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Improving Sentiment Analysis using Negation Scope Detection and Negation Handling

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Abstract: Negation is one of the challenges in sentiment analysis. Negation has an immense influence on how accurately text data can be classified. To find accurate sentiments of users this research identifies that the impact of negations in a sentence needs to be properly handled. Traditional approaches are unable to properly determine the scope of negations. In the proposed approach Machine learning (ML) is used to find the scope of negations. Moreover, the removal of negative stopwords during pre-processing leads to the flipped polarity of sentences. To resolve these challenges this research proposes a method for negation scope detection and handling in sentiment analysis. First, negation cue (negative words) and non_cue words are determined, these negation cue and non_cue words in addition to lexical and syntactic features determine the negation scope (part of sentence affected by cue) using the Machine Learning (ML) approach i.e. Conditional Random Fields (CRF). Subsequently, in negation handling the sentiment intensity of each token in a sentence is established, and affected tokens are processed to determine the final polarity. It is revealed that sentiment analysis with negation handling and calculated polarity gives 3.61%, 2.64%, 2.7%, and 1.42% increase in accuracy for Logistic regression, Support Vector Machine, Decision Tree (DT), and Naive Bayes (NB) consecutively for Amazon food products dataset. Consecutively, 9.4%, 3%, and 2% improvement for Logistic Regression (LR), Support Vector Machine (SVM), and Naive Bayes for electronic dataset.

Keywords: : Conditional Random Field, Decision Tree, Logistic Regression, Machine Learning, Naive Bayes, Support Vector Machine.

1. Introduction

The proposed work demonstrates negation scope detection with various syntactic and lexical features trained using CRF then this scope is used for negation handling. Further, sentiment classification of reviews is done using a customized stopwords list and calculated polarity of reviews after negation handling by considering the impact of negations on each word in a sentence. Finally, sentiment analysis is performed on these sentences. In the proposed work a customized stopwords list is being used that only removes limited words from sentences. But, this list will not remove negations like can't, wouldn't, etc. that affect the polarity of sentences. This method deals with explicit negations where negative words are present in the data and the results depict that the accuracy of sentiment analysis is enhanced with the use of negation handling.

Sentiment analysis is a key sub-domain of natural language processing, which is an integral part of ML technology. This technology space is catalyzed by how well human language is understood, making it necessary for global firms to stay competitive. Businesses analyze the emotions and attitudes of customers towards a product by performing sentiment analysis of reviews and feedback provided by customers over numerous e-commerce and social media platforms. In such analysis, some challenges make it arduous to gauge the real emotions of consumers, and negation is identified as one such key challenge. Negations refer to negative words in a sentence that can affect the orientation of sentiments. It is one of the linguistic phenomena that leads to flipping the polarity of reviews or feedback and results in wrong predictions of sentiments. For instance, *"I hate this product less than I used to"*, here, *"less than I used to"* act as a sentiment shifter. Some other examples are *"fairly good, but not of my style"*, *"I don't dislike this movie"*, where *"not"* and *"don't"* are the negations and if removed will lead to sentiment orientation change [1]. Literature review revealed that during the classification of sentiments, usually the stopwords (no, I, we, you, they, the, not, is, am, are, cannot, etc.) are removed in the preprocessing phase given by [2], [3], [4], [5], [6], [7], [8], and [9] because it helps to bring down the dimensions of text for classification. Some of the negative stopwords are responsible for accurate sentiment predictions, however, if eliminated may lead to polarity flipping. For instance, *"He is not a bad boy"*, here *"not"* is one of the stopwords and its removal may flip the

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polarity of the sentence. Negations may be implicit and explicit given by [10] and this research deals with explicit negations. Explicit negations are those negations in which negation cue is present (no, not, nothing, don't etc.) in the sentence. The adverse impact of negations on the sentiment orientation of text has been spotted by [1], [11]. Many approaches such as rule-based [11], [12], regular expression based [13], lexicon-based [14], semantic, syntactic, and linguistic features-based given by [15]. Rule-based and lexicon approaches have limited scope and are unable to handle complex linguistic structures due to domain dependency. It also requires human intervention for creation and maintenance. However, ML approaches are better and minimize the manual work given by [16], [16] for negation scope detection. UCM-I [17] and UCM-II [13] are two rule-based approaches used for negation cue and scope detection. These two approaches properly finding negation cues and scopes but UCM-II [12] was not able to properly manage the sentences having two or more scopes corresponding to cues in a sentence. Moreover, UCM-I [17] also works well but it fails to determine the proper scope of negations when subject and object of some events are negated. In the Proposed approach these shortcomings are handled using ML approach to find the scope of negations. According to the literature, it is revealed that there are very few approaches that perform negation handling and sentiment analysis [16], [18] after negation scope detection and handling. Numerous approaches perform only negation cue and scope detection. In this research, not only negation cues and scope are detected but we also handle the impact of negation and find the correct polarity of the sentence then sentiment analysis is done using Amazon datasets. In the proposed approach, negation scope detection is performed using CRF and sentiment analysis using supervised ML [19] classifiers such as SVM, LR, DT, and NB. As per our literature knowledge, few ML approaches [1], [15], [16], [18], [20] and [21] utilize negation scope detection, and handling in sentiment analysis. Among these approaches, only [21], [1], and [21] are compared with the proposed approach for sentiment analysis after negation handling. In the proposed approach LR exhibits 85%, 86%, and SVM exhibits 85%, 83% accuracy for product and electronics datasets. This accuracy is improved as compared to [21], [1], and [20] but the performance of NB declined to 71%, 70% as compared to [1]. For scope detection, the proposed approach gives a 98% f-score which is better than [22], [23], [17] and [12].

This article is divided into six sections where sections 1 and 2 lead with an introduction and related work. Sections 3 to 6 explain the proposed methodology, results, and the final comparison to existing approaches, and conclusion.

2. Related Work

The rule-based approach is a static and manual technique to resolve the negation challenge. It involves the manual creation of regular expressions to handle negations but due to the dynamic nature of negation, these static rules are unable to determine all the contextual relations among all the words. NegEX is one such negation handling approach used in the medical domain and due to its static nature, it may cause wrong predictions of patient data given by [24]. One of the limitations of this work is the wrong interpretation of word's sentiment if same word appears more than once in a sentence. For instance, *"the patient was placed under neutropenic precaution, and two days later the patient was no longer neutropenic"*. In this sentence first *"neutropenic"* was interpreted by the model as positive and second as negative. To minimize this error rate, a DEEPEN algorithm was proposed that can consider dependency relations among all the words. It uses the Stanford dependency parser (SDP) and helps to reduce incorrect predictions with an accuracy of 91% and 97% given by [13]. One of the major limitations of this work is some of the dependency relations generated by SDP are not accurate for clinical data because the SDP was created using English web Treebank. This tree bank contains only the sentences of newsgroups, weblogs etc. Lexicon-based approach makes use of pre-annotated lexicons which consist of words and their sentiment intensity. SentiWordNet (SWN) is one such lexicon that provides various English words and their polarity given by [18], and an antonym dictionary given by [25] for assigning antonyms. A lexicon-based sentiment analyzer with negation handling for the Urdu language also improves the efficiency of sentiment analysis due to the use of a vast lexicon for the Urdu language, effective negation handling, intensifiers, and context-dependent words for the Urdu language given by [14]. However, this approach has some limitations such as it assigns neutral sentiment to a sentence in the absence of any positive or negative word, for instance *"Is there any solution to this problem?"*. Although, the polarity of this sentence is positive. Lexical approaches were unable to determine the dependency of words, so the semantic disambiguation technique given by [18] was proposed to find the sentiments of sentences. Here, correct negation words were determined by including grammatical relations among words. Rule-based and lexical approaches require manual work for creation and maintenance. For automation and better results ML approaches are used by [16]. Once these models are trained with the required data, they can make predictions according to learned patterns. In [16] it was revealed that due to the presence of multiword cues the classifier performs wrong classifications. In [26] Explicit negations were handled using ML approaches and it was revealed that the performance was improved with negation handling. While performing negation handling it is essential to maintain the semantics of words in a sentence. So, a feature-based negation handling model was introduced that can extract semantic and syntactic features such as lexicon features, POS, n-gram, and morphological features. The inclusion of these features with negation handling enhanced the accuracy of SVM, NB, and DT for sentiment analysis of tweets given by [15]. In [20] a mathematical modelling approach was introduced for negation handling in sentiment analysis, but this approach has several limitations such as it interprets wrong polarity of sentences when there are multiple positive and negative parts in a sentence. However, proposed approach handle this by finding the proper scope of negative words in a sentence using CRF. In proposed approach negation scope detection, handling is done and finally the sentences generated after negation handling are used for sentiment analysis.

3. Proposed Methodology for Negation Scope Detection and Handling in Sentiment Analysis

This section presents the research methodology used for negation cue, scope detection, negation handling, and sentiment analysis of user review as shown in Figure 1. Here, processed Conan Doyle dataset is trained using various lexical and syntactic features for BIO (begin, inside, outside) labels prediction. After performance evaluation, this trained CRF is used for scope prediction in Amazon dataset. Finally sentiment analysis is done before and after negation handling.

A. Data collection

In this research, Conan Doyle's (Sherlock) story dataset annotated with negation cue and scope is used to train and test CRF for negation scope prediction using BIO (beginning, inside, outside) labels. This dataset is collected from GitHub, and another two datasets used in this research are related to consumer reviews (electronics and food products) collected from amazon.com and kaggle.com. These datasets consists of various attributes such as UserId, profile name, helpfulness numerator, helpfulness denominator, score, time, summary and text. Among all these attribute score and text attributes are used in the proposed method. These datasets consist of various anomalies removed by applying data cleaning.

B. Data cleaning and transformation

In data cleaning, all the numbers, special characters, HTML tags, and hyperlinks are removed from the dataset. Data cleaning ensures there should not be any unwanted characters present in the data, increasing the dimensions of the data given by [27]. Further, each sentence is split into different rows to work with each word in that sentence. Subsequently, these datasets are used for negation scope prediction, negation handling, and sentiment analysis of reviews with and without negation handling.

C. Negation Cue and scope detection

Negation cue prediction is considered a classification problem and 0, 1 (cue, non_cue) is assigned to all the tokens in the dataset. 1 is assigned to tokens annotated with B_cue and 0 is assigned to other tokens. Also, an additional lexicon of cues is provided for better prediction of cues. Negation cues may impact the polarity of words in a sentence, and negation scope helps to determine those affected words. To determine the correct scope of cues various syntactic and lexical features of cues, tokens, and neighboring tokens are required. These features help to predict the scope in the form of BIO labels in a sentence. In this work ML approach is used to find the scope of negation which perform well as compared to static approaches.

1) Features for Scope Detection

It is an important phase for a machine [2] learning model to be more specific and efficient about predictions. The feature of raw data helps the model to learn and predict the patterns of data. In this research, various token-level features have been extracted and transformed into vector form for the predictions of the negation scope. Various token level features of targeted word, preceding and subsequent word of the targeted word such as parts of speech (POS) tag, lemma of cue and token are extracted.

$$(lemma_{i+1}, POS_{i+1}, lemma_{i-1}, POS_{i-1}, lemma_i, POS_i)$$

Along with the features of cue and token, the neighboring features of cue and token are also used for negation scope prediction. All these features are vectorized and provided to the classifier for scope prediction in data. In addition to these features, a lexicon of explicit cues is also provided. All features used for scope prediction are mentioned in Table 1. The final list of lexical and syntactic features used to detect the scope is determined by performing various experiments. In these experiments, we used different lexical and syntactic features, and it was revealed that both lexical and syntactic features are important for scope prediction. This list of features improves the prediction of BIO labels rather than using other combinations of lexical and syntactic features. Natural Language ToolKit (NLTK) provides WordNetLemmatizer() to find the root word and the POS tagger provides noun, verb, adjective, adverb, etc. tags to the words in a sentence. These tags help to determine the syntactic structure and text information of a sentence. To find the relationship among all the neighboring words the features of neighboring words such as chain of POS, lemma, cue and focused word, etc. are also provided to CRF for BIO labels prediction. Figure 2 shows the dependency graph for the sentence *"not good i would never buy it again"*. This figure represents the dependencies using edges and nodes which shows the semantic relationship among these edges and nodes. To find the path between *"not"* and *"buy"*, it is required to traverse the path between these two nodes. The critical path between *"not"* and *"buy"* is neg ↑ccomp, number of traversed nodes is 2. Similarly, the path between the node *"again"* and *"good"* is ↓advmod ↑ccomp.
Table 1 shows various lexical feature such as POS tag and lemma of cue and focused word. Along with the features of cue and focused words chain of features is also provided for neighboring words. Similarly, syntactic features such as dependency information for cue and neighboring words are also provided in the form of features as shown in Figure 2.

2) Training and Testing of CRF for Scope Prediction using BIO Labels

The whole dataset is split into train (80%), and test (20%) data for training and testing of CRF. In ML, the CRF is mainly used for sequence labeling tasks by considering the label of dependent tokens. CRF is a class of probabilistic graphical models that learn various features and patterns of input text during training. Based on the learned patterns it

TABLE I. FEATURES USED FOR NEGATION SCOPE PREDICTION

Feature	Description
Token	Focused word
BOS	Beginning of sentence
EOS	End of sentence
Cue	Negative word
Lemma_cue	The root form of the cue
POS_cue	Parts of speech of the cue
Chain_lemma	Lemma of neighboring words
Chain_POS	Parts of speech of neighboring words
Dependency information	Traversed syntactic dependency direction and relation of the edge
Critical path	Shortest dependency path from cue to the focused token
Nodes	Count of nodes to be traversed in the critical path

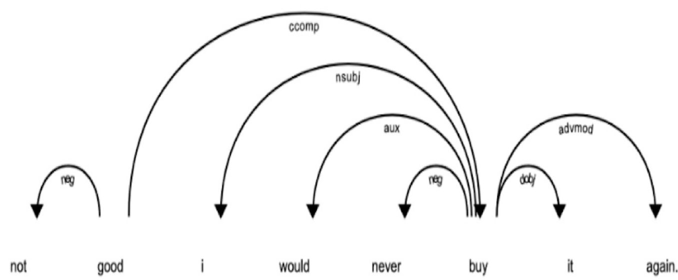

Figure 1. Dependency graph of a sentence.

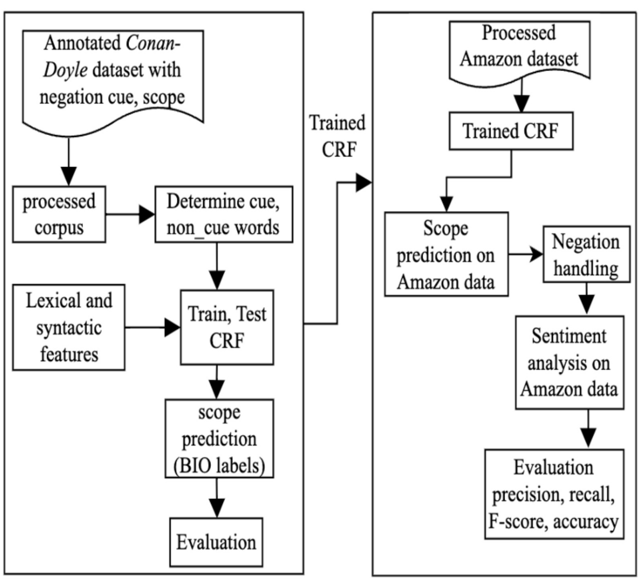

Figure 2. Proposed methodology for negation detection and handling in sentiment analysis.

predicts the labels of each token [28] shown in Equation 1. The conditional probability of labels Y for a given input sequence W can be represented as

$$P(Y\ |W) = \frac{1}{Z(W)} \prod_{i=1}^{m} exp\Big(\sum_{j=1}^{n} \lambda_j.f_j(y_i, y_{i-1}, w, i)\Big) \quad (1)$$

Where:

$P(Y|W)$ denotes the conditional probability of label sequence Y given input sequence or token W.
$Z(W)$ denotes the partition function which, for a given input sequence, normalizes the probability to sum up to 1 over all possible label sequences.
λ_j are the weights/parameters associated with each feature.
$f_j(y_i, y_{i-1}, w, i)$ represents a feature function that finds the relationship between negation cues and label sequence at position i.
y_i, y_{i-1} represent the BIO labels that can be B (begin), I (inside), or O (outside) or negation_cue for token w at position i.

This function checks the presence of negation at position i and the model learns the weights λ_j of features during training and based on the learned relationships model predicts the labels of tokens in the prediction step. CRF works with two types of features i.e. document specific features and word embedding features. In Equation 1 CRF is trained with both features. In Figure 1 CRF is trained and tested on Conan Doyle dataset for BIO labels prediction. Then the trained CRF model is stored in a Python pickle file, this trained model is used to make predictions of BIO labels on Amazon dataset as shown in Figure 1 and the predicted BIO labels are shown in Table II. Consequently, negation handling, polarity prediction of reviews, and sentiment analysis is done on Amazon datasets using predicted polarity (1, 0, -1). Table II shows the sentence number, token number corresponding token and predicted BIO of each token in a sentence.

D. Negation Handling

Scope of negation cues are predicted in the form of BIO labels then determine the sentiment strength of each token in a sentence using SWN. Next, flip the polarity of each word inside the BIO scope i.e. affected by the negation cue, and make the value of cue=0. The polarity of each sentence is calculated by the sum of all the polarities of tokens in a sentence. Here, a threshold of 0.7 is used if the calculated polarity is less than 0.7 then it is given a polarity score of -1 for greater than it is 1 and equal to 0.7 it is considered as 0. This final predicted polarity is considered for the final sentiment analysis of reviews.

TABLE II. Displays the predicted BIO Labels on the Amazon Dataset

Sent_no	Token_no	Token	BIO_Label
74	2	is	I_scope
74	3	okay	I_scope
74	4	i	I_scope
74	5	would	I_scope
74	6	not	B_cue
74	7	go	B_scope
75	1	no	B_cue
75	2	tea	B_scope
75	3	flavor	I_scope
75	4	at	I_scope
75	5	all	I_scope

TABLE III. Displays the Accuracy and F-Score of CRF for Negation Scope Prediction

CRF	Accuracy	F-Score
Train Data	99.7%	99.7%
Test Data	98.4%	98.3%

TABLE IV. Results of sentiment analysis for Product dataset before Negation Handling

Amazon (Food Products Dataset)				
Before negation handling				
ML Model	F-Score	Recall	Precision	Accuracy
LR	81.9 %	82.9 %	81.1 %	83.0 %
SVM	81.5 %	82.4 %	80.7 %	83.2 %
DT	73.2 %	73.3 %	73.4 %	73.0 %
NB	68.7 %	67.7 %	69.8 %	70.0 %

TABLE V. Results of sentiment analysis for Product dataset after Negation Handling

Amazon (Food Products Dataset)				
After negation handling				
ML Model	F-Score	Recall	Precision	Accuracy
LR	86.2%	86.3%	86.1%	86.0%
SVM	85.5%	85.6%	85.4%	85.4%
DT	75.4%	75.4%	75.5%	75.4%
NB	69.2%	68.7%	69.9%	71%

TABLE VI. Results of sentiment analysis for Electronics dataset before Negation Handling

Amazon (Electronic Dataset)				
Before negation handling				
ML Model	F-Score	Recall	Precision	Accuracy
LR	82.4%	82%	83%	84.4%
SVM	74.5%	74.5%	74.6%	81%
DT	67.3%	67.3%	67.3%	67.4%
NB	68.5%	68.6%	68.5%	68.6%

TABLE VII. Results of sentiment analysis for Electronics dataset after Negation Handling

Amazon (Electronic Dataset)				
After negation handling				
ML Model	F-Score	Recall	Precision	Accuracy
LR	85.1%	85.5%	85.2%	85.2%
SVM	75.49%	75%	76%	83.4%
DT	67.4%	67.5%	67.4%	67.4%
NB	69.2%	68.7%	69.8%	70%

E. Sentiment Analysis

Sentiment analysis of Amazon datasets is performed using the predicted polarity. This calculated polarity is used in the next phase of sentiment analysis. The classification of sentences is executed using supervised ML algorithms due to their enhanced performance in classification given by [19]. SVM, LR, DT, and NB classifiers are used before and after the negation handling of reviews. Before negation handling, the sentiment analysis is done using original polarity, and post negation handling the sentiment analysis is performed using the predicted polarity by the proposed system. The results indicate an improvement in the classification performance after negation handling and all the used classifiers are given below.

1) Logistic Regression (LR)

For multiclass classification LR uses Equation 2 as shown below to predict the output.

TABLE VIII. DISPLAY THE COMPARISON OF VARIOUS APPROACHES FOR NEGATION SCOPE PREDICTION USING CONANDOYLE DATASET (SHERLOCK)

Paper	Approach	F-score
[12]	Rule based	76.03%
[13]	Rule based	62.65%
[18]	ML (Deep parsing system)	88.2%
[23]	ML(SVM)	76.23%
Proposed approach	ML(CRF)	98.3%

TABLE IX. COMPARISON OF VARIOUS APPROACHES FOR SENTIMENT ANALYSIS AFTER NEGATION HANDLING.

Paper	Dataset	Approach	Accuracy	Precision	Recall	F-score
[1] Xia et al.	Electronics	LR	83.4%	_	_	_
		SVM	83%	_	_	_
		NB	82.5%	_	_	_
[29]Li et al˙	Electronics	SVM(stacking)	83%	_	_	_
[20] Punetha et al˙	Products	NEGVOT	83%	84%	81%	80%
Proposed approach	Product	LR	86%	86.1%	86.3%	86.1%
		SVM	85.4%	85.4%	85.6%	85.5%
		NB	71.1%	69.9%	68.7%	69.2%
Proposed approach	Electronics	LR	85.2%	85.2%	85%	85.1%
		SVM	83.4%	76%	75%	76%
		NB	70%	69.8%	68.7%	69.2%

$$\text{P(Y=1}|X) = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_n x_n)}} \quad (2)$$

Where :

$P(Y = 1 \mid X)$ represents the probability of the class label 1 for given input feature X.

e represents the base of natural logarithm.

$\beta_0, \beta_1, \beta_2, \ldots, \beta_n$ represents the coefficients (weights) corresponding to each feature $x_1, x_2, \ldots, x_n$.

x_0, set to 1, corresponding to the intercept term.

2) Support Vector Machine (SVM)

SVM is a supervised ML model that is used to resolve regression and classification challenges. It is used to resolve linear and non-linear problems by generating hyperplanes to separate different data points into different categories. SVM performs classification using Equation 3 given below.

$$\text{f(x)} = \text{sign}\left(\sum_{j=1}^{n} \alpha_j y_j \langle x, x_j \rangle + b\right) \quad (3)$$

where :

$f(x)$ represents a decision function that determines the class labels for input x. x_0 is set to 1, corresponding to the intercept term.

α_j represents the Lagrange multiplier that is determined during training.

y_j denotes class labels.

x_j denotes class labels.

$\langle x, x_j \rangle$ represents the dot product between the support vector x_j and the input vector x.

b represents the bias.

3) Decision Tree (DT)

It is a supervised ML model that can be used for both regression and classification problems. It is in tree form and consists of three parts i.e. branch, internal node and leaf node. Branch represents decision, internal node represents feature and leaf represents label. This algorithm selects the best features based on entropy and gini impurity etc. and continue until some criteria are met. Then it makes predictions by traversing the tree from root to leaf node [27].

4) Naive Bayes (NB)

It is a probabilistic classification model that can be used for both binary and multi-class classification problems by considering the probability of each element [27]. It is an easy-to-implement and fast algorithm that converges faster than LR and requires less training data. NB predicts the output according to Equation 4 given below.

NB selects the class that maximizes posterior probability $P(C \mid X)$ for classification.

$$\text{P(C}|X) \propto P(C).\prod_{i=1}^{n} p\left(x_i|C\right) \quad (4)$$

Where :

$P(C \mid X)$ represents the posterior probability of class C for feature X.

$P(C)$ represents the probability of element belong to class C.

n represents the number of features x_i is the i^{th}feature in the instance.

4. Experimental Setup and Results

In this research, all the implementation has been executed on Jupyter Notebook using Python 3.7 along with 16 GB RAM and i7 processor. In this research, three datasets are used as discussed in section 3.1. Among all these datasets Conan Doyle's (Sherlock) story dataset is used to train and test CRF with lexical and syntactic features described in section 3. Then this trained CRF is

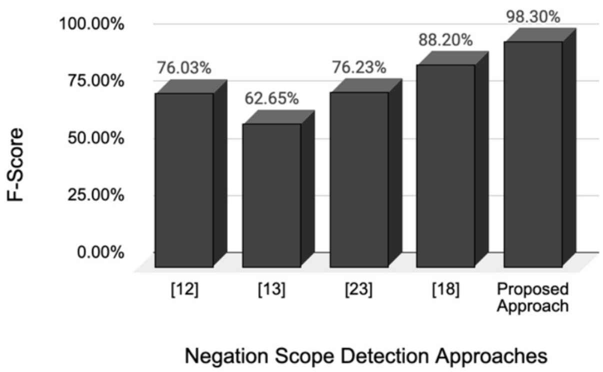

Figure 3. Comparison of various approaches and the proposed method for negation scope detection.

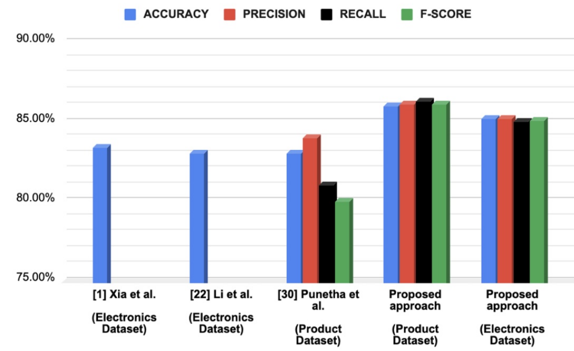

Figure 4. Performance comparison of various sentiment analysis approaches across electronic and product datasets.

used to predict the scope of negation on Amazon datasets. Further, negation handling is performed on Amazon datasets and sentiment analysis is done after and before negation handling using LR, SVM, DT, and NB with K=5 (K stands for K-fold cross-validation) as shown in Table IV, V, VI and VII and the detailed description of implementation is given in the various parts of section 3.

Table III shows the training and test results of the CRF for negation scope prediction. According to the results, the performance of CRF is pretty good for negation scope prediction in comparison to approaches given in Table VIII. From Tables IV and V, it is identified that LR and SVM, DT, and NB give better performance for all metrics after negation handling. Table IV and V shows that there is 3.61%, 2.64% 2.7% and 1.42% increase in accuracy for LR, SVM, DT and NB for food product dataset. Consecutively, 9.4%, 3%, and 2% improvement for LR, SVM, and NB for electronic dataset.

5. Discussion and Comparison

Table VIII shows the performance of the proposed approach is better as compared to other approaches for scope prediction. Table IX shows the comparison of the proposed approach with [1], [20] and [21] for sentiment analysis after negation handling. In all these approaches different datasets are used but comparison is performed only with products and electronics datasets because these are common datasets among proposed and compared approaches.

Table IX demonstrates that the accuracy of sentiment analysis after negation handling gives better performance as compared to other approaches. LR gives 86%, 85%for both datasets which is better than [1], [20], and [29]. SVM also gives an improved accuracy of 85% and 83.4%, but NB performs poorly compared to [1] for sentiment classification after negation handling. In case of f-score, the proposed approach performs poorly with 71% for product dataset but NEGVOT gives 80% score. Also, figure 4 shows that NEGVOT performs well in precision, recall and F-score for NB. NEVGOT also gives improved precision and recall score of 84% and 81% as compared to SVM on the electronics dataset. Figure 3 shows the performance comparison of the proposed approach and various approaches using F-score for negation scope prediction. From Figure 3 it is revealed that the proposed approach gives a 98.3% score which is 11.3% enhancement compared to [22].

From the literature, we found most of the approaches limit their work up to negation cue and scope detection and there are limited approaches that perform negation handling and sentiment analysis after finding negation cues and their scope. However, the proposed work also has a few limitations for instance, if the model is unable to find the negation properly then it can cause a wrong prediction of the scope and polarity of the sentence which can cause the wrong classification of sentences. To resolve these challenges we will try to enhance the performance of the proposed work using deep learning techniques in our future work.

6. Conclusion and Future Directions

Negation is responsible for affecting the orientation of sentiments. To resolve this challenge and to improve sentiment accuracy a negation scope detection, and handling approach is proposed. Various experiments were carried out on different datasets using the proposed approach and the results revealed that the majority of ML classifiers enhance the accuracy of sentiment analysis with negation handling. Hence, it can be inferred that the proposed approach when used with sentiment analysis proves to be more efficient. However, in this research, only explicit negations are handled. In future work, explicit negations may be analyzed using deep learning techniques. Moreover, in the future, the proposed method may also be applied to mixed language datasets.

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