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Stance Detection with Sentiment Analysis and Sarcasm Detection

Minor Project Report

Semester VI

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CERTIFICATE

This is to certify that the project report carried out on "**Stance Detection with Sentiment Analysis and Sarcasm Detection**" by the 3rd year students:

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Have successfully completed their project in partial fulfilment of their Degree in Bachelor of Technology in Computer Science and Engineering.

Dr. Saritha S. K.
(Minor Project Mentor)

DECLARATION

We, hereby declare that the following report which is being presented in the Minor Project Documentation Entitled as "**Stance Detection with Sentiment Analysis and Sarcasm Detection**" is an authentic documentation of our own original work and to best of our knowledge. The following project and its report, in part or whole, has not been presented or submitted by us for any purpose in any other institute or organization. Any contribution made to the research by others, with whom we have worked at Maulana Azad National Institute of Technology, Bhopal or elsewhere, is explicitly acknowledged in the report.

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ABSTRACT

Stance detection on social media is an emerging opinion mining paradigm for social and political applications. Social Media channels allow for people to express their views and opinions about any public topics. Public sentiment related to future events, such as demonstrations or parades, indicate public attitude and therefore may be applied while trying to estimate the level of disruption and disorder during such events.

We can often detect from a person's utterances whether he/she is in favor of or against a given target entity— their stance towards the target. However, a person may express the same stance towards a target by using negative or positive language.

We decided to factor the sentiment of tweet along with detecting the stance of a target-entity. Stance detection is related to, but different from, sentiment analysis. Sentiment analysis determines whether a piece of text is positive, negative, or neutral based on the text presented. Also, we have noted that sentiment analysis doesn't take into account sarcasm of the text so we have taken that as a factor also. In stance detection, systems are to determine favor-ability towards a given selected target of interest. The target of interest may not be explicitly mentioned in the text and it may not be the target of opinion in the text.

We propose a multilevel framework which takes into consideration the sentiment and the presence of sarcasm in the text and provides us with the overall stance towards the target.

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INTRODUCTION

1.1 Background

Stance detection is the task of automatically determining from text whether the author of the text is in favor of, against, or neutral towards a proposition or target. The target may be a person, an organization, a government policy, a movement, a product, etc.

One can infer from Barack Obama's speeches that he is in favor of stricter gun laws in the US. Similarly, people often express stance towards various target entities through posts on online forums, blogs, Twitter, YouTube, Instagram, etc. Automatically detecting stance has widespread applications in information retrieval, text summarization, and textual entailment. Over the last decade, there has been active research in modeling stance.

The task undertaken can be formulated as follows - given a target-entity, the framework must gather all tweets posted by users about it and provide a sentiment and its stance towards the target. The model will also provide an overall stance based on the tweets gathered.

For example - *Target: Donald Trump*

Tweet: Joe Biden is the only sane presidential candidate.

In the given tweet our target entity is not mentioned directly yet it is extracted for stance detection. To utilize social media data to its maximum extent we have to consider all factors to gain an opinion. Factors include considering tags relevant to target entity, sentiment analysis of tweet, and detection of sarcasm.

LITERATURE REVIEW AND SURVEY

Literature on stance detection includes [Somasundaran and Wiebe 2010] where a stance detection approach was presented, based on sentiment and arguing features, along with an arguing lexicon automatically compiled. This approach was reported to perform better than baseline systems which were distribution-based and unigram-based systems [Somasundaran and Wiebe 2010]. In studies such as [Walker et al. 2012a,b], it was concluded that considering the dialog structure of online debate posts improved stance classification performance on these posts.

In [Ebrahimi et al. 2016], a log-linear model for stance classification in tweets was proposed where the interactions between the stance target, stance, and sentiment were modeled. In [Gadek et al. 2017], the authors showed that extracting and using contextonyms ("contextually related words") helped improve stance detection in tweets. In [Sobhani et al. 2017], a data set for multi-target stance detection was presented together with experiments on this data set. Another recent topic closely related to stance detection is argumentation (or, argument) mining. The aim of the argumentation mining task is to identify the particular arguments, related components, and relations in natural language texts [Nguyen and Litman 2015]. These texts are usually in the form of on-line debates, legal documents, and student essays [Nguyen and Litman 2015]. There are also studies that performed joint argument mining and stance detection [Sobhani et al. 2015].

The paper, Multi-Task Stance Detection with Sentiment and Stance Lexicons,by Yingjie Li and Cornelia Caragea, on which we based most of our research on proposed an attention-based multitask learning framework and integrate lexicon information to achieve better performance. Their experimental results show that that model outperforms state-of-the-art deep learning methods for this task.

GAPS IDENTIFIED

In our literature review, it is identified that while stance detection is a highly researched topic, one of the major drawbacks is that while analyzing sentiment of a tweet, sarcasm present in the tweet is not given consideration. This can give misleading results, when a level of the framework is solely dependent on sentiment analysis.

Further, it is also observed that no feature is provided to present the overall stance of a target entity. With the high influx of tweet every seconds, it is hardly useful to know the stance of every tweet. Rather we are more inclined to be certain on the overall public stance. Adding on to that, the lack of datasets present on the topic of research also cause a stagnancy in the research and we cannot further our study without the provision of more datasets.

PROBLEM DEFINITION

Social media is a vital part of interaction with public. Twitter has now become an important medium to stay up to date with the worldly on-goings. From every politician, celebrity to smallest brands, have their presence on Twitter.

Twitter 2019 Usage Stats showed -

- **500 million tweets are sent per day.**
- **Twitter users spent an average of 3.39 minutes on the social networking platform per session.**
- 83% of 193 UN member countries have a Twitter presence.

On the basis of these stats, it is inferred that a fairly accurate public stance of trending topics be it political actions, debates, controversial topics from analysing social media posts on Twitter can be gathered. With access to social media data, it can interpret the sentiment towards the entity.

The created system analyses the posts that user post on the given web platform and analyse it according to the model previously trained and displays the stance of the post while mentioning its target and to show the extent of correctness of the same, sentiment and sarcasm detection of the same post have also been incorporated.

PROPOSED WORK AND METHODOLOGY

4.1 Proposed Work

To overcome the drawbacks of the methods that are reviewed above, a new model for stance detection is proposed. In this model, many techniques are combined to reach our final goal of emotion extraction. The steps for the process are documented below.

1. **Stance Detection Model:** A model for Stance Detection using attention-based framework and incorporating stance lexicon is proposed. The model will be using logistic regression and will calculate stance on the basis of the target in question.

2. **Sarcasm Detection Model:** When the stance of a particular statement is considered, none of the models incorporate the fact that whether the statement is sarcastic or not. Therefore, the use of a sarcasm detection model using the LSVC model is proposed.

3. **Sentiment Analysis Model:** In order to incorporate sentiment analysis in the calculation of stance for a tweet towards a particular target, the use of a sentiment analysis model is proposed using logistic regression in order to depict the sentiments with which the stance was made.

In addition to this,

Natural Language Processing (NLP) is also used to process textual data.

4.2 Methodology

We intend to use a ML-based approach for stance detection combined with sentiment and sarcasm detection for the project as it has been proven that stance detection for Twitter can be improved by combining the two approaches: during the first stage sarcasm and sentiment of text is detected, during the second stage a machine learning model to determine the stance is applied that uses the aforementioned models as reference.

1. Import certain libraries like pandas (for data analysis), numpy (for multi-dimensional arrays), nltk (natural language processing), pickle (serializing and deserializing objects) and sklearn (machine learning and statistical modelling).

2. **Data Gathering:** Getting the corpus of data that will be used to train and test the model aka the classifier. We have elected the use of manual retrieval of data mined from various sources. We have used the SemEval-2016 dataset for stance detection, a twitter dataset for sentiment analysis and a headlines dataset for sarcasm detection.

3. **Pre-processing text:** Tokenize the text. Cleaning it out by removing stop words, numbers, punctuations, html tags, twitter handles, time stamps of the message, and embedded links and videos etc. Such information is largely irrelevant and may cause false results to be given by our

system. The remaining words are also lemmatized in this step and any tweet data which does not have significant meaning and should not be used for analysis is eliminated.

4. **Count Vectorization:** Converting the textual words to their numeric representation (vectorizing text). This step is needed for training ML models. Simply put machines don't understand text, they get the numbers.

5. **Training:** Transformed data at this stage is split into training and testing sets. The training set is used to train the ML classifier by providing both the features and labels as inputs. The key point here is "experimentation"; there is no one-size-fits-all algorithm. Some classifiers are good with sentences, some are better with words etc. Some common classification algorithms are: Naïve Bayes, Support Vector Machine Deep Learning (neural nets), Logistic Regression.

6. **Model Creation:** Create an attention-based framework along with sentiment analysis and sarcasm detection for stance detection.

7. **Testing:** The model will then be tested with the testing data-set

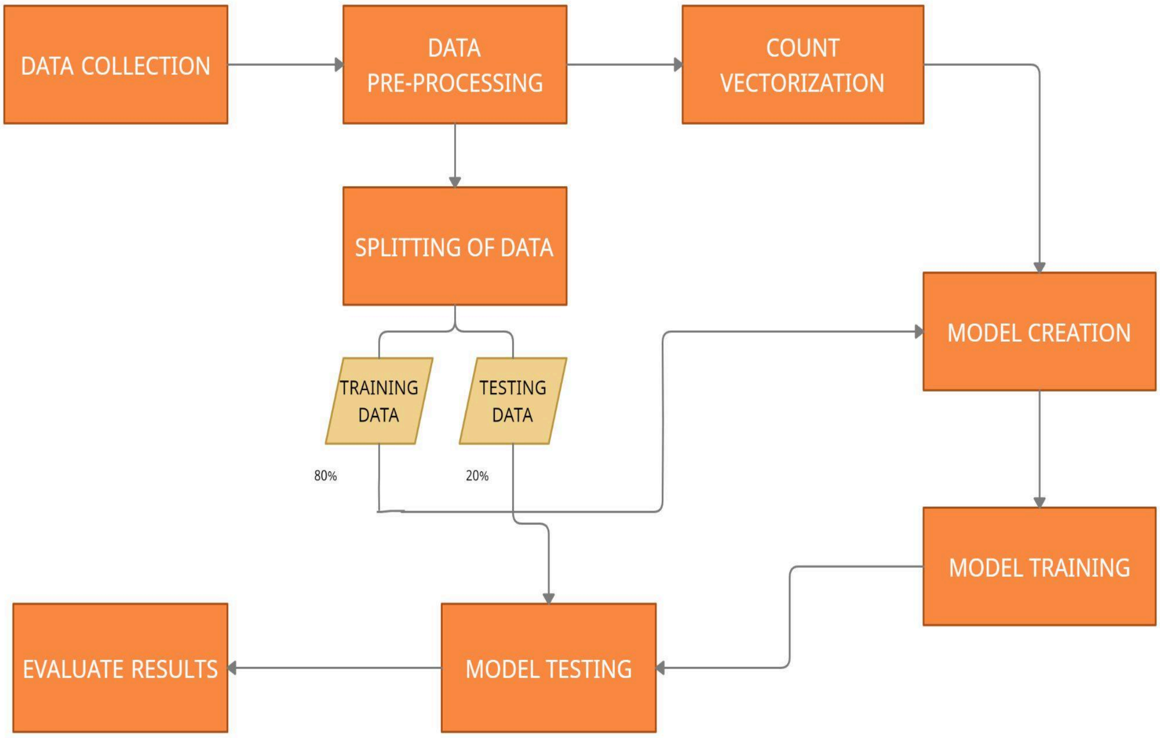

Fig. 1 Process Flowchart

4.3 Models Used

4.3.1 Linear Support Vector Classifier

SARCASM DETECTION

We used the LSVC method in our sarcasm detection model. The objective of a Linear SVC (Support Vector Classifier) is to fit to the data you provide, returning a "best fit" hyperplane that divides, or categorizes, your data. From there, after getting the hyperplane, you can then feed some features to your classifier to see what the "predicted" class is. The sarcasm detection model has an accuracy of 83%.

Fig. 1. Accuracy of the sarcasm detection model

Past studies in **Sarcasm Detection** mostly make use of Twitter datasets collected using hashtag-based supervision but such datasets are noisy in terms of labels and language. Furthermore, many tweets are replies to other tweets and detecting sarcasm in these requires the availability of contextual tweets.

To overcome the limitations related to noise in Twitter datasets, this **News Headlines Dataset** for Sarcasm Detection is collected from The Onion website which aims at producing sarcastic versions of current events
and HuffPost website which collects real news headlines.

We have used this dataset from Kaggle to train and test our model. Each record consists of three attributes:

- is_sarcastic: 1 if the record is sarcastic otherwise 0
- headline: the headline of the news article
- article_link: link to the original news article. Useful in collecting supplementary data

	article_link	headline	is_sarcastic
0	https://www.huffingtonpost.com/entry/versace-b...	former versace store clerk sues over secret 'b...	0
1	https://www.huffingtonpost.com/entry/roseanne-...	the 'roseanne' revival catches up to our thorn...	0
2	https://local.theonion.com/mom-starting-to-fea...	mom starting to fear son's web series closest ...	1
3	https://politics.theonion.com/boehner-just-wan...	boehner just wants wife to listen, not come up...	1
4	https://www.huffingtonpost.com/entry/jk-rowlin...	j.k. rowling wishes snape happy birthday in th...	0

Fig. 2. News Headlines Dataset before pre-processing

	article_link	headline	is_sarcastic
0	https://www.huffingtonpost.com/entry/versace-b...	former versace store clerk sues over secret b...	0
1	https://www.huffingtonpost.com/entry/roseanne-...	the roseanne revival catches up to our thorn...	0
2	https://local.theonion.com/mom-starting-to-fea...	mom starting to fear son s web series closest ...	1
3	https://politics.theonion.com/boehner-just-wan...	boehner just wants wife to listen not come up...	1
4	https://www.huffingtonpost.com/entry/jk-rowlin...	j k rowling wishes snape happy birthday in th...	0

Fig. 3. News Headlines Dataset after pre-processing

Here before finalizing a model, we implemented 4 different models. After applying all the models, the score was as follows:

Table I. Testing scores of different Sarcasm Detection models

S.No.	Model Name	Testing Score

1.	Linear Support Vector Classifier	83.75
2.	Gaussian Naïve-Bayes	73.80
3.	Logistic Regression	83.08
4.	Random Forest Classifier	79.71

It can be seen that the best scorer is the **Linear Support Vector Classifier** with an **accuracy** of **83.75%**. And remaining models have accuracies nearer to Linear Support Vector Classifier. Therefore, we have chosen the best one.

```
Classification Report
              precision    recall  f1-score   support

           0       0.85      0.86      0.86       746
           1       0.82      0.81      0.82       590

    accuracy                           0.84      1336
   macro avg       0.84      0.83      0.84      1336
weighted avg       0.84      0.84      0.84      1336
```

```
Confusion Matrix
[[640 106]
 [111 479]]
```

Fig. 4. Precision, Recall and F-1 Score for Sarcasm Detection

Fig. 5. Confusion Matrix for Sarcasm Detection

```
['A man cleans his apartment once every relationship'] : 1
['Could hillary clinton have what it takes to defeat the democrats in 2008?'] : 0
```

Fig. 6. User Input tested for Sarcasm Detection Model

The target class variable is imbalanced, where "Is Sarcastic" values are more dominating than "Is Not Sarcastic".

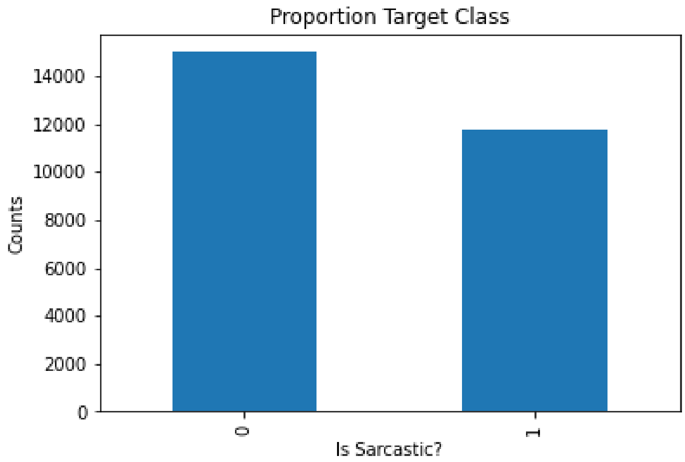

Fig. 7. Proportion Target Class for Sarcasm Detection Dataset

Fig. 8. Most common words in sarcastic headlines

Fig. 9. Most common words in non-sarcastic headlines

4.3.2 Logistic Regression

Logistic regression is named for the function used at the core of the method, the logistic function. We have used Logistic Regression model in our stance detection and sentiment analysis model. Both have a decent accuracy and give precise outcomes.

```
Accuracy 78.56073316375314 %
```

Fig. 10. Accuracy of the sentiment analysis model

```
Accuracy 58.50694444444444 %
```

Fig. 11. Accuracy of the stance detection model

The logistic function, also called the sigmoid function was developed by statisticians to describe properties of population growth in ecology, rising quickly and maxing out at the carrying capacity of the environment. It's an S-shaped curve that can take any real-valued number and map it into a value between 0 and 1, but never exactly at those limits.

1 / (1 + e^-value)

Where e is the base of the natural logarithms (Euler's number or the EXP() function in your spreadsheet) and value is the actual numerical value that you want to transform. Below is a plot of the numbers between -5 and 5 transformed into the range 0 and 1 using the logistic function.

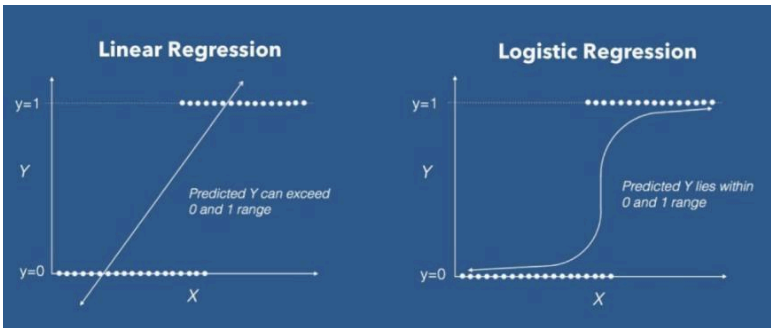

Fig. 12. Comparison between Linear and Logistic Regression

STANCE DETECTION

The dataset we have used to train our **stance detection** model is the SemEval-2016 dataset. A dataset of tweets manually annotated for stance towards given target, target of opinion (opinion towards), and sentiment (polarity). More than 4000 tweets are annotated for whether one can deduce favorable or unfavorable stance towards one of five targets ‘Atheism’, ‘Climate Change is a Real Concern’, ‘Feminist Movement’, ‘Hillary Clinton’, and ‘Legalization of Abortion’.

```
         Target                                               Tweet   Stance
ï»¿ID
\n1    Atheism  He who exalts himself shall      be humbled; a...  AGAINST
\n2    Atheism  RT @prayerbullets: I remove Nehushtan -previou...  AGAINST
\n3    Atheism  @Brainman365 @heidtjj @BenjaminLives I have so...  AGAINST
\n4    Atheism  #God is utterly powerless without Human interv...  AGAINST
\n5    Atheism  Morality is not derived from religion, it prec...  AGAINST
```

Fig. 13. Stance Detection Dataset before pre-processing

```
         Target                                               Tweet   Stance
ï»¿ID
\n1    Atheism  exalts shall humbled humbles shall exalted mat...  AGAINST
\n2    Atheism  rt prayerbullets remove nehushtan previous mov...  AGAINST
\n3    Atheism  brainman heidtjj benjaminlives sought truth so...  AGAINST
\n4    Atheism  god utterly powerless without human interventi...  AGAINST
\n5    Atheism  morality derived religion precedes christopher...  AGAINST
```

Fig. 14. Stance Detection Dataset after pre-processing

We have used **multinomial logistic regression here**. It is a classification method that generalizes logistic regression to multiclass problems, i.e. with more than two possible discrete outcomes. The performance reports for the stance detection model are as follows:

```
Classification Report
              precision    recall  f1-score   support

     AGAINST       0.63      0.74      0.68       291
       FAVOR       0.56      0.41      0.47       156
        NONE       0.49      0.46      0.47       129

    accuracy                           0.59       576
   macro avg       0.56      0.53      0.54       576
weighted avg       0.58      0.59      0.58       576
```

```
Confusion Matrix
[[214  39  38]
 [ 69  64  23]
 [ 59  11  59]]
```

Fig. 15. Precision, Recall and F-1 Score for Stance Detection

Fig. 16. Confusion Matrix for Stance Detection

```
['Trump is better than Hillary'] : AGAINST
```

Fig. 17. User Input tested for Stance Detection Model

The target class variable is imbalanced, where "AGAINST" values are more dominating than “FAVOR” and “NONE”.

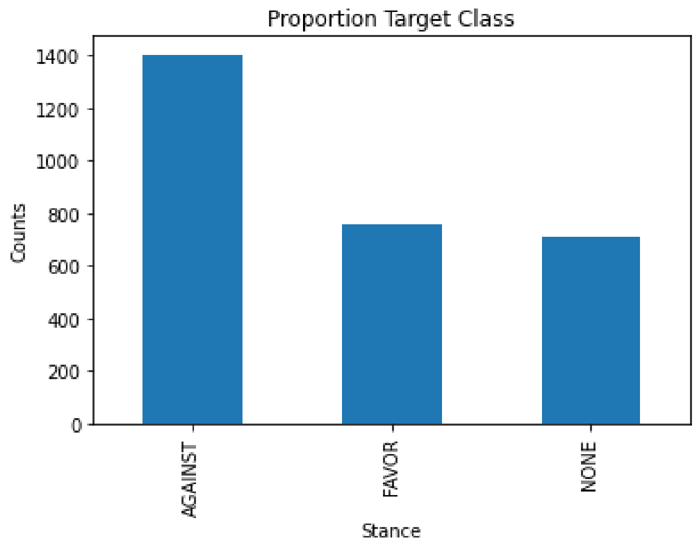

Fig. 18. Proportion Target Class for Stance Detection Dataset

Fig. 19. Most common words in Against tweets

Fig. 20. Most common words in Favor tweets

Fig. 21. Most common words in None tweets

SENTIMENT ANALYSIS

The dataset that we have used for **sentiment analysis model** training is the sentiment140 dataset from Kaggle. It contains over 1,600,000 tweets extracted using the twitter API. The tweets have been annotated (0 = negative, 1 = positive) and they can be used to detect sentiment.

ï»¿	id	label	tweet
0	1.0	0.0	is upset that he can't update his Facebook by ...
1	2.0	0.0	@Kenichan I dived many times for the ball. Man...
2	3.0	0.0	my whole body feels itchy and like its on fire
3	4.0	0.0	@nationwideclass no, it's not behaving at all....
4	5.0	0.0	@Kwesidei not the whole crew

Fig. 22. Sentiment140 Dataset before pre-processing

```
      id  label                                         tweet
ï»¿
0    1.0    0.0  upset update facebook texting might cry result...
1    2.0    0.0  kenichan dived many time ball managed save res...
2    3.0    0.0                    whole body feel itchy like fire
3    4.0    0.0                   nationwideclass behaving mad see
4    5.0    0.0                               kwesidei whole crew
```

Fig. 23. Sentiment140 Dataset after pre-processing

Here too before finalizing a model, we implemented 5 different models. After applying all the models, the score was as follows:

Table II. Accuracy scores of different Sentiment Analysis models

S.No.	Model Name	Accuracy

1.	Naïve Bayes	76.87%
2.	Logistic Regression	78.56%
3.	Linear Support Vector Classifier	61.28%
4.	Ada Boosting	56.69%
5.	Random Forest Classifier	70.12%

It can be seen that the best scorer is the **Logistic Regression** with an **accuracy** of **78.56%**. Therefore, we have chosen the best one.

We have used Binomial or binary logistic regression here. It deals with situations in which the observed outcome for a dependent variable can have only two possible types, "0" and "1". The performance reports for the sentiment analysis model are as follows:

```
Classification Report
              precision    recall  f1-score   support

         0.0       0.80      0.81      0.81     61075
         1.0       0.76      0.76      0.76     49787

    accuracy                           0.79    110862
   macro avg       0.78      0.78      0.78    110862
weighted avg       0.79      0.79      0.79    110862
```

Fig. 24. Precision, Recall and F-1 Score for Sentiment Analysis

```
Confusion Matrix
[[49340 11735]
 [12033 37754]]
```

Fig. 25. Confusion Matrix for Sentiment Analysis

On testing the model for user inputs:

```
['Trump is a good candidate'] : 1.0
['Could hillary clinton have what it takes to defeat the democrats in 2008?'] : 0.0
```

Fig. 26. User Input tested for Sentiment Analysis Model

The target class variable is imbalanced, where "Negative" values are more dominating than “Positive”.

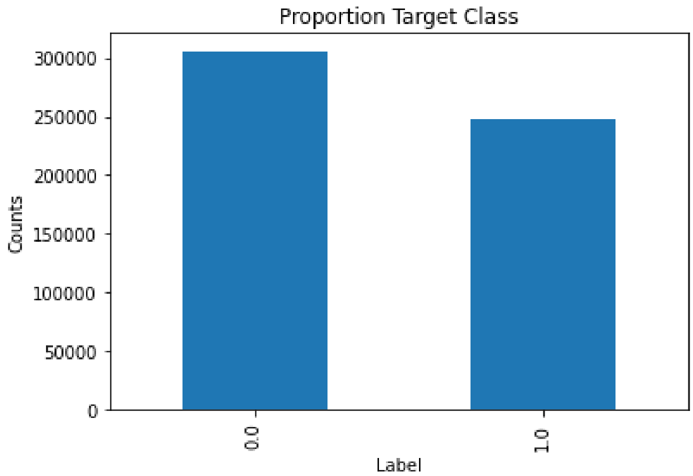

Fig. 27. Proportion Target Class for Sentiment140 Dataset

Fig. 28. Most common words in Negative tweets

Fig. 29. Most common words in Positive tweets

RESULTS AND DISCUSSION

We have built a website which enables us to predict the stance, presence of sarcasm and the sentiment behind a tweet. Our models have a decent accuracy and provide instantaneous results.

In our project, we have provided a platform where we can post tweet on a collection of target-entities and provide a stance, sentiment and sarcasm of the tweet. We have also added a feature where we have shown the overall stance of any target.

The future scope of our project, we wish to remove the restriction of target and dynamically update the target entities without requiring retraining of the models multiple times. We also endeavour to link our sarcasm and sentiment models.

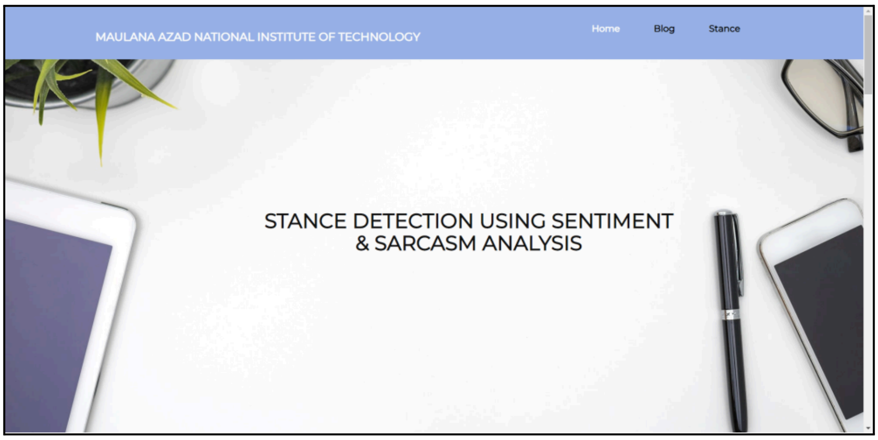

Fig. 30. Snapshot of Home Page

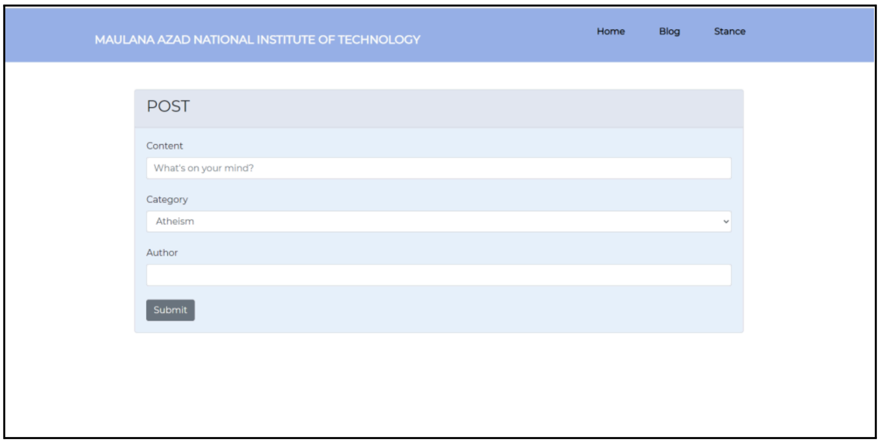

Fig. 31. Snapshot of Post Form

Fig. 32. Snapshot of Target Stance

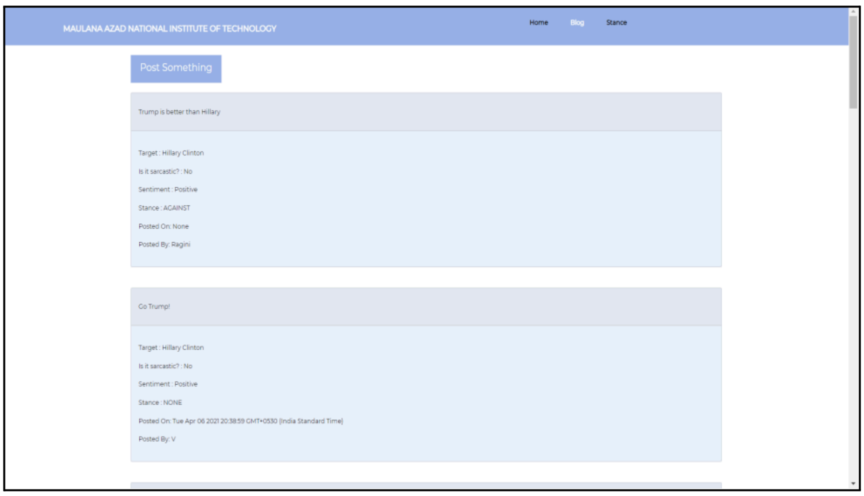

Fig. 33. Snapshot of Blog

CONCLUSION

From our research we concluded that stance detection will remain an important feature in this social media age. The different models have shown us there is room from improvement and experimentation in stance detection.

We can often detect from a person's utterances whether he/she is in favor of or against a given target entity— their stance towards the target. However, a person may express the same stance towards a target by using negative or positive language. We show that while knowing the sentiment expressed by a tweet is beneficial for stance classification, it alone is not sufficient. The sentiment analysis has a minuscule effect on detecting the accurate stance due to the complexity of stance modelling on social media. Stance can be in favor, against or none towards a target and it can have any sentiment positive negative or neutral.

We intend to present an exhaustive review of stance detection techniques on social media, including the task definition, different types of targets in stance detection, features set used, and various machine learning approaches.

To sum up, we have built a multi-level framework which will be based on ML models and stance and sentiment analysis. In our project we have taken sarcasm as a factor also. By determining whether text is sarcastic or not we have a better insight to detect the stance of the tweet. The project we have built provided with fairly accurate results and gives an overall stance of the target-entity in real time.

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