

# FEATURE SELECTION USING SWARMS IN PARALLEL FOR CLASSIFYING AFFECTIVE AND INFORMATIVE CONTENT

Neeba E. A and S. Koteeswaran

Department of Computer Science Engineering, VelTech Dr. RR & Dr. SR Technical University, INDIA

## ABSTRACT

**Aims:** Electronic media are being utilized in recent time for obtaining medical information and even advice. There is a variety of healthcare information present in the web. For instance, there are blogs on personal experiences of particular illnesses or even discussion forums for patients and even peer-reviewed journals and so on. In the current work, content analyses of healthcare information present in the internet is carried out for obtaining overview on medical content present that makes use of higher-level features delineating medical as well as affective content in blogs. Features selection is the process of selecting relevant attributes on the basis of particular measurements. Optimization of this process is carried out through Particle Swarm Optimization (PSO) as well as Bacterial Foraging Optimization (BFO). The former is an evolutionary computational as well as intelligent swarm method which owes its inspiration to the group activity of flocks of birds or schools of fish. The latter owes its inspiration to the foraging strategies of the bacteria for achieving required variable settings in a successful manner. The bacterium mimicked is the *E. coli* which exhibits chemo taxis, swarming, tumbling, reproduction, elimination as well as dispersal behavior. BFO is generally complex and so much research has been performed for making it simpler as well as obtaining more rapid convergence. The accuracy of classifications relies on the system being created through the usage of historical information which estimates labels of unlabeled instances in an accurate fashion. In the current work, Bacterial Foraging Particle Swarm Optimization (BFPSO) learning protocol is suggested.

Published on: 18<sup>th</sup>– August-2016

### KEY WORDS

Opinion Mining (OM), Particle swarm optimization (PSO), Bacterial Foraging Optimization (BFO) Algorithm and Bacterial Foraging Particle Swarm Optimization (BFPSO)

## INTRODUCTION

Blogs as well as other social media information are increasingly influencing large numbers of people and therefore sophisticated access to the information is required to be given. Because various user groups possess various requisites on the kinds of data queries, search engines are to be capable of enabling patients as well healthcare professionals to discover the appropriate results. The results should also be capable of being filtered with regard to authors (doctors or patients), information kind (affective or informative) or even polarity (negative or positive sentiments) [1].

A vast range of healthcare related data is present in the web. There are several sites with information regarding all kinds of diseases, treatments and even healthcare in general. These kinds of information are provided by various user groups such as doctors, patients, insurance companies and even hospitals [2]. Biomedical research is present in websites like PubMed. Vast quantities of social media technologies also possess healthcare related information. These may be query and answer type, wikis, reviews, encyclopedias and even blogs, which is the primary focus in the current study.

The distinction of affective and informative posts is identical to the issue of subjectivity analysis. The primary variation in the current method and existing techniques for subjectivity analysis is that the proportion of affective to informative content is inefficiently made use of for the purpose of classification and particularly, with the target of medical blogs. Ni et al suggested in [3] a machine learning protocol for the classification of informative as well as affective posts in blogs which is related to the method employed in the current work. Their method varies from the current one in the features made use of: they utilize words as features whereas in the current method, medical concepts as well as polarity are utilized. The focus in the current work comprises medical texts in English which is distinct from blogs.

At the time of classification of documents [4], the quantity of words that are utilized as features are regarded, although merely a few terms in the text denote sentiments in actuality. The additional attributes are to be discarded because they bog down the process of classifying the documents because there are too many words greater than what is required which in turn leads to loss in accuracy because the classifier employed has to take these words into consideration as well. Utilization of lesser number of features is beneficial and so, features selection is employed for removal of non-required features. Features selection refers to the procedure of the archive being run through before classifiers are trained for removing non-required attributes. This permits classifiers to fit models to the problem sets in an expeditious manner because there is lesser data for consideration, resulting in improved accuracy.

The objective of features selection is the simplification as well as reduction in time of the training procedure. Few classifiers like k-Nearest Neighbor perform poorly when the quantity of features is high. Hence, it is of great importance to choose features selection methods that reduce quantity of features with no reduction in the performance of OM. Features selection chooses subsets of the initial features set. Optimality of features subset is assessed through evaluatory criteria. When dimensionality of domains expands, the quantity of features (N) also rises. Discovering optimum features subset is an intractable process and several issues with regard to features selection are proven to be NP-hard [5].

Bacterial Foraging Optimization Algorithm (BFOA) is becoming increasingly popular across disciplines because of its biological motivations as well as elegant architecture. Hybridization of BFOA with several protocols is being explored for examining its local as well as global search characteristics in a separate manner. It has already been employed in several real world issues and has proven its efficacy over several variations of Genetic Algorithm (GA) as well as Particle Swarm Optimization (PSO). Mathematical models, adaptations as well as alterations of the protocol form a significant chunk of the studies into BFOA in the future.

The new Bacterial Foraging Particle Swarm Optimization (BFPSO) learning protocol performs integration of the advantages of the BFO global search capacity as well as the PSO rapid convergence learning machine for minimization of their shortcomings. Population-based BFPSO learning strategy resolves poorly-defined, non-linear, complicated, multi-dimensional optimization issues [6]. Evolutionary BFPSO learning protocols directed by particular fitness functions are an effective technique for acquiring approximate code books in a huge, complicated images space.

In this paper, feature selection based evolutionary BFO-PSO is evaluated. Section 2 shows the literature surveys, section 3 explains the methodologies used in research, section 4 discussed the obtained results and section 5 concludes the work.

## RELATED WORKS

Basari et al [7] focused on binary classifications that classifies into two classes which are positive as well as negative. The former displays good opinion messages while the latter expresses bad opinions messages regarding particular movies. Justification had its basis in the accuracy levels of SVM with the validation procedure utilizing ten-fold cross validation as well as confusion matrices. Hybrid PSO was utilized for improving selection of optimal variable for solving dual optimization issue. Results revealed an enhancement in accuracy levels from 71.87% to 77%. Li et al [8] improved the performance capacity of ABC protocol, with a hybridized ABC (HAB) protocol wherein swarming activity of BFO is brought into ABC for performing local searches. The suggested techniques' performances were studied with the usage of six numerical benchmark functions and the acquired outcomes were contrasted with that of ABC as well as BFO. The outcomes from experiments revealed that the suggested technique was very efficient in resolving numerical benchmark functions apart from providing excellent solution quality as well as convergence to the global optima, specifically on multi-modal functions.

Computational performances are enhanced through usage of basic features selection in almost all studies. Opinion mining involves the identification of the polarity of opinions conveyed on an entity in a particular test. However several OM applications are not viable due to the huge amounts of attributes that occur in the archive. Isabella& Suresh [4] tested a set of features selectors in a systematic manner with regard to their efficacy in the improvement of the performance of classifiers for opinion mining. Reviews of movies are utilized for opinion mining in the particular work. Gupta et al [9] suggested a technique for automated features selection for aspect term extractions as well as sentiments classifications. The suggested method has its basis in the PSO principle and carries out features selection within the learning model of Conditional Random Field (CRF). Experimental

evaluation was carried out on the benchmark setup of SemEval-2014. Aspect-based Opinion Mining Shared Task display F-measure values of 81.91 % as well as 72.42 % for aspect term extractions in laptop as well as restaurant fields, correspondingly. The technique provides classification accuracy of 78.48 % for the latter and 71.25 % for the former.

BFOA is vastly acknowledged as an excellent global optimization protocol which is popular because of its distributed optimization as well as control. BFOA owes its inspiration to the group foraging activity of the *Escherichia coli* bacteria. BFOA is already attracting several experts due to its efficacy in the resolution of real-world optimization issues occurring in various application fields. The biological base underlying the foraging scheme of the *E. coli* bacteria is simulated and is employed as a simplistic optimization protocol. Das et al [10] details the traditional BFOA and then presents an analysis of the dynamics of the simulated chemotaxis stage with the assistance of basic mathematical models. Picking up from the study, it offers a novel adaptive variation of BFOA, wherein chemotactic step size is modified on the fly as per current fitness of virtual bacteria. Analyses on the dynamics of reproductive operators are also detailed apart from hybridization of BFOA with other optimization methods.

## METHODS

Various source of healthcare related information may be found on the web. The current work has its focus on social media tools, specifically, answer portals, wikis, reviews as well as blogs that are popular or are published by huge institutions like the Mayo clinic or the National Library of Medicine.

### Dataset

Mayo Clinic provides excellent care to all patients each day via integrated clinical practices, education as well as research. The Mayo Clinic Model of Care is characterized by excellent quality, medical care provided with compassion in a multi-speciality integrated academic institution. The main objective is the fulfilling of requirements of the patients and this is achieved through the embracing of several core attributes.

Mayo Clinic possesses twelve general blog sites for individuals looking for information or support regarding particular health or medical topics, ranging from Alzheimer's to sexual health. Bloggers publish comments and interact with Mayo Clinic professionals and other users. Mayo has the following blogs: Mayo Clinic Health Policy Center blog ([healthpolicyblog.mayoclinic.org](http://healthpolicyblog.mayoclinic.org)) for news as well as conversations regarding health care reform efforts. A blog companion ([sharing.mayoclinic.org](http://sharing.mayoclinic.org)) to the Sharing Mayo Clinic newsletter for patients as well as the entire Mayo Clinic community for connecting as well as sharing stories and experiences.

### Bacteria Foraging Algorithm (BFO)

Bacteria foraging optimization (BFO) protocol is a novel division of meta-heuristics algorithms. It is a population-based optimization method formulated by the simulation of the foraging activity of *E. coli* bacteria [11]. In real life, locomotion at the time of foraging is attained through sets of tensile flagella. These assist *E. coli* bacteria to perform tumbling or swimming, the two fundamental operations carried out by bacteria for foraging [12]. When the flagella are rotated clockwise, all flagella pull on the cell which leads to movement of flagella in an independent manner and the bacteria move for finding nutrient gradients. Rotation of flagella counter-clockwise enables the bacteria to perform swimming at a rapid rate. In this protocol, bacteria undergo chemotaxis, wherein they favor movement toward nutrient gradients and avoidance of toxic environments. Typically, bacteria travel further distances in friendly environments. BFO imitates the four basic operations present in actual bacterial systems. These are chemotaxis, swarming, reproduction as well as elimination/dispersal for solving the non-gradient optimization issue. The fundamental operations of BFOA are detailed here:

**Chemotaxis:** At the time of foraging, wherein bacteria are to trace, handle as well as ingest nutrients, *E. coli* bacteria travel towards nutrients through the assistance of flagella by either swimming or tumbling. In the former, they travel in a particular direction and in the latter, they alter the direction of searches. The above mentioned two ways of movement are constantly performed during the entire lifetime of the bacteria for moving in arbitrary routes and discovering appropriate amounts of positive nutrients.

**Swarming:** Here, after successfully discovering the direction of optimal food position, bacteria that possess knowledge regarding the best route toward the nutrients try to transmit this information to the others by means of an attraction signal. This signal communications between cells in *E. coli* bacteria is denoted by (1):

$$\begin{aligned}
 J(\theta, D(j, k, l)) &= \sum_{i=1}^N J_{CC}(\theta, D(j, k, l)) = A + B \\
 A &= \sum_{i=1}^N \left[ -d_{\text{attract}} \exp \left( -W_{\text{attract}} \sum_{m=1}^D (\theta_m - \theta_m^i)^2 \right) \right] \\
 B &= \sum_{i=1}^N \left[ h_{\text{repell}} \exp \left( -W_{\text{repell}} \sum_{m=1}^D (\theta_m - \theta_m^i)^2 \right) \right]
 \end{aligned} \tag{1}$$

wherein  $\theta$  refers to the location of the global optimal bacterium until  $j$ th chemotactic,  $k$ th reproduction, as well as  $l$ th elimination stage while " $\theta_m$ " refers to the  $m$ th variable of the global optimal bacterium.  $J(\theta, D(j, k, l))$  denotes objective function assessments, " $N$ " refers to the total quantity of bacteria while " $D$ " refers to the total variables to be optimized. The other variables like " $d_{\text{attract}}$ " refers to the depth of attracting signals transmitted by a bacterium while " $W_{\text{attract}}$ " refers to the width of attracting signals. The signals " $h_{\text{repell}}$ " as well as " $W_{\text{repell}}$ " refer to the height as well as width of repellent signals between bacteria (wherein attractants refer to signals for nutrients whereas repellents refer to signals for toxic environments).

**Reproduction:** During the procedure of swarming, bacteria form groups in the positive nutrients gradients that lead to increases in bacteria concentrations. Once the groups of bacteria are ranked as per their health value, bacteria with the worst health value die whereas bacteria with greatest health value reproduce and divide into two so as to maintain constant population.

**Elimination-Dispersal:** On the basis of environmental conditions like temperature changes, toxic environments or even presence of food, the population of bacteria might either alter in a steady or abrupt manner. At this phase, set of bacteria in restricted regions (local optimum) will be discarded or the group might be dispersed into novel food locations in the ' $D$ ' dimensional search space. Dispersal potentially flattens chemotaxis advancements. Once dispersal is done, bacteria might be situated near excellent food sources and chemotaxis is supported for identification of presence of nutrients. The processes mentioned above are iterated till optimal solutions are attained.

### Feature Selection based Bacteria Foraging Optimization

The extricated features are decreased more through usage of BFO for removal of redundant as well as non-relevant attributes. Resultant features subset is the most representative one. In all dimensions of search spaces, bacteria positions are their 0 or 1, wherein they indicate whether the feature is chosen or not correspondingly as needed features for the subsequent generation. In every iteration of the chemotaxis stage, all bacteria tumble to novel arbitrary positions. Position of  $i$ th bacteria in  $j$ th chemotaxis as well as  $k$ th reproduction stage is given by (2):

$$\Theta^i(j, k) = F_1, F_2, \dots, F_m \tag{2}$$

Wherein  $m$  refers to the length of features vector extricated. Every  $F_z = 1$  or 0 ( $z=1,2,\dots,m$ ) on the basis of whether  $z$ th feature is chosen or not for the subsequent round.

### Particle Swarm Optimization (PSO)

Particle Swarm Optimization [13] is begun with a set of arbitrarily distributed particles designated with certain random velocities. The particles travel in the  $d$ -dimensional problem space, cluster and result in convergence at global optima. The motion of particles in search space is as per the flying experiences of all individuals as well as their neighbors in the swarm population (swarm intelligence (SI)). Assume the  $i$ th particle in the swarm is at positioned at  $x_{id}(t)$  travelling with velocity  $v_{id}(t)$ . Then, position as well as velocity of the particle at subsequent iteration is  $x_{id}(t+1)$  as well as  $v_{id}(t+1)$ , correspondingly, which is represented as(3):

$$\begin{aligned}
 v_{id}(t+1) &= w \cdot v_{id}(t) + c_1 \cdot r_1 [p_{id}(t) - x_{id}(t)] + c_2 \cdot r_2 [g_d(t) - x_{id}(t)], \\
 x_{id}(t+1) &= x_{id}(t) + v_{id}(t+1)
 \end{aligned} \tag{3}$$

In the equation above, variable  $w$  refers to inertia constant which maintains a balance between local as well as global search.  $c_1$  as well as  $c_2$  refer to acceleration constants.  $r_1$  as well as  $r_2$  refer to two independently created arbitrary numbers that are uniformly distributed in the interval  $[-1, 1]$ .  $P_{id}(t)$  denotes coordinates of the optimal position found so far by the  $i$ th particle (local optimum), while the coordinates of optimal position found as of yet by the complete swarm (global optimum) is denoted by  $g_d(t)$ .

### Feature Selection based Particle Swarm Optimization

A novel features selection method is suggested by investigation of how PSO [14] may be employed for finding optimum features subset or rough set decreases. Particle Swarm Optimization is certainly beneficial for features selection because particle swarms will find optimal features combination when they travel through the problem space. Particle Swarm Optimization frequently discovers optimum solutions rapidly with such limits. Fitness functions are denoted by (4):

$$Fitness = \alpha * \gamma_R(D) + \beta * \frac{|C| - |R|}{|C|} \quad (4)$$

Wherein  $\gamma_R(D)$  refers to the classification quality of condition feature set  $R$  related to decision  $D$ ,  $|R|$  refers to the '1' number of a position or length of chosen features subset.  $|C|$  refers to the total quantity of features.  $\alpha$  as well as  $\beta$  refer to two variables relating to the importance of classification quality as well as subset length,  $\alpha \in [0, 1]$  as well as  $\beta = 1 - \alpha$ .

### Bacterial Foraging-Particle Swarm Optimization (BFPSO) in parallel

In this kind of hybrid combination, PSO carried out global searches and yields almost perfectly optimum solutions in a rapid manner after which follows a local search through BFO that fine-tunes solutions and provides optimal solutions of excellent accuracy. PSO possesses a basic shortcoming of being forced into local optima however it has excellent convergence speeds while BFOA possesses the shortcoming of low convergence speeds but the advantage of not being forced into local optima.

After a certain set of complete swims, resultant solutions are stored in descending order. In the current method, after chemotactic steps are completed, all bacteria further get mutated by a Particle Swarm Optimization [15] operator. In this phase, all bacteria are stochastically attracted toward gbest positions and local searches in various regions are handled by BFOA.

The primary aim of BFPSO features selection phase is the reduction of features of the issue prior to supervised NN classification. In all the wrapper protocols utilized, BFPSO resolves optimization issues through usage of evolution techniques and has proven to be an excellent one.

The stages for PSO-BFOA comprise:

1. Population is initialized and this is common to both PSO as well as BFOA.
2. The protocols of PSO as well as BFOA are run in parallel.
3. Optimal solution is acquired amongst PSO as well as BFOA.

### Classification Algorithm

#### Naïve Bayes (NB)

Naïve Bayes [16] is a popular probabilistic classifier and was built for incorporating unlabeled data. The job of learning of generative models is the estimation of variables through usage of labeled training data solely. The predicted variables are utilized by the protocol for classifying novel documents through the calculation of which class the specified document is a part of. Naïve Bayesian classifier functions thus:

Let there be a training set of instances with class label  $T$ .  $k$  classes  $C_1, C_2, \dots, C_k$  are present. All samples comprise  $n$ -dimensional vectors  $X = \{x_1, x_2, \dots, x_n\}$ , denoting  $n$  assessed values of  $n$  features,  $A_1, A_2, \dots, A_n$  correspondingly.

Classifiers sort the provided sample  $X$  so that it is part of the class possessing the greatest posterior probability. This means that  $X$  is estimated to be a part of the class  $C_i$  if and only if



$$P(C_i | X) > P(C_j | X) \text{ for } 1 \leq j \leq m, j \neq i \quad (5)$$

Hence class that makes maximum  $P(C_i | X)$  is discovered. Maximal value of  $P(C_j | X)$  for class  $C_i$  is known as the maximal posterior hypothesis. Bayes' theorem states:

$$P(C_i | X) = \frac{P(X | C_i)P(C_i)}{P(X)} \quad (6)$$

- Solely the value of  $P(X | c_i)P(c_i)$  is to be made maximum because for every class, value of  $P(X)$  is equal. If priori probabilities,  $P(C_i)$  of the class are unknown, then it is presumed that all classes are probably equal, i.e.  $P(C_1) = P(C_2) = \dots = P(C_k)$ , and will hence maximize  $P(X | C_i)$ . Else, value of  $P(X | c_i)P(c_i)$  is made maximum. Prior probabilities of a class are predicted by (7):

$$P(C_i) = \text{freq}(C_i, T) / |T| \quad (7)$$

For computing  $P(X | C_i)$ , a great deal of computational cost is required because the provided datasets comprise of various features. For reducing computations when evaluating  $P(X | c_i)P(c_i)$ , conditional class independence of naïve assumptions is made. Values of class label features of the provided instance are assumed to not be conditionally dependent on each other. This is represented by (8):

$$P(X | C) \approx \prod_{k=1}^n P(x_k | C_i) \quad (8)$$

### K-Nearest Neighbor (KNN)

K-Nearest Neighbor [17] classifier for patterns recognition as well as classification wherein particular test tuples are contrasted with set of training tuples which are almost identical. kNN protocol is a very simple technique for resolving classification issues. It frequently provides competitive outcomes and possesses several considerable benefits over many other data mining techniques. Offering more rapid as well as accurate recommendations to the user with favored qualities as an outcome of direct application of similitude or distances for the purposes of classification, kNN is considered extremely effective as well as dependable for understanding customer behavior as well as trends regarding a specific event or entity.

## RESULTS

Table 1 to 3 shows the classification accuracy, precision and recall respectively. Figure 2 to 4 shows the result graph for classification accuracy, precision and recall respectively.

**Table 1 Classification Accuracy**

	EBFO	PSO	PSO-EBFO
Naïve Bayes Classifier	0.8547	0.8705	0.9032
KNN	0.8495	0.8558	0.8989

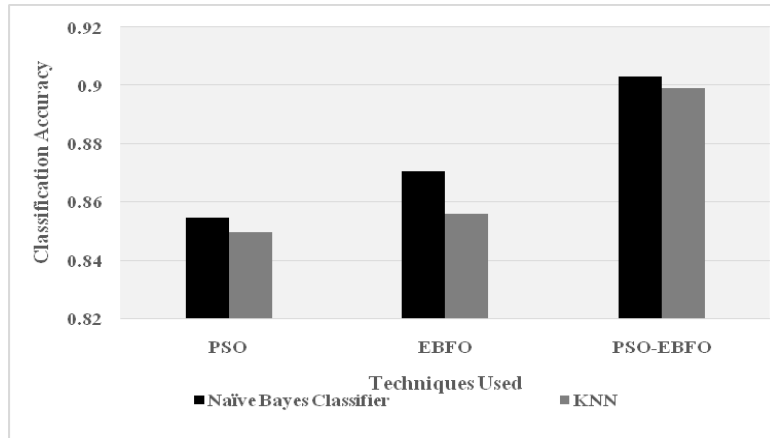


Fig. 2. Classification Accuracy

Table 1 and figure 2 shows the classification accuracy of Naïve Bayes performs better than KNN. Results shows that the accuracy of Naïve Bayes with PSO-EBFO performs better by 10.79% than Naïve Bayes with PSO and by 3.69% than Naïve Bayes with EBFO. Similarly the accuracy of KNN with PSO-EBFO performs better by 6.02% than KNN with PSO and by 5.46% than KNN with EBFO.

Table 2 Precision

	EBFO	PSO	PSO-EBFO
Naïve Bayes Classifier	0.815833	0.859933	0.8943
KNN	0.8366	0.845533	0.890533

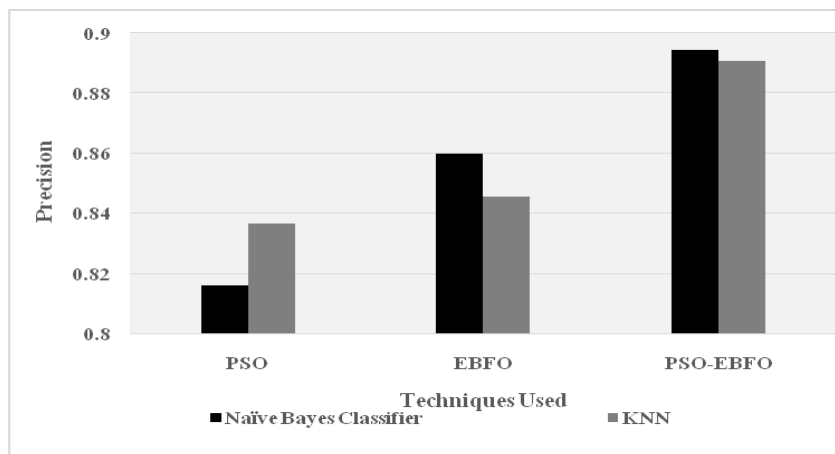


Fig. 3. Precision

Table 2 and figure 3 shows the classification accuracy of Naïve Bayes performs better than KNN. Results shows that the accuracy of Naïve Bayes with PSO-EBFO performs better by 9.18% than Naïve Bayes with PSO and by 3.92% than Naïve Bayes with EBFO. Similarly the accuracy of KNN with PSO-EBFO performs better by 6.25% than KNN with PSO and by 5.18% than KNN with EBFO.

Table 3 Recall

	EBFO	PSO	PSO-EBFO
Naïve Bayes Classifier	0.805	0.8644	0.8969
KNN	0.840467	0.845233	0.892633

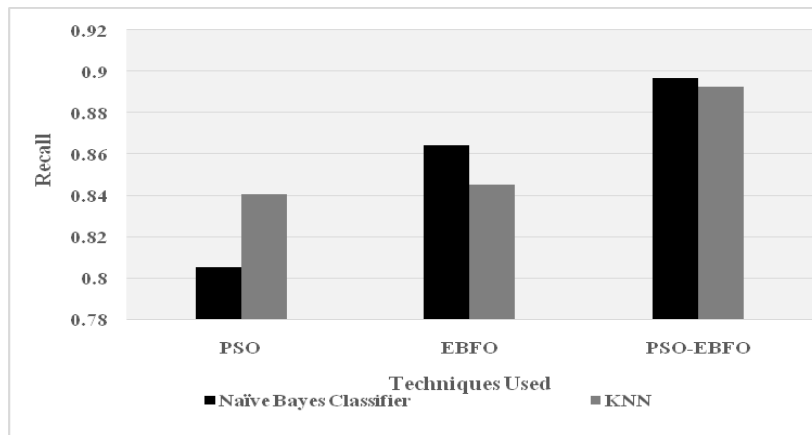


Fig. 4. Recall

Table 3 and figure 4 shows the classification accuracy of Naïve Bayes performs better than KNN. Results shows that the accuracy of Naïve Bayes with PSO-EBFO performs better by 5.52% than Naïve Bayes with PSO and by 3.69% than Naïve Bayes with EBFO. Similarly the accuracy of KNN with PSO-EBFO performs better by 5.65% than KNN with PSO and by 4.91% than KNN with EBFO.

## CONCLUSION

Automatic tracking of attitudes, sentiments as well as opinions on online forums, blogs as well as news sites is a favored tool for supporting statistical analyses by organizations and even private users. In the current work, a new method for classification of affective as well as informative posts in medical datasets is suggested. A novel BF oriented by PSO optimization protocol is suggested. The protocol joins PSO as well as BFO for exploiting PSO's capacity for exchanging social information as well as BF's capacity for discovering novel solutions through eliminations/dispersals. For experiments, classifiers such as Naïve Bayes and k nearest neighbor is used. PSO-EBFO performs better than PSO and EBFO. Experimental result shows that the classification accuracy of Naïve Bayes performs better than KNN. Results shows that the accuracy of Naïve Bayes with PSO-EBFO performs better by 10.79% than Naïve Bayes with PSO and by 3.69% than Naïve Bayes with EBFO. Similarly the accuracy of KNN with PSO-EBFO performs better by 6.02% than KNN with PSO and by 5.46% than KNN with EBFO. Also the precision and recall for proposed PSO-EBFO performs in a better way than PSO and EBFO techniques.

## CONFLICT OF INTEREST

The authors declare no conflict of interests.

## ACKNOWLEDGEMENT

None

## FINANCIAL DISCLOSURE

None.

## REFERENCES

- [1] Denecke, K., & Nejd, W. (2009). How valuable is medical social media data? Content analysis of the medical web. *Information Sciences*, 179(12), 1870-1880.
- [2] Goeriot, L., Na, J. C., Min Kyaing, W. Y., Khoo, C., Chang, Y. K., Theng, Y. L., & Kim, J. J. (2012, January). Sentiment lexicons for health-related opinion mining. In *Proceedings of the 2nd ACM SIGHIT International Health Informatics Symposium* (pp. 219-226). ACM.
- [3] X. Ni, G.R. Xue, Y. Yu, Q. Yang, Exploring in the Weblog Space by Detecting Informative and Affective Articles, in: *WWW'07: Proceedings of the 16<sup>th</sup> International Conference on World Wide Web*, 2007, pp. 181-190.
- [4] Isabella, J., & Suresh, R. (2012). Analysis and evaluation of Feature selectors in opinion mining. *Indian Journal of Computer Science and Engineering (IJCSE)*, 3(6).



- [5] A.L. Blum and R.L. Rivest. Training a 3-node neural networks is NP-complete. *Neural Networks*, 5:117 – 127, 1992.
- [6] Korani, W. M., Dorrah, H. T., & Emara, H. M. (2009, December). Bacterial foraging oriented by particle swarm optimization strategy for PID tuning. In *Computational Intelligence in Robotics and Automation (CIRA), 2009 IEEE International Symposium on* (pp. 445-450). IEEE.
- [7] Basari, A. S. H., Hussin, B., Ananta, I. G. P., & Zeniarja, J. (2013). Opinion mining of movie review using hybrid method of support vector machine and particle swarm optimization. *Procedia Engineering*, 53, 453-462.
- [8] Li, L., Zhang, F. F., Liu, C., & Niu, B. (2015, June). A hybrid Artificial Bee Colony algorithm with bacterial foraging optimization. In *Cyber Technology in Automation, Control, and Intelligent Systems (CYBER), 2015 IEEE International Conference on* (pp. 127-132). IEEE.
- [9] Gupta, D. K., Reddy, K. S., & Ekbal, A. (2015). PSO-ASent: Feature Selection Using Particle Swarm Optimization for Aspect Based Sentiment Analysis. In *Natural Language Processing and Information Systems* (pp. 220-233). Springer International Publishing.
- [10] Das, S., Biswas, A., Dasgupta, S., & Abraham, A. (2009). Bacterial foraging optimization algorithm: theoretical foundations, analysis, and applications. In *Foundations of Computational Intelligence Volume 3* (pp. 23-55). Springer Berlin Heidelberg.
- [11] Passino, K. M. (2002). Biomimicry of bacterial foraging for distributed optimization and control. *Control Systems, IEEE*, 22(3), 52-67.
- [12] Rajinikanth, V., & Latha, K. (2012). Controller parameter optimization for nonlinear systems using enhanced bacteria foraging algorithm. *Applied Computational Intelligence and Soft Computing*, 2012, 22.
- [13] Patnaik, S. S., & Panda, A. K. (2012). Particle swarm optimization and bacterial foraging optimization techniques for optimal current harmonic mitigation by employing active power filter. *Applied Computational Intelligence and Soft Computing*, 2012, 1.
- [14] Wang, X., Yang, J., Teng, X., Xia, W., & Jensen, R. (2007). Feature selection based on rough sets and particle swarm optimization. *Pattern Recognition Letters*, 28(4), 459-471.
- [15] Kora, P., & Kalva, S. R. (2015). Hybrid bacterial foraging and particle swarm optimization for detecting Bundle Branch Block. *SpringerPlus*, 4(1), 1-19.
- [16] Buche, A., Chandak, D., & Zadgaonkar, A. (2013). Opinion mining and analysis: a survey. *arXiv preprint arXiv:1307.3336*.
- [17] Sharma, V., & Gonnade, M. S. (2015). A Survey on Recommendation System Based on K-Nearest Neighbor Algorithm and Sentiment Analysis.

\*\*DISCLAIMER: This published version is uncorrected proof; plagiarisms and references are not checked by IIOABJ; the article is published as it is provided by author and approved by guest editor.