Volume 65, Issue 3, 2021

Journal of Scientific Research

Institute of Science,

Banaras Hindu University, Varanasi, India.

Sentiment Analysis of Social Media Tweets on Farmer Bills 2020

Mukhtiar Singh*[1], Vishal Goyal[1], Sahil Raj[2]

[1]Department of Computer Science, Punjabi University, Patiala, India.
mukhtiarrai73@gmail.com*, vishal.pup@gmail.com
[2]School of Management Studies, Punjabi University, Patiala, India. dr.sahilraj47@gmail.com

***Abstract*: Online media has become the stage for expressing interest and criticize the things and policies of the organizations and government. Every internet user has the freedom to express their view and share their felling on this platform. In the context of India, the Government promulgated the farmers related to three acts, and the population of India especially farms are opposing these three acts. The farmer community and other related communities are worried about the implementation of these acts. At least 70% of the population in India dependents on agriculture and they have shown resentment against these acts on a social media platform and have expressed their reviews. These communities have been used more than one language for expressing their views about these acts. Multiple languages have been mixed with those having different rules of grammars, which have become a challenging task for researchers to analyses the sentiments from such platforms. In this paper, the author projected statistical technique to perform sentiment analyse based on extracted agriculture tweets containing mixed content of English and Punjabi languages. In addition to this, we focused on the accuracy and performance of the agriculture data-set for the prediction of the sentiment on the tested data-set.**

***Index Terms:* Sentiment Analysis, Agriculture, Farmer Acts, Code-Mixed, Text data, Government Policies.**

I. INTRODUCTION

Nowadays online media has become the means of communication such as Facebook, Twitter, LinkedIn, etc. (Yang et al., 2013) (Fazil & Abulaish, 2018). People of different age groups and working groups are active on such communication channels. They openly express their views and opinions related to different products and policies of the organizations and Government. In India, the Union Government passed three farm acts and people have shown resentment and opposed these acts on different social media platforms. India has the second rank in the list of agriculture producers (*Top Agricultural Producing Countries*, n.d.). There are more than 70% of the population-based on the agriculture domain (Nagaraja et al., 2019). Different communities are dependent on agricultural produce. Especially, in the rural areas of India are dependent on this domain (Arora, 2013). The Indian Government passed three agriculture-related farmer-bills ordinance, 2020, namely- (1) protection and empowerment (*The Farmers' Produce Trade and Commerece(Promotion and Facilitation)*, n.d.), (2) Facilitation and promotion (*The Farmers (Empowerment and Protection) Agreement on Price Assurance and Farm Services Bill, 2020*, n.d.), and The Essential Commodities (*The Essential Commodities (Amendment) Bill, 2020*, n.d.). As per the statements of the Indian Government these bills were introduced for the betterment of the Indian farmers but the farmers do not agree with the Government they have shown their resentment on different online media such as Facebook, Twitter, YouTube, etc. They have made different WhatsApp groups and Facebook pages and YouTube channels to oppose the farm's acts or bills. Almost all agriculture economists and consultants were batting for these reforms within the agriculture sector. To analyse the sentiments of the expert groups and the farmers from the social media platform the sentiment analysis plays a vital role research and development field.

In the present scenario, the importance of sentiment analysis has been increased due to the vast development of social media (Beigi et al., 2016). The analysis of views and opinions of the people from different online platforms has become a need of the hour. People have the freedom to freely write content on the internet or openly express their opinions.

In this study, the authors extracted the textual data from social media related to three farm acts passed by the Indian Government and the farmers have opposed the same acts. Such opinions have been expressed by using Natural language

* Corresponding Author

processing which can work in the decision-making process in different domains (Ghosh, 2009). The purpose of our research we have proposed a novel textual data analysis tool for sentiment analysis for farm acts passed by the Indian Government as summarized below:

- The authors generated a dictionary of English and Punjabi code mixed language from the comments collected from Facebook, Twitter, and YouTube related to farm acts. The dictionary is created after the extensive cleaning process.
- Ours proposes a textual data analysis using a statistical tool for sentiment analysis from the generated dictionary of the English and Punjabi code mixed language.
- Parameters such as accuracy, F1-score are used to check the reliability of our proposed system.
- A confusion matrix of positive, negative, and combined sentences based on the Fivegrams and Trigrams approach was developed.

The paper categorized into the sections. In 1st_section represented the conceptual Framework of Sentiment Analysis. 3rd_section presents related research work. In 4th_section explains the proposed methodology, used in our approach. Section 5 depicts results and experiments, whereas Section 6 concludes the paper.

II. Conceptual Framework of Sentiment Analysis

In our research, we have identified some areas of research where sentiment analysis has been used for the identification and judgment of the behavior of people. The different articles published in such areas are presented in Table 1.

Table 1: Conceptual Framework of Sentiment Analysis

Author(s)	**Area of Research**	**Method(s)**	**Work Performed(s)**
(Komarek et al., 2020)	Worked on major risks associated with agriculture published between 1974 and 2019.	Temporal_Scale,Geographic_Focus, and Study_ method.	The Impotence of each risk was depicted and also focused on conceptual issues in agriculture.
(Georgiadou et al., 2020)	Performed sentiment analysis of UK-EU Brexit negotiations over the Twitter.	International negotiation toolbox.	Revealed negative or positive feelings on the data-set Brexit
(Hürlimann et al., 2016)	Brexit Twitter Sentiment Gold Standard.	Sampling and Filtering, Annotation, Agreement, Consolidation	Opinions about government and politicians were analyzed.
(Jones et al., 2017)	Agricultural systems science.	Economic optimization and simulation models.	Agricultural system tools and methods are designed, developed, and implemented for the next generation.
(Meuwissen et al., 2019)	Farming systems in Europe and beyond.	The conceptual and methodological framework was presented.	Farmers feeling distressed about transformation.
(de las Heras-Pedrosa et al., 2020)	COVID-19	Digital ecosystems.	Analysis of emotions and sentiments on Spaniards in COVID-19 pandemic.
(X. Wang et al., 2020)	Public opinions toward COVID-19.	Twitter streaming API.	Compared the sentiments of California and New York Twitter users towards COVID-19.
(Samuel, Rahman, et al., 2020)	COVID-19	Novel sentiment polarity based.	Implemented at high and anticipation level sentiment analysis and mixed with relatively lower levels of sadness and fear.
(Samuel, Ali, et al., 2020)	COVID-19	Machine learning (ML) classification n with Naive Bayes classifier.	Identified COVID-19 fear sentiment progression.
(Alguliyev et al., 2019)	Sentiment analysis of e Government.	SONEX	This showed that the synthesis of microblogging

			websites does not reflect on the situation of real-life.
(Hubert et al., 2018)	Public issues discussed between citizens and government	Event drops, and Extended Hasse Diagrams.	Analyzed the government presence and citizen participation.
(Singh et al., 2018)	Demonetization policy implemented by the Indian government.	State-wide analysis.	Depicted the positive and negative impact of demonetization policy by sentiments analysis from initial days to last days.
(Singh et al., 2019)	Sentiment analysis of GST implemented by the Government of India.	Pragmatic	The sentiment was performed to analyzed the negative side that raised lead the Indian Government to take actions accordingly.
(Zavattaro et al., 2015)	Opining-mining the local Government of the U.S.	Systematic random sample.	The sentiment of tweets in context to U.S. local_ Government was performed and found neutral.

III. Related Work

Sentiment analysis researchers have been studied for a few years back. Till now, sentiment analysis of contents written in a single language was the focus of the research (Dashtipour et al., 2016), whereas over the last few years the interest of the researcher has been moved towards mixed code textual data written in two or more languages. It has been noticed that people who like to express their views and feelings on online social media platforms like to use two more languages (Lantz-Andersson, 2018). Focusing on the field of agriculture, (Fetanat et al., 2015) created an agricultural information system by collecting organized agricultural datasets (Fetanat et al., 2015). Patterns in data are extracted by data mining so that a knowledge base will be generated to facilitate decision making in agricultural corporations. (Mittal & Agarwal, 2013) have analyzed the different data-mining techniques used for agriculture domain. It has been suggested that the proper usage data analysis can contribute higher profits. (Palepu & Muley, 2017) highlighted the importance of data mining for soil analysis (Palepu & Muley, 2017). (Fetanat et al., 2015) have used regression techniques to analyze the data and highlighted the effect of chlorophyll on the carnality of flowers. They have also used agricultural data used for the analysis (Fetanat et al., 2015). (Majumdar et al., 2017) were used some techniques such as CLARA, PAM etc., to prove the best optimizations for maximizing the crop production. They also analyzed the clustering techniques and also proved that the results of DBSCAN and CLARA are better as compare to PAM.

IV. Proposed Methodology

A) *Data collection*

In our experimentation, the data is collected from Facebook, Twitter, and YouTube social media platforms. The collected data is related to farm acts passed by the Indian Government. We selected English-Punjabi code mixed data from Twitter, Facebook, and YouTube. A total of 95800 comments have been collected. After the collection of data, the cleaning process is performed for the generation of a dictionary for better results of the proposed approach.

B) *Data cleaning*

Cleaning of data plays a vital role after cleaning of data. A chunk of undesirable information is always present within the data. So it becomes significant to apply preprocessing to the text so that undesirable data can be removed. Besides pre-processing step is used to remove the un-required tokens such as #tags, punctuation's, repetitions of the characters, URLs, spaces between words, emotions. In the proposed system following pre-processing steps are applied for the removal of special symbols.

- **Language Identification:** This step is used to extract the relevant data. As social media users express their opinion or emotions using their mother language or other official languages. So it is very complicated to extract the relevant text data from the micro-blogging websites. So, we inspected the text data based on the geographical area from the micro-blogging websites containing data in both English and Punjabi language has been used. With the help of regular expression, we extracted the code mixed text.
- **Emoticons removal:** The emoticons, such as 😀😓😫😟 are very prevalent on micro-blogging sites all the emoticons were removed.
- **Punctuation removal:** In the proposed research, a punctuation mark also has removed. If exist in the text, it has removed any single quotes.
- **Abbreviation removal:** Abbreviations include mostly slang's. These types of words are very useful and important for sentiment analysis but it is added to the complexity of analysing sentiments. To normalize all these words the proposed method has used an abbreviations list. For example u ("you"), y ("why"), etc.
- **Hashtags removal:** These are the special symbols that are widely used for subject naming, like #iPad, #news.

- **URL's** and user references (identified by tokens "https" and "@") are removed for analyzing the text of the sentence.
- **Hyperlinks** These are the links to some other web-pages. These are found in the comments also. To analysing the sentiments of the farmers have removed such type of URLs from the collected data-set.
- **Multiple Character Repetitions or Wordplay** are being widely used on micro-blogging sites where usually informal language is used in the text like "Kisan are very angryyyyyyyyyyy", "Kisan Union Jindabaaaaaaaaddddd!" etc. Certain alphabets are repeated more than once. Such types of words add to the complexity as these words are not found in any dictionary. The proposed system has replaced the occurrence of such repeating letters with regular expression.

C) *Data pre-processing*

- **Tokenization** is the process of breaking down a word in such a way so that computers can understand text into words. It separates a piece of text data into smaller meaningful units called tokens. White space and punctuation can be used to separate individual tokens of a sentence (Mittal & Agarwal, 2013). In the proposed system a code mixed statement of tokens is given as an input to the language Identifier. Separation of tokens belonging to English and Punjabi language is done by appending /eng and /pun respectively and the token that belongs to both English and Punjabi Language is appended by /both. Consider a code mixed statement:- "Sat shri kaal kisan veero, carry on."will be tokenized as Sat/both shri/pun akaal/pun kisan/pun veero/pun carry/eng on/eng.

- **Lowercase Conversion:** The proposed system converts all the characters within the word into lowercase to match with the proposed English-Punjabi code mixed dictionary as it contains all the words in lowercase.

- **English-Punjabi Sentiment Words (EPSW):** By using the N-gram approach a dictionary containing both positive and negative words have been generated.

- **Acronyms:** These days micro-bloggers use the minimum number of alphabets to type a text quickly like f9 (fine), gr8 (great), 10m (10 men), w8 (wait), etc., These words should be normalized to get the sentiment analysis of the text.

- **Phonetic Typing:** In this type, speech sounds are represented visually. A word can be pronounced in different ways among different language dialects, which results in different spellings of the same word when written in Roman script. The pronunciation of a word depends upon the dialects of a language. For instance, the Punjabi word 'ਬਹੁਤ' ('Very' in English) could be written in multiple ways such as- bahut, bht, bahot.

- **N-Grams** are one of the most frequently used approaches (Go et al., 2009), (Srivastava et al., 2019) and (W. Wang & Wu, 2011). N-grams are a sequence of n words. As the name suggests 2-gram(bigram) is having two words in sequence such as "come here" likewise 3-gram(trigram) contains three words in a sequence as "how are you" similarly 4-gram (four words), and 5-gram (five words). (Shoukry & Rafea, 2012) studied that reflect that in dealing with bigrams performance cannot be improved. (Mountassir et al., 2013) and (Mohammed Rushdi-Saleh, 2011) studied and found that Trigrams give more accuracy. In this study, we have tried the n-gram approach up to Fivegrams and found that the results of Fivegrams are similar to the Trigrams approach for English-Punjabi code mixed text. The kind of n-gram also depends upon the type of domains.

D) *Generation of dictionary*

In order to convert unstructured data into structured data, dictionary has been generated. The system accuracy is always depends upon the quality or size of the dictionary. In order to increase the polarity capacity of the dictionary comprehensive review was performed on the generated dictionary manually by adding or removing words. The distribution of the data-set is categorized into three types of contents like positive words have assigned polarity 1 and negative words are presented by -1 and neutral words have assigned the polarity 0.

V. Experimental Results

This section presents results-experimental that has been carried out for the proposed approach.

A) *Datasets*

The data is collected from Twitter, Facebook, YouTube, and group chats from WhatsApp groups respectively. For experimentation, the multilingual English-Punjabi textual data collected for the period of 20, August 2020 to 03, October 2020. A total of 95,800 comments are collected and the data is stored in text files having extensions (.csv) and (.txt).

Table 2: Corpus statistics of English-Punjabi Data

English-Punjabi Language	Total Size (Sentences)
Total Number of Sentences or comments	95,800 sentences
The average length of each Sentence or comment	12 words
The average number of sentences per post	1 sentence
Tokenization size	11,73,778 words

Based upon the English and Punjabi code-mixed lexicon approach, the sentiment lexicon approach determines the polarity of the sentence. For the frequency of the sentences in the corpus, we need to normalize the value between 0 and 1.

Because there was a huge variation in the frequency of the word and if we use direct frequency value in finding the polarity of the sentence it gave us wrong results. Some of the sentence frequency is either low or high. To normalize the polarity frequency score we used the following equations:

$$\mathbf{POS}_{\mathbf{SCORE}_i} = \frac{\mathbf{PF}_i}{\mathbf{PF}_i + \mathbf{NF}_i}$$

$$\mathbf{NEG}_{\mathbf{SCORE}_i} = \frac{\mathbf{NF}_i}{\mathbf{PF}_i + \mathbf{NF}_i}$$

B) *Finding polarity*

In the polarity finding step, the proposed system checks the polarity such as positive or negative of all the words in a sentence. Words like State Name, Country Name, Pronoun, etc. do not affect the polarity of the sentence are considered neutral. We find both negative as well as positive polarity score using this equation:

$$\mathrm{POL}_{\mathrm{POS}} = \sum_{i=0}^{n} \mathrm{POS}_{\mathrm{SCORE}_{i+1}}$$

$$\mathrm{POL}_{\mathrm{NEG}} = \sum_{i=0}^{n} \mathrm{NEG}_{\mathrm{SCORE}_{i+1}}$$

C) *Experimental setup*

In experiments, we have used statistical tools at sentence level for analysis of sentiment polarity of the English-Punjabi code-mixed data-set. The experiment is performed on Linux Mint OS (i.e., Linux Mint 19.2 Cinnamon) with an Intel Core i3 processor and 4 GB RAM. A novel statistical tool using a dictionary-based data set is proposed and working of the same is as follows:

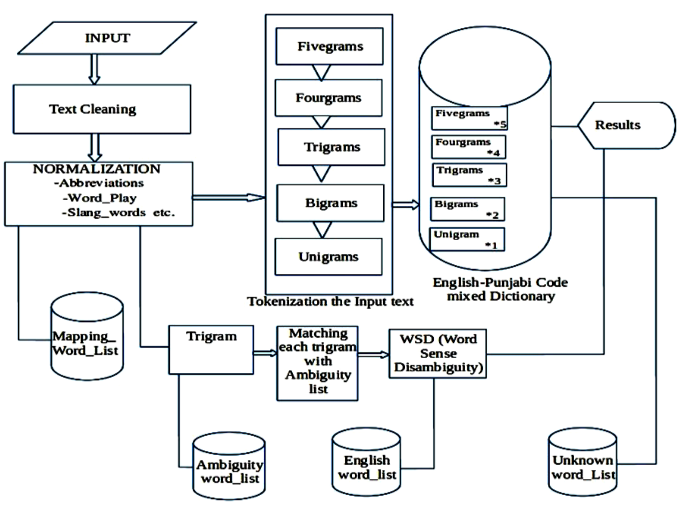

Figure 1: System architecture of Sentiment analyzer

D) *Performance metrics*

The results are evaluated using parameters (such as Recall, F1-score, Accuracy, and precision). 200 sentences were randomly selected and are evaluated manually and by a statistical tool. We faced and devised on evaluating sentiment analysis. Those sentiments which have positive sentiment (marked as positive) and sentiments which have negative sentiment (marked as negative). Then, about class positive: True-Positive (TP), False-Positive (FP), True-Negative (TN), and False-Negative (FN). The results are presented below:

Table 3: Confusion Matrix

Fivegrams approach			**Trigrams approach**		
200*3=600	**Actual Correct**	**Actual Incorrect**	**200*3=600**	**Actual Correct**	**Actual Incorrect**
Predicted Correct	TP=166	FP=34	**Predicted Correct**	TP=167	FP=33
Predicted Incorrect	FN=68	TN=330	**Predicted Incorrect**	FN=66	TN=33
True Positive (TP): The system predicted yes, and they are yes True Negative (TN): The system predicted no, and they are no False Positive (FP): The system predicted yes, but they are no False Negative (FN): The system predicted no, but they are yes					

Table 3 depicts the confusion matrix for the total sum of predicted and true tags of positive, negative, and neutral sentences, i.e. combined confusion matrix. The confusion matrix shows predicted tags on y-axes and true tags on x-axes. It is seen that the Fivegrams approach is similar to the results up to the Trigrams approach.

E) *Sentiment classification performance metrics*

Generally, sentiment classification performance is measured by using parameters. This is the normal approach to compute these indexes which depends upon the confusion matrix. The equations of these indexes given bellow:

Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
F1-Score	$\frac{2(Recall*Precision)}{(Recall*Precision)}$

All measurements (mentioned are above) are practically represented. TP (True-Positive) is the rate by which true positive is determined as true and TP (True-Negative) is the rate by which true negative sentences are expected to be negative. The rate at which the method predicts results correctly is represented as accuracy. The positive predictive rate is also known as precision is used to calculate. The percentage degree of various techniques on accuracy of micro-blogging content is presented by researchers (Gelman & Hill, 2006). The accuracy of each technique is calculated of the positive, negative, or neutral proportion. The accuracy for the Fivegrams approach and Trigrams approach is presented in Table4. In Table 4, the results by a statistical tool in form of parameters in context to Fivegram and Trigram approaches are illustrated.

Table 4: Precision, Recall, F1 Score and Accuracy of Proposed System

Metrics	Fivegrams approach	Trigrams approach
Accuracy	82%	83%
Precision	0.8291457286432161	0.8341708542713567
Recall	0.7081545064377682	0.7155172413793104
F1-Score	0.763888888888889	0.7703026241299304

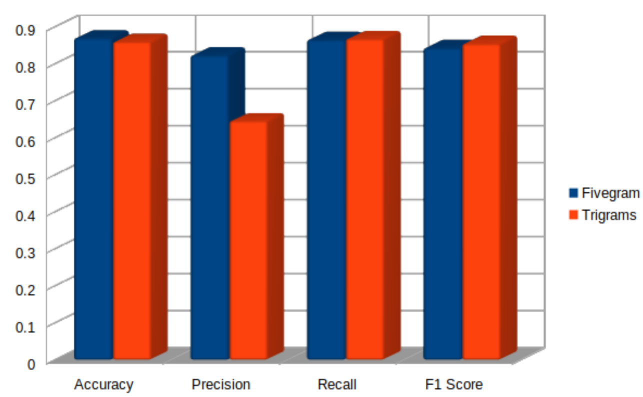

Figure 2: Results (accuracy, precision, recall, and f1-score) over Dataset.

Although the proposed statistical tool is based on a sentence level, it can care for the ordering of sentences at most times. The authors presented the results among the Fivegrams and Trigrams approach in evaluating the correctness percentage of achievement of the coverage parts in an agriculture sentence. As shown in Figure 2, the Fivegrams approach and Trigrams approach accuracy has 83% and 82% respectively, followed by total sentiment score.

Conclusion

In this paper, the authors have extracted the text data and sentiment analyzed, from social media users, in agriculture field by using a labelled corpora. The data related to agriculture domain has been collected from micro-blogging websites and then cleaning and pre-processed. A statistical technique is applied at the sentence level for the identification of sentiment polarity of the English-Punjabi multilingual text data. In experimentation, results showed an accuracy of up to 83% with an F-1 measure of 0.77. The success of the statistical technique depends on the quality of labeled corpora. Besides using such a robust data-set, the accuracy achieved is acceptable. The authors analyzed in this paper that results up to the Fivegrams approach and Trigrams approach which depicted the better results. In the future, our plan will explore the other methods and techniques of sentiment analysis. There is still room for improvement by including some parameters, such as the domain, features, and classifiers.

References

Alguliyev, R. M., Aliguliyev, R. M., & Niftaliyeva, G. Y. (2019). Extracting social networks from e-government by sentiment analysis of users' comments. *Electronic Government*, *15*(1), 91–106. https://doi.org/10.1504/EG.2019.096576

Arora, V. (2013). Agricultural Policies in India: Retrospect and Prospect. *Agricultural Economics Research Review*, *26*(2), 135–157. http://www.indianjournals.com/ijor.aspx?target=ijor:aerr&volume=26&issue=2&article=001&type=pdf

Beigi, G., Hu, X., Maciejewski, R., & Liu, H. (2016). An overview of sentiment analysis in social media and its applications in disaster relief. *Studies in Computational Intelligence*, *639*(January), 313–340. https://doi.org/10.1007/978-3-319-30319-2_13

Dashtipour, K., Poria, S., Hussain, A., Cambria, E., Hawalah, A. Y. A., Gelbukh, A., & Zhou, Q. (2016). Multilingual Sentiment Analysis: State of the Art and Independent Comparison of Techniques. *Cognitive Computation*, *8*(4), 757–771. https://doi.org/10.1007/s12559-016-9415-7

de las Heras-Pedrosa, C., Sánchez-Núñez, P., & Peláez, J. I. (2020). Sentiment analysis and emotion understanding during the COVID-19 pandemic in Spain and its impact on digital ecosystems. *International Journal of Environmental Research and Public Health*, *17*(15), 1–22. https://doi.org/10.3390/ijerph17155542

Fazil, M., & Abulaish, M. (2018). A Hybrid Approach for Detecting Automated Spammers in Twitter. *IEEE Transactions on Information Forensics and Security*, *13*(11), 2707–2719. https://doi.org/10.1109/TIFS.2018.2825958

Fetanat, H., Mortazavifar, L., & Zarshenas, N. (2015). The Application of Data Mining Techniques in Agricultural Science. *Ciência e Natura*, *37*, 108. https://doi.org/10.5902/2179460x20760

Gelman, A., & Hill, J. (2006). *Data analysis using regression and multilevel/hierarchical models*. Cambridge university press.

Georgiadou, E., Angelopoulos, S., & Drake, H. (2020). Big data analytics and international negotiations: Sentiment analysis of Brexit negotiating outcomes. *International Journal of Information Management*, *51*(October), 102048. https://doi.org/10.1016/j.ijinfomgt.2019.102048

Ghosh, S. (2009). Application of natural language processing (NLP) techniques in e-governance. *E-Government Development and Diffusion: Inhibitors and Facilitators of*

Digital Democracy, 122–132. https://doi.org/10.4018/978-1-60566-713-3.ch008

Go, A., Bhayani, R., & Huang, L. (2009). Twitter Sentiment Classification using Distant Supervision. *Processing*, 1–6.

Hubert, R. B., Estevez, E., Maguitman, A., & Janowski, T. (2018). Examining government-citizen interactions on twitter using visual and sentiment analysis. *ACM International Conference Proceeding Series*. https://doi.org/10.1145/3209281.3209356

Hürlimann, M., Davis, B., Cortis, K., Freitas, A., Handschuh, S., & Fernández, S. (2016). A twitter sentiment gold standard for the Brexit referendum. *ACM International Conference Proceeding Series*, *13-14-Sept*, 193–196. https://doi.org/10.1145/2993318.2993350

Jones, J. W., Antle, J. M., Basso, B., Boote, K. J., Conant, R. T., Foster, I., Godfray, H. C. J., Herrero, M., Howitt, R. E., Janssen, S., Keating, B. A., Munoz-Carpena, R., Porter, C. H., Rosenzweig, C., & Wheeler, T. R. (2017). Brief history of agricultural systems modeling. *Agricultural Systems*, *155*, 240–254. https://doi.org/10.1016/j.agsy.2016.05.014

Komarek, A. M., De Pinto, A., & Smith, V. H. (2020). A review of types of risks in agriculture: What we know and what we need to know. *Agricultural Systems*, *178*(October 2018), 102738. https://doi.org/10.1016/j.agsy.2019.102738

Lantz-Andersson, A. (2018). Language play in a second language: Social media as contexts for emerging Sociopragmatic competence. *Education and Information Technologies*, *23*(2), 705–724. https://doi.org/10.1007/s10639-017-9631-0

Majumdar, J., Naraseeyappa, S., & Ankalaki, S. (2017). Analysis of agriculture data using data mining techniques: application of big data. *Journal of Big Data*, *4*(1). https://doi.org/10.1186/s40537-017-0077-4

Meuwissen, M. P. M., Feindt, P. H., Spiegel, A., Termeer, C. J. A. M., Mathijs, E., de Mey, Y., Finger, R., Balmann, A., Wauters, E., Urquhart, J., Vigani, M., Zawalińska, K., Herrera, H., Nicholas-Davies, P., Hansson, H., Paas, W., Slijper, T., Coopmans, I., Vroege, W., … Reidsma, P. (2019). A framework to assess the resilience of farming systems. *Agricultural Systems*, *176*(May), 102656. https://doi.org/10.1016/j.agsy.2019.102656

Mittal, N., & Agarwal, B. (2013). Sentiment Analysis of Hindi Review based on Negation and Discourse Relation. *Sixth International Joint Conference on Natural Language Processing*, *October*, 57–62. http://www.aclweb.org/website/old_anthology/W/W13/W13-43.pdf#page=57

Mohammed Rushdi-Saleh, M. T. M.-V. (2011). OCA: Opinion Corpus for Arabic. *Journal of the American Society for Information Science and Technology*, *64*(July), 1852–1863. https://doi.org/10.1002/asi

Mountassir, A., Benbrahim, H., & Berrada, I. (2013). Sentiment classification on arabic corpora: A preliminary cross-study. *Document Numerique*, *16*(1), 73–96. https://doi.org/10.3166/DN.16.1.73-96

Nagaraja, G. S., Soppimath, A. B., Soumya, T., & Abhinith, A. (2019). IoT Based Smart Agriculture Management System. *CSITSS 2019 - 2019 4th International Conference on Computational Systems and Information Technology for Sustainable Solution, Proceedings*, *4*, 1–5. https://doi.org/10.1109/CSITSS47250.2019.9031025

Palepu, R. B., & Muley, R. R. (2017). *An Analysis of Agricultural Soils by using Data Mining Techniques*. *7*(10), 1–7.

Samuel, J., Ali, G. G. M. N., Rahman, M. M., Esawi, E., & Samuel, Y. (2020). COVID-19 public sentiment insights and machine learning for tweets classification. *Information (Switzerland)*, *11*(6), 1–22. https://doi.org/10.3390/info11060314

Samuel, J., Rahman, M. M., Nawaz Ali, G. G. M., Samuel, Y., & Pelaez, A. (2020). Feeling Like It is Time to Reopen Now? COVID-19 New Normal Scenarios based on Reopening Sentiment Analytics. *ArXiv*. https://doi.org/10.2139/ssrn.3604802

Shoukry, A., & Rafea, A. (2012). Sentence-level Arabic sentiment analysis. *Proceedings of the 2012 International Conference on Collaboration Technologies and Systems, CTS 2012*, 546–550. https://doi.org/10.1109/CTS.2012.6261103

Singh, P., Dwivedi, Y. K., Kahlon, K. S., & Sawhney, R. S. (2019). Smart Monitoring and Controlling of Government Policies Using Social Media and Cloud Computing. *Information Systems Frontiers*, *1*, 1–23.

Singh, P., Sawhney, R. S., & Kahlon, K. S. (2018). Sentiment analysis of demonetization of 500 & 1000 rupee banknotes by Indian government. *ICT Express*, *4*(3), 124–129.

Srivastava, A., Singh, V., & Drall, G. S. (2019). Sentiment analysis of twitter data: A hybrid approach. *International Journal of Healthcare Information Systems and Informatics*, *14*(2), 1–16.

The Essential Commodities (Amendment) Bill, 2020. (n.d.). Retrieved October 12, 2020, from https://www.prsindia.org/sites/default/files/bill_files/Essent%0Aial Commodities %28Amendment %29 Act%0A%2C 2020.pdf

The Farmers' Produce Trade and Commerece(Promotion and Facilitation). (n.d.). Retrieved October 12, 2020, from https://www.prsindia.org/sites/default/files/bill_fi%0Ales/Farmers Produce Trade and%0A Commerce %28Promotion and Facilitation%0A%29 Act%2C 2020.pdf.

The Farmers (Empowerment and Protection) Agreement on Price Assurance and Farm Services Bill, 2020. (n.d.). Retrieved October 12, 2020.

Top Agricultural Producing Countries. (n.d.).

Wang, W., & Wu, J. (2011). Emotion Recognition Based on CSO&SVM in E- Learning. *2011 Seventh International Conference on Natural Computation*, *1*, 566–570.

Wang, X., Zou, C., Xie, Z., & Li, D. (2020). *Public opinions towards COVID-19 in California and New York on Twitter*. *1*, 1–17.

Yang, C., Harkreader, R., & Gu, G. (2013). Empirical evaluation and new design for fighting evolving twitter spammers. *IEEE Transactions on Information Forensics and Security*, *8*(8), 1280–1293.

Zavattaro, S. M., French, P. E., & Mohanty, S. D. (2015). A sentiment analysis of U.S. local government tweets: The connection between tone and citizen involvement. *Government Information Quarterly*, *32*(3), 333–341.

***