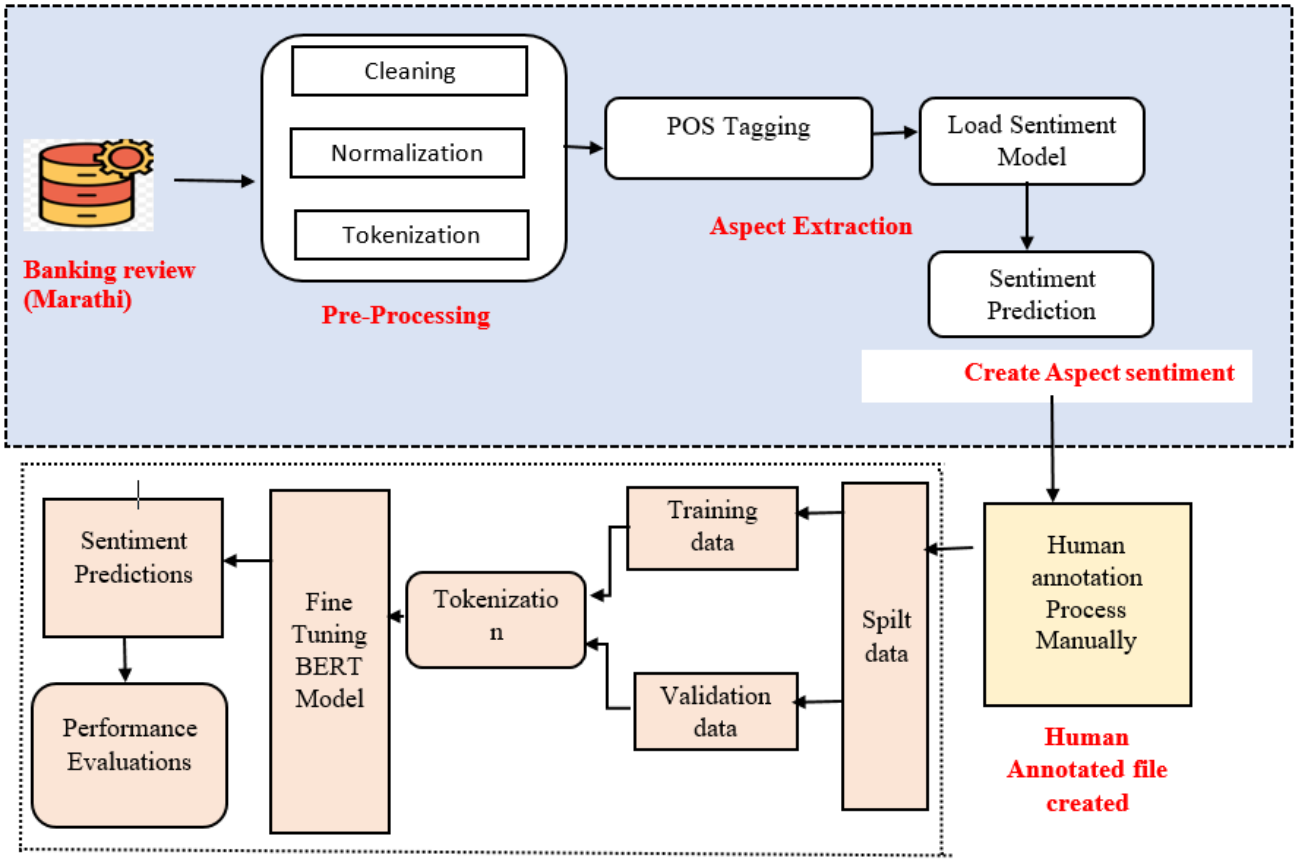

Figure 1: Methodology of ABSA in Marathi language.

3.1 Data Collection and Annotation Process

Aspect based sentiment analysis in Marathi review is very few available in Marathi language that's why we download banking review dataset in English language in kaggle. After downloading we translated all review in Marathi language.

The dataset was manually marked concerning various pre-determined points of interest related to the banking sphere and they included quality of services, employee behaviour, online services, loan professions, account management, infrastructure, security, fees, accessibility, and other points. Sentiment labels were applied on each of the identified aspects to depict the expressive opinion polarity: either negative (0), neutral (1), or positive (2). Such multi-aspect annotation protocol allows a review to include sentiments about several aspects simultaneously. The annotation process was repeated in order to ensure uniformity and accuracy. An elaborate annotation policy was developed with examples to support annotators to recognize features and assign valid sentiment labels. To first validate the aspect categories and refine the aspect categories, a subset of data were first manually inspected and annotated. In order to maintain the quality of annotation, the following protocol was followed:

(1) Original Annotation: An annotation of a chosen part of the dataset was done manually by annotators who were experts in the field of natural language processing and sentiment analysis.
(2) Review and Refinement: There was a manual inspection of the annotated dataset assuring the presence of all aspect categories and sentiment labels being strictly applied in accordance with the developed guidelines.
(3) Prevention of conflicts: When uncertainties occurred in the annotation or disagreements emerged during the annotation process, then the disputed annotations would be reconsidered and improved after the group discussing process in order to guarantee standardization.

The resulting annotated corpus was then transformed into an aspect sentiment structured dataset (aspect sentiment rows.csv), with each data entry corresponding to a review, the aspect associated with that review and the sentiment label assigned to that aspect.

3.2 Dataset Statistics

Table 1: Description of Dataset

Dataset Property	Value
Total reviews	1000
Extracted aspects	3115
Avg aspects per review	3.11
Sentiment classes	Positive / Neutral / Negative
Language	Marathi
Domain	Banking

Table 2: Present Sentiments counts in dataset

sentiment_label	negative	neutral	positive	Total
इंटरनेट	1	4	2	7
एटीएम	6	290	15	311
कर्ज	0	1	0	1
कर्मचारी	1	48	10	59
खाते	1	21	9	31
खात्या	1	1	0	2
खात्यात	0	2	0	2
डेबिट कार्ड	2	160	24	186
पगार खाते	9	413	75	497
व्यवहार	5	303	45	353
शुल्क	14	429	20	463
सुविधा	1	9	1	11
सेवा	12	300	109	421

3.3 Data Pre-processing Steps

3.3.1 **Removal of Missing Reviews:** The first stage of pre-processing was systematic searching and deleting of the reviews with missing or empty textual fields. [20]Textless reviews will not be able to provide substantial information that can be used in sentiment analysis and aspect extraction. As such, no such records were retained to ensure that the remaining textual data only contained valid data and could be used to continue the processing process to maintain the quality and robustness of the dataset required to train and evaluate it. Ejection of Duplicate Reviews: Redundant records may be a result of the separate records of either a web-scraping process[21]. These duplications can create biasness and, thus, distort the performance of machine-learning models by disproportionately aligning certain perspectives. To avoid this phenomenon, repetitive reviews were identified and eliminated according to a similar textual content. This will help to control the fact that every review has a specific informational value in its analysis, which fosters fair and accurate experiment results.

3.3.2 Unicode Normalization: Taking into consideration the fact that the corpus is rendered in the Devanagari script, Unicode normalization was used to standardize character encoding [22]. Often the same grapheme can exist with different Unicode forms and this creates an inconsistency in text processing. The difference between these variants is brought into a homogenous encoding schema by use of normalization that ensures similarity of character representation. This operation optimizes the effectiveness of tokenization, lexical matching and consequential natural-language-processing operations[23].

3.3.3. Whitespace Normalization: The whitening of the space was performed in order to remove unnecessary spaces, tabs and newline characters among the review text. Irregular spacing easily manifests in run of erroneous formatting in unprocessed textual data when acquisition or scraping the data. These issues of erroneous whitespace may have a negative effect on tokenization and downstream analytics. Subsequently, multiple whitespaces were condensed to one whitespace and leading or trailing whitespaces

were ignored. This protocol cleans the dataset and removes all inappropriate data to be used in the subsequent processing and model construction[24].

3.3.4. Tokenization: is a vital part of natural language processing as it involves breaking down a sentence or review into smaller linguistic segments (also referred to as tokens) that normally represent words or otherwise semantically relevant units. [25]In the ongoing study, every review or the review of Marathi banking was divided into tokens in order to enable later textual analysis. The process converts raw textual data into a structured format that can be processed using machine learning and deep learning algorithms. Breaking down sentences into lexical items, the analytical model is more suited to depicting syntactic patterns, contextual relations and salient words related to banking services and customer experiences. This step presupposes an exceptional importance in the context of the aspect-based sentiment analysis, as the system will be able to identify particular lexical elements connected with specific aspects like quality of the service, charges, transactions or accounts[26].

3.3.5. Stop Word Removal: Following the tokenization process, stop-word removal was carried out to remove the words that appear frequently and which have little meaning when used in the context of sentiment analysis[27]. The common pronouns, conjunctive, auxiliary and functional stops, like aah (this), aaani (with), aahjeen (mine) and aahjeee, are typical examples of stop-words. Though these lexical words are ubiquity in any ordinary language, they, on average, add insignificant information to the recognition of sentiment polarity or aspect extraction. Noise in the dataset is minimized through the deletion of stop-words where it also assists in making the textual representation more efficient[28]. The dimensionality reduction during this procedural step also enables machine learning models to refine their focus on semantically meaningful terms that are associated with any banking services, transactional processes, and customer feedback, which can enhance the work of the entire sentiment analysis system.

Figure 2: Stopword word Counts

3.2 Aspect Term Extraction

Aspect Term Extraction (antespectre) is a major feature of aspect-based sentiment analysis, which focuses on the extraction of particular aspects or features that are expressed in customer reviews. In the current study, the aspect terms were identified in the reviews about the Marathi banking with the aim of determining the specific banking services or characteristics that were being discussed by the clientele. These points serve as the points of expressed opinion in the reviews that include: service (सेवा), charges (शुल्क), transactions (व्यवहार), account (खाते), debit card (डेबिट कार्ड), and ATM (एटीएम). The extraction was done through a lexicon based approach combined with linguistic pre-processing approaches. After the cleaning step of the dataset based on tokenization and stop-word elimination, relevant nouns, noun phrases, were identified as potential aspect terms. Since the aspects in consumer reviews may often be represented by the means of nouns that characterize products or services, candidate terms were chosen and then filtered with the help of a given lexicon of banking-oriented aspects. This vocabulary uses specialized vocabulary in the field of the banking services to ensure that only meaningful features are maintained. Once the aspect terms are identified, each of the reviews can have a single aspect or several aspects, thus allowing the dataset to encode more than one aspect-sentiment relationship in any given review. The aspects that were extracted were then used to create a structured data set, in which each row includes the review text, the specific aspect, and the sentiment label[29]. This systematic deployment allows creating and testing machine learning and deep learning models to do aspect-based sentiment classification of Marathi banking reviews. Following figure shows the frequency of aspect in dataset.

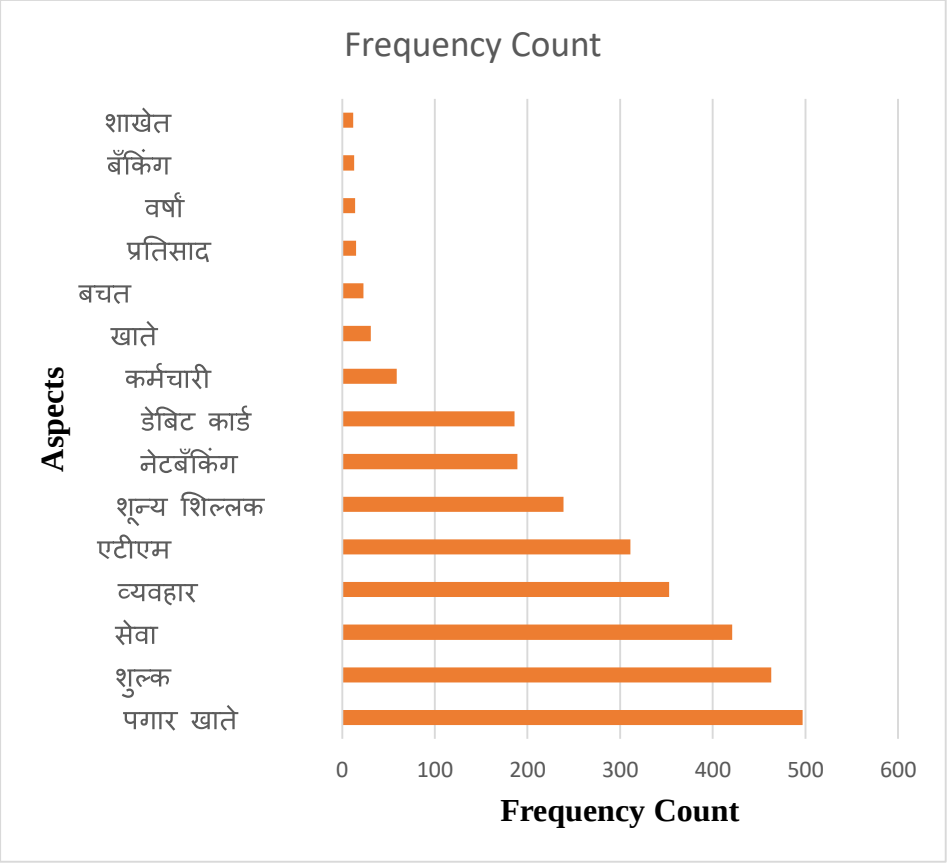

Figure 3: Frequency count of aspect in dataset

3.3 Experimental Setup

The experimental framework to be used is aimed at the comparison between transformer-based models that were set up and a set of baseline deep-learned and conventional machine-learned models in the area of aspect-based sentiment analysis on corpora of Marathi banking review. It included three pre-trained transformer-based architectures including those of IndicBERT, Multilingual BERT, and XLM-RoBERTa all designed to accept multilingual textual information and specifically exhibit certain effectiveness in low-resource languages like Marathi. The models have been fine-tuned on the annotated corpus to include contextual model of aspect-specific sentiment. A set of base models was also instantiated to help provide a comparative analysis. Traditional machine-learning models involved a Support Vector Machine (SVM) but modern deep-learning models include Bidirectional Long Short-Term Memory (BiLSTM) networks, though a variant that optional attacks an attention mechanism to focus representational interest on prominent lexical objects within the review to make sentiment predictions is also present. Model training followed a common set up to ensure that the architectures are compared on an equal basis. The AdamW scheme was used with 2 x 10- 5 as the learning rate in parameter optimisation. The batch size was set at fourteen (14) and training was done between three to five epochs based on convergence diagnostics. The maximum input sequence length was limited to one hundred and twenty objects of input (128) to support variably-length reviews and consequently to trade-off between the computational demands of computation and the conservation of the relevant context. The effectiveness of both models was checked using standard classification measurements, i.e., accuracy, precision, recall, and F1 -score, and hence, is able to provide a grounded evaluation of the models in predicting the level of sentiment polarity of aspects.

3.4 Aspect-Level Sentiment Classification

Aspect-level sentiment classification forms a crucial phase in aspect-based sentiment analytics framework, the aim of which is to determine the sentiment polarity associated with any single detected aspect in a review. Throughout the aspect-level sentiment classification, in contrast to the conventional sentiment analysis, which assigns one sentiment label to every review, the sentiment polarity of individual aspects that are mentioned and discussed in the text is delineated. In the current study, after the extraction of aspect terms in the Marathi banking reviews, the association of the aspect term with the review passage was done so as to know whether the sentiment about the aspect was positive, neutral or negative. To carry out aspect level sentiment classification, the dataset was converted into structured format in which each record included the review, the extracted aspect and the sentiment label. This form allows one review to add several aspect-sentiment pairs, and thus it allows affording a finer picture of customer perception regarding various banking services including service quality, charges, debit cards, transactions, and account-related facilities. The system of machine-learning and deep-learning models were applied in order to categorize aspect-based sentiment polarity. The comparative analysis of traditional baseline methods like Support Vector Machine with the deep-learning neural networks like Bidirectional Long Short -Term Memory and Attention based BiLSTM was conducted. Besides, the model of transformers, including IndicBERT, Multilingual BERT, and XLM-Roberta, were fine-tuned on the annotated corpus to obtain context-related semantic representations of Marathi textual specificity. The models were learning labeled aspect sentiment pairs and assessed using standard classification measures, which are accuracy, precision, recall, and F1score. This methodological practice will help to conduct a detailed review of the ability of

each model to recognize sentiment related to individual aspects of banking, and thus provide more information about customer experiences and satisfaction with the specific banking products.

1. Algorithm 1: Aspect-Based Sentiment Analysis for Marathi Banking Reviews

Input:

R = {r1, r2, ..., rn} // Set of Marathi banking reviews

H = { (ri, aj, yi) } // Human-annotated subset with aspect aj and sentiment yi

Output:

A = { (ri, aj, ŷi) } // Aspect-wise sentiment predictions

Begin

1. Initialize Marathi POS tagger using Stanza
2. Load pretrained Transformer sentiment model
3. // -------- Data Pre-processing --------
4. For each review ri in R do
5. Clean and normalize text of ri
6. End For
7. // -------- Aspect Extraction --------
8. For each review ri in R do
9. Apply POS tagging to ri
10. Extract all tokens tagged as NOUN
11. Remove duplicate nouns
12. Store extracted nouns as aspects Ai
13. End For
14. // -------- Aspect-wise Sentiment Prediction --------
15. For each review ri with aspect set Ai do
16. For each aspect aj in Ai do
17. Construct input text T = concatenate(aj, ri)
18. Predict sentiment label ŷi using Transformer model
19. Store (ri, aj, ŷi) in A
20. End For

21. End For

22. // -------- Evaluation Using Human Annotations --------

23. Initialize evaluation set E = ∅

24. For each human-annotated instance (ri, aj, yi) in H do

25. Find corresponding predicted label ŷi in A

26. Add (yi, ŷi) to evaluation set E

27. End For

28. // -------- Performance Measurement --------

29. Compute Precision, Recall, F1-score, and Macro-F1 on E

30. Return A

End

4. Results Analysis and Discussion

In this part, the results of the proposed model of sentiment analysis based on aspects are provided. Accuracy, precision, recall and F1-score are standard metrics used to evaluate the performance of the model. The findings are discussed to learn the efficiency of the model in categorizing feeling on the aspect level. The results of the experimental findings are discussed in detail to emphasize the main observations and findings.

Table 3: Result of ABSA

Class	Precision	Recall	F1-Score	Support
Negative (0)	0.7778	0.5833	0.6667	24
Neutral (1)	0.9653	0.9766	0.9709	512
Positive (2)	0.9080	0.9080	0.9080	87
Accuracy			**0.9518**	623
Macro Avg	0.8837	0.8226	0.8485	623
Weighted Avg	0.9500	0.9518	0.9504	623

Normal metrics of the model were used to measure the performance of the sentiment classification model including precision, recall, F1-score and accuracy. Table represented the results of the classification experiment. The generalizing model achieved an accuracy of 95.18 per cent on a test set of 623, so showing strong predictive ability regarding sentiment polarity. In terms of the neutral class (1), the model acquired the best performance with a precision of 0.9653, recall of 0.9766, and F1 -score of 0.9709 on 512 samples. The implication of these results is that the model is very effective at getting the neutral sentiments, which are the most prevalent class in the data, right. The high recall indicates that most cases of neutral were identified. Compared to the positive class (2), it was observed that the model achieved precision of 0.9080,

recall of 0.9080 and F1 -score of 0.9080 on 87 samples. These statistics demonstrate that the model is consistent and has good performance in identifying positive sentiments that are expressed in the reviews. In contrast, the negative group (0) had a relatively poor performance with a precision of 0.7778, importance of 0.5833 and F1 -score of 0.6667 on 24 samples. The decreased recall value denotes that some of the negative samples have been misidentified something that it would be possible to explain by the fact that there is a class imbalance in the data, as the number of negative sample is much lower than that of the neutral and positive classes. The macro-average F1-score of 0.8485 means the overall balanced performance of the model on all classes regardless of their frequencies. As a contrast, the weighted-average F1-score of 0.9504 portrays strong overall performance provided that the distribution of classes is considered. The difference in the macro and weighted averages highlights the skew in the sentiment classes, highlighting the nature of the neutral class as the dominant one in the data set. In general, the findings reveal that the given model is effective to represent sentimental patterns in Marathi bank reviews in case of both neutral and positive sentiments. Nevertheless, the negative-class performance might be improved with the help of such measures as data balancing or augmentation.

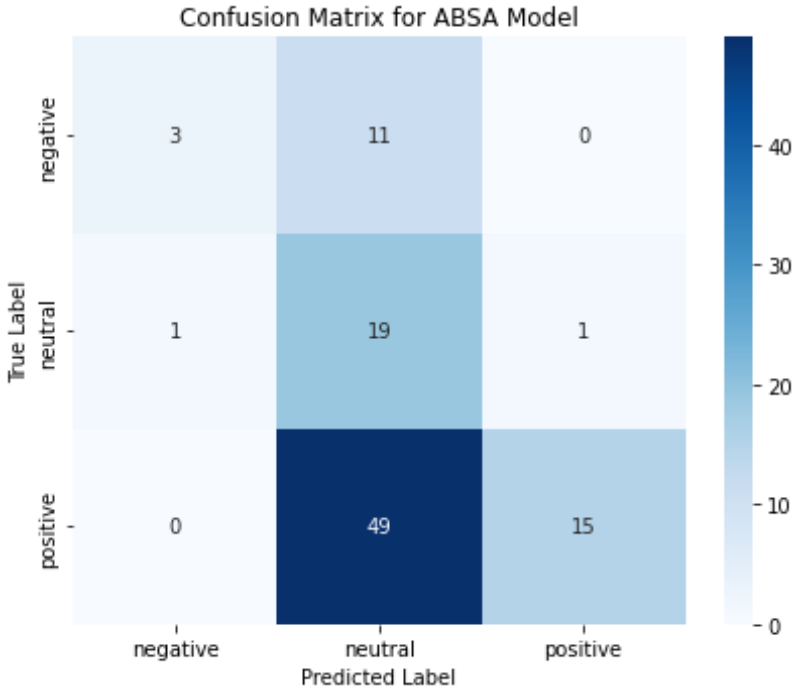

Figure 4: Confusion matrix of Sentiment Analysis

Figure X illustrates the confusion matrix of the sentiment analysis model in reference to three sentiment categories namely negative, neutral and positive. Correctly classified instances are represented by diagonal entries, and the misclassifications are represented by two off-diagonal entries. Within the negative group, the model rightly identified three cases; it also falsely identified eleven of the cases as being neutral. This trend shows that sometimes this model confuses negative feelings with neutral ones, which could be explained by the fact that sometimes negative expressions are not pointed but implicit in the reviews. In the neutral category, the model showed a better performance capturing nineteen of the correct classification and means two errors the model applied (instances moved to the negative category and instances moved to the positive category). This result indicates that this model is good at detecting

neutral expressions of sentiment. On the positive class eleven cases were correctly categorized, and forty-nine cases were misplaced under the neutral category. This result shows that large percentage of positive sentiments are viewed as neutral, which may be due to the fact that the positive expressions in some of the reviews are not emphasized strongly. By and large, the confusion matrix shows that the given model is the most effective in identifying the neutral sentiments, some positive and negative cases can be mistaken as the former. This trend is consistent with the distribution of the data in terms of the classes, the prevailing ones being the neutral sentiments. Methodological techniques that could be essential to improve minority sentiment class detection include data balancing and data augmentation, or class - weighted training.

5. Conclusion

The paper has suggested an aspect-based sentiment analysis model to Marathi banking reviews to elicit the fine-grained customer sentiments. Normalization, stop-word removal and tokenization were the methods that were used to pre-process the dataset to enhance the quality of the data. Relevant banking aspects were extracted in the reviews through a lexicon-based approach. The information was formatted into aspect sentiments pairs and thus several sentiments could be obtained in a review. Different models, such as machine learning, deep learning and transformer-based models were used to classify the sentiment. The experimental findings proved that transformer-based models performed better than baseline models. The model was good in detecting both the neutral and positive sentiments and the performance of the negative sentiment was relatively low. Sentiment distribution analysis helped to receive important insights on customer opinions of various banking services. The presented strategy is efficient in managing the text in the Marathi language and helps advance the study of the low-resource language processing. The way forward in work could be to enhance performance among minority classes and increase the data to generalize better.

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