A novel approach based on Encoder Decoder technique for detecting Implicit Aspects

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Abstract: Natural Language processing is a subset of Artificial Intelligence and one of the most important tasks in today's world. Different tasks such as prediction, sentiment detection, aspect detection, sarcasm detection, translation from one language to another, emotion detection, etc. fall under Natural Language processing. Customer sentiment gathered from online social media websites gives organizations valuable insights about their products and services. The objective behind gathering the sentiments is to understand the needs and the choices of the customers so as to improvise and enhance the products and services for the customer. In the domain of mobile reviews, customers express their opinions about multiple features of the product. Knowing the sentiment about different features of the product is necessary. Features can be categorized as implicit or explicit. The explicit aspects are clearly mentioned in the review whereas implicit aspects are not mentioned and are indirectly referred to in the review. In aspect detection, recognizing the implicit aspects is very important as the owner of the review might be describing different opinions on different aspects of mobiles. A lot of study has been done on extracting explicit aspects while there are quite a few gaps in research while extracting implicit aspects. In this study, we have used Co-occurrence matrix technique, rule based method and encoder decoder technique with supervised learning method to find the implicit aspects in mobile reviews. The novelty of this research is that in the domain of mobile reviews, encoder decoder technique has been used in conjunction with supervised learning as a backup. Our method can detect explicit as well as implicit aspects. The encoder decoder technique gives us a good performance with an accuracy score of 82% in comparison to the co-occurrence matrix technique and rule based method. Our work will help other researchers working in same domain.

Keywords: Implicit aspect Detection, Natural Language Processing, Neural networks, Unstructured Data

1. INTRODUCTION

In this day and age, social media has become a trend and all people want to be a part of it. Be it from making reels, recording and posting videos on Youtube, posting images on Pinterest and Instagram, etc. everyone wants to be trendy and earn fame and money. The trends are not only limited to teenagers and adults. Even senior citizens and minors want to be a part of the bandwagon. Websites and apps like Twitter/X have different hash tags and many trending topics. Each person based on his/her liking posts their own opinions and observe what is the majority saying. Likewise, mobile phone companies send their newly to be launched phone to trendy people and ask them to review and test it and post their opinions on Youtube, Twitter, Instagram, Facebook, etc. Some opinions are posted through videos, images, comparison charts, home page of the mobile phone, text reviews and so on. One problem of sentiment analysis is the presence of sarcasm in text. Researchers have used syntactic information, semantic information, lexical information, machine learning, deep learning, etc. to detect the presence of sarcasm in text.

In a recently launched mobile phone, the reviewers posted in detail about different aspects of the phone such as display, camera, speakers, selfie camera, ultra wide angle camera, battery life, charging time, etc. The people watching these videos or reading about it on social media websites get influenced. Also, many people are interested in specific features of the phone such as camera, dust resistance rating, under water rating, etc. and depending on the expert opinions of the reviewers on different aspects, the people decide to buy or not to buy the mobile phone. Each and every aspect of the phone is explained by these reviewers, which makes people realize and understand the significance of each and every aspect of the mobile phone.

Keeping these things in mind, we decided to focus on aspect detection for mobile phones. Also, people tend to write reviews in a way that the feature(s) is not directly mentioned in the review. Detecting these aspects for a normal person can be difficult as well as for a machine. For example, the mobile review is “My phone of XYZ company has an outstanding back camera but not so good selfie camera. It is smooth and doesn’t lag”. Here, the aspect “camera” is clearly mentioned in the review and hence, it is an explicit aspect. However, the mobile being smooth (aspect: touch) and lag (aspect: usability) are not directly mentioned in the review. Hence, touch and usability are implicit aspects. Our study is focused on finding implicit aspects in the mobile reviews.

The contributions of this paper are:

- We extracted mobile reviews from Twitter. Also, we have our own custom dataset which we got from posting a questionnaire.
- Preprocessing techniques such as tokenization, removal of stop words, lemmatization was done on the datasets.
- Word embedding was done to convert text to vectors.
- Unsupervised learning techniques of Co-occurrence matrix, rule based method and encoder-decoder are used to detect the implicit aspects.
- A novel approach has been adopted by using encoder-decoder technique in the domain of mobile reviews for implicit aspects having supervised learning as a backup.
- The model was judged on different performance metrics.

2. LITERATURE REVIEW

Li S. et al. [1] introduced the concept of tokens while generating aspects from reviews. They stressed on the importance of extracting the aspects with their categories and finding the sentiment of the reviews. The tokens were used to reduce the length of the reviews and to understand the semantics of the reviews. The datasets were of restaurants and laptops from Amazon portal.

Li H. et al. [2] worked on finding the opinions for each aspect mentioned in the reviews. They proposed a graph based approach to find the aspects. Dependency trees were used for finding the opinions. They strengthened the syntactic dependencies by gathering syntactic structure & knowledge. The reviews were on restaurants and laptops from SemEval datasets.

Sun X. et al. [3] proposed a novel dependency graph method to extract the aspects with their sentiments from SemEval datasets of laptop and restaurant reviews. They focused on finding the relationships between the words and gathering semantic information.

Ren S. et al. [4] focused on extracting the opinion triplets from reviews by using semantic and syntactic information. An encoder was used to extract the semantic and syntactic information. This was useful as it depicted the relationships between the opinions and the aspects.

Dhanith J. et al. [5] used BERT model for word embeddings. The input vector is joined with the aspect vector followed by a hidden vector which is used in conjunction with GRU to get optimal weights. It helps in extracting the syntactic and semantic features of the reviews. Five datasets were used for training and testing.

Gong H. et al. [6] proposed a capsule network for feature level sentiment analysis. BERT was used for vector generation and Bi-GRU for understanding the semantics of the text. CNN was used to extract important words from the text and discard all other words. Dataset was of Twitter and SemEval 2014.

Mhaske N. et al. [7] worked on making an annotated dataset for Marathi language reviews. They made summaries of the aspects. A lexicon based approach was adapted due to the large scale of reviews. The reviews were annotated using a rule based approach.

Zhao H. et al. [8] made graph attention networks for finding sentiment between an aspect and it’s entity. Semantic information was also extracted for determining the category of the feature. POS tagging was done to find the dependencies between the features and their categories. Clustering was done for categorizing the features in their respective categories.

Zhang M. et al. [9] implemented a model for opinion mining at aspect level to capture semantic information. They reasoned that sentences which do not have an aspect could be having a hidden aspect. However, since the review could be large and there could be many words between the opinion and the clue about the aspect. Therefore, they implemented a model which kept semantics knowledge which in turn benefitted in having long distance relationships between the aspects and their opinions.

Radi M. et al. [10] stressed on the importance of context of opinions when aspects are not directly mentioned in the review. The neural network framework used syntactic context information to find the dependency relations between the opinions and the aspects. The framework worked on two tasks separately. First task was the sentiment classification and the other was the determination of exact aspects for the opinion expressed.

Agathangelou P. et al. [11] proposed a neural network framework to detect implicit and explicit aspects. They made a pipeline of 4 blocks. The first two blocks were for the encoder, the third block for the decoder and the last one for prediction and Conditional Random Fields (CRF). The CRF method helped establish the linear relationships between the words found in a sequence.

Aziz K. et al. [12] used BERT for gathering context information and to find the relationships between words in a dataset. A graph based convolution network was proposed to use the linguistic features and the word pairs were also extracted.

Taheri A. et al. [13] proposed an augmentation method to increase the size of existing datasets of aspect extraction. They used a special character to generate augmented sentences. The advantage of the augmentation method was to conserve the context and the meaning of the opinions and the aspects in the reviews. Their model worked well on limited data also.

Busst M. et al. [14] proposed an ensemble Bi-LSTM technique to detect implicit and explicit aspects. They worked on SemEval datasets of laptops and restaurants and used BERT word embeddings.

Su H. et al. [15] used a prototype based approach and demonstration to find the sentiment of aspects in laptop and restaurant reviews. The semantics were extracted of the opinions to find the sentiment of the individual aspects. They used existing prototypes for the task.

Maroof A. et al. [16] worked on extracting implicit aspects from mobile reviews. Further, they categorized the aspects & assigned sentiment to them. They implemented a hybrid approach. Initially, a rule based method was used to gather the opinions w.r.t. aspect categories. Then, they used machine learning & deep learning for classification. The framework was specific to the domain of mobile reviews, services and worked on a aspect based annotated dataset. Their model could extract multiple implicit aspects (if any). BERT technique was used to perform aspect based sentiment analysis.

Nie Y. et al. [17] focused on gathering the quadruple of feature, opinion, sentiment and category. They made a pointer based non autoregressive framework with latent variable learning to extract the quadruple. A graph based structure was used in the final stage.

Murtadha A. et al. [18] used semantic information of the dataset to make an auxiliary sentence for extracting the implicit features. BERT model is used on the auxiliary sentence to understand the representation of features. They worked on finding implicit features on a dataset from Yahoo website of London homes.

Kabir M. et al. [19] extracted implicit and explicit features using frequency, syntax dependency & Conditional Random Fields method. Their focus was on gathering compound aspects along with the explicit and implicit aspects. They worked on the standard SemEval datasets of laptops and restaurants as well as an Amazon dataset.

Parkar A. [20] proposed a co-occurrence, clustering and classification based approach to detect implicit aspects in mobile reviews.

Zhang H. et al. [21] put focus on gathering the quadruple of sentiment, opinion, category and feature. They also put focus on the role of ChatGPT in opinion mining.

Altaf A. et al. [22] worked on ABSA for cricket reviews in Urdu language. They extracted the aspects and their sentiments and the categories of aspects. Classifiers were used to do these tasks. Additionally, implicit features were also extracted using their method.

Duan Z. et al. [23] introduced a thinking framework on opinion mining. They used common sense and thinking chain capabilities to detect the implicit sentiment analysis in laptop and restaurant reviews.

Youssef L. et al. [24] worked on aspects and their categories. They had a list of categories and the task was to identify and classify a review/sentence into a particular category. They used transformers in this task. The dataset was on hotels in Arabic language.

Dadap M. et al. [25] implemented Bi-LSTM model for gathering aspects & perform sentiment analysis. The Bi-LSTM model was used in conjunction with a rule based method on news articles with an F-score of 42%.

Li Y. et al. [26] found the relations between the aspects and the opinions using hierarchical masking & attention based layers so as to understand the semantics. They worked on a global level and reviews were of Korean language. The dataset was of reviews on laptops and restaurants.

Kit B. et al. [27] used machine learning models to find aspects and their sentiment. The dataset was of movies. Logistic regression & decision tree classifiers were used for prediction of features. Polarity detection was done using Logistic Regression & Multinomial Naïve Bayes classifiers. They concluded that decision tree is good for feature prediction & Logistic Regression is good for polarity detection.

Jiang X. et al. [28] pointed out the problems in prediction of aspects in relation to datasets, neural networks, etc. They proposed a scope detection model which determines if the contents of the review are related to the aspects. A biaffine based model was added to check the process of extracting the features. A simplified clause was made then to find the polarity of the features. They worked on English and Chinese datasets for this task.

Table number II, shows a detailed view of the literature review

3. DATASETS

We have extracted data from the Twitter website. We put the query of “mobile reviews” and extracted 13918 reviews from Twitter. The downloaded data from Twitter has different columns such as “Tweet id”, etc. Some reviews were available as links. So, we visited the link and copied the reviews to our dataset. In addition, we have also prepared a questionnaire and have got around 1000 reviews from the questionnaire responses. The questionnaire has columns such as “Brand of Mobile”, “Model Name”, columns on multiple features and lastly a column stating the final review of the mobile user about his mobile. Additionally, we have manually annotated 200 mobile reviews with their respective implicit aspects. The manual annotation was necessary so as to accommodate supervised learning (neural networks) as a backup for encoder decoder technique.

4. TECHNIQUES USED TO DETECT IMPLICIT ASPECTS

Initial research on detecting implicit aspects was using association rule mining, co-occurrence matrix, ontology, clustering, dependency parsing and so on. However, more recently researchers have adopted deep learning (DL) techniques such as encoder-decoder, etc. to detect implicit aspects.

We discuss a few of the techniques here:

A. Co-occurrence matrix

Co-occurrence matrix is a very popular tool in making relations in the form of a table. It can depict the similarities and differences between words in a dataset. In its prime form, the co-occurrence matrix will use frequency of the terms which are matching within a specified window size. In co-occurrence matrix, we include all the words in the dataset which leads many times to a sparse matrix. Using pre-processing techniques like removing stop words, we can reduce the density of the matrix which leads to better accurate results as well as faster processing and execution.

To construct a co-occurrence matrix, we import python libraries such as nltk (preprocessing of text) and pandas (DataFrame). Pre-processing techniques like tokenization, removal of stop words, converting text to lowercase, etc. are applied. A window size is chosen for the matrix which depends on the dataset and the application. Word pairs are then generated for words which appear consecutively in the text. Unique words could be kept (if necessary). The matrix is initialized and it is filled with values. Once done, a DataFrame is created for better understanding.

The co-occurrence matrix helps in understanding the semantics of the words involved in the dataset. Additionally, a dimensionality reduction technique can be used to reduce the dimension of the matrix which in turn leads to the matrix being denser and less sparse. The co-occurrence matrix in turn can be used as an input to many machine learning classifiers. It can be used in the tasks of topic modeling, sentiment analysis, emotion detection, aspect extraction, etc.

The co-occurrence matrix sometimes suffers from sparse data and scalability. Also, the window size should be chosen carefully depending on the size of the dataset.

In our study, we have imported the pandas and nltk library. “re” library is used for text preprocessing. Lemmatization was done on the dataset. N-grams technique is used to extract nearby words. Word2Vec model is used to convert text to word embeddings. Dataset was split in the ratio of 80:20. For each review, we have extracted the nouns and adjectives and appended them to the co-occurrence matrix.

B. Rule Based method

Association rule mining is finding patterns and relationships between words in a dataset. In data mining as well as Natural language processing, rules are used to carry out tasks such as recommendation systems, market basket analysis, etc. We have the option to make our own customized rules.

For the rule based method, we imported numpy and pandas library. Combinations of features & opinions were created from the dataset. We have extracted the aspects and their opinions. Nouns and the opinions are stored in lists of python and then depending on the outcomes (implicit aspects) of the model, we have filtered out everything except for the aspects to detect the correct implicit aspect(s).

C. Encoder-Decoder

The encoder-decoder model is a well-known technique to detect words in a sequence. An important part of the encoder decoder model is that the lengths of the inputs and outputs can be different. At the encoder stage, the input is fed word by word to the encoder. In the encoder, every unit takes a word at a time of the input given, stores information about it and passes it forward. With reference to Fig. 1, the input sequence is passed as x_1, x_2, x_3,…x_n. Each of this input sequence goes through multiple recurrent units in the encoder where each unit has a hidden state to store relevant information about the input words.

The hidden state h_j for each word is calculated as shown in “1”:

$$h_j = f(w^h * h_{j-1} + w^{hx} * x_j) \qquad (1)$$

In the above formula, the weights are applied to the prior situation h_j_{-1} and the input x_j to find the hidden state h_j.

The last vector keeps all context information from all the input given to the encoder. It in turn will be the first hidden state for the decoder of the model.

The decoder contains a stack of several recurrent units where each produces an output y_j for each step. Each unit of the decoder works similar to the encoder unit. The outcome is computed by using softmax activation function by multiplying the weights with the value of the hidden state.

D. Supervised Learning

In supervised learning, the outcome of the review/sentence is known beforehand. The common way to do supervised learning is by using machine language classifiers and deep learning classifiers. Commonly used machine language classifiers are LR, NB, DT, etc. In deep learning, we use techniques like RNN, CNN, LSTM, Bi-LSTM, neural networks, BERT, etc. In the recent trends, deep learning is widely used as neurons are used to calculate the outcome of the review/sentence. Deep learning classifiers take additional time than machine learning classifiers. The neurons pass information along with the corresponding weights in forward and backward passes to improve and understand the context for getting the outcome of the review/sentence correct.

For this study, we have imported nltk package, pandas package and gensim package. Preprocessing steps such as stripping unnecessary characters, converting text to lowercase, removal of stop words, etc. was done. Word2Vec model was used for converting text to vectors. Spacy library was used for English language. We have used a neural network for finding implicit features. We have used sequential dense layer model with relu activation function, sigmoid function and softmax activation function to classify and predict the implicit aspects. Entropy function for finding the loss value & Adam optimizer to optimize it. We made a batch size of 50 with 1000 epochs.

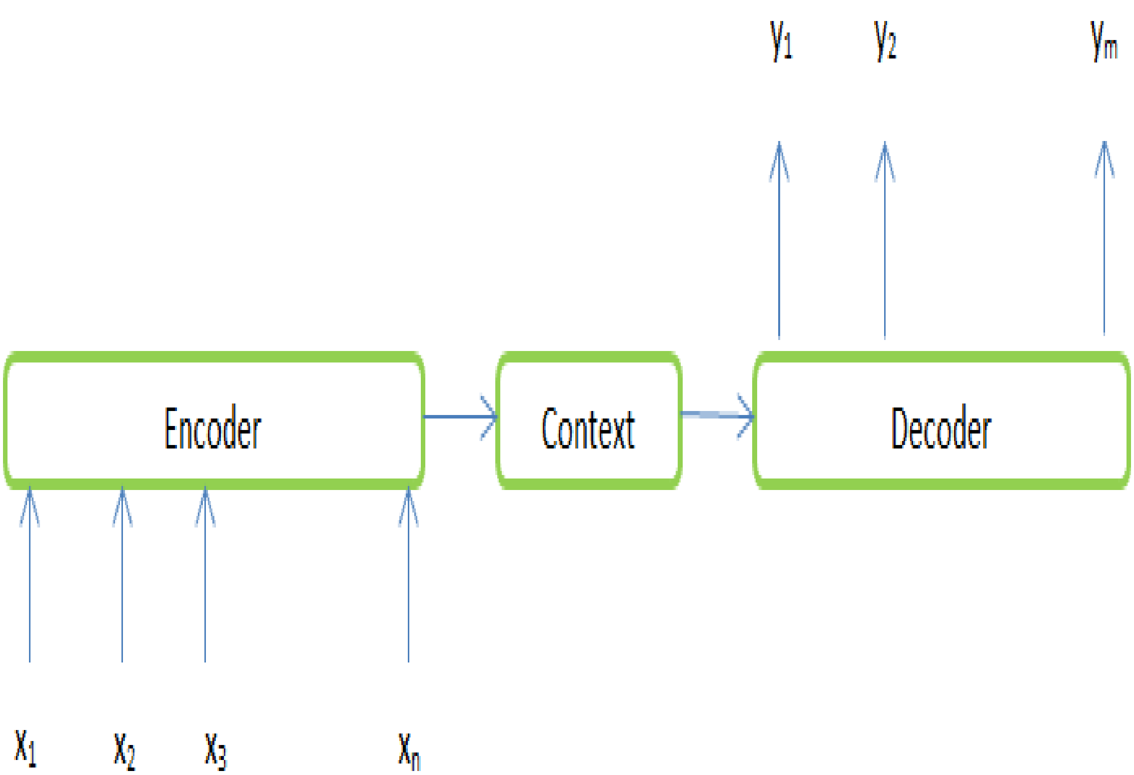

Figure 1. Encoder-Decoder Architecture

5. METHODOLOGY

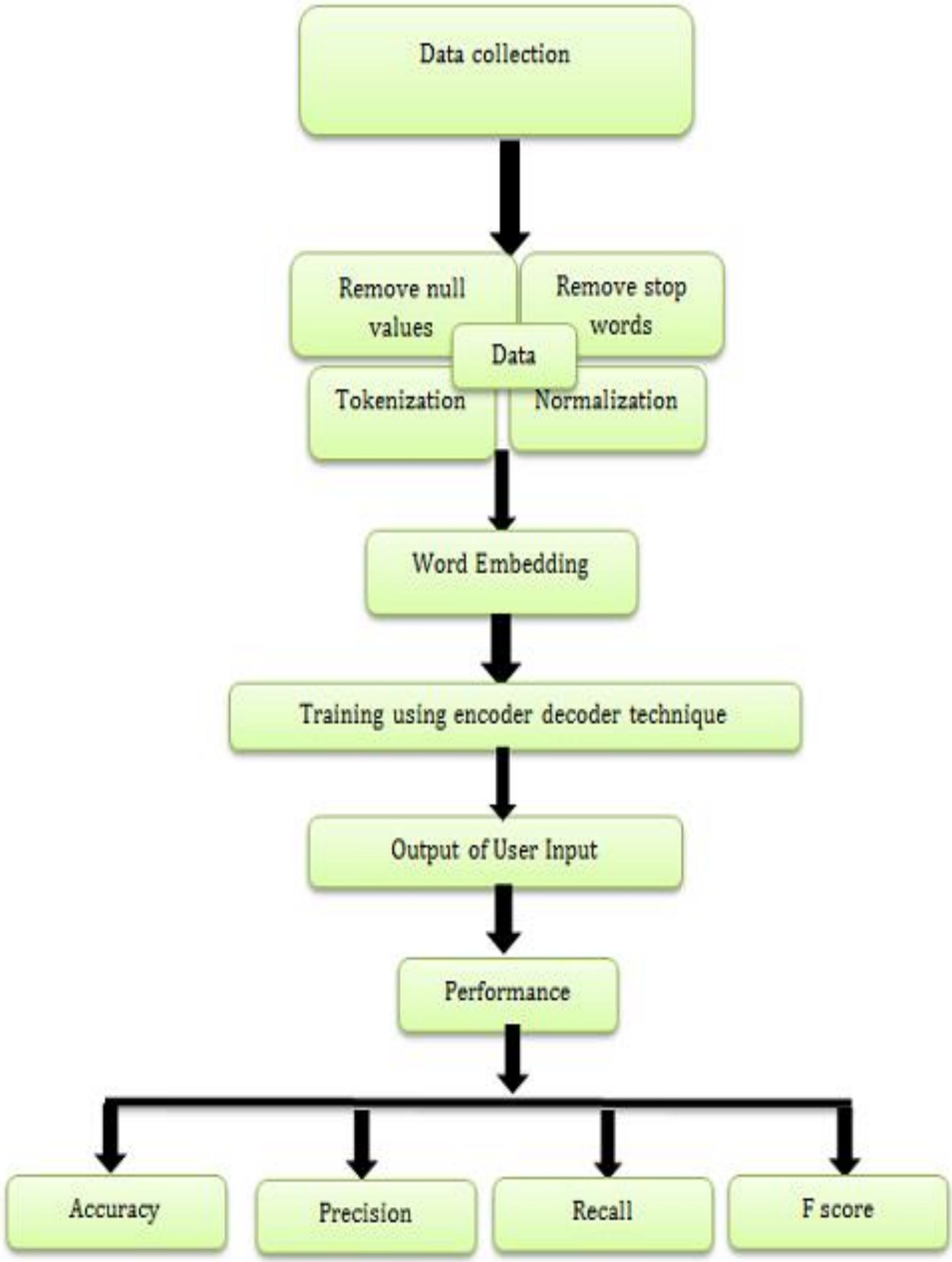

Figure 2. Methodology used for this study

The methodology used for this study is shown in Fig. 2. Pre-processing techniques such as tokenization, removing unwanted symbols, removing of null values, conversion of words to lowercase, normalization, etc. was done initially on the dataset. Parts of Speech tagging was done to extract the relevant nouns and adjectives from the reviews. We used word2vec model to convert text to vectors.

Keras library was used for the implementation of encoder-decoder technique. Long Short Term Memory technique is used to learn long term dependencies in the dataset. Sigmoid function for activation & soft max activation function to convert the vectors in a probability distribution and we have normalized the data. Entropy function for finding the loss value & Adam optimizer to optimize it.

We used techniques such as co-occurrence matrix, encoder-decoder and rules on the unstructured data to understand the patterns and relationships. The existing dataset was used to train the model and then any random input was fed to the model. The performance was noted down in the form of evaluation metrics. We have used supervised learning as an alternative to the proposed model i.e. just in case, the proposed model does not give the output, then supervised learning will predict the output.

6. RESULTS

Enlisted below are some examples of sentences which are given as inputs to the model and the corresponding outputs for the same.

- **Input:** The phone is light but huge.
  Output: size, weight
  Here, the important words to consider are light and huge. The aspects are missing. The model gives the output as size for the opinion “huge” and weight for the opinion “light”.

- **Input:** i am bored with the silver look.
  Output: screen
  Here, the important word to consider is the silver look. The aspect is missing. The model gives the output as screen for the opinion “look”.

- **Input:** phone drains quickly.
  Output: battery
  Here, the important words to consider are the phone’s battery draining quickly. The aspect is missing. The model gives the output as battery for the opinion “drains”.

- **Input:** you have to buy better one.
  Output: phone
  Here, the user has put his/her opinion about buying a better phone. The aspect is missing. The model gives the output as phone for the opinion “better one”.

- **Input**: The clarity of the pictures taken is fabulous on this phone.
  Output: camera
  Here, the user has put his/her opinion about the clarity of the pictures taken on the phone. The aspect is missing. The model gives the output as camera for the opinion “clarity “and “pictures”.

- **Input**: My iPhone supports 256 GB.
  Output: memory
  Here, the user has put his/her opinion about the total memory in the phone. The aspect is missing. The model gives the output as memory for the opinion “256 GB”.

- **Input**: The Google pixel is outstanding in functionality but very expensive.
  Output: price
  Here, the user has put his/her opinion about the phone been expensive. The aspect is missing. The model gives the output as price for the opinion “expensive”.

7. OVERVIEW OF EVALUATION METRICS

The model is judged on different performance measures. The ones used in our study are:

A. *Accuracy (A)*

The proportion of rightly classified instances to the entire instances evaluated, giving an overall performance measure. However, it may not be reliable for imbalanced datasets where one class predominates.

B. *Precision (P)*

The proportion of rightly classified positive instances out of all the positives is defined as precision. It highlights the model's reliability in positive predictions, especially critical when the loss of false positives is high.

C. *Recall (R)*

The ratio of rightly classified positive cases to the entire cases is defined as recall. Reflecting to ensure all correctly classified cases are taken into consideration.

D. *F-score (F)*

This performance metric will work the best on unbalanced datasets with precision and recall considered for calculation.

TABLE I. COMPARISON OF TECHNIQUES USED

Dataset	Methodology	Accuracy	Precision	Recall	F score
Twitter + Questionnaire	Co-occurrence matrix	64	13	11	13
	Rule method	66	79	79	87
	Encoder Decoder	82	76	93	83

All values in the table are in percentages

TABLE II. SUMMARIZED LITERATURE REVIEW

References	Objective	File source	Proportion	Language	Evaluation metrics
[1]	To extract quadruple of aspect, category, opinion & sentiment	Amazon	Laptop & Restaurant reviews	E	SG-ACOS method P: 60.3 R: 62.1 F: 61.2
[2]	To extract opinions of aspects	O	Laptop & Restaurant reviews	E	ASC-GCN method A: 91.1 F: 75.1
[3]	To extract sentiment triplet	O	Laptop & Restaurant reviews	E	ACK-EDG method P: 70.7 R: 63 F: 66.6
[4]	To extract sentiment triplet	O	Laptop & Restaurant reviews	E	S2ESTE method P: 77.2 R: 73.8 F: 75.5
[5]	To identify multiple aspects in reviews	O	Twitter, SemEval, laptop	E	SSA-GRU-AE method A: 89.7 F: 71.4
[6]	To identify aspects in reviews	Twitter SemEval	Laptop & Restaurant reviews	E	AGCDFF method A: 86.1 F:79.3
[7]	To annotate reviews for aspect identification	O	Movie reviews	Marathi	Lexicon + Rule based method F: 76
[8]	To find aspects with their categories	O	Laptop & Restaurant reviews	E	Graph Attention Networks A: 91.5 F: 76.1
[9]	To find missing aspects in reviews	O	Laptop & Restaurant reviews	E	KS-AISA method A: 89.9 F: 94.3
[10]	To find aspects using context information	O	Laptop & Restaurant reviews	E	ATCAD F: 76
[11]	To find implicit and explicit aspects	O	Laptop & Restaurant reviews	E	Wo-SE method A: 98
[12]	To find aspects in reviews	O	Laptop & Restaurant reviews	E	ASTE method F: 73.8
[13]	To improve performance of aspect extraction	O	Laptop & Restaurant reviews	E	Back Translation method A: 83 F: 75
[14]	To extract aspects	O	Laptop & Restaurant reviews	E	Ensemble Bi-LSTM method A: 94.5 F: 89.4
[15]	To extract sentiment of aspects	O	Laptop & Restaurant reviews	E	PD-ABSA A: 87.3 F: 81.3
[16]	To extract implicit aspects	Self-annotated dataset	Mobile reviews	E	Rule based approach A: 80 F: 78
[17]	Quadruple extraction	SemEval	Laptop & Restaurant reviews	E	PBNA framework P: 60.4 R: 51.1 F: 55.2
[18]	To gather implicit aspects	Yahoo	Locations	E	BERT-ASC A: 85 F: 94
[19]	To extract implicit and explicit aspects	SemEval Amazon	Laptop & Restaurant reviews Camera reviews	E	HFSC method P: 91 R: 89.5 F: 91.2
[20]	To gather implicit aspects	Online dataset	Mobile reviews	E	CCC method
[22]	To extract aspects in Urdu language	Customized dataset	Sports reviews	Urdu	ML & DL classifiers A: 71 F: 80
[23]	To find implicit sentiment analysis	SemEval	Laptop & Restaurant reviews	E	ERNIE Bot 4 + SAoT model F: 76.5
[24]	To categorize reviews	Online dataset	Hotels	Arabic	AraBERT model F: 71

[25]	To perform aspect based sentiment analysis	Online dataset	News articles	E	Bi-LSTM + rule based method F: 42
[26]	To find polarity of aspects in reviews	Online datasets	Laptops, Restaurants, Twitter	Korean	DMAA method A: 76 F: 70
[27]	To find aspects and sentiment	IMDB website	Movies	English	Decision Tree & Logistic Regression A: 98
[28]	To check if review contains aspect terms	SemEval	Laptops, Restaurants	E	Scope detection model F: 90.8
		Taobao.com	Furniture, Kitchen, Chandlery	Chinese	

The evaluation metric data is out of 100 & "E" stands for English & "O" for online datasets

8. Comparative Analysis

In Table number I, we have compared the three techniques that we have used for detecting implicit aspects. The co-occurrence matrix technique gives an accuracy score of 64% and the rule based technique gives an accuracy of 66%. The encoder-decoder model has an accuracy of 82% & f-score of 83%. From Table number I, we can conclude that encoder decoder technique gives the best performance.

9. Conclusion

Detection of implicit aspects in text is a challenge and it is difficult to spot. In this study, we have used unsupervised techniques to detect implicit aspects in mobile reviews dataset. Based on data scrapped from Twitter and our questionnaire, we train the unsupervised techniques to spot implicit aspects in our dataset. The initial steps of removal of null values, tokenization, normalization, etc. are done on the dataset. Word embedding techniques have been used to convert text to vectors.

Encoder decoder technique gives the best evaluation measure with an accuracy score of 82% and f-score of 83% on our dataset.

For future work, we would go ahead for a better evolutionary method than our existing techniques.

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