ISSN 2278-3091
Volume 8, No.1.3, 2019
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse7181.32019.pdf
https://doi.org/10.30534/ijatcse/2019/7181.32019

A Preliminary Study on Mechanism and Measurement of Trustworthiness on a Crowdsourcing Platform

Muhammad Alif Basar, Nursuriati Jamil, Siti Khatijah Nor Abdul Rahim
Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, 40450 Shah Alam, Malaysia,
areleafs@gmail.com, lizajamil@computer.org, sitikhatijahnor@tmsk.uitm.edu.my

ABSTRACT

Crowdsourcing is becoming a norm among Internet users as it can be a convenient and cost-saving way of obtaining information or input into a task by enlisting a crowd of people. However, data obtained through a crowdsourcing platform may not be reliable and may lead to misinformation or misleading conclusions. Therefore, the need to evaluate and measure the trustworthiness of crowdsourced data is of utmost importance. In this paper, existing methods of evaluating the trustworthiness of data gathered from a crowdsourcing platform is studied. The aim is to investigate the different mechanism and measurements of trust and reliability of crowdsourced data. As implementation of evaluating trustworthiness is domain dependent, we selected the relevant mechanisms and measurements to be considered in our proposed speech emotion annotation in a crowdsourcing platform. After further studies, we decided to adapt and integrate selected mechanisms and measurements from the incentive, quality of participant and system control methods to be implemented in our proposed work in the future.

Key words : Crowdsourcing platform, crowdsourced data, speech emotion annotation, trustworthiness.

1. INTRODUCTION

Crowdsourcing is an efficient way of collecting data suitable for many tasks requiring a crowd of participants for the same objective to solve a problem [1]. The participant can either be random or trained to provide outputs over a set of tasks or to optimize a task design. The crowd can easily be sourced from the Internet and bypass many protocols and procedures otherwise required for a survey. It can also become another option of providing a mass amount of data to many applications while saving cost. Crowdsourcing can be useful when the traditional way of obtaining data labels or tagging is expensive [2]. For example, the traditional way of annotating emotions in spontaneous speech audio samples may become very expensive as it requires either random or selected professional human-participants, equipment or studio. Furthermore, the participant's welfare also needs to be taken care of during the annotation process. With crowdsourcing implemented, the cost of equipment and studio can significantly be reduced as the annotation can be done anywhere as long as the participant has an Internet connection. Breaking a large task objective into smaller tasks enabled great flexibility in crowdsourcing. The crowdsourcing model may provide a researcher with access to various new possibility and ideas, opportunities for reaching people across the globe, optimize the application process and reduce costs.

However, the trustworthiness and reliability of the data gathered from a crowdsourcing exercise are still questionable [3][4]. Computing solution using inaccurate crowdsourced data is risky and may lead to the wrong conclusion in solving a problem or innovation, in some cases, threatening. In many speech emotion recognition applications such as robotics, advanced health monitoring, and language synthesis, accurate recognition of emotion is a critical factor. Untrustworthy data may lead to the wrong conclusion as well as action taken reacting to the speech. An example of a poor trustworthy data in crowdsourcing is Wikipedia, where many measures were taken to solve the inaccurate information uploaded and preserving the trust on the data provided by the crowd [5].

Trustworthiness in crowdsourcing data collection often presented several challenges. One of the most pressing challenges is the fact that the participant motivation to complete the task is not easily defined [4]. Some participant may complete a task for passion and pride, while others are merely to increase their monetary capital [6]. An example of crowd motivation is for YouTube; a participant can either upload a video out of passion like teaching others with new knowledge and skills. On the other hand, another participant uploads a video to reach many views as YouTube provides an excellent monetary incentive that allows a YouTuber to earn millions in their pocket. Good incentive model may affect the motivation level of a participant resulting in producing reliable and trustworthy data [4].

Another challenge is the quality of crowdsourced data [4]; this is related to the expertise of the crowd itself. Some task requires eminent domain expert, for example, recognizing emotion in a specific language accent or dialect speech requires the participant to understand the dialect or at least the language. Crowdsourcing data quality is also often questionable because there are many damage data from a fake survey, fake reviewer, and social media spammer [4]. For example, a participant may fake his or her gender in an online survey that requires a gender-based result. This fake answer affects the research result as it may lead to the wrong conclusion.

In this paper, we conduct a preliminary study on the approaches to enhance the trustworthiness and reliability of the data in a crowdsourcing platform. In general, there is three categories of approaches: 1) Incentive and Motivation [7], 2) Quality of Participant (also known as Reputation [4], Ranking [8] or Rating [9][10], and 3) System Control. We review their domain and purpose of the crowdsourcing platform, quality mechanism and measurement as reported in the literature. Furthermore, we compared how trustworthiness enhancements were implemented to provide insights for our crowdsourcing research. The findings of this study are further used as guidelines for the implementation of a crowdsourcing platform for spontaneous speech emotion recognition. This paper is organized as follows: Section II discusses the related work of speech emotion annotation in crowdsourcing platform. In Section 3 to 5, the three common approaches of evaluating trustworthiness are described. This is followed by the discussion of the each approaches in Section 6 and concludes with the selections of mechanisms and measurements in Section 7.

2. RELATED WORK

In spontaneous speech emotion recognition, crowdsourcing is used to get as many participants for contributing new audio sample or identify emotion in an audio sample provided by the platform. The participant is no longer required to physically attend the annotation process [2]. This model may provide a researcher with access to various new possibilities and ideas, opportunities for learning from people across the globe, optimized the annotation process and consequently reduced costs. However, the trustworthiness and reliability of the crowdsourced data may be questionable [3].

Emotion labelling or also known as emotion annotation of spontaneous speech is a challenging task. A major issue of such studies is that they rely on a manual annotation which is usually rather subjective [11]. The real challenge in recognizing emotion featured in spontaneous speech is difficult because it is hard to distinguish one emotion from the other [12]. For example, when we talk about happy emotion featured in a speech; some people may annotate it differently. Currently, collecting at scale using the manual method is very expensive because participants may vary in when and to what degree they experience the desired emotion [13]. For example, the participants sat in a soundproof studio, with each of them has individual headset equipped. They listened to few audio samples trying to describe an emotion featured; the process should be done as neutral as possible. Moreover, if the annotation process required more participants or participant with expertise, the cost will greatly increase to cater the needs of room/studio, equipment, and participant's welfare.

Web-based crowdsourcing enables the annotation of many annotators from multitude of subjects in the Internet community, making it faster and cheaper than employing a small group of highly trained annotators [14]. Hence, online crowdsourcing would allow more participants with less cost as the process can be done anywhere online. The participant is no longer required to attend the annotation process physically [14]. Yet, with this approach, the reliability and trustworthiness are still in question as there are many spammers and malicious annotators that provide low quality data [13]. In order to solve or reduce the problem to minimal, we investigated three common approaches of trustworthiness measurement on a crowdsourcing platform.

3. INCENTIVE AND MOTIVATION

Incentive and motivation approach is one method that is extensively studied in online community in myriad of implementations. Its basic mechanism is quite simple as the participant gets certain kind of rewards after finishing a specific task. This method has been improvised many times by either enhancing the reward, action mechanism, architecture or its protocol. Implementing bad incentive method may result in paying monetary rewards for useless data [7].

In Table 1, we compared five crowdsourcing implementations using incentive and motivation approach. This approach provides incentive to the crowdsourcing participant with different kinds on incentive such as utility-related incentives [7], system credits or virtual credits [15], or monetary rewards [16][17]. The mechanism of rewarding the incentives is domain-dependent. For example, Trucentive [7] depends on another contributor/participant to receive the incentive, while [16] used response time to reward the contributor. As for the measurement of the contributed data, all the work presented in Table 1 shows that the quality of the data is determined by the motivation of contributors/participant via incentive approach.

4. QUALITY OF PARTICIPANT

Ranking is another common method used in crowdsourcing to evaluate the trustworthiness of the crowdsourced data. The basic mechanism of ranking requires a matrix of user ranking based on their contribution quality or endorsement from other users. A reputation score is computed as an indicator to determine the trust level of a participant. However, determining the ranking technique of the participants is still a fundamental issue of ranking approach. For example, the common problem in aggregate ranking and collaborative ranking [8] is always tied down with the score/grade in the ranking matrix which is domain specific. For example, the accuracy ranking of [10] is based on the accuracy of the contributed data, while reputation ranking of [8] is determined by the endorsement of high-rank participants.

Table 1: Comparisons of different implementations of incentive and motivation approach.

Method/Domain	Aim	Quality Mechanism	Quality Measurement
TruCentive [7] *Car-parking system*	Prevents fake and malicious participants from spamming the parking service with unreliable data.	The contributor reward is tied with the availability of parking that is validated by another user.	Contributor stated the availability of the parking space and the consumer looking for the parking validated that the parking is indeed available.
Price Model based on the number of participants [15] *Chinese MCM Problem B*	Maintains a participant's motivation on a specific task to preserve the quality of data.	The number of participants affects the amount of reward given to each participant.	The fewer people contributed in a particular task, the higher the incentive given to the participant
Price Model based on participant creditworthiness [15] *Chinese MCM Problem B*	Maintains a participant's motivation and stimulates enthusiasm to complete the task in time.	The reputation of a participant affects the incentive/reward for each task.	In the same task, a higher grade/creditworthiness of a participant gets a higher bonus incentive.
Kalman Filters [16] *Mobile Crowdsourcing*	Provides a good incentive plan to the participant to encourage them to provide trusted data in real-time, under limited cost.	Participant gets their incentive based on their contribution and response time.	The faster a participant contributes data, the more bonus incentive he received. The incentive is given to the participant after he validated the data quality.
All-pay contest model [17] *General Crowdsourcing*	Provides a flexible incentive cost to encourage participant to contribute high-quality data.	An incentive method using auction-based framework for a dynamic reward system.	Participant bids his reward based on their contribution's quality and effort.

Table 2: Comparisons of different implementations of Quality of Participant approach.

Method/Domain	Aim	Quality Mechanism	Quality Measurement
EndorTrust [4] *Task-base crowdsourcing*	Validate and predict the trustworthiness of a participant in contributing high quality data.	Using reputation mechanism as metric indicator to indicate a participant's trustworthiness as well as to indicate a participant's motivation.	Participant connected to each other via endorsement link that represents trust in task solving relationship. Those endorsement links has their score.
Maximum likelihood estimation [8] *Ranking optimization for crowdsourcing*	Further reduce overhead of unnecessary data in crowdsourcing data collection.	Maximum likelihood estimation (MLE) technique to estimate the participant reputation score under Bradley-Terry-Luce parametric model.	Compute matrix manifold optimization algorithm [8] to recover low-rank participant ranking in performance matrix with pairwise.
User Rating based Screening (URS) [9] *Image quality assessment*	To ensure the quality of the results in image quality assessment.	Detecting bad participant based on participant level of rating disagreement with the opinion's mean [9].	Compute the trustworthiness relationship between user ratings of a participant with a standard global rating.

Analysis of the Honeypots accuracy [10] *Data visualization*	To evaluate trustworthiness of a participant as collaborators.	The score will determine the rank of accuracy of a participant by comparing data from normal participant (student) with specialist (domain expert) over a series of task/questions.	Comparing score of trusted participant must meet the requirement of minimum accuracy of 45% to maximum of 100%. Then the participant is ranked according to the accuracy.

In Table 2, the comparison summary of four implementations of Quality of Participant is presented. Reputation score is a favourite mechanism of this approach as can be seen from the work of [4] and [8]. In [4], the trust rank of participants is measured using endorsement link. On the other hand, the reputation score of the participants are computed and ranked in a performance matrix in [8]. A standard rating is used in [9] as a benchmark to rank participant levels of trust. Meanwhile, a participant must meet a minimum accuracy score of 45% based on a series of task/questions in [10]. The score is determined by comparing against domain expert answers.

5. SYSTEM CONTROL

Recently, various research explored crowdsourcing trustworthiness to enhance system control [2][3][18] in order to improve trust in crowdsourcing data collection. Yet, the real challenge is either we can create a standard design of system control that is able to evaluate the trustworthiness contribution of data by the participant [3]. Several trustworthiness methods in system control are such as to evaluate task process for participant to contribute [6], material contribution (e.g. video, audio, coordinate) [3][19], algorithm in optimizing ranking score [10].

Table 3 summarizes four works to measure trust in a crowdsourcing platform. In System Control method, a system is used to evaluate trustworthiness of the crowdsourced data by applying filtering mechanism [3] [15], task scores [6] and protocols [18]. The system further decided on the trustworthiness of the contributed data or participants by the computed scores [3][6][18] or time taken to finish a task [15].

Table 3: Comparisons of different implementations of System Control approach.

Method/Domain	**Aim**	**Quality Mechanism**	**Quality Measurement**
Media references [3] *Emotion Recognition*	Increase trustworthiness of crowdsourcing emotion recognition annotated data.	To get initial score, a participant is required to annotate several "gold" standard audio samples. Filtering iterative assessment method is used during the annotation and the iterations stopped after the participant's performance dropped to a certain level.	By evaluating the filtering method and reference videos, the performance of the participant is compared with the provided scores. Thus, the system can decide which data can be considered trusted.
Motivation-aware task assignment [6] *General Crowdsourcing*	To match a task to a participant, the data is evaluated by trusted and reliable participant in the same domain expert.	Initial series of task were given to a participant to capture motivation and expertise. Based on this experience, suitable new tasks are assigned to the participant	Participant underwent several "test" tasks and scores were calculated for each test. System evaluated the score to determine which task is suitable for the participant bases on their motivation or expertise.
Filtering Spam [15] *Questionnaire*	Untrustworthy participants were filtered by the time duration given in contributing the crowdsourced data.	Applied filtering spam during task completion that consist two criteria: - Trap task/question - Task duration filter	- Trap task/question: to test whether a participant completed a task carefully or not. - Task duration filter: any task completed less then estimated duration is identified as spam.
Mushra-like tests [18] *General Crowdsourcing*	To evaluate trustworthiness and quality of audio contributed by the participant.	Using Multiple Stimuli with Hidden Reference and Anchor (MUSHRA) protocol for the subjective assessment of intermediate audio quality.	Compared several stimulations with reference to each other's stimulation. Quality is scaled from 0 to 100 using a set of sliders [18]

6. DISCUSSION

Various trustworthiness methods were introduced by researcher to preserve the trustworthiness and reliability of the crowdsourced data. These methods are domain specific, thus a lot of factors need to be considered before adopting any of the specified methods. In the following subsections, we discussed the pros and cons of each method to justify our proposed methods for speech emotion annotation using crowdsourcing.

6.1 Incentive and Motivation

Annotating emotions in speech requires a person who is native to the language spoken in the speech. This person can be a contributor and also to validate the contributed annotation. In TruCentive [7], fake and malicious participants were reduced by requiring the availability of the parking space being validated by other participants. TruCentive improvised the limitation of traditional bidding-based dynamic incentives by enhancing the protocol where the reward was tied with the availability of parking that was validated by other user. The mechanism used by TruCentive is that when a contributor stated the availability of a parking space, the consumer who was looking for the parking validated that the parking was indeed available. This mechanism can be applied well in speech emotion annotation as the process also required another person to validate the annotated emotion of the contributor.

6.2 Quality of Participant

An expert opinion is important in speech emotion annotation. Therefore, we believe that having a reliable high-rank participant as a mechanism to sustain reliability of the crowdsourced data is crucial. The implementation of EndorTrust [4] and Analysis of the Honeypots accuracy [10] are two examples that can be adapted to our speech emotion annotation crowdsourcing platform. EndorTrust offered validation of participant trustworthiness via endorsement metric indicator. We can ensure that the new participant is trusted based on the endorsements from high rank participant. In addition to the ranking status of a participant, we also planned to give incentives to participants that raised their rankings when giving reliable endorsement. The incentive mechanism of [10] that used creditworthiness measurement will be used to encourage trusted data from high-ranked participant. A high-rank participant, however, may not provide high accuracy crowdsourced data. In order to ensure the quality of the high-rank participant, we will also adapt the accuracy mechanism from [10] to enhance trustworthiness of our crowdsourcing platform.

6.3 System Control

Motivation-aware task assignment [6] method can be implemented in our proposed crowdsourcing platform as setup assistance for the system to do initial ranking. Newly registered participant will undergo series of tasks (in the pretence of a tutorial) to capture their initial motivation and to determine their expertise. The trustworthiness system will automatically use that data to assign suitable task category to the participant. The user is allowed to re-take the test to evaluate their level and score for better task with better incentive. Filtering Spam of [15] will also be adapted in our proposed crowdsourcing platform as minimum time duration to annotate emotion in speech is required. The task duration filter used in [15] is a good measurement to be used by the system to identify a spammer. If a participant annotates the speech segment in less than the minimum time duration, the system will labeled the participant as a spammer.

7. CONCLUSION

This study explored existing methods to measure and enhanced the mechanisms of evaluating trustworthiness in a crowdsourcing platform. Even though crowdsourcing for data is a cheaper and faster approach of collecting data, various precautions need to be in place as the participants and contributors may not be reliable and trustworthy [20]. The mechanism of improving data reliability varies as it depends on the domain application [21] of the crowdsourcing platform. For our speech emotion annotation work, we proposed to reach to the Internet users to annotate emotions in Malay language spontaneous speeches. Based on the preliminary study, some mechanisms of reliability that will be implemented are as follows:

- Participants and contributors must be familiar with the language to be annotated. The person must understand the language to validate the correctness of the entry contributed by others. An appropriate incentive will be given for each validated entry to motivate further participation. The participants will be required to perform several tasks during enrolment to ensure he/she is qualified to contribute.
- Participants and contributors will be ranked based on their expertise in annotating the correct emotions. The higher the rank, the more trust is assumed to the person. A high-ranked participant will further endorse new participants based on the validated correct annotated emotions. Incentives will also be given for reliable endorsements for encouragement. The mechanism of ranking will be done using endorsement metric indicator. Another mechanism, which is accuracy ranking, will also

be employed to enhance the measurement of trustworthiness.

- Due to the complicated mechanisms and tedious measurements of trustworthiness implementation, automation is a necessity to reduce human error. An intelligent agent is needed to perform intelligent ranking [22] of the participants based on their performance of the assigned tasks. Time duration is another parameter that needs to be considered by the intelligent agent. The implementation will require the use of machine intelligence [22] to successfully execute the ranking and accuracy measurement.

ACKNOWLEDGEMENT

Due acknowledgement is accorded to the Ministry of Education and Institute of Research, Management and Innovation, Universiti Teknologi MARA for the funding received through the Fundamental Research Grant Scheme, 600-RMI/FRGS 5/3 (019/2017).

REFERENCES

1. X. Li, H. He, and J. S. Baras. **Trust-aware optimal crowdsourcing with budget constraint,** in *Proc. IEEE International Conference on Communications (ICC),* 2015, pp. 1176-1181.
2. J. Smith, A. Tsiartas, V. Wagner, E. Shriberg, and N. Bassiou. **Crowdsourcing emotional speech,** In *Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP),* 2018, pp. 5139-5143. https://doi.org/10.1109/ICASSP.2018.8462224
3. A. Burmania, S. Parthasarathy, and C. Busso, **Increasing the reliability of crowdsourcing evaluations using online quality assessment.** *IEEE Transactions on Affective Computing*, Vol. 7, No. 4, pp. 374–388, 2016. https://doi.org/10.1109/TAFFC.2015.2493525
4. C. Wu, T. Luo, F. Wu, and G. Chen, **EndorTrust: An endorsement-based reputation system for trustworthy and heterogeneous crowdsourcing**. In *Proc. IEEE Global Communications Conference (GLOBECOM),* San Diego, CA, 2015, pp. 1-6.
5. S. Karim, U. Shaikh, and Z. Asif. **Motivating crowdworkers by managing expectations**. In *Proc. International Conference on Research and Innovation in Information Systems (ICRIIS).* Langkawi, 2017, pp. 1-4. https://doi.org/10.1109/ICRIIS.2017.8002539
6. J. Pilourdault, S. Amer-Yahia, S. Basu Roy, and D. Lee. **Task relevance and diversity as worker motivation in crowdsourcing**, In *Proc. IEEE 34th International Conference on Data Engineering (ICDE)*, Paris, 2018, pp. 365-376. https://doi.org/10.1109/ICDE.2018.00041
7. B. Hoh, T. Yan, D. Ganesan, K. Tracton, T. Iwuchukwu, and J.-S. Lee, **TruCentive: A game-theoretic incentive platform for trustworthy mobile crowdsourcing parking services**. In *Proc. 15th International IEEE Conference on Intelligent Transportation Systems*. Anchorage, AK, 2012, pp. 160-166. https://doi.org/10.1109/ITSC.2012.6338894
8. J. Dong, K. Yang, and Y. Shi, **Ranking from crowdsourced pairwise comparisons via smoothed matrix manifold optimization**, In *Proc. IEEE International Conference on Data Mining Workshops (ICDMW).* New Orleans, LA, 2017, pp. 949-956. https://doi.org/10.1109/ICDMW.2017.130
9. V. Hosu, H. Lin, and D. Saupe, **Expertise screening in crowdsourcing image quality**. In *Proc. Tenth International Conference on Quality of Multimedia Experience (QoMEX).* 2018, pp. 1-6. https://doi.org/10.1109/QoMEX.2018.8463427
10. G. R. Franciscani, R. Santos, M. Boaventura, P. D Bernardina, W. Meira, and R. C. de M. Minardi, **Experimental evaluation of crowdsourcing on the characterization of data visualization**, *2017 Brazilian Conference on Intelligent Systems (BRACIS)*, Uberlandia, 2017, pp. 432-437. https://doi.org/10.1109/BRACIS.2017.75
11. T.L. Nwe, S.W. Foo, and L.C. de Silva, **Speech emotion recognition using hidden Markov models**. *Speech Communication*, Vol. 41, No. 4, pp. 603-623, 2003. https://doi.org/10.1016/S0167-6393(03)00099-2
12. N. Apandi, and N. Jamil, **An analysis of Malay language emotional speech corpus for emotion recognition system**, In *Proc IEEE Industrial Electronics and Applications Conference (IEACon).* Kota Kinabalu, 2016, pp. 225-231. https://doi.org/10.1109/IEACON.2016.8067383
13. R. Snow, B. O'Connor, D. Jurafsky, and A.Y. Ng, **Cheap and fast—but is it good? evaluating non-expert annotations for natural language tasks,** in *Proc. Conf. Empirical Methods Natural Language Process.*, Honolulu, HI, USA, Oct. 2008, pp. 254–263. https://doi.org/10.3115/1613715.1613751
14. F. Getahun, and M. Kebede, **Emotion identification from spontaneous communication**. In *Proc. 12th IEEE International Conference on Signal-Image Technology & Internet-Based Systems (SITIS),* 2016 Nov 28, pp. 151-158. https://doi.org/10.1109/SITIS.2016.32
15. Y. Niu, Y. Zhang, and M. Song, **Pricing models for crowdsourcing tasks based on geographic information**. *In Proc. IEEE/ACIS 17th International*

Conference on Computer and Information Science (ICIS), Singapore, 2018, pp. 794-797. https://doi.org/10.1109/ICIS.2018.8466433

16. E. Mitsopoulou, I. Boutsis, V. Kalogeraki, and J.Y. Yu, **Cost-aware incentive mechanism in mobile crowdsourcing systems**. *2018 19th IEEE International Conference on Mobile Data Management (MDM)*, Aalborg, 2018, pp. 239-244. https://doi.org/10.1109/MDM.2018.00042
17. T. Luo, S. S. Kanhere,, S.K. Das, and H.-P. Tan, **Incentive mechanism design for heterogeneous crowdsourcing using All-Pay contests**. *IEEE Transactions on Mobile Computing*, Vol. 15, No. 9, pp. 2234–2246, 2016. https://doi.org/10.1109/TMC.2015.2485978
18. M. Cartwright, B. Pardo, G.J. Mysore, and M. Hoffman, **Fast and easy crowdsourced perceptual audio evaluation**, *2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Shanghai, 2016, pp. 619-623. https://doi.org/10.1109/ICASSP.2016.7471749
19. O. Zach, M. Seufert, M Hirth, M Slanina, and P. Tran-Gia, **On use of crowdsourcing for H. 264/AVC and H. 265/HEVC video quality evaluation**. In *Proc. 2017 IEEE 27th International Conference Radioelektronika (RADIOELEKTRONIKA*), 2017 Apr 19, pp. 1-6. https://doi.org/10.1109/RADIOELEK.2017.7937581
20. A. Hämäläinen, F.P. Moreira, J. Avelar, D. Braga and M.S. Dias, **Transcribing and annotating speech corpora for speech recognition: A three-step crowdsourcing approach with quality control.** *In Proc. First AAAI Conference on Human Computation and Crowdsourcing, 2013 Nov 3, pp. 30-31.*
21. P. Thakur, and Shrivastava, R. **A review on text based emotion recognition system**, *International Journal of Advanced Trends in Computer Science and Engineering*, Vol. 7, No. 5, pp. Sept – Oct 2018, pp. 67-71. https://doi.org/10.30534/ijatcse/2018/01752018
22. J. Mor, N. Kumar, D. Rai, **An improved crawler based on efficient ranking algorithm**, *International Journal of Advanced Trends in Computer Science and Engineering*, Vol. 8, No. 2, pp. 119-125, 2019. https://doi.org/10.30534/ijatcse/2019/04822019