

FEATURE SELECTION USING IMPROVED SHUFFLED FROG ALGORITHM  
FOR SENTIMENT ANALYSIS OF BOOK REVIEWSMadhusudhanan<sup>1</sup> and Srivatsa<sup>2</sup><sup>1</sup>Anna University, Chennai, Tamilnadu, INDIA<sup>2</sup>Department of Computer Science and Engineering, Prathyusha Engineering College, Chennai, TN, INDIA

## ABSTRACT

Sentiment Analysis refers to a method to identify and mine subjective data from texts, sorted as either positive or negative. Features selection means selecting the best subsets of features for classifications from larger sets which will invariably comprise of unnecessary and repetitive data. Shuffled Frog Leaping Algorithm (SFLA) denotes a metaheuristic optimizing mechanism that imitates the memetic evolutionary activity of frogs searching for the place which possesses most quantity of food. In the current work a hybrid SFLA is utilized for sentiment analysis alongside 2-OPT local search algorithm, for the purpose of reviewing books. Outcomes from experiments reveal the efficacy of the suggested technique.

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## KEY WORDS

Sentiment analysis, Feature selection, Shuffled Frog Leaping Algorithm (SFLA)

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## INTRODUCTION

Sentiments, opinions and impressions are a major component of most human behavior [1]. They determine the way in which individuals think, take actions and so on. Over the last couple of years, web documents have gained a lot of interest as a resource of opinions and impressions. This has resulted in research into mechanisms for the purpose of automated extraction and analysis of individuals' opinions from online texts like consumer reviews, web blogs, and news sites' comments and so on.

Book reviews may be utilized as a mega citation [2] that comprises two major elements to be appraised. These are (1) credibility, which indicates research quality which the reviewer judges the writer to possess and (2) writing quality, which indicates the writing style quality as assessed by the reviewer. These two features generate a book review credibility-quality scale. The accessibility of several machine-readable documents from the web, has led to an increase in this. Simultaneously, machine learning techniques in Natural Language Processing (NLP) as well as Information Retrieval (IR) were significantly advanced in terms of practical utility, thereby generating easily accessible corpora. Current opinion mining (OM) as well as sentiment analysis denotes a domain of research at the juncture of IR as well as NLP, while sharing certain features with other domains like text mining as well.

Sentiment classification [3] may be developed as a supervised learning method comprising two classes: positive or negative. Reviews are typically utilized for training and evaluating information. Current supervised learning methods may be utilized for classifying sentiments, like K-nearest neighbors (KNN) or fuzzy classifier. A major part in sentiment classification is the choosing of optimal sets of features.

Typically utilized characteristics in sentiment classification include: (1) terms and the frequency that comprise single words and (2) word n-grams and the frequency or presence. These aspects are greatly utilized for classifying sentiments and are proven to be efficient for the job. Part-of-speech data also indicates sentiments in reviews [4]. Opinion/Sentiment words are phrase or words which imply either positive or negative feelings. For example, well, excellent, and great are words with positive connotation while worse, inferior, and awful have negative connotations. Although opinion words are typically adjectives or adverbs, nouns or verbs may be utilized to convey emotions as well. In a similar fashion, negation words are also crucial for evaluating polarities of

sentences as they are capable of transforming sentiments orientations. Syntactic dependency words utilized are dependency based characteristics created from dependency trees or through parsing. The quantity of high-dimensional features is mentioned and to enhance precision of classification, features selection methods are utilized.

Feature Selection (FS) [5] refers to selecting subsets of features from documents. Feature Selection is carried out by retaining words with the greatest score as per predefined metrics of the prominence of the word. High dimensionality of features space is an issue for text classification. Plenty of feature valuation measures that are notable include Information Gain (IG), term frequencies, chi-square, expected cross entropies, odds ratios, weight of evidence of texts, mutual information, Gini Index and so on.

Feature selection is the procedure of choosing the smallest subset of M features from original set of N features, such that features space is best decreased as per specified criteria. When the dimensionality of domains expand, quantity of features N also becomes larger. Discovering the optimal features subset is typically difficult and several issues with regard to features selection are NP-hard [6].

In the previous couple of years, automated text classification has been thoroughly researched and machine learning methods like Bayesian classifiers, decision trees, KNNs, Support Vector Machines (SVM), Neural Networks (NN), Rocchio's have achieved great advancements.

SFLA is a meta-heuristic optimizing approach that is inspired by the activities of frogs during their search for a locale with the most quantity of food [7]. SFLA, initially proposed by Eusuf and Lansey, may be utilized to resolve several complicated optimization issues that are non-linear, not differentiable as well as multimodal [8].

An enhanced SFLA (ISFLA) is utilized to analyse reviews of books. Section 2 deals with relevant literature; Section 3 discusses methodology utilized; Section 4 reveals outcomes of experiments and Section 5 concludes the work.

## RELATED WORKS

Basari et al [9] studied binary classifications having two classes: positive, that shows good opinions or negative, that shows bad opinions. Justifications on the basis of precision degree of SVMs with the evaluation procedure utilized 10-fold cross evaluation as well as confusion matrices. Hybrid Particle Swarm Optimization (PSO) enhanced the choosing of most optimal variable to resolve dual optimizing issue. Outcomes proved enhancement in precision levels from 71.87% to 77%.

Sharma &Dey [10] looked into the implementation possibilities of five typically utilized features selection approaches in data mining as well as seven classification approaches with a basis in machine learning to analyze opinions in a dataset filled with online movie reviews. The study revealed that features selection enhances sentiment based classification's performance, with a dependency on the approach utilized as well as quantity of features chosen. Outcomes from experiments reveal that GR provides most optimal performance in sentiment features selection while SVM outperformed the rest in sentiment based classification.

Dey [11] identified an implementation of features selection approached in analyzing sentiments and studies their execution with regard to recall and precision. Features selection approaches as well as common sentiment features lexicons like HM, GI as well as Opinion Lexicon were utilized to analyze a movie reviews data set comprising around 2000 reviews. Outcomes from experiments reveal that IG provided excellent results consistently while GR provided best results in terms of sentiment features selection. It was also revealed that the a classifier's performance relies on the quantity of representative features chosen from the texts.

Baek et al [12] compiled 75,226 customer reviews on Amazon.com through the usage of a web data crawler. Further data was also acquired through sentiment analysis. Outcomes revealed that peripheral cues like review rating as well as reviewer credibility, as well as central cues like review content determine the usefulness of a review. On the basis of dual process theories, it is revealed that customers observed various data resources of reviews, according to their needs be it merely searching for information or for valuating substitute products.

Xiong et al [13] observed the polarity of Chinese statements utilizing appraisers, degree adverbs, negations and so on, and presented a novel rule-based approach. The model merges three kinds of words in the predetermined rules; it uses the word distances of the rules as restrictions; it uses the strengths of appraisers as well as degree adverbs as items of the rules. It then uses PSO to get optimal variables of the rules like thresholds of restrictions as well as adjustment of strengths. Moreover, it makes use of the Chinese lexicon 'HowNet' as a resource for Chinese sentiments. Results prove that the approach outperforms with regard to better accuracy, recall as well as F1.

## METHODOLOGY

### DATASET

A fresh data set for sentiment domain adaptations by choosing Amazon reviews for books. All reviews comprise a rating (0-5 stars), the name of the reviewer, their location, the product's name, title for the review, date as well as the content of the review itself. A review with a rating over three stars was labelled positive; a review with a rating less than three stars was labelled negative while the remaining were removed due to ambivalent polarity. Once this sorting was completed, there were 800 samples of both positive and negative reviews so that the data set has a balanced composition. [14].

Tokenization refers to the procedure of splitting a set of text into meaningful words (stems), phrases or symbols. The tokens can be used further for parsing (syntactic analysis) or text mining. Tokenization is generally considered easy relative to other tasks in text mining and also one of the uninteresting phases. However, errors made in this phase will propagate into later phases and cause problems.

Stop words are function words like prepositions, articles, conjunctions and pronouns, providing language structure instead of content. These terms do not affect category discriminations. Additionally, common words like 'a' and 'of', may be removed as they recur frequently so that it is not discriminating for a specific class. Generic terms are detected by a threshold on the quantity of documents the term appears in, for instance, if it is present in more than 50% of the texts, or through the provision of a stop word list. Stop words are language as well as field-specific. On the basis of the classification tasks, removal of terms that are crucial predictors may be risked, for instance, the term 'can' discriminates between aluminium as well as glass recycling.

Word stemming is a rough pseudo-linguistic procedure which discards suffixes for reducing words to their stem. For instance, the words searching, searched, searches may be conflated to one stem – search. The common practice of stemming or lemmatizing, combining several word forms like plural or verb conjugation into one singular word decreases features number to be regarded.

Within Parts of Speech (PoS), the total contents of the text are denoted by unigram as well as N-gram, and are split into two categories: the first comprising single terms known as unigram, the second comprising multi-words known as N-gram. Those features with greatest relevance are regarded for sentiment classification.

### FEATURE EXTRACTION

In sentiment analysis, extracting features is the most difficult task as it needs the usage of NLP methods for automated identification of features in the opinions being analysed. The task is more challenging when considering opinions regarding stores as the features in the particular field are not pre-specified. Apart from the most apparent feature (cost of the available product) other significant features are site usability, delivery costs as well as time, dependability of store, customer care as well as packaging of products. Weighted frequency statistic is Term Frequency Inverse Document Frequency (TFIDF) statistic that computes a weight for every term reflecting its importance. The term's relevance to a specific document depends on how many words it has. This is why TFIDF denominator is adjusted for words number in a document. It is also adjusted for number of records (or documents) having the word (terms appearing on many records are down-weighted).

### TERM FREQUENCY - INVERSE DOCUMENT FREQUENCY (TF-IDF)

Every term in the document is designated a weight based on the number of times it recurs in the text. It is known as term frequency [15].  $tf(t,d)$  is a normalized frequency so as to avoid bias toward larger documents. Term frequency possesses a major issue every term is regarded with equal importance during the assessment of relevance in a request. In the real world however, particular terms have almost no power in determining the character of the document.

$$idf(t, d) = \log \frac{N}{1 + \{d \in D : t \in d\}}$$

Where,  $|D|$ : Total quantity of documents in the archive,  $|d \in D : t \in d|$ : quantity of documents wherein the term is present.  $idf(t,d) \neq 0$ .

If a term is not available in the archive the formula changes to  $1 + |d \in D : t \in d|$ .

Then  $tf-idf$  is computed as:

$$tfidf(t, d, D) = tf(t, d) \times idf(t, d)$$

Otherwise put,  $tfidf(t, d, D)$  designates to term  $t$ , a weight in document  $d$ .

### FEATURE SELECTION

Features selection techniques minimize the original set through the removal of non-relevant features for sentiment classification in order to enhance classification precision and minimize the runtime of learning models.

### INFORMATION GAIN (IG)

Entropy is a typically utilized information theory metric that qualifies the purity of a random set of samples. It is the basis of IG feature ranking techniques [16]. The entropy metric is regarded as an assessment of a system's unpredictability and if entropy is assumed as  $H(Y)$ , then IG is given by:

$$IG = H(Y) - H(Y / X) = H(X) - H(X / Y)$$

IG is a symmetrical metric. The information obtained regarding Y after observation of X is the same as the information obtained regarding X after observation of Y. A shortcoming of the IG criterion is that it is biased in favour of features with more values even when they are not more informative.

### SHUFFLED FROG LEAPING ALGORITHM (SFLA)

SFLA [17] is a population based arbitrary search algorithm that owes its inspiration to natural memetics. Here, a population of probable solutions defined by a set of frogs is split into various communities known as memeplexes. Every frog in the memeplexes performs a local search. In all memeplexes, a single frog's activity may be shaped through the activity of other frogs and it evolves in a memetic evolutionary process. Once a particular set of memetic evolution stages are done, memeplexes are pressured to merge and fresh memeplexes are generated through shuffling. Local searches and the shufflings prevail till a convergence criterion is fulfilled.

### PROPOSED IMPROVED 2-OPT -SFLA FOR FEATURE SELECTION

An enhancement algorithm that is essentially a basic local search heuristic for resolving TSP, 2-OPT is suggested. Though, failings of 2-OPT include the fact that its performance is greatly reliant on the initial solution given and that it does not possess a global search technique to avoid local minima through uphill moves. Hence, hybrid algorithms are required to merge a global search heuristic with 2-OPT local search model. In the current work, a hybrid 2-OPT-ISFLA, is suggested that merges the global search ISFLA with the local search 2-OPT. [Figure -1] below, illustrates the suggested model

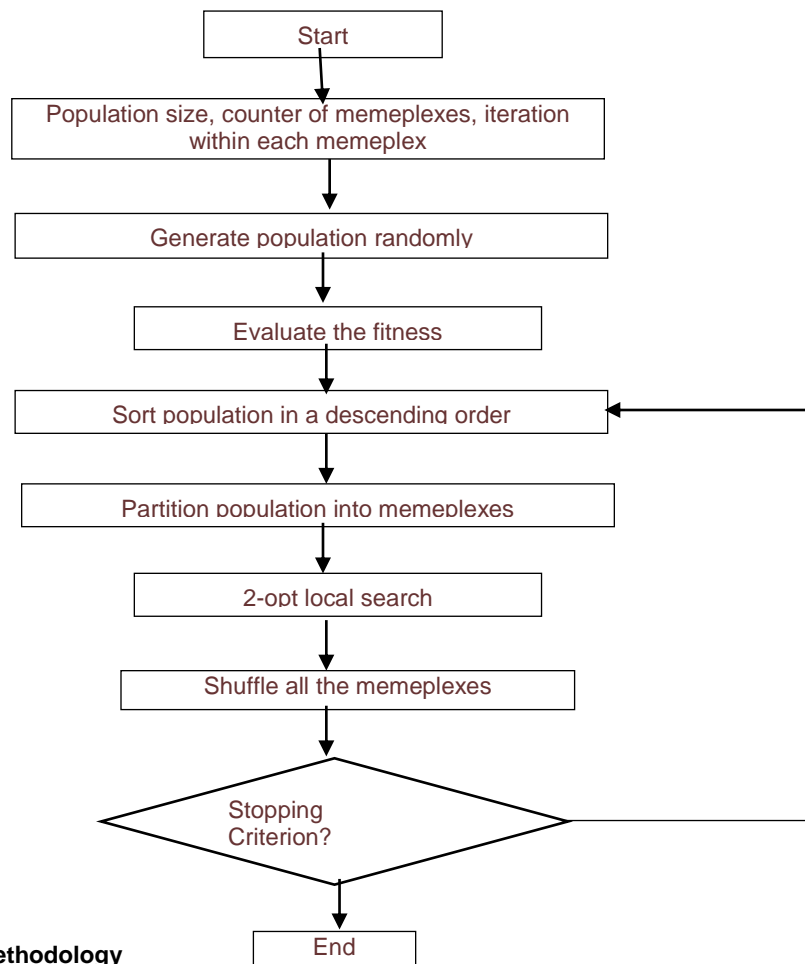


Fig: 1. Flow chart for proposed methodology

ISFLA is suggested alongside 2-OPT local search algorithm and amongst the outcomes, the most optimal solutions are extracted through features selection methods. If the outcome got is 0, then it means that it is not selected and if it is 1, then it means that it is selected.

## CLASSIFIER

### FUZZY CLASSIFIER

Classification [18] is a supervised learning issue that accepts labelled data examples and creates a classifier which sorts the data into several predetermined classes. The classification issue may be resolved through fuzzy logic. Fuzzy logic utilizes fuzzy set theories, wherein a parameter belongs to one or more sets, with a certain level of membership. Fuzzy logic when employed in computers, permits them to mimic human reasoning procedures, quantify non-precise data, take decisions on the basis of ambiguous and partial information, and yet, through the application of a 'defuzzification' procedure, reach definitive conclusions. Fuzzy classifiers comprise interpretable if-then rules denoting features as well as output class of the format:

$$R_j : \text{if } x_{p1} \text{ is } A_{j1} \text{ and } x_{pn} \text{ is } A_{jn} \text{ then class } C_j$$

Wherein  $A_{j1}, \dots, A_{jn}$  refer to antecedent fuzzy sets of input parameter  $x_{p1}, \dots, x_{pn}$  and  $C_j$  is an output class label.

Opinions words are by nature, fuzzy. For instance, the words (as well as the boundaries between them) bad, poor, awful are not apparent. Therefore, fuzzy logic is capable of representing these kinds of subjective terms and assigning them to classes with certain degrees of membership. This implies that these terms are in fuzzification stage. Definition of fuzzy sets for the words requires basis in expert opinions. Because all opinions are fuzzy, the meaning behind opinion terms may be understood in various ways. Fuzzy logic, therefore is an effective method for consideration for the proper extraction, analysis, categorization as well as summarization of opinions. This is because [19]:

- Fuzzy logic is malleable, in a conceptual aspect, simple to comprehend and is built for handling inaccurate information such as opinion terms.
- Fuzzy logic has its basis in natural languages and therefore is adequate for resolving fuzziness in human conveyed opinions.
- Sentiment classification in several recent studies employ supervised machine learning methods such as Support Vector Machine or Naïve Bayes methods.
- Fuzzy logic is an intelligent control method that depends on human-like expertise through usage of if-then rules.
- Already present OM methods as well as mechanisms are capable of classifying opinions into positive, negative or neutral classes only.
- Fuzzy logic permits improved classification of sentiments with appropriate strength designated to every opinion level. This assists in the improvement of classification accuracy.
- Subjective terms are fuzzy by nature and more so when it is with regard to opinion mining. As opinions are typically conveyed in a fuzzy nature, for instance, awesome shoes, pretty dress, cheap bike etc. and in several situations, it is hard to comprehend the level of fuzziness and if it is too awesome, too pretty or too cheap. The idea of fuzzy logic is something that could easily be dismissed by the ignorant or poorly-informed as a trivial issue or even an insignificant one. It does not refer to fuzziness of logic but rather logic of fuzziness and particularly the logic of fuzzy sets.

### K NEAREST NEIGHBOR (KNN)

KNN[20] classifier is the most simple sample based learning model. On the basis of distance functions, KNN designates class of an unknown object to the class of a known training object. Training samples with class labels are needed. The distances between unknown objects and the training samples are calculated. It then designates the class label of the training sample closest to that of the unknown object.

KNN [21] comprises two stages: Training and Classification. In the first, the training samples are vectors with class labels in multi-dimensional feature spaces. Here, feature vectors as well as class labels are stashed. In the next stage, K refers to a user-defined constant, a request or test point which is an unlabeled vector is sorted by designating a label that is the most frequent of the K training sample closest to the request point. Otherwise put, KNN contrasts the inputted feature vector against a library of reference vectors and the request point is labelled with the closest class of the feature vector in the library. This method of sorting request points on the basis of their distance to points in a training dataset is simple and efficient at the same time.

## RESULTS AND DISCUSSION

[Table -1] gives the summary of outcomes. [Figure -2] to 6depict the results for classification accuracy, sensitivity for positive, sensitivity for negative, Positive predictive value for positive and Positive predictive value for negative respectively.

Table: 1. Summary of results

	IG-KNN	IG-Fuzzy	SFLA-KNN	SFLA-Fuzzy	ISFLA-KNN	ISFLA-Fuzzy
Classification Accuracy	85.25	87.25	89.06	90.94	91.25	92.13
Sensitivity for positive	0.835	0.86	0.8925	0.905	0.9063	0.92
Sensitivity for negative	0.87	0.885	0.8888	0.9138	0.9188	0.9225
Positive predictive value for positive	0.8653	0.8821	0.8892	0.913	0.9177	0.9223
Positive predictive value for negative	0.8406	0.8634	0.8921	0.9058	0.9074	0.9202

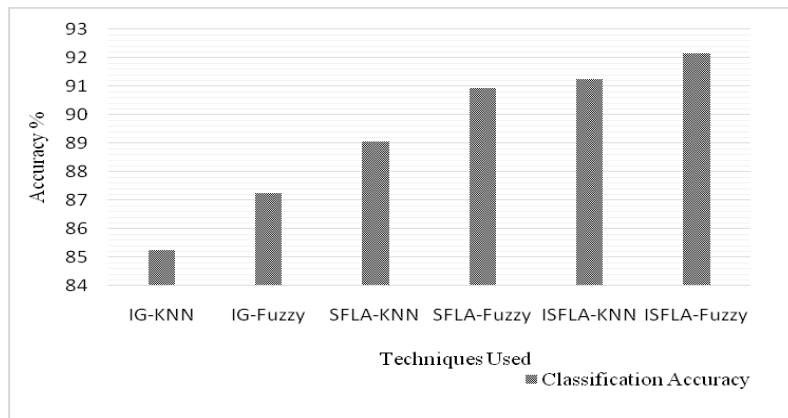


Fig:2. Classification Accuracy

From [Table -1] as well as [Figure -2] it is observed that classification accuracy of fuzzy classifier outperforms KNN classifiers. ISFLAoutperformsIG and SFLA. Results show that accuracy of ISFLA-Fuzzy performs better by 5.44% than IG-Fuzzy, by 1.3% than SFLA-Fuzzy.

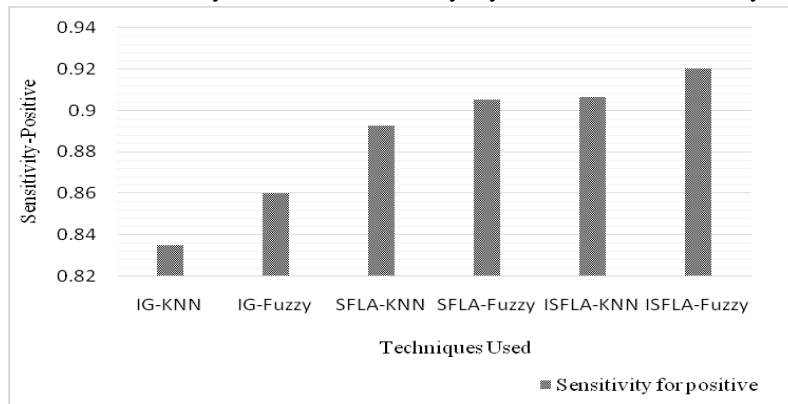


Fig: 3.Sensitivity for Positive



From [Table -1] as well as [Figure -3] it is observed that the sensitivity for positive of fuzzy classifier outperforms KNN classifiers. ISFLA outperforms IG and SFLA. Results show that sensitivity for positive of ISFLA-Fuzzy performs better by 6.74% than IG-Fuzzy, by 1.64% than SFLA-Fuzzy.

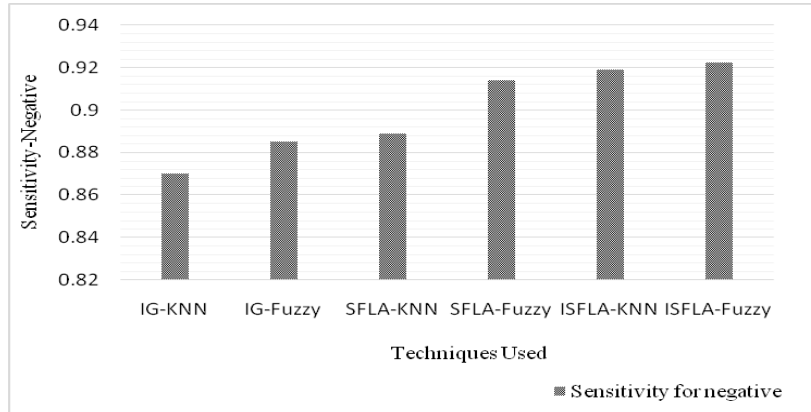


Fig: 4. Sensitivity for Negative

From [Table -1] as well as [Figure -4] it is observed that the sensitivity for negative of fuzzy classifier outperforms KNN classifiers. ISFLA outperforms IG and SFLA. Results show that sensitivity for negative of ISFLA-Fuzzy performs better by 4.15% than IG-Fuzzy, by 0.95% than SFLA-Fuzzy.

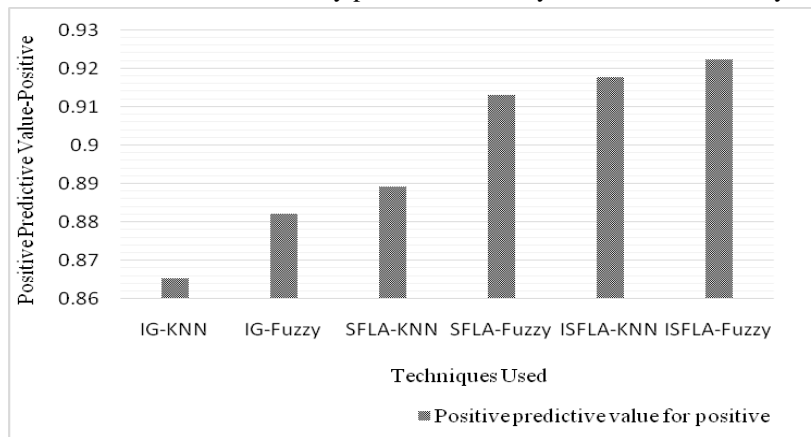
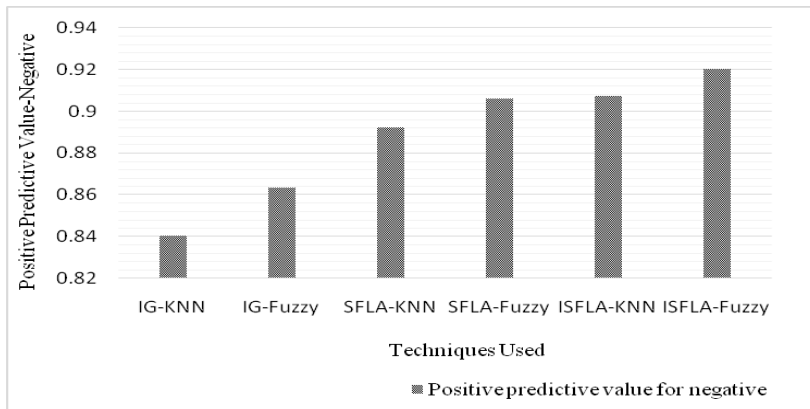


Fig: 5. Positive predictive value for positive

From [Table -1] as well as [Figure -5] it is observed that positive predictive value for positive of fuzzy classifier outperforms KNN classifiers. ISFLA outperforms IG and SFLA. Results show that positive predictive value for positive of ISFLA-Fuzzy performs better by 4.46% than IG-Fuzzy, by 1.01% than SFLA-Fuzzy.



**Fig. 6. Positive predictive value for negative**

From [Table -1] as well as [Figure -6] it is observed that the positive predictive value for negative of fuzzy classifier outperforms KNN classifiers. ISFLA outperforms IG and SFLA. Results show that positive predictive value for negative of ISFLA-Fuzzy performs better by 6.37% than IG-Fuzzy, by 1.58% than SFLA-Fuzzy.

## CONCLUSION

Shuffled Frog Leaping Algorithm (SFLA) is used with local search protocol for book reviews in sentiment analysis. Experimental outcomes reveal that the classification accuracy of fuzzy classifier outperforms KNN classifiers. Improved Shuffled Frog Leaping Algorithm (ISFLA) outperforms IG and SFLA. Outcomes reveal that accuracy of ISFLA-Fuzzy is better by 5.44% than IG-Fuzzy, by 1.3% than SFLA-Fuzzy. In a similar manner, suggested approach performs in better for other metrics as well.

## CONFLICT OF INTEREST

The authors declare no conflict of interests.

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## FINANCIAL DISCLOSURE

The authors report no financial interests or potential conflicts of interest.

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