ISSN- 2394-5125 VOL 07, ISSUE 15, 2020

CLUSTERING PERFORMANCE VALIDATION OF KOHONEN SELF-ORGANIZING MAPS-EXPONENTIAL DECAY AVERAGE RATE OF CHANGE (KSOM-EDARC) IMPLEMENTED ON FIRE DISASTER TWEETS

Edwin F. Galutira

Faculty of Computer Engineering,
Department of Computer Engineering, Mariano Marcos State University,
City of Batac, Philippines

efgalutira@gmail.com

Article History: Received 11/9/2019; Revised 11/11/2019; Accepted 11/7/2019

ABSTRACT: Cluster validity assessment is one of the very important in the field of clustering analysis. The previous introduction of the Kohonen Self-organizing Maps – Exponential Decay Average Rate of Change (KSOM-EDARC) in the area of clustering paved the way for further exploration of its clustering capability. This is one of the recent enhancement of Kohonen Self-organizing Maps (KSOM), which enhances the learning rate decay function of the algorithm using the Exponential Decay Average Rate of Change (EDARC). Previous studies show that the clustering performance of the enhanced algorithm is better than the conventional algorithm. The assessment was made using visual analysis and comparison on the learning rates of the improved algorithm against the traditional KSOM. Hence, this paper provides a cluster validity assessment on the performance of the KSOM-EDARC and KSOM using three internal validity index to validate the performance of the two algorithms further. The Silhouette Index (SI), Calinski-Harabaz Index (CHI), and Davies-Bouldin Index (DBI) are used to validate the clustering results of the algorithm. The Fire Disaster Tweets Dataset was used for clustering by the two algorithms. The average index values and the percentage difference between the two algorithms were determined. Based on the results recorded by the indices of the two algorithms, the KSOM-EDARC produced well separated and denser cluster results compared with the KSOM. The study concluded that KSOM-EDARC has better and improved performance and a better solution than the traditional algorithm.

KEYWORDS:*Clustering, Cluster Validity, Validity Index, Data Mining, Learning Rate*

1.0 INTRODUCTION

Data mining is the extraction of suitable patterns or mining knowledge from massive amounts of data through the application of correct algorithms, tools, and techniques

[1]. Clustering is one of the essential and prominent data mining techniques wherein, it partitions an unlabeled dataset and organized similar objects in the form of a cluster [1]. The organization is based on the similarities of objects with respect to similarities of measure among objects [2].

Kohonen Self-Organizing Feature Maps (KSOM) is prominent in the field of data mining, mainly clustering high-dimensional or multi-dimensional data [3], [4]. KSOM is an unsupervised neural network that represents high-dimensional or multi-dimensional data into one, two, or in particular cases, into three-dimensional space [5]. Space is a representation of the input vectors of the training samples, and it is called a map [6], [7]. KSOM is specially designed for clustering, visualization, and abstraction of high-dimensional data [8], [9]. The elementary of the SOM is the flexible competition of nodes in the output layer; not only one node (the winner) is updated, but also its neighbors are adjusted [9]–[11]. The Kohonen network can adapt to recognize groups of data and relatively similar classes to the others. The SOM has only two layers: the input layer and the output layer. The input layer is one-dimensional, while the output layer consists of radial units typically organized in two dimensions [9], [10], [12]–[14]. KSOM is used for a variety of tasks, and it is handy to find regularities in a large volume of data through it [8], [15].

One of the recent enhancement of the KSOM is the Kohonen Self-organizing Maps – Exponential Decay Average Rate of Change (KSOM-EDARC). The KSOM-EDARC used the principle of the average rate of change and presented a new learning rate decay function of the KSOM called the Exponential Decay Average Rate of Change (EDARC) [15]–[17]. The studies showed an illustrative comparison of the performance of the KSOM-EDARC and the conventional KSOM by applying the two algorithms in color and image clustering. Results showed that the KSOM-EDARC produces a better result compared to the traditional KSOM based on the learning rates of the two algorithms, as illustrated in Figure 1[15]–[17].

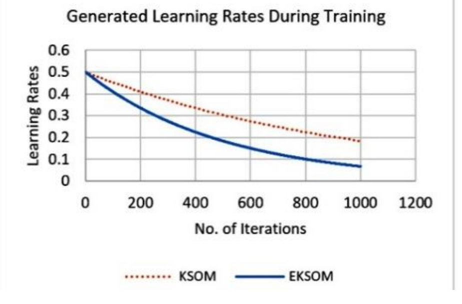


Figure 1: Learning Rates Generated by KSOM and EKSOM Used for the Evaluation

The KSOM is unsupervised learning and knows no pre-determined output [18]. This type of learning is very advantageous for data visualization and organization tasks correlated to the traditional neural networks. KSOM uses competitive learning where the specific Best Matching Unit (BMU) in the network is determined to having the most significant influence and spreads out to its neighboring neurons with a lesser influence [13]. It further explained that the inputs are presented to the nodes, and the weighted sum of the nodes are calculated using a Euclidean Distance. Also, all the networks are iterated, and the node with the closest matching output magnitude is chosen to receive additional training denoted as the BMU. The training is extended to its neighborhood surroundings [18].

All Neural Network (NN) has an essential module that occurs during the training/classification phase called learning [19]. After training a NN, it generates results known as the production phase. This phase uses a different form of learning archetypes, learning guidelines, and learning algorithms. A learning algorithm is a mathematical approach in updating neural weights during the training process [20]. Supervised and unsupervised NN uses learning rules and learning algorithms, producing a different impact on the results [19]. In a high-dimensional data where extensive training samples are introduced to the network, problems on the learning rate arise. An algorithm becomes inadequate to produce valuable results if there are too many neurons in the networks and the dimensionality of the input exceeded by the computation capacity of the network [21].

The learning rate of a NN is one of the most influential hyper-parameters to tune for training [22], [23]. Careful choice of learning rate (step size) schemes leads to faster convergence and lower error rates [20], [24]–[26]. This clearly emphasizes that the convergence of a NN algorithm is highly affected by choice of learning rate [19]. Theconvergence of the algorithm is greatly affected by the proper selection of changes in the learning rate during the training process [20]. Initial steps can afford to take larger steps enabling a rapid increase in the objective function. Still, during the latter part of the training iteration, smaller steps are essential to descend into finer features of the loss landscape [24]. The figure below depicts the different choices of learning rates [27].

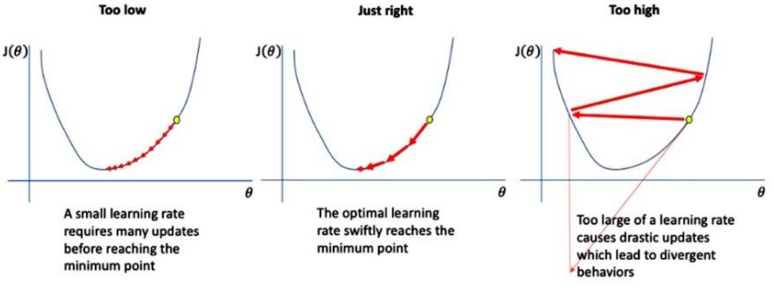


Figure 2: Choices of Learning Rates

The figure shows that too small value for the learning rate will take a longer training time to arrive at a minimum point, and too high value for the learning rate causes divergence behaviors and will not arrive at convergence. Whereas the right value of learning rate can afford to take a bigger step at the outset of the training and swiftly arrives at the minimum point towards convergence [27]. Also, an excessively large learning rate moves afar in the right path, wandering around a valley or minimum in the error surface, affecting the generalization accuracy [20]. The conventional KSOM algorithm uses the following learning rate decay function.

$$L(t) = L_0 \exp(-\frac{t}{\lambda}) \qquad (1)$$

The initial learning rate is represented by L_0, t is the current iteration, and λ is the maximum no. of iterations.

In the study of Galutira et al., the learning rate decay function of the KSOM was modified using the principle of Average Rate of Change, combining it to the exponential decay function of the algorithm. Their study came up with the EDARC as the new function of the enhanced KSOM [15]–[17]. The function presented as follows.

$$L(t) = L_0 \exp\left(-\frac{\Delta d}{\lambda}\right) \qquad (2)$$

where the initial learning rate is represented by L_0, Δd change in d with respect to t, and λ is the maximum no. of iterations.

The results shown from the previous studies, based on the learning rates and visual analysis of the clustered results, the KSOM-EDARC produced better clustering results compared to the conventional KSOM.

Despite the recorded success of KSOM-EDARC on the previous studies, there was no presented validation on the clusters produced by the algorithm over the traditional one. Hence, this study evaluates the cluster validity of the KSOM-EDARC alongside with the conventional KSOM through the use of internal validity indices to further validate the goodness of the clustering performance of the enhanced algorithm. The evaluation is based on the clustering results of the algorithms applied in the Fire Disaster Tweets Dataset.

2.0 METHODOLOGY

To evaluate the performance of the two algorithms, a simulation program was developed using the Python 3.6 programming language. Sckitlearn library was used for the analysis of the datasets and clustering results [28], [29].

2.1 Data Collection

The dataset used for evaluation in this study is the Fire Disaster Tweets Dataset. The dataset is a part of the Natural Disaster Tweets Dataset, which is a compilation of posted tweets during the natural crisis from different parts of the world, which is publicly available. This dataset was downloaded from CrisisLex.org as part of the CrisisLexT26[30], [31]. It composed of four types of crises. The typhoon, flood, fire, and earthquake. For evaluation, only the fire type of crisis was used for clustering in

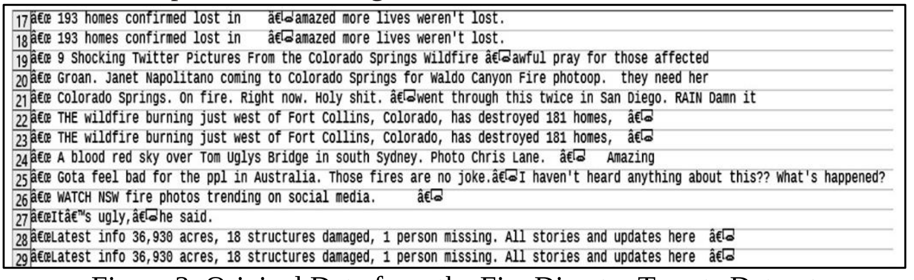
ISSN- 2394-5125 VOL 07, ISSUE 15, 2020

this study. The Fire Disaster Tweets Dataset has 1720 instances [32]. The table below presents a description of the dataset used.

Table 1: Natural Disaster Tweets Dataset Description

Crisis	**No. of Classes**	**Associated Task**
Earthquake	6	1) Affected individuals
Fire	6	2) Infrastructure and utilities
Flood	6	3) Donations and volunteering
Typhoon	6	4) Caution and advice
		5) Sympathy and support
		6) Other Useful Information

Figure 3 shows a portion of the original data from the Fire Disaster Tweets Dataset.



17	â€œ 193 homes confirmed lost in â€ amazed more lives weren't lost.
18	â€œ 193 homes confirmed lost in â€ amazed more lives weren't lost.
19	â€œ 9 Shocking Twitter Pictures From the Colorado Springs Wildfire â€ awful pray for those affected
20	â€œ Groan. Janet Napolitano coming to Colorado Springs for Waldo Canyon Fire photoop. they need her
21	â€œ Colorado Springs. On fire. Right now. Holy shit. â€ went through this twice in San Diego. RAIN Damn it
22	â€œ THE wildfire burning just west of Fort Collins, Colorado, has destroyed 181 homes, â€
23	â€œ THE wildfire burning just west of Fort Collins, Colorado, has destroyed 181 homes, â€
24	â€œ A blood red sky over Tom Uglys Bridge in south Sydney. Photo Chris Lane. â€ Amazing
25	â€œ Gota feel bad for the ppl in Australia. Those fires are no joke.â€ I haven't heard anything about this?? What's happened?
26	â€œ WATCH NSW fire photos trending on social media. â€
27	â€œItâ€™s ugly,â€ he said.
28	â€œLatest info 36,930 acres, 18 structures damaged, 1 person missing. All stories and updates here â€
29	â€œLatest info 36,930 acres, 18 structures damaged, 1 person missing. All stories and updates here â€

Figure 3: Original Data from the Fire Disaster Tweets Dataset

2.2 Pre-processing, Feature Extraction, and Testing

The features of the dataset were extracted using Bag-of-words or “Bag of n-grams” representation [33], [34]. Countvectorizer, Vectorizer, and reshape was applied to the original string dataset [29]. Before the dataset was trained, basic language pre-processing has to be performed to remove special characters, stop words, lowercase conversion, stemming, and tokenizing. Data sanitation and reduction were also performed before the dataset was subjected to training. Figure 4 shows a pre-processed data from the dataset.

ISSN- 2394-5125 VOL 07, ISSUE 15, 2020

16	“ 193 homes confirmed lost in ” amazed more...
17	“ 193 homes confirmed lost in ” amazed more...
18	“ 9 Shocking Twitter Pictures From the Colorad...
19	“ Groan. Janet Napolitano coming to Colorado S...
20	“ Colorado Springs. On fire. Right now. Holy s...
21	“ THE wildfire burning just west of Fort Colli...
22	“ THE wildfire burning just west of Fort Colli...
23	“ A blood red sky over Tom Uglys Bridge in sou...
24	“ Gota feel bad for the ppl in Australia. Thos...
25	“ WATCH NSW fire photos trending on social med...
26	“It’s ugly,” he said.
27	“Latest info 36,930 acres, 18 structures damag...
28	“Latest info 36,930 acres, 18 structures damag...

Figure 4: Data on Fire Disaster Tweets After Pre-processing

2.3 Evaluation

The validity of the clustering results was evaluated by comparing their scores or indicesthrough the use of the Silhouette Index, Calinski - Harabaz Index, and Davies – Bouldin Index[35]. These three clustering evaluation tools are described as follows:

Silhouette Index (SI): This evaluation index is used to validate the clustering performance based on the pairwise distinction between and within-cluster separation [36]. The score/index is measured within the range of -1 for inaccurate clustering and +1 for highly dense clustering. Scores close to zero imply overlapping of clusters. The higher the score of the SI, the denser, and well separated the clusters are [37].

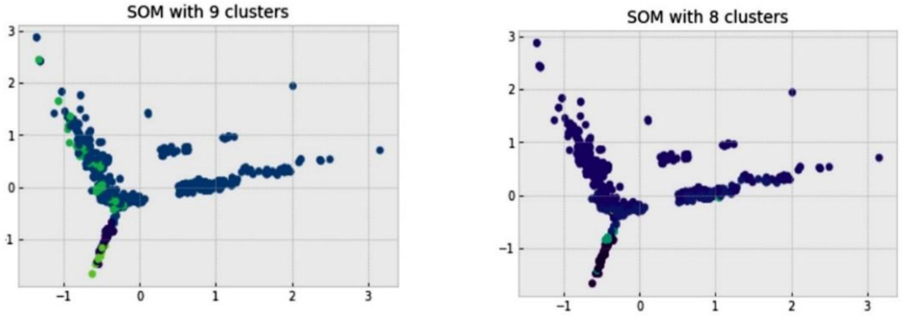
Calinski – Harabaz Index (CHI): It is sometimes called a Variance Ratio Criterion (VRC). Evaluation of cluster validity using CHI is based on the average between- and within-cluster sum of squares. It measures the separation of cluster centers based on the maximum distance, and compactness of clusters is measured based on the sum of distances between objects with respect to their cluster center. The scores in CHI are similar to SI, where the higher the score is, the denser and well-separated clusters are [36].

Davies – Bouldin Index (BDI): The derivation of DBI is more straightforward than that of the Silhouette Index. The index is calculated as the average of all the similarities of clusters. The smaller the value of the DBI, the better the results produced by the algorithm. In DBI, zero is the lowest possible score, and the values closer to zero implies a better partition of clusters [37].

3.0 RESULTS AND DISCUSSIONS

Before the algorithms were subjected to clustering, the number of neurons was set to 5x5, initial learning rate = 0.5, and iterations = 1000. The following figures are plotted sample clustering results on the dataset facilitated by the KSOM-EDARC and the KSOM.

ISSN- 2394-5125 VOL 07, ISSUE 15, 2020



(a) (b)

Figure 5: Sample Clustering Result of KSOM-EDARC (a) and KSOM (b) on Fire Disaster Tweets Dataset

It can be noticed from Figure 5 that the results of KSOM-EDARC are better, as shown by the denser and well-separated clusters.

3.1 Validity Measurements

The validity of the clustering performance of the KSOM-EDARC and KSOM was evaluated based on their validity index. Table 2 shows the measured index from the clustering results.

Table 2: Validity Index of KSOM-EDARC and KSOM

RUN	KSOM-EDARC			KSOM		
	SI	**CHI**	**DBI**	**SI**	**CHI**	**DBI**
1	0.039	22.426	3.293	0.007	10.627	4.295
2	0.014	21.113	4.145	0.010	18.741	4.232
3	0.039	18.873	3.055	0.030	18.378	3.795
Ave.	**0.031**	**20.804**	**3.498**	**0.016**	**15.915**	**4.107**

The table reflects that the SI and CHI values are higher than the SI and CHI values of KSOM. The values imply that the KSOM-EDARC is a better clustering solution than that of KSOM. Also, the KSOM-EDARC generated lower DBI values than the KSOM. The DBI values of the KSOM-EDARC has surpassed the clustering performance of the KSOM.Further, the computed average of KSOM-EDARC as compared to the average recorded by the KSOM clearly shows that the enhanced algorithm has a better performance than the conventional algorithm, as illustrated by the line graph below in Figure 6.

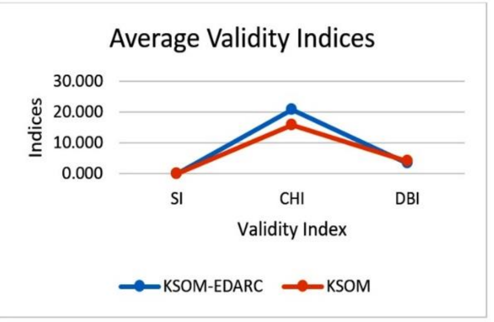


Figure 6: Line Graph of the Average SI, CHI, and DBI Values of KSOM-EDARC and KSOM

The figure above illustrates the average indices of the two algorithms, as reflected in Tables 2 and 3. The graph shows that KSOM-EDARC has a better performance than the traditional KSOM, as indicated by the index values of the two algorithms.

3.2 Performance Improvement of KSOM-EDARC Over the KSOM

The improvements of the enhanced algorithm wereanalyzed by computing the percentage difference on the average index values of the two algorithms. The table below presents the average index values and the percentage differences between the two algorithms.

Table 3: Average Index Values and Percentage Difference of KSOM-EDARC Over the KSOM

ALGORITHM	SI	CHI	DBI
KSOM-EDARC	0.031	20.804	3.498
KSOM	0.016	15.915	4.107
%Diff	1.500	30.717	14.843

The KSOM-EDARC recorded percentage difference of 1.5% of SI value, and 30.72% on CHI value higher than the SI, and CHI values of KSOM. Also, the DBI value of the KSOM-EDARC is lower by 14.84% against the traditional algorithm. The values signify that the performance of KSOM-EDARC has improved compared to the performance of the KSOM. Notably, the percentage difference of the algorithm shows that the KSOM-EDARC has surpassed the clustering capability of the KSOM by producing well separated and denser cluster results.

4.0 CONCLUSIONS AND FUTURE WORKS

Clustering has been widely used in various domains to address problems related to data mining, Data Science, Artificial Intelligence, and other related fields. One of the essential aspects of clustering is the validity of the cluster results produced by the algorithm. Previous studies show that the KSOM-EDARC is better than the traditional KSOM based on their learning rates and visual analysis on the clustering results of the algorithms.

Hence in this study, the validity of the cluster results of the two algorithms was evaluated and analyzed using the SI, CHI, and DBI. The percentage improvement of the KSOM-EDARC was also examined. Based on the results, the enhanced algorithm produced better cluster results compared to the clustering results of the conventional algorithm. Therefore, KSOM-EDARC is a better solution than the traditional KSOM by producing denser and well-separated cluster results as validated by the three internal validity indices.

Future studies will explore the performance of the KSOM-EDARC in comparison with the clustering performance of the different clustering algorithms.

ACKNOWLEDGMENTS

TheauthorwouldliketothankDr. Arnel C. Fajardo and Dr. Ruji P. Medina for their invaluable contributions to the completion of this study.

REFERENCES

[1] A. A. A. Esmin, R. A. Coelho, and S. Matwin, "A review on particle swarm optimization algorithm and its variants to clustering high-dimensional data," *Artif. Intell. Rev.*, vol. 44, no. 1, pp. 23–45, 2015.

[2] A. Ahmad, R. Yusof, and Y. Mitsukura, "Pheromone-based Kohonen Self-Organizing Map (PKSOM) in clustering of tropical wood species: Performance and scalability," *2015 10th Asian Control Conf. Emerg. Control Tech. a Sustain. World, ASCC 2015*, 2015.

[3] L. Yang, Z. Ouyang, and Y. Shi, "A modified clustering method based on self-organizing maps and its applications," *Procedia Comput. Sci.*, vol. 9, pp. 1371–1379, 2012.

[4] M. Lotfi Shahreza, D. Moazzami, B. Moshiri, and M. R. Delavar, "Anomaly detection using a self-organizing map and particle swarm optimization," *Sci. Iran.*, vol. 18, no. 6, pp. 1460–1468, 2011.

[5] X. Qiang, G. Cheng, and Z. Li, "A survey of some classic Self-Organizing Maps with incremental learning," *ICSPS 2010 - Proc. 2010 2nd Int. Conf. Signal Process. Syst.*, vol. 1, pp. 804–809, 2010.

[6] S. B. Wankhede, "Analytical Study of Neural Network Techniques: SOM, MLP and Classifier-A Survey," *IOSR J. Comput. Eng. Ver. VII*, vol. 16, no. 3, pp. 2278–661, 2014.

[7] N. Bourgeois, M. Cottrell, B. Déruelle, S. Lamassé, and P. Letrémy, "How to improve robustness in Kohonen maps and display additional information in Factorial Analysis: Application to text mining," *Neurocomputing*, vol. 147, no. 1, pp. 120–135, 2015.

[8] E. Khvorostukhina, A. L'Vov, and S. Ivzhenko, "Performance improvements of a Kohonen self-organizing training algorithm," *Proc. 2017 IEEE Russ. Sect. Young Res. Electr. Electron. Eng. Conf. ElConRus 2017*, pp. 456–458, 2017.

[9] K. Gopalakrishnan and S. Khaitan, "Enhanced Clustering Analysis and

Visualization Using Kohone's Self-Organizing Feature Map Networks," *Int. J. Comput.*, vol. 2, no. 6, pp. 64–71, 2008.

[10] K. G. Sheela, "An Efficient Hybrid Neural Network model in Renewable energy systems," no. 978, pp. 359–361, 2012.

[11] L. P. Chen, Y. G. Liu, Z. X. Huang, and Y. T. Shi, "An improved SOM algorithm and its application to color feature extraction," *Neural Comput. Appl.*, vol. 24, no. 7–8, pp. 1759–1770, 2014.

[12] A. Abubaker and A. Altayeb, "Kohonen Nural Network Based Approach to Voltage Weak Buses / Areas Identifiers," University of Khartoum, 2009.

[13] X. Qiang, G. Cheng, and Z. Wang, "An overview of some classical Growing Neural Networks and new developments," *ICETC 2010 - 2010 2nd Int. Conf. Educ. Technol. Comput.*, vol. 3, pp. 351–355, 2010.

[14] R. Wehrens and L. M. C. Buydens, "Self- and super-organizing maps in R: The kohonen package," *J. Stat. Softw.*, vol. 21, no. 5, pp. 1–19, 2007.

[15] E. F. Galutira, A. C. Fajardo, and R. P. Medina, "A Novel Learning Rate Decay Function of Kohonen Self-Organizing Maps Using the Exponential Decay Average Rate of Change for Image Clustering," *Proc. 2nd Int. Conf. Nat. Lang. Process. Inf. Retr. - NLPIR 2018*, pp. 55–59, 2018.

[16] E. F. Galutira, A. C. Fajardo, and R. P. Medina, *A Novel Kohonen Self-organizing Maps Using Exponential Decay Average Rate of Change for Color Clustering Edwin*, vol. 67. Springer Singapore, 2019.

[17] V. Piuri, V. E. Balas, S. Borah, and S. S. S. Ahmad, *Intelligent and Interactive Computing*. 2018.

[18] S. P. Lim and H. Haron, "Cube kohonen self-organizing map (CKSOM) model with new equations in organizing unstructured data," *IEEE Trans. Neural Networks Learn. Syst.*, vol. 24, no. 9, pp. 1414–1424, 2013.

[19] Y. Bodyanskiy, O. Vynokurova, V. Savvo, T. Tverdokhlib, and P. Mulesa, "Hybrid Clustering-Classification Neural Network in the Medical Diagnostics of the Reactive Arthritis," *Int. J. Intell. Syst. Appl.*, vol. 8, no. 8, pp. 1–9, 2016.

[20] E. Germen, "a Novel Approach for Learning Rate in Self Orginizing Map (Som)," *ANADOLU Univ. J. Sci. Technol. A - Appl. Sci. Eng.*, vol. 19, no. 1, pp. 144–152, 2018.

[21] I. C. Peace and S. A. Ita, "Effect of Learning Rate on Artificial Neural Network in Machine Learning," vol. 4, no. 02, pp. 359–363, 2015.

[22] M. Claesen and B. De Moor, "Hyperparameter Search in Machine Learning," no. February, 2015.

[23] Y. Kanada, "Optimizing neural-network learning rate by using a genetic algorithm with per-epoch mutations," *Proc. Int. Jt. Conf. Neural Networks*, vol. 2016-Octob, no. March, pp. 1472–1479, 2016.

[24] V. Chaudhary, R. S. Bhatia, and A. K. Ahlawat, "A constant learning rate self-organizing map (CLRSOM) learning algorithm," *J. Inf. Sci. Eng.*, vol. 31, no. 2, pp. 387–397, 2015.

[25] A. Senior, G. Heigold, M. Ranzato, and K. Yang, "An empirical study of learning rates in deep neural networks for speech recognition," *2013 IEEE Int. Conf. Acoust. Speech Signal Process.*, pp. 6724–6728, 2013.

[26] D. Wilson and T. Martinez, "The need for small learning rates on large problems," *IJCNN'01. Int. Jt. Conf. Neural Networks. Proc. (Cat. No.01CH37222)*, vol. 1, pp. 115–119, 2001.

[27] J. Jordan, "Setting the learning rate of your neural network.," *Data Science*, 2018. [Online]. Available: https://www.jeremyjordan.me/nn-learning-rate/. [Accessed: 18-Mar-2019].

[28] L. H. Richard, "Learning to Program with Python," *John Wiley Sons Inc.*, p. 310, 2013.

[29] K. Reitz, "Python Guide Documentation," 2018.

[30] A. Olteanu, C. Castillo, F. Diaz, and S. Vieweg, "CrisisLex: A Lexicon for Collecting and Filtering Microblogged Communications in Crises," *Proc. Eighth Int. AAAI Conf. Weblogs Soc. Media*, vol. 35, no. 2, p. 9, 2015.

[31] A. Olteanu, S. Vieweg, and C. Castillo, "What to Expect When the Unexpected Happens: Social Media Communications Across Crises," *Proc. 18th Conf. Comput. Support. Coop. Work Soc. Comput.*, pp. 994–1009, 2015.

[32] I. P. Benitez, A. M. Sison, and R. P. Medina, "An improved genetic algorithm for feature selection in the classification of Disaster-related Twitter messages," *ISCAIE 2018 - 2018 IEEE Symp. Comput. Appl. Ind. Electron.*, pp. 238–243, 2018.

[33] R. Zhao and K. Mao, "Fuzzy Bag-of-Words Model for Document Representation," *IEEE Trans. Fuzzy Syst.*, vol. 26, no. 2, pp. 794–804, 2018.

[34] Y. Zhang, R. Jin, and Z. H. Zhou, "Understanding bag-of-words model: A statistical framework," *Int. J. Mach. Learn. Cybern.*, vol. 1, no. 1–4, pp. 43–52, 2010.

[35] I. K. Ariana, R. S. Hartati, I. K. Gede, D. Putra, N. Kadek, and A. Wirdiani, "Color Image Segmentation using Kohonen Self-Organizing Map (SOM)," vol. 6, no. 2, pp. 865–871, 2014.

[36] Y. Liu, Z. Li, H. Xiong, X. Gao, and J. Wu, "Understanding of internal clustering validation measures," *Proc. - IEEE Int. Conf. Data Mining, ICDM*, pp. 911–916, 2010.

[37] B. Desgraupes, *Clustering Indices*, no. November. University Parist Ouest, 2017.