Sentiment Classification on Telugu Twitter Data Set

K. David Raju[#1], Dr. Bipin Bihari Jayasingh[#2], Dr. Vijayapal Reddy[#3]

[#1]*Research Scholor, Rayalaseema University,KURNOOL, AP, kolluridavid@gmail.com*

[#2]*Professor, Dept of IT, CVR College of Engineering, Telangana, bipinjayasingh2017@gmail.com*

[#3]*Professor, Dept of CSE, Matrusri Engineering College, Telangana, drpvijayapalreddy@gmail.com*

***Abstract*— Social networking services such as Facebook and Twitter and social media hosting websites such as Flickr and YouTube have become increasingly popular in recent years. One key factor to their attractiveness worldwide is that these sites and services allow people to express and share their opinions, likes, and dislikes, freely and openly. This development has fuelled a new field known as sentiment analysis and opinion mining with the goal of extracting people's sentiment from text to assist customers in their purchase decisions and vendors in enhancing their reputation. This emerging field has attracted a large research interest, but most of the existing work focuses on English text. Hence, in this thesis, we studied sentiment analysis of Telugu text retrieved from a well-known social media site, namely Twitter. Specifically, we studied the topic of target-dependent sentiment analysis of Telugu Twitter text, which has not been addressed in Telugu language before. We developed a system that will acquire Telugu text from Twitter and extract users opinions towards different topics and products.**

***Keywords*— Sentiment Classification, Twitter dataset, Telugu language, N-grams, F1 measure**

I. Introduction

Social networking has dramatically changed our lives and the way that we interact with the world [1]. Recent research shows that millions of people are using social network services such as Facebook and Twitter for various purposes, such as finding and sharing information, making friends and entertaining themselves [2]. Our decision-making process is very often influenced by other people's opinions. Most of us seek our friends', family members' or co-workers' recommendations before making important purchase decisions or before eating at a specific restaurant or watching a new movie. Sometimes we even base our decision solely on these opinions. This behaviour is greatly facilitated by the current expansion of social media websites such as Twitter, Facebook and YouTube, which make other people's opinions widely and easily available [3]. Facebook, blogs, Twitter and customer reviews are considered the most effective tactics for mobilizing consumers to talk up products online [5]. 97% who made a purchase based on an online review found the review to be accurate [6]. 93% of Yelp.com users say that visiting the website leads to a local purchase, and 80% of them visit Yelp before spending money [6]. In a study conducted by social networking site myYearbook, 81% of respondents said they had received advice from friends and followers relating to a product purchase through a social site. 74 % of those who received such advice found it to be influential in their decision. 76% of respondents on a consumer review survey said they would always compare prices online before buying a personal technology item. 70% would research different brands and models online, while 61% would read online reviews [6]. 73% of mothers trust online community recommendations, and 44% of them use social media for brand/product recommendations [4]. 67% of shoppers spend more time online after recommendations from online community of friends. 61% of people rely on user reviews for product information or research before a buying decision is made [7]. 53% of people on Twitter recommend companies and/or products in their tweets, with 48% of them delivering on their intention to buy the product. 34% have turned to social media to air their feelings about a company. 26% to express dissatisfaction, 23% to share companies or products they like [4]. With more than 82 million user-generated posts in 2008 [7], there is clearly no lack of online customers' reviews and opinions. The problem, however, is that the available information is confusing and/or overwhelming [1]. Moreover, this huge customers' interest in product reviews and online opinions is matched with an even bigger attention from the manufacturers and vendors of these products. In fact, many businesses now have a dedicated team of people to read and analyze what customers say about their products and services in social media sites or review sites. Not stopping there, they often go one step further and track what customers say about their rivals' products. One key issue is that the amount of social media data and reviews is too huge [8]. These issues and problems have been the driving force behind an emerging field known as opinion mining, the objective of which is to interpret human sentiment and emotions into hard data[9].

Currently, people are commonly found writing comments, reviews, blog posts in social media about trending activities in their regional languages. Unlike English, many regional languages lack resources to analyze these activities. Moreover, English has many datasets available, however, it is not the same with Telugu. Telugu is a Dravidian language, native to India. It ranks third by the number of native speakers in India and fifteenth in the Ethnologue list of the most spoken languages world- wide. Over the last decade, there has been an increment in movie review sites, newspaper websites, tweets, comments and other blogposts, etc., written in Telugu. Labeling these reviews with their sentiments would provide a brief summary to the readers. In this paper, we attempted to perform sentiment analysis in Telugu and classify a sentence with positive or negative polarity.

II. Literature Survey

Sentiment analysis involves many tasks. Four of the important tasks are: data preprocessing, class labeling, annotation granularity, and sentiment source and target identification. Data preprocessing task is vital especially for the text collected from social media websites because it is unstructured and full of spelling mistakes and peculiarities. Some of the preprocessing tasks include: spell checking [9], and stop words removal. In natural language processing, stop words are words that do not carry meaning and are thus removed prior to classification. There is no predefined list of stop words, but most researchers remove function words. Stemming is the process of reducing words to their original root such as for instance replacing the words “computer” and “computing” by their common root, “comput” [10]. In sentiment analysis, we first have the two-class classification problem, which categorizes text as subjective or objective. The polarity classification can be categorized either using binary classification as positive/negative [11], or using multi-class classification by predicting the degree of positivity or negativity of the text.

Sentiment polarity classification can be conducted at the document-, sentence or phrase levels. Document-level polarity categorization tries to classify sentiment overall in long text documents such as movie reviews, news articles, Web forum postings and blogs [10]. Sentence-level polarity categorization attempts to classify positive and negative sentiment for each individual sentence. There has also been work on phrase-level classification with the purpose of seizing multiple sentiments that may exist within a single sentence. Features extraction is one of the most important phases in sentiment analysis because the classification of tweets at the end depends on the features used. Syntactic features, such as N-gram, POS, and punctuation, are the most used features in sentiment analysis [12]. Semantic features are used to annotate data to express the presence or absence of semantic properties. There are many stylistic text features such as frequency of letters, number of characters per word, frequency of function words (e.g., “of”, “for”, “to”), inclusion of URL or re-tweet, frequency of digits and frequency of special characters. Research effort on sentiment analysis focused more on both syntactic and semantic features while stylistic features have received modest research interest. Three main approaches are used in sentiment classification studies: machine learning techniques, link analysis algorithm, and score-based methods. These techniques can work in conjunction with each other to improve sentiment classification, or they can be used independently. The input to these methods is a document, sentence, or phrase, and the output specifies whether the input text carries a positive, negative, or neutral sentiment. Classification algorithms use a feature vector to build a model of the input text from which to derive which sentiment class it belongs.

Telugu has neither a large annotated dataset and tools nor any pre-trained models. Telugu data requires indispensable preprocessing for information extraction and sentiment extraction. Sentiment analysis has attracted much research interest in the last decade, mostly in the English language. Researchers have analyzed sentiments in a variety of domains: movie reviews, news articles, blogs, forums, product reviews, and more recently social media data [12]. In the last few years, Telugu language sentiment analysis has started to attract some research interest as well [13].

III. Proposed System

The proposed system consists of six main stages.

1. Data Acquisition stage, tweets about five topics – namely “Jabardasth”, “Special status”, “Sunrisers”, “Modi”, and “Cinema” – were collected.
2. Tweet-Filtering stage aims at simplifying the annotation stage by removing duplicate tweets, re-tweets (i.e., the process of reposting someone else’s tweet to share it with friends), etc.
3. Annotation, where the tweets are annotated depending on the specified topic. For instance, the “Modi” tweets will be tagged with a word that describes the sentiment towards “Modi” expressed in those tweets. For example, “I love Modi” will be tagged with the word “positive” because it has positive emotion towards “Modi”.
4. Data Preprocessing where tags are added, words are normalized, spam tweets are removed, etc.
5. Feature identification, where stylistic, syntactic, and semantic features are extracted, and the features that yield better results are selected using features selection algorithms.

6. Classification, where the decision to annotate the tweet as negative, positive or neutral towards a specific topic is made using a trained machine-learning algorithm.

Generating a model for sentiment analysis is usually a lengthy pipelined process. It consists of the six phases presented in Figure 1. The first phase is typically Data Acquisition, followed by Tweet-Filtering phase, then Data Annotation phase, Data- Preprocessing phase, Feature Identification phase, and finally Classification Phase.

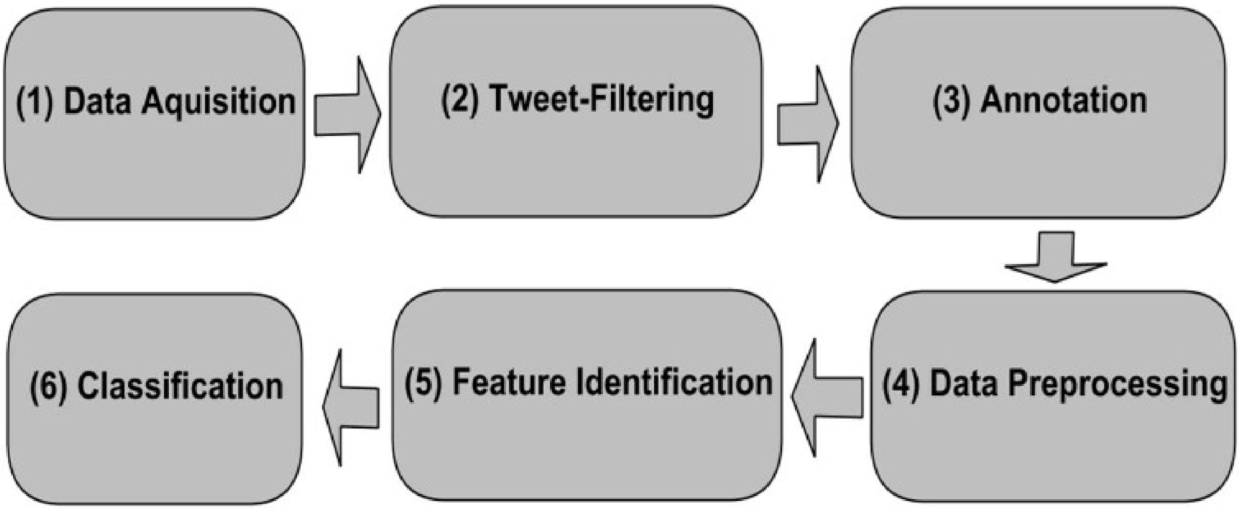

Figure 1: Model generation process

Figure 1 shows the steps of the process we followed to generate our system model. In the data acquisition phase, we acquired data from Twitter to train our system, namely 53496 of Telugu tweets regarding 4 different topics such as “Jabardasth”, “Special status”, “Sunrisers” and “Modi”. After collecting the data from Twitter, we found that the collected tweets have many problems that will affect the annotation process accuracy. For instance, we found many repeated tweets. Removing those tweets will improve the annotation process and thus the classification accuracy. After making sure we had unique tweets, we asked two native Telugu speakers to annotate the data i.e., to label each tweet as positive, negative, or neutral towards a specific target. we needed to preprocess the tweets before extracting features from them, including steps such as: normalization, spam detection, tagging, stemming, POS tagging. Feature Identification consists of two steps: features extraction and features selection. In the features extraction step, we identified different types of features: lexical, semantic and stylistic, and we examined their effectiveness on the classification accuracy. In the features selection step, we only retained the features that improved the classification accuracy significantly and we tested the significance statistically using paired sample t-test. In other words, this step is where training is performed and the model is built, consisting of the final feature set. In this phase, we examined a three- way classification which entails classifying tweet as positive, negative or neutral. Whereas the two-phase classification method meant classifying the text as subjective vs. objective, while in the second phase, we further classify the subjective text as either positive or negative. We found that the two-phase classification yield to better results and thus we used it in the deployed system.

IV. Feature Extraction

This section describes the three types of features such as syntactic features, semantic features, and stylistic features.

A. Syntactic Features

In our first experiment, we wanted to know which N-gram features give the best performance. Thus, we ran experiments using all N-grams for N<=4 and 6 combinations of them, as listed in Table 1. We did not preprocess the data before running this experiment because this was our first experiment and we wanted to establish what N-gram would render the best

Performance so that we can use it to run all the other experiments. We used NB classifier with a presence vector where the features are the words N-grams and evaluated its performance using 10-fold cross- validation. The results presented in Table 18 show that using a unigram only yields the best performance and therefore we carried out all the remaining experiments with unigrams. This result was expected because higher order N-grams leads to a very sparse feature space, which will not help the machine-learning algorithm in detecting pattern. The conclusion we reached is similar to Pang et al. who reported that unigram outperform bigrams.

N-grams Features	Modi		Sunrisers		Jio Phone		Special Status	
	Acc	*F1*	*Acc*	*F1*	*Acc*	*F1*	*Acc*	*F1*
Unigram	**64.24**	**58.86**	**85.18**	**80.80**	**60.21**	**49.15**	**59.94**	**57.14**
Bigram	56.46	41.10	82.19	74.15	58.50	43.63	47.86	32.66
3-gram	56.46	41.10	82.19	74.15	58.50	43.63	46.94	30.33
4-gram	56.46	41.10	82.19	74.15	58.50	43.63	46.94	30.33
Unigram + bigram	*60.10*	48.92	82.19	74.15	58.50	43.63	*55.05*	48.37
Bigram+3-gram	56.46	41.10	82.19	74.15	58.50	43.63	47.09	30.69
3-gram+4-gram	56.46	41.10	82.19	74.15	58.50	43.63	46.94	30.33
Unigram+bigram+3-gram	57.62	43.60	82.19	74.15	58.50	43.63	51.53	41.04
Bigram+3-gram+4-gram	56.46	41.10	82.19	74.15	58.50	43.63	46.94	30.33
Unigram+bigram+3-gram+ 4-gram	56.79	41.82	82.19	74.15	58.50	43.63	48.78	34.44

Table 1: Experiments using all N-grams for N<=4 and 6 combinations

We have extracted three features related to punctuation, namely the total number of punctuation marks as well as the numbers of question marks and exclamation marks in a tweet. Question marks and exclamation marks are counted in the number of punctuation marks. Some researchers reported that question mark ("?") and exclamation mark ("!") are the most associated punctuation marks with subjective text and emotions. Thus, we decided to give them two separate attributes to give them more weight in the classification process.

B. Semantic Features

We have extracted nine semantic features, which are presented in Table 2 with their definitions. To extract these attributes, we had first to build a lexicon manually. To do so, we collected 18989 Telugu tweet about different topics such as "Jio phone", "Nokia", "Samsung" "Toyota", "Nissan", "Camry", "Android", "Sansilk", etc. Then, we extracted unigrams from those tweets and asked a human annotator to label those unigrams as positive or negative. We specifically excluded from the annotation process words that can be positive or negative depending on the context they are used in. For example, the word "fast" can be positive in this tweet, "Jio phone updates install very fast", and it can be negative in this tweet "Jio phone battery runs out very fast".

Attribute Name	Definition
noPosWords	Number of positive words in the tweet. For example, "I love Arab Idol and adore the jury member" in this tweet there are 2 positive words namely "love", and "adore".
noNegWords	Number of negative words in the tweet. For example, "This restaurant food disgusts me I hate this restaurant" in this tweet we have two negative words namely "disgust", and "hate".
noPosEmo	Number of positive Emoticons. For example, "I'm soo happy :) ;)" has two positive emoticons.
noNegEmo	Number of Negative Emoticons. For example, "I'm soo sad : (;(" has two positive emoticons.
nolaugh	Number of laughters. For example, "hahaha did you see yesterday show @user it was funny loool" in this tweet we have 2 laughters namely "hahaha" and "loool".
shortPos	The shortest distance between a positive word and the target of the sentiment in characters (incl. spaces).
shortNeg	The shortest distance between a negative word and the target of the sentiment in characters (incl. spaces).
nearPos	1 if the distance between the nearest positive word and the target word is shorter than the distance between the nearest negative word and the target word, 0 otherwise.
nearNeg	1 if the distance between the nearest negative word and the target word is shorter than the distance between the nearest positive word and the target word, 0 otherwise.

Table 2: Nine semantic features

C. Stylistic Features

We wanted to see how classification accuracy would be affected if we only included words with a specific frequency. In other words, should we include any word that appears in the dataset as a feature or should we include only words that appear more often than a given threshold? We conducted this experiment with preprocessed tweets and unigrams, testing with both frequency and presence vectors, and using five different classifiers. We experimented with words frequency greater than 1, 2, and 3. The results are presented in Table 3, where the notation "1>" means word frequency greater than 1 and similarly for notations "2>" and "3>". Three of the four datasets reached their best accuracy using NB with presence feature-vector namely: "Modi", "Jio phone" and "Special Status". As to which frequency is the best we couldn't reach agreement. Two datasets ("Modi" and "Special Status") reached their best performance using word frequency 2 or more. Also, the average of the four datasets shows that words frequency 2 or more using NB with presence feature-vector yielded the best performance.

Table 3: Word frequency effect of accuracy and F1 score percentages

	Alg.	FV	Modi		Jio Phone		Sunrisers		Special Status		Average	
			Acc.	*F1*	*Acc*	*F1*	*Acc*	*F1*	*Acc*	*F1*	*Acc*	*F1*
>1	***NB***	***Pre.***	**68.05**	**65.35**	85.48	84.65	63.64	60.61	**62.54**	**62.35**	**69.92**	**68.24**
		Freq	60.43	60.49	84.43	84.80	54.55	54.25	59.48	59.53	64.72	64.77
	SVM	***Pre.***	59.11	58.40	85.33	84.87	60.86	60.28	61.93	61.78	66.8	66.33
		Freq	62.75	61.18	85.18	84.24	59.57	58.10	59.63	59.49	66.78	65.75
	PART	***Pre.***	55.46	54.81	85.03	84.51	58.07	57.46	53.52	52.86	63.02	62.41
		Freq	59.77	57.84	86.98	86.22	56.36	53.49	51.99	51.60	63.77	62.29
	AdaBoost	***Pre.***	58.11	49.41	86.08	83.90	58.18	49.16	46.79	43.47	62.29	56.49
		Freq	58.44	49.35	85.93	83.59	57.11	46.61	46.64	43.92	62.03	55.87
	J48 tree	***Pre.***	58.28	55.62	85.78	84.07	62.99	59.33	54.43	52.71	65.37	62.93
		Freq	61.26	58.11	86.53	85.45	59.68	55.51	53.67	53.51	65.28	63.14
>2	***NB***	***Pre.***	63.91	61.52	83.68	83.14	63.96	61.96	61.77	61.71	68.33	67.08
		Freq	60.26	60.55	84.28	84.71	54.01	53.68	59.17	59.23	64.43	64.54
	SVM	***Pre.***	61.26	60.35	85.63	84.97	60.75	59.83	60.24	60.12	66.97	66.32
		Freq	61.59	60.26	85.93	85.27	60.75	59.08	56.88	56.80	66.29	65.35
	PART	***Pre.***	55.46	55.08	80.99	81.13	57.54	58.10	50.15	50.08	61.04	61.10
		Freq	58.28	56.76	**87.57**	**86.74**	56.68	53.80	57.03	56.68	64.89	63.49
	AdaBoost	***Pre.***	58.28	49.53	86.08	83.90	58.18	49.16	46.79	43.47	62.33	56.52
		Freq	58.44	49.35	85.93	83.59	57.11	46.61	46.64	43.92	62.03	55.87
	J48 tree	***Pre.***	58.61	56.22	87.28	85.97	61.18	58.58	55.5	55.15	65.64	63.98
		Freq	60.76	57.40	86.53	85.45	59.68	55.44	52.45	52.20	64.85	62.62
>3	***NB***	***Pre.***	64.4	62.62	84.58	83.90	**64.06**	**62.30**	61.93	61.93	68.74	67.69
		Freq	59.6	59.92	83.68	84.25	54.01	53.68	58.72	58.79	64	64.16
	SVM	***Pre.***	60.1	58.90	85.03	84.68	59.04	57.66	58.41	58.27	65.64	64.88
		Freq	58.44	56.58	86.38	85.62	61.71	59.19	57.65	57.38	66.04	64.69
	PART	***Pre.***	53.15	53.14	81.44	81.56	52.09	52.87	55.5	55.55	60.54	60.78
		Freq	58.94	56.97	86.68	85.74	57.86	55.15	55.66	55.47	64.78	63.33
	AdaBoost	***Pre.***	58.28	49.53	86.08	83.90	58.18	49.16	46.79	43.47	62.33	56.52
		Freq	58.44	49.35	85.93	83.59	57.11	46.61	46.64	43.92	62.03	55.87
	J48 tree	***Pre.***	61.59	58.70	87.28	86.09	60.53	57.95	56.12	55.90	66.38	64.66
		Freq	60.76	57.36	86.53	85.51	59.36	54.79	52.91	52.63	64.89	62.57
	B. Acc.		56.13		82.19		58.07		46.64		60.76	

A paired-samples t-test was conducted to compare the best accuracy reached for each dataset after data cleaning and the best accuracy reached after accounting for word frequencies greater than 1 those numbers are presented in Table 4.

Table 4: Comparison between the best accuracy reached after data cleaning process and considering word frequencies greater than 1

The Dataset	Best accuracy reached after data cleaning process	Best accuracy reached after considering words frequencies greater than 1
Modi	65.89	68.05
Sunrisers	87.43	87.57
Jio Phone	61.93	64.06
Special Status	60.86	62.54
Average accuracy	69.03	70.56

There was a significant difference between the best accuracy reached after data cleaning (M=69.0275, SD=12.457) and the best accuracy reached after considering word frequencies greater than 1 (M=70.56, SD=11.57887); t (3) = -3.213, p = 0.049. These results suggest that including only words that appear 2 or more times in the dataset is useful and can improve accuracy significantly. We have also extracted another set of stylistic attributes, some of them related to Twitter such as Number of usernames in tweet, Number of times the tweet was re-tweeted and Number of hash-tags in the tweet. The other attributes that we extracted include Number of URL in the tweet, and Number of digits.

V. Classification Phase

In this phase, the classification accuracy based on blind-testing is presented. The accuracy is calculated for three-way classification, subjectivity classification and polarity classification. Specifically, those features include unigrams ith frequency two or more, thus, the unigrams that proved to be effective for the classification accuracy.

A. Three-way Classification Accuracy Using Blind Testing

In this experiment, the training dataset consisted of “Modi” dataset, “Jio phone” dataset, “Sunrisers” dataset, “Special Status” dataset and 436 tweets from “Jabardasth” dataset. It included 1736 neutral tweet, 613 positive tweets and 512 negative tweets whereas the testing dataset consisted of the 1409 tweets left from the “Jabardasth” dataset. It precisely included 951 neutral tweets, 114 positive tweets and 344 negative tweets. SVM classifier was used for the testing process. The accuracy obtained is 63.9461 % with Kappa statistic of 0.0739. The confusion matrix of the experiment is presented in Table 5.

Table 5: Confusion matrix of three-way classification blind testing

	Neutral	Positive	Negative
Neutral	851	52	48
Positive	96	15	3
Negative	286	23	35

B. Polarity Classification Accuracy Using Blind Testing

In this experiment, selected attributes revealed in section 6.3.6 were used. The training dataset used was presented in section 6.2.6 and it consisted of 613 positive tweets and 512 negative tweets whilst the testing dataset included 114 positive tweets and 345 negative tweets. SVM classifier was used for the testing process. The accuracy obtained is 58.8235% with Kappa statistic of 0.2069. The confusion matrix of the experiment is presented in Table 6.

Table 6: Confusion matrix of polarity classification blind testing

	Negative	**Positive**
Negative	184	161
Positive	28	86

VI. Conclusions

In this paper, we studied sentiment mining of Telugu Twitter data. We developed a system named Telugu Subjectivity and Sentiment Analysis, which collects tweets from Twitter about specific topics. The topics in our experiments were “Modi”, “Jio phone”, “Sunrisers”, “Special Status” and “Jabardasth”. We called these topics the target of the sentiment and annotated the tweets towards the chosen target as “positive”, “negative”, or “neutral”. We called this process target-dependent sentiment annotation. Our annotators were two native Telugu language speakers. After inner-annotator agreement, we were left with 4696 annotated tweets: 3287 tweets for training (70%) and 1409 for testing (30%). To develop our Telugu Subjectivity and Sentiment Analysis system, two stages were performed. In the first stage, we built a computational model that firstly identifies subjective text and then performs polarity classification. In the second stage, we employed the developed model to classify new tweet instances. The first stage consisted of six phases: Data Acquisition, followed by Tweet-Filtering phase, then Data Annotation phase, Data-Preprocessing phase, Feature Identification phase, and finally Classification Phase. The second stage consisted of four phases: Data Acquisition, Data-Preprocessing phase, Feature Identification phase, and finally Classification Phase.

We conducted several experiments to improve sentiment analysis accuracy. Initially, we tested the effect of data preprocessing on accuracy and we found significant improvement. Then, we examined the effect of several natural language processing tasks such as stemming and Part-of-Speech tagging but they did not prove useful. We extracted stylistic features, semantic features and syntactic features. Then, we tested the effect of the different features types on the sentiment accuracy. We can summarize our research contributions as follows:

1. We developed the first target dependent sentiment analysis system for Telugu language.
2. We experimented with different feature types, classification techniques, and classification algorithms to find which one suits best the given problem.
3. We identified several problems and issues regarding Telugu text (coming from Twitter) collection, annotation, and classification that have never been discussed in previous research.
4. We identified a set of rules that can be followed to facilitate sentiment classification.
5. We proved that manual inspection of Twitter text is necessary in order to identify issues and problems that would never have been identified otherwise.

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