Linguistic Feature-based Classification for Anger and Anticipation using Machine Learning

Kalaimagal Ramakrishnan[1], Vimala Balakrishnan[2] and Kumanan Govaichelvan[2]
[1]*Faculty of Science and Engineering, University of Nottingham Malaysia, Malaysia*
[2]*Faculty of Computer Science and Information Technology, University Malaya, 50603 Kuala Lumpur, Malaysia*

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Abstract: Growing number of online discourses enables the development of emotion mining models using natural language processing techniques. However, language diversity and cultural disparity alters the sentiment orientation of words depending on the community and context. Therefore, this study investigates the impacts of linguistic features, namely lexical and syntactic, in predicting the presence two emotions among Malaysian YouTube users, anger and anticipation. Term Frequency–Inverse Document Frequency (TF-IDF), Unigrams, Bigrams and Parts-of-Speech Tags were used as features to observe the classification performance. The dataset used in this study contains 2500 YouTube comments by Malaysian users on 46 Covid-19 related videos. Comments were extracted from three prominent Malaysian-centric English news channels: Channel News Asia (CNA), The Star News, and New Strait Times, ranging from 16 March 2020 – 30 April 2020 (i.e., first lockdown phase). Random Forest, Support Vector Machine, Logistic Regression, Decision Tree, K-Nearest Neighbour and Multinomial Naïve Bayes were the six classification algorithms tested, with results indicating Support Vector Machine with TF-IDF provided the best performance, achieving accuracy of 76% and 73% for anger and anticipation, respectively.

1 INTRODUCTION

The spread of the infectious respiratory syndrome, COVID-19 has led to countries worldwide to adopt and implement drastic precautionary measures: travel bans, complete or partial lockdowns and stay-at-home orders. Consequently, the severity of the disease spread, and its consequences affected the global human population from various aspects, including economy, education, employment as well as physical and mental wellbeing (Ganasegeran et al., 2020). In par with other countries, the Malaysian government implemented partial lockdown or known as Movement Control Order (MCO) since 18 March 2020. The National Security Council was in-charge of the MCO implementation, and occasional changes were made in the conditions imposed to cope with the pandemic. During this lockdown period, conventional survey-based studies were done to observe the mental health of the citizens (Abdullah et al., 2021; Kassim et al., 2021; Tsan et al., 2020), with findings indicating increased incidences of anxiety and depression among Malaysians.

The use of social media spiked during the COVID-19 pandemic, with users resorting to the platform to seek and share information, provide support for each other etc. Amidst this chaotic period, social media platforms such as Facebook, Twitter and YouTube became a necessity for human interaction, sharing information and providing comfort in a time of need, hence serving as an efficient tool in infusing positive hope among the public (Chen et al., 2020; Limaye et al., 2020). Most importantly, the government agencies including the Ministry of Health and National Security Council used social media to constantly update the public with facts and figures and to live-stream important announcements on YouTube, Facebook, etc. As a matter of fact, studies have reported a significant increase in the use of YouTube among the public for reliable health-related information (Azak et al., 2021).

During a crisis, it is important for governments and other relevant agencies to monitor the public's conditions to obtain situational awareness, and this is made possible through Artificial Intelligence (AI). Specifically, machine and deep learning approaches play pivotal roles in automating social media monitoring and extracting information such as the mental wellbeing of users (Chau et al., 2020; Kumnunt & Sornil, 2020) and emotions

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(Balakrishnan & Kaur, 2019). Existing studies on automated detections using textual communication have explored various features to improve the prediction including sentiment (Singh et al., 2018) and emotion (Balakrishnan & Kaur, 2019), which could be determined through text analytics. Other features include textual or linguistic features such as number of words, number of adjectives, adverbs etc., however such studies are scant. To fill this gap, the present study proposes to develop a machine learning model to examine the impact of linguistic features on comments containing two major emotions, that is, anger and anticipation.

2 RELATED WORK

Emotion mining or detection models are pretrained with words categorized based on models such as Ekman's 6 basic emotions (Fear, Anger, Joy, Sadness, Disgust, and Surprise) and Plutchik's 8 Primary Emotions (Joy, Trust, Fear, Surprise, Sadness, Disgust, Anger, Anticipation). The role of emotion mining has become significant in healthcare as it establishes better understanding on disease related sentiments or frustrations (Balakrishnan & Kaur, 2019). In the context of COVID-19, emotions were identified based on social media textual communications. For instance, A study examined the keyword-based emotion dynamics for tweets and Weibo from February to May 2020 (Li et al., 2020). The authors found an increasing trend of anger for keywords like 'China', 'Trump' and 'Lockdown', whereas worry was closely associated with words like 'syndrome', 'infected', 'finance', 'family' and 'food'. Li et al. (2020) also observed that the presence of angry text documents with the word 'Trump' increased over President Trump's racist remarks on Chinese citizens or him calling them as 'ching chongs'. It is to note that keyword-based models might not work well when the sentiment orientation of words change depending on the cultural and contextual disparity (Kaity & Balakrishnan, 2020).

Meanwhile, with the advent of natural language processing techniques and developments in the field of linguistic theories, linguistic features are used to improve the efficacy of emotion mining. Linguistic features can be divided into several categories: syntactic, lexical, semantic etc. For instance, syntactic feature extraction method includes Parts-of-Speech (POS) tagging, which gives weights to the grammatical role of a word in a document, or N-gram, addressing the association between one word with the consecutive word. On the other hand, lexical features such as word frequencies provide insights into the patterns of word used and the sentimental/emotional content of the text (Rajput et al., 2020). Very few studies have explored linguistic features and their associations with emotions. For example, Kumar and colleagues (Kumar et al., 2020) used POS and Unigram to classify emotions in textual data with a Naïve Bayes (NB) model, with an accuracy over 80%. Sharupa et al. (2020) reported an accuracy of 72% using Multinomial Naive Bayes (MNB) with POS and Unigram. The authors claimed that many studies that employ linguistic features merely study dominant emotions like happiness and sadness, hence the need to explore more emotions.

Few studies were also found targeting non-English text. For example, a Korean corpus was used to train a Support Vector Machine (SVM) model to categorize 10500 tweets into 25 emotions, with an F1 measure value of 0.91 using word bigrams with POS trigram (Jung et al., 2017). Finally, a more recent study from Saudi Arabia included 242,525 Arabic tweets to infer public's attitude towards the COVID-19 pandemic. Testing with three machine learning algorithms: SVM, K- Nearest Neighbours (KNN) and Naïve Bayes, along with the N-gram feature extraction technique, SVM with Bigram coupled with Term Frequency–Inverse Document Frequency (TF-IDF) resulted in the highest accuracy of 85% (Aljameel et al., 2021). Table 1 showcases the list of studies used as a guide to design our experiment.

Table 1: Summary of studies on emotion and linguistic features.

Authors	Features Analysed	Dataset	Results
(Kumar et al., 2020)	POS-tag, Unigram with Bag-of-Words	Sentiment 140 tweets into 4 emotions	NB+Unigram = 82% accuracy
(Jung et al., 2017)	character, word count, n-grams, POS-tags, and emotion keywords (EK)	10500 Tweets into 25 emotions	SVM F-measure = 90.90%
(Sharupa et al., 2020)	POS tagged unigram, Unigram, Bigrams	Sentiment140 tweets into 4 emotions	MNB = 72.3% accuracy

3 METHODOLOGY

The data were gathered from YouTube during the first three phases of lockdown in Malaysia (16 March 2020 – 30 April 2020), specifically targeting a few English-centric media including News Straits Times, Channel News Asia (CNA), and The Star. The comments were scraped using Coberry.com, an open-source YouTube comment exporting tool, which documents the comments as an Excel file. The titles of the videos were scrutinized prior to data collection. Specifically, only videos containing words like 'MCO' and/or 'Covid-19' and 'Malaysia' as part of the title were selected to ensure content- specificity. About 46 videos fit the criteria, and 5372 comments obtained from the selected videos. All the phases illustrated in Figure 1 are elaborated in the following sub-sections.

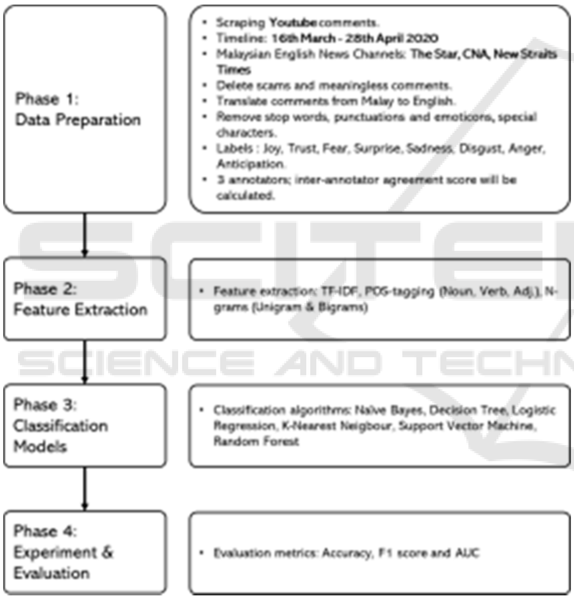

Figure 1: Experimental workflow.

3.1 Data Preparation

Phase one involves data cleaning and pre- processing. Several criteria were used to clean the data, including (i) removal of non-English and non- Malay (i.e., local national language) comments, (ii) removal URLS, spams etc., (iii) removal of short comments (i.e., fewer than four words), and (ii) removal of duplicate entries. This resulted in 3876 usable comments from the initial dataset. Truncated texts that were colloquially used were normalized into their complete form, to prepare the data for translation. For instance, among Malay- language comments, the character 'x' indicates negation, (i.e., synonymous to 'tidak'). As for the English comments, 'pm' for prime minister, 'govt' for government, 'hosp' for hospital and 'Msia' for Malaysia were found. Irrelevant or special characters (e.g., %, & etc.) were removed as they can potentially have a negative effect on the performance of the classification model and reduce accuracy (Balakrishnan et al., 2021). All the Malay comments were then translated to English using Google Translator, and later verified by two language experts, who also provided the corrected versions when the translations were found to be inaccurate.

Example 1: Correctly translated texts:
Original : *Semoga semua rakyat Malaysia terhindar dari virus ini.Amin.*
Google : *May all Malaysians be spared from this virus…Amin.*

Example 2: Manually corrected translations:
Original : *apa pasal pergi kumpul... pasal kau orang*
Google : *What about going to a gathering*
Translated: .... *about you people*
Manually *Why are you gathering… it is because*
Corrected *of you people.*

About 2500 comments were then randomly selected for labelling based on Plutchik's 8 Primary Emotions (i.e., Joy, Trust, Fear, Surprise, Sadness, Disgust, Anger, Anticipation). If the emotions were present, '1' was used, otherwise, '0' was used, to label the eight emotions. Noteworthy, emotions are feelings specific to a situation and its context (Namaziandost et al., 2021), therefore three Malaysian-based linguistic experts were recruited to label the comments. The Cohen's Kappa value was 0.91, hence showing a strong agreement between the annotators. An analysis of the annotation revealed anger (36%) and anticipation (38%) to be the most

3.2 Feature Extraction

A feature can be described as an individual measurable property or dimensions from the selected dataset for the machine learning algorithm to process (Barnard & Opletal, 2020). Feature extraction is a useful step in building a model as it removes redundant and irrelevant data, thus contributes to enhancing learning accuracy of the machine learning model (Kumnunt & Sornil, 2020). Notably, studies have observed that too much features, especially when texts are vectorized, results in redundancy, thus, degrades the performance of the machine learning model (Gopalakrishnan et al., 2020).

This study focuses on two features, namely, syntactic, and lexical features. Individual words in a sentence are referred to as lexical features. It can either be the presence or the frequency distribution of the words in a corpus. Determining word frequencies in any document, for example gives a strong idea about the patterns of word used and the sentimental content of the text (Rajput et al., 2020). The lexical features were extracted using the Term Frequency – Inverse Document Frequency (TF-IDF) method, which designates higher weights to words that are less frequent in a corpus and considers the frequency of occurrence within the document they are used. In other words, words that are commonly present in all documents are assigned smaller weights (Sarkar & Jana, 2019). The Python-based Natural Language Toolkit (NLTK) was used for tagging the syntax of each word based on grammatical functions. The words were tokenized, and POS was tagged accordingly. Both the features were extracted using Python on Jupyter Notebook, specifically using modules such as NLTK, SPACY and SKLEARN

3.3 Classification Model

As the performance of the data classification is dependent on the model and the data quality, it is important to test multiple algorithms. In this study, six algorithms were used in detecting the emotions (i.e., anger and anticipation) using the linguistic features, namely, Multinomial Naïve Bayes (MNB), Logistic Regression (LR), K Nearest Neighbor (KNN), Decision Tree (DT), Random Forest (RF) and Support Vector Machines (SVM). Naïve Bayes is a popular algorithm used for classifying textual documents. It assumes independence between the features. For example, in text classification, the text is considered as sets of words however, independent of each other or their location in the text. Therefore, the probability function for individual text is obtained from the multiplication of the probability of the words and their occurrences relative to the text length (Kaur, 2021). There are several variants to NB, one of which is MNB. The algorithm is deemed to be good for text classification (Rezaeian & Novikova, 2020). Contrarily, LR-based model measures the statistical significance of each independent variable in relation to its probability. It is a robust way of modelling binomial outcome (Shah et al., 2020), which is the presence or absence of emotions in this study. The KNN algorithm focuses on making predictions based on the similarity level, using spatial vectors to compute the similarity. The class prediction is based on the pre-determined numbers of K value, and the difference is studied based on Euclidean distance. In the case of text classification, the training texts are fed as feature vectors. Hence, the class prediction of the incoming text are decided based on the similarity between texts (Shah et al., 2020). SVM is mostly used for classification problems. This method is a statistical classification approach based on the maximization of the margin between in the instances and the hyper-plane. It is referred to as a non-probabilistic binary linear classifier, capable of separating the classes by a large margin, thus can handle infinite dimensional feature vectors. Studies have recommended SVM to be the best text classification method (Al Amrani et al., 2018).

DT is a stratifying method that segregates observations into simpler regions to make predictions. In this study, DT algorithm is applied as previous studies on text classification have tested and recorded improved detection (Bahassine et al., 2016; Pranckevičius & Marcinkevičius, 2017; Shi et al., 2010). Finally, RF is an ensemble learning method which constructs a number of decision trees during training, with varying subsets of the dataset, and provides mode class of each tree as the output (Al Amrani et al., 2018).

3.4 Experiment and Evaluation

All the models were developed using Python and tested on Jupyter Notebook. The performance of the models was evaluated based on several metrics, Firstly, Accuracy is based on the number of correct predictions divided by the total number of predictions made. Secondly, the precision is based on the actual 'true positives' among all predicted positive values. Then, the recall is the actual 'true positives' predicted correctly from the total actual positive values. F1-measure the harmonic mean of precision and recall and the Area Under Curve (AUC) - the two-dimensional area underneath the ROC curve, providing an aggregate measure of performance across all classification thresholds. Discrepancies between these metrics suggests methods to improvise the classification performance, thus it is useful to have more than one metrics to evaluate the model's performance (Requena et al., 2020).

4 RESULTS AND DISCUSSION

4.1 Emotion Distribution

The corpus was labelled based on the presence of emotions according to Plutchik's 8 emotions. Figure 2 depicts the emotion distribution for the 2500 labelled comments, revealing anger (40%; N = 1007) and anticipation (38%; N = 955) to be the two highly expressed emotions among the YouTube users in this study. This could be due to the uncertainty faced due to Covid-19 outbreak coupled with political instability within the country.

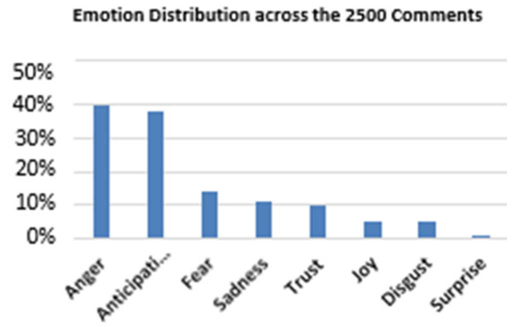

Figure 2: Emotion distributions based on Plutchik's Model.

Table 2 shows the top 15 words associated with each of the emotions (arranged in highest number of frequencies).

Table 2: Top 15 words for anger and anticipation.

Emotions	Top 15 words
Anger	people (274), China (214), government (159), Malaysia (132), virus (117), like (110), please (102), still (101), stupid (100), want (93), mask (91), home (86), go (83), minister (81), many (71), time (68), get (66), country (62), Malaysian (62), cases (62)
Anticipation	Malaysia (184), people (117), good (117), stay (111), virus (84), government (84), please (80), minister (76), home (75), may (69), thank (67), like (66), hope (65), country (64), cases (63), health (63), us (60), Malaysian (59), Covid (58), well (58)

Anger is described as a psychosocial response to subjective experience ranging from mild irritation to extreme rage. Therefore, we can infer that the public has expressed their anger towards the Chinese government, political figures, and irritation due to the delay in controlling the disease spread. Words like 'China', 'government', 'stupid', 'still', 'time', 'minister' are associated with anger in this corpus.

On the other hand, anticipation is the eagerness to predict what comes next (Hodzik, 2013). Therefore, words like 'hope', 'thank', 'may', 'good', 'stay' and 'health' indicate people's expectation towards resolving the crisis. For instance, Example 3 below shows a user motivating fellow citizens to look forward to an improved situation and cautions to ensure older people's safety. In Example 4, the user expresses his/her concern due to the lockdown situation. Both comments express anticipation as the users expects actions from the decision-makers to manage the crisis effectively.

Example 3:
When going gets tough, the tough gets going, Insya Allah Malaysia overcomes this challenge only when time comes. Keep the elderly in home and separate from others. Importantly avoid casualty, this is the time for the young ones to keep the elderlies safe.

Example 4:
Please consider private staffs is not enough. Please do not extend we need money our savings are going to finish. Do not torture us. Malaysians might commit suicide or become mentally ill due to lockdown.

Words could be specific to certain emotions as well. Notably, the word 'mask' is found to be associated with anger. This could be associated with reported incidents of counterfeit masks and insufficient personal protective equipment (PPE) for the general public, especially during the early stages of the pandemic (Nienhaus & Hod, 2020). A sample comment is provided as Example 5 below.

Example 5:
Even DIY is out of stock for masks! No more mask available! Very hard for us to even buy food without masks. The ministry reported that there are not enough masks.

4.2 Impact of Linguistic Features on Anger Classification

Table 3 shows the values of evaluation metrices for the models experimented in predicting anger. It can be observed that SVM (accuracy = 73%; F1- measure = 62%) and LR (accuracy = 73%; F1- measure = 52%) outperformed other algorithms when all the words were treated as unigrams, and vectorized using TF-IDF. On the other hand, verbs and adjectives are identified to be equally important features in aspect-based sentiment analysis(Babu et al., 2020). Therefore, the POS-tagging results show the influence of nouns, verbs, and adjectives individually and in combination for anger prediction. Other combinations of features and algorithms did not outperform the abovementioned two models. Although not related to emotions, our findings are in line with other studies that have showed SVM-TF-IDF to produce the best results for text classifications (Gupta & Baghel, 2018) For example, Gupta & Baghel (2018) found best results were obtained using SVM with TF-IDF and POS (accuracy = 94%; recall = 91%; precision = 93%) based on 100,000 TripAdvisor comments.

NA (Nouns + Adjectives) features enabled RF and DT to make better classifications compared to their respective baseline model. Contrarily, despite the increase of MNB's F1 measure 45% (NA) from 24% (baseline), F1 measure below 50% indicates that MNB is not suitable for this task (Derczynski et al., 2012). This could be due to limited positive classes resulting in class imbalance issue. However, as MNB and KNN never attain F1 values above 50% compared to other models, it can be inferred that these two models are unlikely to be effective for this task.

Nevertheless, SVM remains the better performing algorithm with NA features, achieving accuracy rate of 73%, F1 of 60% and AUC of 77%. As observed in a previous study, nouns and adjectives phrases potentially contain key information to the sentiment orientation of the words (Awan & Beg, 2021). Therefore, the comparable performance of SVM-NA with SVM-Baseline indicates that nouns and adjectives are influential in detecting anger.

4.3 Impact of Linguistic Features on Anticipation Classification

Table 4 shows the values of evaluation metrices for the models experimented in predicting anticipation. SVM emerged to be the best algorithm with the highest accuracy rate at 76% followed by 75% for LR. A similar trend in the performance of RF and DT were also observed, when reduced features were fed to the algorithm. It has been suggested that nouns have higher weights than verbs due to its ability to provide more information. This is because the tendency to use nouns are more than verbs in a sentence (Kieuvongngam et al., 2020). However, for anticipation prediction, verbs alone enabled both RF and DT to achieve F1 above 50%. Compared with SVM-baseline, the best performing model, RF-Verb provides the second-best classification based on all three evaluation metrices (Accuracy = 73%, F1 = 53%, AUC = 75%).

Verbs refer to words that indicate an object's or person's motion, action, belonging to a category or quality, hence, contributing to the overall meaning of the discourse (Fidyati & Rajandran, 2020). This helps to classify comments that express expectations, eagerness, and anticipation (Hodzik, 2013). It is also noted that MNB's F1 increased from 1% (baseline) to 22% (NA), however, the lack of robustness shows that is not suitable for emotion classification with vectorized words.

Table 3: Performance metrics for linguistic feature-based detection for anger.

Model / Features	MNB			LR			KNN			SVM			DT			RF		
	Acc.	F1	AUC	Acc.	F1	AUC	Acc.	F1	AUC	Acc.	F1	AUC	Acc.	F1	AUC	Acc.	F1	AUC
Baseline	.66	.24	.79	.73	.54	**.82**	.67	.41	.70	**.73**	**.62**	.80	.65	.53	.60	.69	.48	.77
Bigram	.62	.28	.68	**.68**	.41	.68	.59	.40	.52	.67	.43	**.69**	.53	**.45**	.52	.64	.43	.66
N	.67	.35	**.73**	**.68**	.40	.73	.61	.30	.58	.66	**.50**	.71	.62	.49	.58	.66	.48	.71
A	.65	.31	.66	.63	.11	.62	.63	.36	.65	.54	.35	.58	.66	.56	.65	**.68**	**.58**	**.73**
V	.61	.19	.62	.60	.25	.63	.63	.37	.66	.56	.16	.47	.64	**.53**	.62	**.65**	.52	**.69**
NV	.67	.35	.75	.68	.44	**.75**	.59	31	.54	**.68**	**.54**	.73	.62	.53	.61	.66	.50	.70
NA	.71	.45	.78	.71	.49	**.78**	.63	.24	.56	**.73**	**.60**	.77	.67	.52	.65	.70	.51	.75
VA	.67	.38	.70	**.68**	.42	**.71**	.62	.27	.57	.67	**.50**	.69	.63	.47	.60	.67	.47	.66

Note: Baseline = Unigram, N= Nouns only, A=Adjectives only, V= Verbs only, NV = Nouns + Verbs, NA = Nouns + Adjectives, VA = Verbs + Adjectives.

Table 4: Performance metrics for linguistic feature-based detection for anticipation.

Model / Features	MNB			LR			KNN			SVM			DT			RF		
	Acc.	F1	AUC	Acc.	F1	AUC	Acc.	F1	AUC	Acc.	F1	AUC	Acc.	F1	AUC	Acc.	F1	AUC
Baseline	.70	.01	.75	.75	.43	**.81**	.73	.45	.67	**.76**	**.56**	.78	.67	.46	.61	.74	.38	.77
Bigrams	.60	.12	.70	.63	.43	**.72**	.60	.44	.62	**.66**	**.52**	.71	.53	.42	.57	.62	.38	.70
N	.71	.21	.67	.71	.26	**.70**	.69	.20	.57	**.71**	**.43**	.69	.65	.39	.57	.71	.37	.67
A	.68	.04	.56	.70	.28	.68	**.73**	.40	.70	.64	.00	.52	.71	.51	.65	.71	**.53**	**.73**
V	.69	.06	.50	.68	.20	.66	.73	.41	.70	.67	.21	.41	.71	**.54**	.66	**.73**	.53	**.75**
NV	.70	.18	.69	.72	.28	**.73**	.70	.11	.56	**.72**	**.46**	.70	.66	.41	.58	.72	.37	.69
NA	.72	.22	**.73**	**.73**	.32	.75	.66	.21	.55	.72	**.45**	.73	.67	.43	.59	.73	.43	.71
VA	.71	.20	.67	**.72**	.30	**.68**	.68	.25	.56	.70	**.41**	.66	.67	.38	.59	.69	.32	.65

Note: Baseline = Unigram, N= Nouns only, A=Adjectives only, V= Verbs only, NV = Nouns + Verbs, NA = Nouns + Adjectives, VA = Verbs + Adjectives

5 CONCLUSION

The present study developed linguistic feature- based emotion detection (anger and anticipation) using machine learning algorithms. Experiments conducted using YouTube comments gathered during the initial phase of Covid-19 lockdown in the country revealed the role of POS features specific to anger and anticipation prediction. Combinations of nouns and adjectives improved the performance of RF for anger prediction whereas verbs improved RF performance for anticipation prediction. Overall, SVM + Unigram, vectorized with TF-IDF yielded the best results in predicting both anger and anticipation.

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