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Chapter 13

Designing of Latent Dirichlet Allocation Based Prediction Model to Detect Midlife Crisis of Losing Jobs due to Prolonged Lockdown for COVID-19

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13.1 Introduction

Midlife crisis (MLC), included in the dictionary first in the 60s, indicates the psychiatric symptom of lack of self-dignity and self-confidence that can happen to humans at the middle age. Although we cannot strongly say that this self-humiliation phase is a typical phenomenon, there may be many changes in life and stressors that cause midlife emotional crisis. As per the studies and researches performed in medical science, people suffering from this syndrome are prone to react differently. The fatigue, anxiety, stress, and many other psychological factors of a mid-40 urban person who is highly attached in the virtual world may lead him or her to exaggerate on the social platform. Social concern makes us aware of the fact that urban life is comparatively busier and engulfed in exertions. It is also evident that people are socially disconnected in real life and super active in electronic social media in the present time frame. The present effect of the pandemic situation and the long-term lockdown has made its impact on human society. People are pushed in an unknown atmosphere where they face death, fear of uncertainty, and even fear of unemployment. People of different ages have their psychological syndrome. With Natural Language Processing (NLP) methods and sentiment analysis, we can trace these victims who are suffering from depression. We can find several research papers in the field of sentiment
analysis, which show us paths to identify depressive behavior among microblog users. We experience that there is a lack of systematic and accurate algorithms in finding proper depressive disorder.

**Our contribution:** Surprisingly, recognizing symptoms of MLC using sentiment analysis and NLP and finding an optimal methodology to solve this problem is yet to achieve. We aim to formulate a highly efficient mechanism that will detect depressive sentences more accurately. In our work, we try to formulate an optimal mechanism implementing the concept of topic modeling with the help of the well-known theory of Latent Dirichlet Allocation (LDA), which will help us to detect those users of social platforms who are expectedly suffering from common depression and the problem of MLC.

### 13.2 Literature survey

Extracting snippets from a sentence collected from social media such as twitter and finding its polarity is the most obvious way of analyzing a user’s sentiment. These can be compared with some predefined threshold values, which will trigger a depressive person’s resultant. We mainly focus on twitter data as we can get a huge dataset from here very easily. There are several opensource tools to collect and preprocess twitter data. Gaikar, Chavan, Indore, and Shedge (2019) thus proposed a hybrid method of depression detection using SVM (Support Vector Machine) and Naïve Bayes classification. Similar work is done by Uddin, Bapery, and Mohammad Arif (2019) on purely Indian and subcontinental backgrounds. They selected several parameters and proceeded further step-by-step by tuning all the parameters. We can see that causes of the MLC can be quite different for males and females. Some recent researches, as Park and Lee (2002); Yoo, Kim, and Kim (2003); Wong, Awang, and Jani (2012), point out the causes of this psychological phenomenon among women of different geographical regions. We can find a couple of other depression detection mechanisms by Giuntini, Cazzolato, and dos Reis (2020). X Tao uses Twitter data as a strong platform for its experiment to produce a multistage detection mechanism (Tao et al., 2019). Also, in Biradar and Totad (2019); Ziwei and Chua (2019); Orabi, Buddhitha, Orabi, and Inkpen (2018); Kumar, Sharma, and Arora (2019), and Islam, Kabir, and Ahmed (2018), depressive phrases are detected from social platforms, especially from Twitter data by Biradar et al., Orabi et al., Bernice et al., Kumar et al. and Islam et al. Cacheda, Fernandez, Novoa, and Carneiro (2019) have applied the random forest technique to find depressive phrases. Another multimodal approach can be found in Shen et al. (2017) for the same problem domain.

Depression at the age of 40 can occur due to many reasons. Wethington (2000) in her work shows general medical issues of middle-aged person. Acute suffering from this problem may even lead to severe health damage: even death. In Waskel (1995), we get a glimpse of it where Sherley has
described the fact of MLC and relation between depression and death. All the above literature is from medical science.

Apart from all the general cases of depressive disorder in human psychology, the recent outbreak of the COVID-19 virus has created a shiver worldwide. People are afraid of ill health, death, economic slowdown, recession, job loss, anxiety for self-health and family health, and many more. This has been geared up by long-term home quarantine and isolation from society. One such case study has been done in Shevlin et al. (2020), taking sample data from the UK people. Similar studies have been done by Aldwin and Levenson (2001) and Huang & Zhao (2020) discussing mental health at the age after 40. Mamun (Mamun & Griffiths, 2020) has shown the effect of COVID-19 among the people of Bangladesh in his very recent work. Depression caused by COVID-19 can be also seen among people of other countries. From the work of Liu, Zhang, Wong, Hyun, and “Chris” Hahm (2020) and Grover et al. (2020) we can conclude to the fact that people are getting more depressive in the span of lockdown. Visualizing and experiencing the current scenario worldwide, we have tried to apply some methods to understand the status of mental health of a certain group of humans irrespective of geographical location or financial status. As the present world is more virtual and less physical, we have opted for a social platform to analyze. The area of machine learning is the most appropriate for this study. We prefer topic modeling (Canini et al., 2009; Anandkumar et al., 2012), as it is a well-known tool for understanding and segregating sentiments. The modeling using LDA, as described by Blei (Blei, Ng and, Jordan; Blei, Ng, & Jordan, 2003), is the most relevant and easy process that uses joint probability (Newman, Smyth, Welling, & Asuncion, 2008) to specify the distribution and categorize words in different topics. Then, these topics are interlinked with separate documents where we can explain the sentiments in the percentage of topics. The entire process works on the Bayesian network (Newman et al., 2008). With this mechanism’s help, machine learning and sentiment analysis become more efficient in human behavior prediction and forecasting shortly.

Reviewing all the relevant research documents, we became astonished that the sector of the mental phase of middle-aged people is still untouched concerning sentiment analysis and socioeconomic prediction. We aim to target this issue through remote analysis using topic modeling. Rest of the part of the chapter describes the problem formulations and solutions to them. The section Methodology describes in brief the actual problem area in several subsections. First we describe the symptoms of MLC and then we design the prediction model. Next we show the results and discuss on it. Following this part we draw a conclusion and also mention the future scopes of this problem.

13.3 Methodology

While we were going through news relating to COVID-19, we experienced that people all around the world are not only affected by the virus physically,
but they have been mentally affected also. Mankind is suddenly put into total confinement. Surely it is very hard to change one’s lifestyle in just one night or within a couple of hours. Initially, we all were thinking about the severity of the pandemic. We were managing to cope with limited resources, but gradually as the lockdown grew longer and longer, people started to exaggerate. There is certainly no need of research to understand that humanity is compelled to undergo a mental illness. Numerous documents are there to prove this statement also. However, as we all know that different age groups have different mental maturity and stability, certainly different people from separate age groups express their feelings separately. People falling under the age group $30 - 60$ are outstanding in the context that they are already at a threshold of their lives. The sudden outbreak of this pandemic has created a full nonidentical expression for them. They are mature enough to analyze the long-term consequence of this outbreak, and that single factor has triggered unparalleled feelings in them. They are scared of the disease, the economic shutdown, which is evident due to limitations created by lockdown, long-term social impacts, and many more. As a result, they engulf in the sea of depression, resulting in other physical illnesses. However, their sole feeling is hard to identify because often, people from this age group neglect their mental health and sublimely express their inner feelings. In our study, we have tried to identify this particular case of depression through the tweets and make a temporal analysis of this factor. We have taken the help of simple generative probabilistic model LDA by first understanding the theory behind it and then applying it.

### 13.3.1 Distinguishing midlife crisis symptoms

An MLC is not an official diagnostic. Moreover, that is the reason that we cannot tabularize the symptoms and remedies for them. Clinical researches are performed based on person-to-person questioner to a significant amount (Liu et al., 2020). It is often seen that abrupt change in behavior can be seen in the form of negligence in self-hygiene, mood swings, weight gain or loss, change in sleep habits, irritation, feeling of distress, fatigue, loneliness, suicidal tendency, and many more. Women have a biological reason for this crisis period (Yoo et al., 2003). All these emotions are likely to reflect a person’s daily life. Even what he does in his daily routine or what he writes in the social platform will silently show up his condition. Adding to all these already existing facts, this sudden outbreak of COVID-19 introduced thousands of new thoughts in peoples’ minds (Grover et al., 2020; Cullen, Gulati, & Kelly, 2020). A man in his mid-40s has begun to think differently to match his lifestyle with this new danger. With his knowledge and experience, he has started to think about his family’s financial security, fear of job loss, health hazards of the elders of his family, and the future of the children. He has started to find ways to avoid all the risks.

Moreover, urban life has been confined in the four walls, creating mental pressure on the inhabitants. They are being obliged to stay at home doing
nothing much and being super active in virtual walls. All these factors stimulate depression slowly and silently in everyone’s mind, but people in midlife being more prone to the illness.

13.3.2 Designing of the prediction model

We prefer twitter data as our document’s base because this platform is the most convenient medium to have a large set of data. It is obvious that whatever is posted related to COVID-19 is not of depression, nor they all post affairs related to job loss or recession. There are numerous posts of other words relating to other issues also. We try to concentrate on the fact that every tweet must not explicitly mention the relevant topics; we have to figure them out. Certainly, a single tweet will relate to multiple keywords, and one word may be categorized in different topics. We want to pull those posts made by people of age 30–50 years. We first try to group the words into relevant topics, such as “depression,” “pessimism,” “death,” “job loss,” “optimistic,” “joy” and obviously, “COVID-19,” and “corona virus.” Then the allocation method is formulated for the words that may fall under each category above. Here cross-reference happens. The sampling documents we take are the tweets in a short period in the outbreak of COVID-19 and midway of lockdown. The sampling after that is performed following Poisson distribution and Dirichlet distribution.

The prediction model is described as follows:
1. Load $n$ tweets from neutral tweet dataset.
2. Load $n$ tweets from depressive tweet dataset.
3. Merge neutral tweet dataset and depressive tweet dataset and shuffle the tweets.
4. Cleanse tweet dataset, that is, expand contractions, remove emojis, remove punctuations, filter stop words.
5. Make bag of words corpus from tweet dataset with most frequent words.
6. Create LDA model from bag of words corpus.

13.3.3 Application of LDA and statistical comparison

LDA is the simplest and compact way of topic modeling. The whole process follows the plate notation, referred by Blei (Blei et al., 2003; Blei, Ng and, Jordan). To train our model, we need to formulate the bag of words very carefully to get the desired output.

13.3.3.1 Formulation of Dirichlet distribution

In order to train our model, we need to choose our posterior probability and prior probability values. As the dataset is the bag of words, which form a multinomial distribution, we need a conjugate prior to this distribution. Therefore we
formulate the Dirichlet distribution, which is conjugate to the multinomial distribution. To speak specifically, Dirichlet distribution is a distribution of beta distribution, and also can be derived from gamma distribution. The parameters $\alpha$ and $\beta$ (Blei, Ng and, Jordan) are tuned so that we can filter our dataset to have more precise results. In order to do this, we follow the equation Eq. (13.1).

$$\text{Dir}(p; \alpha) = \frac{1}{B(\alpha)} \prod_{i=1}^{\alpha} p_i^{\alpha_i - 1}$$  \hspace{1cm} (13.1)$$

where the normalizing constant is the multinomial beta function, which can be expressed in terms of gamma function (Blei, Ng and, Jordan) in Eq. (13.2)

$$B(\alpha) = \frac{\prod_{i=1}^{\alpha} \Gamma(\alpha_i)}{\Gamma(\sum_{i=1}^{\alpha} \alpha_i)}$$  \hspace{1cm} (13.2)$$

In application, we need to find a simple generative model, which may determine that the word $w_i$ ($i \in 1, 2, \ldots, n$) from the searched tweet is a depressive tagged word and reflects job loss. Our model must assign nonzero probability to $w_i$. Besides, it should also satisfy exchangeability. Each word is assigned a unique integer $x \in [0, \infty)$, and $C_x$ is the word count in the Dirichlet process.

The probability that the word $w_{i+1}$ is depressive is

$$\frac{C_x}{C + \alpha}$$

and the probability that the word $w_{i+1}$ is an optimistic one is

$$\frac{\alpha}{C + \alpha}$$

13.3.3.2 Categorization in Bayesian model

In Bayesian probability theory, one of the joint probability events is the hypothesis, and other event is data. We wish to examine the truth of the data, given the hypothesis. In our experiment, we have a dataset $D$. To examine new data, we shall observe some part of the data, while we have to assume some other part of the data. Therefore we are to find a $\theta$ so that

$$h_0 (\text{observed } w_i) \approx (\text{assumed } w_i).$$  \hspace{1cm} (13.3)$$

Next, we find the likelihood of training dataset assuming that the training cases are all independent of each other.

The continuous generative model of Bayesian probability leads us to determine $t$ such that $\sim N(\mu_{\text{depressive _wi}}, \sigma^2_{\text{depressive _wi}})$; where $\theta = (\mu_{\text{depressive _wj}}, \mu_{\text{nondepressive _wj}}, \sigma_{\text{depressive _wj}} \ldots \ldots)$

the measurement of the probability that a word $w_{ij}$ is depressive is
\[
P(\text{depressive}|t) = \frac{P(t|\text{depressive})P(\text{depressive})}{P(t|\text{depressive})P(\text{depressive})P(t|\neg\text{depressive})P(\neg\text{depressive})}
\]

(13.4)

\(\theta\) is derived by applying maximum likelihood.

### 13.3.3.3 Concept of topic modeling

Before determining the model, we apply Latent Semantic Analysis over our testing data. For each tweet, the Latent Semantic Index formulate a word-document matrix and calculate each cell value with the value computed from the calculation of \((\text{word-topic distribution} \times \text{topic importance} \times \text{topic-document distribution})\).

After determining the value for \(\theta\), we now finally approach for the construction of our final model. A pictorial reference to our model is like Fig. 13.1.

We confine our search for tweets in a short period of time and for people with age group of 30–50 years. Twitter API (Application Programming Interface) does not reveal user profile and specifically the age of a user. So we have to pull information from third-party applications. As the most discussed issue worldwide is the coronavirus now, it is not so hard to find relevant tweets in this short span. We collect sample tweets with the keywords “COVID-19”, “CORONAVIRUS,” and “JOB LOSS” and feed these inputs to the model.

Mathematically we want to find the probability as below:

\[
P(\theta_{1:M}, z_{1:M}, \beta_{1:k}|D; \alpha_{1:M}, \eta_{1:k})
\]

Where we work on \(M\) tweets, each tweet having \(N\) words; topics are having a distribution \(\theta\) of \(k\) events; \(z\) is total topics, \(\alpha\) and \(\eta\) are parameter vectors; \(\beta\) is distribution of words; and \(D\) is our dataset.

### 13.4 Result and discussion

We observe the output in several stages. First, we can view the Bag_Of_Words in the form of word cloud. The fetched word cloud shows distribution of depressive and nondepressive words, as shown in Fig. 13.2.

![FIGURE 13.1 Simple model description of the application of latent Dirichlet allocation (LDA).](image-url)
The word cloud is formed as a result of our experiment and the dataset is taken from this word cloud.

We observe the searched tweet in the next milestone, where we find the score computed by the LDA method. Each tweet, fetched singly, shows the probability of negativity after running the method in Fig. 13.3.

FIGURE 13.2  Word cloud formed in the examination using latent Dirichlet allocation (LDA).

FIGURE 13.3  The probability of negativity.
For the graphical representation of the desired result, we compute the depressive and nondepressive score of tweets, as shown in Fig. 13.4. Ultimately we get the result in the chart format shown in Fig. 13.5.

### FIGURE 13.4  Score chart of tweets.

| Tweet#  | Depression Score | Non-Depression Score |
|---------|------------------|----------------------|
| Tweet #52 | 0.5              | 0.5                  |
| Tweet #53 | 0.25             | 0.75                 |
| Tweet #54 | 0.58             | 0.42                 |
| Tweet #55 | 0.58             | 0.42                 |
| Tweet #56 | 0.5              | 0.5                  |
| Tweet #57 | 0.7              | 0.3                  |
| Tweet #58 | 0.83             | 0.17                 |
| Tweet #59 | 0.5              | 0.5                  |
| Tweet #60 | 0.62             | 0.38                 |
| Tweet #61 | 0.5              | 0.5                  |
| Tweet #62 | 0.83             | 0.17                 |
| Tweet #63 | 0.58             | 0.42                 |
| Tweet #64 | 0.58             | 0.42                 |
| Tweet #65 | 0.37             | 0.63                 |
| Tweet #66 | 0.82             | 0.18                 |
| Tweet #67 | 0.41             | 0.59                 |
| Tweet #68 | 0.37             | 0.63                 |
| Tweet #69 | 0.5              | 0.5                  |
| Tweet #70 | 0.62             | 0.38                 |
| Tweet #71 | 0.25             | 0.75                 |
| Tweet #72 | 0.91             | 0.09                 |
| Tweet #73 | 0.5              | 0.5                  |
| Tweet #74 | 0.78             | 0.22                 |
| Tweet #75 | 0.5              | 0.5                  |
| Tweet #76 | 0.71             | 0.29                 |
| Tweet #77 | 0.59             | 0.41                 |
| Tweet #78 | 0.72             | 0.28                 |
| Tweet #79 | 0.5              | 0.5                  |
| Tweet #80 | 0.59             | 0.41                 |

### 13.5 Conclusion and future scope

In recent days, many studies on the analysis and prediction of spread of COVID-19 have been performed. Some of those works were done by Poonia et al.; Kumari et al. (2020); Bhatnagar et al. (2020). After researching a minimal set of data, we have found that people of a particular age group are conscious about the pandemic situation, socioeconomic state, and income source. These facts drive them to end mental issues that they are becoming a victim of depressive disorder. This area has opened numerous scopes to...
explore sentiment analysis (Kumar, Rama Rao, Nayak, & Chandra, 2020) using many approaches similar to the application of Probabilistic Density Functions. The present work was performed with a unigram bag of words, and future work may include an N-gram approach. There are scopes of finding a solution to the same problem domain using mixture models and EM (Expectation-Maximisation) algorithms. Also, the application of collapsed Gibbs sampling and Monte Carlo algorithm is yet to be achieved. So far, we have learned that the algorithm we used can squeeze the extensive collection of documents to shortened length, grouped according to the usage. In our next works, we shall try to optimize this property and build our algorithm for the same problem domain. Also the present approach is open to apply on a broader area of research. We shall apply this solution in finding MLC in different scenario and different time frame. At the end, we hope to build a stronger and more specific model to detect the solution of MLC in every possible domain in social media platform.

References

Aldwin, C. M., & Levenson, M. R. (2001). Stress, coping, and health at mid-life. The Handbook of Midlife Development, 188–214.

Anandkumar, A., Foster, D. P., Hsu, D., Kakade, S. M., Liu, Y. -K. (2012). A spectral algorithm for latent dirichlet allocation, Advances in Neural Information Processing Systems 25,
Bhatnagar, V., Poonia, R. C., Nagar, P., Kumar, S., Singh, V., Raja, L., & Dass, P. (2020). Descriptive analysis of COVID-19 patients in the context of India. *Journal of Interdisciplinary Mathematics, 1–16.*

Biradar, A., & Totad, S. G. (2019). Detecting depression in social media posts using machine learning. In K. Santosh, & R. Hegadi (Eds.), *Recent Trends in Image Processing and Pattern Recognition. RTIP2R 2018. Communications in Computer and Information Science* (1037). Singapore: Springer. Available from https://doi.org/10.1007/978-981-13-9187-3_64.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2002). Latent Dirichlet Allocation. *University of California, Berkeley, Berkeley, CA 94720.*

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet Allocation. *Journal of Machine Learning Research, 3*, 993–1022, Submitted 2/02; Published 1/03.

Cacheda, F., Fernandez, D., Novoa, F. J., & Carneiro, V. (2019). Early detection of depression: Social network analysis and random forest techniques. *Journal of Medical Internet Research, 21*(6), e12554. Available from https://doi.org/10.2196/12554, PMID: 31199323, PMCID: 6598420.

Canini, K., Shi, L., & Griffiths, T. (2009). Online inference of topics with latent Dirichlet allocation. In Artificial Intelligence and Statistics, pp. 65–72.

Cullen, W., Gulati, G., & Kelly, B. D. (2020). Mental health in the COVID-19 pandemic. *QJM: An International Journal of Medicine, 113*(5), 311–312. Available from https://doi.org/10.1093/qjmed/hcaa110.

Gaikar, M., Chavan, J., Indore, K., & Shedge, R. (2019). Depression detection, and prevention system by analysing tweets (March 23, 2019). Proceedings: Conference on Technologies for Future Cities (CTFC), Available at SSRN: https://ssrn.com/abstract=3358809 or https://doi.org/10.2139/ssrn.3358809.

Giuntini, F. T., Cazzolato, M. T., dos Reis, M. D. J. D., et al. (2020). A review on recognizing depression in social networks: Challenges and opportunities. *Journal of Ambient Intelligence and Humanized Computing.* Available from https://doi.org/10.1007/s12652-020-01726-4.

Grover, S., et al. (2020). Psychological impact of COVID-19 lockdown: An online survey from India. *Dental Science—Review Article, 62*(4), 354–362.

Huang, Y., & Zhao, N. (2020). Generalized anxiety disorder, depressive symptoms and sleep quality during COVID-19 outbreak in China: A web-based cross-sectional survey. *Psychiatry Research, 288*, 112954. Available from https://doi.org/10.1016/j.psychres.2020.112954.

Islam, M. R., Kabir, M. A., Ahmed, A., et al. (2018). Depression detection from social network data using machine learning techniques. *Health Information Science and Systems, 6*(8). Available from https://doi.org/10.1007/s13755-018-0046-0.

Kumar, E. R., Rama Rao, K. V. S. N., Nayak, S. R., & Chandra, R. (2020). Suicidal ideation prediction in twitter data using machine learning techniques. *Journal of Interdisciplinary Mathematics (JIM), 23*(1), 117–125.

Kumar, A., Sharma, A., & Arora, A. (2019). Anxious depression prediction in real-time social data (March 14, 2019). International Conference on Advances in Engineering Science Management & Technology (ICAESMT), Uttaranchal University, Dehradun, India, Available at SSRN: https://ssrn.com/abstract=3383359 or https://doi.org/10.2139/ssrn.3383359.

Kumari, R., Kumar, S., Poonia, R. C., Singh, V., Raja, L., Bhatnagar, V., & Agarwal, P. (2020). Analysis and predictions of spread, recovery, and death caused by COVID-19 in India. Big Data Mining and Analytics, IEEE.
Liu, C. H., Zhang, E., Wong, G. T. F., Hyun, S., & “Chris” Hahm, H. (2020). Factors associated with depression, anxiety, and PTSD symptomatology during the COVID-19 pandemic: Clinical implications for United States young adult mental health. *Psychiatry Research, 290*, 113172. Available from https://doi.org/10.1016/j.psychres.2020.113172.

Mamun, M. A., & Griffiths, M. D. (2020). First COVID-19 suicide case in Bangladesh due to fear of COVID-19 and xenophobia: Possible suicide prevention strategies. *Asian Journal of Psychiatry, 51*, 102073. Available from https://doi.org/10.1016/j.ajp.2020.102073.

Newman, D., Smyth, P., Welling, M., & Asuncion, A. U. (2008). Distributed inference for latent Dirichlet allocation. *Advances in Neural Information Processing Systems*, 1081–1088.

Orabi, A. H. and Buddhitha, P., Orabi, M. H., & Inkpen, D. (2018). Deep learning for depression detection of twitter users, Proceedings of the Fifth Workshop on Computational Linguistics and Clinical Psychology: From Keyboard to Clinic, pp. 88–97.

Park, G. J., & Lee, K. H. (2002). A structural model for depression in middle-aged women. *Korean Journal of Women Health Nursing, 8*(1), 69–84. Available from https://doi.org/10.4069/kjwhn.2002.8.1.69.

Shen, G., Jia, J., Nie, L., Feng, F., Zhang, C., Hu, T., . . . Zhu, W. (2017). Depression detection via harvesting social media: A multimodal dictionary learning solution. *In IJCAI*, 3838–3844.

Shevlin, M., McBride, O., Murphy, J., Miller, J. G., Hartman, T. K., Levita, L., . . . Bennett, K. M., (2020). Anxiety, depression, traumatic stress, and COVID-19 related anxiety in the UK general population during the COVID-19 pandemic.

Tao, X., Dharmalingam, R., Zhang, J., Zhou, X., Li, L., & Gururajan, R. (2019). Twitter analysis for depression on social networks based on sentiment and stress, 2019 6th International Conference on Behavioral, Economic and Socio-cultural Computing (BESC), Beijing, China, pp. 1–4, doi: 10.1109/BESC48373.2019.8963550.

Uddin, A. H., Bapery, D., & Mohammad Arif, A. S. (2019). Depression analysis of Bangla social media data using gated recurrent neural network, 2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT), Dhaka, Bangladesh, pp. 1–6. DOI: 10.1109/ICASERT.2019.8934455

Waskel, S. A. (1995). Temperament types: Midlife death concerns, demographics, and intensity of crisis. *The Journal of Psychology, 129*(2), 221–233. Available from https://doi.org/10.1080/00223980.1995.9914960, Routledge.

Wethington, E. (2000). Expecting stress: Americans and the “Midlife Crisis. *Motivation and Emotion, 24*, 85–103. Available from https://doi.org/10.1023/A:1005611230993.

Wong, L. P., Awang, H., & Jani, R. (2012). Midlife crisis perceptions, experiences, help-seeking and needs among multi ethnic Malaysian women. *Women and Health, 52*–58. Available from https://doi.org/10.1080/03630242.2012.729557.

Yoo, E. K., Kim, M. H., & Kim, T. K. (2003). A study of the relationship among health promoting behaviors, climacteric symptoms and depression of middle-aged women. *Korean Journal of Women Health Nursing, 9*(4), 479–488. Available from https://doi.org/10.4069/kjwhn.2003.9.4.479.

Ziwei, B. Y., & Chua, H. N. (2019). An application for classifying depression in tweets ICCBD 2019: Proceedings of the 2nd International Conference on Computing and Big Data, pp. 37–41. Available from https://doi.org/10.1145/3366650.3366653.