Chapter 8

Discussion And Conclusion

8.1 Discussion

Researchers in various fields, including world politics, communication services, investigative reporting, commercial businesses and so on are making substantial use of text on and from social media. SM text may also be utilized as a leading indicator to follow changing opinions toward important or challenging subjects. Machines generally cannot comprehend basic human terms due to their intricacy, subjective experience, and uniqueness. Enormous volume of textual data makes advanced analytical methods excellent for large-scale data processing. Nevertheless humans are still better at comprehending languages. Among several analytical domains, one in which humans excel to machines is the capacity to detect sentiments. The impact of social media on our life and society, particularly, our governance and administration, our political system, are now hot topics.

On a global scale, social media platforms such as Facebook, Twitter, Instagram, YouTube, and TikTok enable interactive one-to-many or many-to-many communication. Social media has positive connotations for creative engagement, political participation, and promotion during any event. The internet follows the vision of freedom (like freedom of thought, freedom of opinion, freedom of speech and expression, and freedom of information) inspired by technological advancements. Individuals and small groups can use social media to make themselves visible and heard, and to share their thoughts with a larger audience or group of followers.

While connectivity, engagement are boon of the SM, there is a fair share of evils as well. During the COVID-19 crisis, the level of disinformation reached a point where it could jeopardize the democratic decision-making process. Crises have always been a time when people's emotions and anxiety levels run very high. These appeared to come to a peak on social media platforms, where citizens and self-proclaimed experts offered unscientific advices on Covid-19 or attempt to identify allegedly guilty parties and fabricate conspiracy theories by combining facts and false interpretations. During elections and disasters, societal and political manipulation is a matter of major concern on social media.

8.2 Summary and Contributions

According to the research goals outlined in Chapter 1, we summarize and highlight the main findings and contributions of the work done.

8.2.1 RQ1: What roles do SM play in e-Governance and the public interaction with the government?

We studied the presence and activities of Indian ministries in social media, identifying 46 Facebook and Twitter accounts of different ministries under Government of India (GoI). Our observations are summarized below according to sub-questions raised in the Introduction.

SQ1. *How many ministries use social media platforms and which social media?*

We found eight social media platforms used by different GoI ministries. Out of them, every ministry is found to use Facebook and Twitter in common. Only one ministry uses all 8 platform, i.e Ministry of External Affairs. More than 85% ministers have social media accounts.

SQ2. *What type of topics do they discuss on social media?*

Topics discussed by the ministries on social media are primarily the meetings and projects related to the government. Railways projects, GST, different development schemes, Pradhan Mantri yojna (PM projects) are found frequently in their social media accounts. We classified the ministries' Twitter and Facebook data into seven classes to see which ministry data is high and in which type. In Twitter, most of the posts across the user classes belong to the Pass-along category, while in Facebook, news is the major post-type. Other two post categories are status and conversational.

SQ3. *How active are different GoI ministries and their officials in the social media? How often do they post or re-post here?*

We explored the activities of different GoI ministries in terms of total number of messages posted so far as well as their rate of posting per day. We categorized the ministries based on their usage and activities in social media platforms: first through posting activity level of ministries, and then through time-series analysis. In posting activity, we found that the Ministry of Railways and Ministry of Agriculture are most active. In time-series analysis, Ministry of Railways is seen posting messages or tweets and retweets very actively on daily basis. The ministries reply immediately to the public questions or posts or when they are online.

SQ4. *How do the Departments interact among themselves through social media? Outside the officialdom, do they mutually refer to each other in public domain through social media?*

We studied the inter-connection among the ministries – how much they are connected to each other through social media. We find the Ministry of Information and Broadcasting (MIB) is a good hub and good authority as well as having good PageRank. Good hub means the ministry is well-connected to other ministries and good authority means other ministries refer to the concerned ministry. The ministry (MIB) belongs to super active group, and, the public participation with the ministry is also very good. The ministry of Food Processing Industries is a good hub, but with low authority and low PageRank scores. It means the ministry follow many other ministries, but without much reciprocity. The PMO account is one of the most shareable account among all - the average number of posts shared among ministries is 11-15 tweets per day by PMO. Links to content created by the user (blog/video/picture) and the reports of breaking news and personal eyewitness accounts of news events are shared. Tweets that represent a live discussion of an identifiable event like: election, wishes for a birthday or festivals, who won the election, sports, etc are also posted.

SQ5. *How is the public participation with the ministries or Government departments on social media? How do these two stakeholders of e-Governance interact or exchange through social media?*

We analysed public participation in the ministries' posts, how many people like the ministries' posts and how do they follow the ministries. We found that public like India DST ministry the most, but people mostly follow the Prime Minister of India (PMO). During the election, the ministries engage more in the social media timeline. Public at large like the ministries' tweets when there are some announcements of new schemes, Budget announcements, festivals celebration, and GST, etc. Ministry of Coal mostly shares photos and videos compared to posting text. The ministry of minority affairs was found to have the lowest number of followers, while PMO the highest on both Facebook and Twitter. Number of followers is observed to be proportional to the volume of activity of the ministries. The Ministry of Minority Affairs belongs to the low active group, while the Prime Minister of India (PMO) belongs to the super active group.

8.2.2 RQ2: How politics affect society (A study on people's opinions during PEI 2019)?

We explored multi-task learning for categorising posts from six different datasets on Hindi and English data (four datasets for English and two for Hindi). We proposed an emotion-based Multi-Task Learning with the Convolution Network (MTL-CN) method for the classification task in order to classify hate speech and offensive content in both Hindi and English using multiple labels. We used the Deepmoji library to identify emotions. We discovered that using the MTL framework to identify hate speech significantly increases model's capacity in hate speech detection. Regardless of the languages, the MTL-CN outperforms the baseline model for all the datasets. We demonstrated the effectiveness of our technique for identifying offensive language and hate speech. The experiments show that using a multitask learning framework, learning context is especially advantageous because of the important connections between tasks. We also considered the effects of incorporating emotional information, which proved to be beneficial. This is because offensive language and hate speech are frequently linked to negative emotions. As a result, inflammatory language and hate speech are connected to sentiment analysis.

8.2.3 RQ3: How do people react to political campaigns?

Several ML techniques are tried along with two deep learning techniques for irony detection in our study. Among the ML techniques, LR seems to be the best and consistent for both the datasets used in terms of F_1 scores. k-NN does not seem to work good for irony detection tasks. However, as far as accuracy is concerned, NB performs the best. The deep learning techniques are not found to be better than ML ones for irony detection tasks on the IGE-2019 dataset, however comparable (F_1 scores) or better (accuracy) on SE-2018 data (See Figure 6.7, 6.8, 6.9, 6.10). Deep learning models were pre-trained on data from general domain, hence they worked well for SE-2018 data, but can not perform the same on domain-specific data. BERT exhibits better performance over ELMo because of its inherent capability of capturing context through deep bi-directional nature at multiple layers.

In the ensembling experiments, EMLT performs better than the average of the individuals for both the datasets, but can not beat the best performer (see Figure 6.7, 6.11). On the contrary, ensembling betters individual performances of deep learning techniques. The improvement is particularly prominent in SE-2018 dataset since deep learning models are pre-trained from general domain.

In the domain adaptation experiments also, BERT outperforms ELMo individually and provides the best accuracy among all. Here ensembles do not work well in general.

Nevertheless, ensembling as a technique is useful and can offer decent results in a resource-constraint environment when training data is not sufficient.

8.2.4 RQ4: How disaster affect people's life (A study on COVID-19)?

We created a Hindi dataset for sentiment analysis on social media during crisis. During CoVID-19 pandemic, Hindi data of one month's time over Twitter was collected during April 2020 to May 2020. The dataset cleaned and then annotated with three classes: positive, negative and neutral for simple sentiment detection task. The dataset showed dominance of a sense of negativity in the SM during the period. Even though good number of positive tweets were there with equal number of neutral ones, people held comparatively more negative to neutral views during lockdown possibly because of anxiety and uncertainties looming large that time. We explored application of several machine learning and deep learning classifiers for the sentiment analysis tasks.

8.3 Proposed Methods and Findings

Technology has enormously changed our lifestyle, not only in how we communicate but in our attitude and relationships with people of different ages living in the same society in both positive and negative ways. In this thesis, we investigated how use of social media text from different areas, along with the least amount of annotated data of Hindi and English, can be utilized to achieve state-of-the-art results by extending the existing deep learning approaches. Specifically, this thesis has focused on three aspects of social media for Hindi and English languages: creation of standard SM datasets for e-governance, election and disaster managements and studying the sectors using data analytics tools.

8.3.1 RQ1: What roles do SM play in e-Governance and the public interaction with the government?

Various administrations and government agencies, including ministries, use social media to communicate quickly and interactively. Their communications include official notifications, announcements, warnings, advisories, and their personal opinions and views. We study five research questions based on the use of Facebook and Twitter by 46 ministries of the Government of India. In our study, We found that ministries used eight social media platforms; only one ministry used all of them, while the rest used Facebook and Twitter regularly. Many topics are discussed in a ministry discussion, including government projects, meetings, budgets, development, agriculture, and events. Twitter is the most active social media platform for 70 percent of ministries, while Facebook is the most popular platform for 12 percent. On Facebook, about 35% of ministries are highly active, while on Twitter, 12% are highly active. In our analysis of communication among ministries on Twitter, We observed that they engage in social media interactions with each other. Social media is also a popular way for the public to follow government departments or ministries. After reviewing the use of Facebook and Twitter in Government, We can conclude that both are being used for informal and formal communication by Government departments in India to share information and seek public opinion.

8.3.2 RQ2: How politics affect society (A study on people's opinions during IGE 2019)?

With the rise of social media, netizens have been inspired to engage in political activities by twittering, updating statuses, blogging, and viewing videos on YouTube. Much anonymous personal information may be aggregated to gauge public opinion in an unobtrusive manner thanks to the increased use of social media sites for self-expression, interaction, and socialization. Social media allows us to collect and analyze public opinion more efficiently than traditional methods. From the Twitter streams focusing on Indian Genral Election 2019 in Hindi and English we generated two datasets for studying hate speech and offensive content and irony content respectively.

Due to linguistic diversity and user usage patterns, identifying hate and offensive speech content on social media platforms for different major languages is a challenge. Few studies, such as the FIRE HASOC track, have examined hate speech and offensive terminology on social media in Hindi. We introduce here an emotion-based multi-tasking learning with the convolution network (MTL-CN) model for multi-label classification of hate and offensive speech content identification in Hindi and English. The text's universal, task-specific, and emotional characteristics are all captured by MTL-CN. Additionally, MTL-CN saves time and effort by eliminating the need for individualised task-by-task learning. For Hindi and English, I see that MTL-CN performs better than single-task learning.

8.3.3 RQ3: How do people react to political campaigns?

Irony detection in sentiment analysis is an emerging area. Social media is set ablaze with a profusion of ironic and sentimental posts during election times. Amid the intense political rivalries leading up to the 2019 general election in India, we compiled a collection of social media posts to create and annotate a dataset for the irony detection task. To distinguish between ironic and non-ironic posts, we used a variety of classification techniques. Two deep learning-based classifiers (BERT and ELMo) along with their different ensemblings and eight different machine learning classifiers (kNN, DT, RF, LR, MNB, SGD, XGBoost, and SVM) were used. In order to compare the results, we also trained the systems using a different dataset (SemEval 2018). All of the classification techniques that were tried in our domain-specific dataset performed well in terms of popular metrics. Deep learning based techniques performed better than ML-based techniques on general domain dataset but not on domain-specific dataset (IGE 2019). Deep learning techniques when combined produced, on average, better results than when used separately. Although the performance of domain adaptation was lower than expected, it was not entirely disappointing. When trained on general data and tested on specific data, domain adaptation can be adopted without a doubt, but not the other way around. A future task that could be attempted is joint training, which involves training systems on two or more datasets.

8.3.4 RQ4: How disaster affect people's life (A study on COVID-19)?

In this work, we present a corpus of Hindi text with annotation for sentiment analysis. We achieved a high inter-annotator agreement in terms of Cohen's Kappa Coefficient. The corpus consisted of 10,011 tweets annotated with three standard emotions, namely Positive, Negative, and Neutral. We believe that this resource will benefit the researchers to address new challenges in the Natural Language Processing domain for a low resource language like Hindi. We also presented a baseline supervised system architecture used for the classification algorithms and presented our results for each class in Precision, Recall, and F_1 scores. We applied and showcased the performance of different ML and DL classifiers. While SVM found to be the best among ML classifiers for Hindi sentiment detection on our data, BiLSTM with BERT and FastText was the overall best performer among all (considering ML as well as DL).

8.4 Future Scopes

There are plenty of further studies possible in many directions.

- **Character Embeddings:** In the recent past, character-based embeddings have proved promising. We tried word embeddings. We would like to investigate whether these representations can bring about better results in various sentiment analysis tasks like irony detection.

- **Joint Training:** Domain adaptation is a promising area where available data is limited. As a technique, it can certainly be adopted when trained on general data and tested on a specific data but not the vice-versa. We did not try joint training, i.e. training systems on two or more datasets - a task that can be attempted in future.

- **Language verticals:** India is a multi-lingual country. In social media, people prefer informal communication in native languages. However, most of the Indian languages are resource-scarce. Building social media datasets in these languages can be taken up.

- **Code-mixed Data:** In the related context, most of educated people in India are bilingual, or tri-lingual. People often mix two or more languages in informal communication of social media. Code-mixing and code switching is very common phenomenon. Building such SM data is of paramount importance.