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Hybrid Intelligent Techniques for Text Categorization

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Abstract

Text categorization is the task in which text documents are classified into one or more of predefined categories based on their contents. This paper shows that the proposed system consists of three main steps: text document representation, classifier construction and performance evaluation. In the first step, a set of pre-classified text documents is provided. Each text document is initially preprocessed in order to be split into features, these features are weighted based on the frequency of each feature in that text document and eliminate the non-informative features. The remaining features are next standardized by reducing a feature to its root using the stemming process. Due to the large number of features even after the non-informative features removal and the stemming process, the proposed system applies specific thresholds to extract distinct features which represent that text document. In the second step, the text categorization model (classifier) is built by learning the distinct features which represent all the pre-classified text documents for each sub-category of main categories; this process can be achieved by using one of the supervised categorization techniques that is called the rough set theory. Thereafter, the model uses a pair of precise concepts from the above theory that are called the lower and upper approximations to classify any test text document into one or more of main categories and sub-categories. In the final step, the performance of the proposed system is evaluated. It has achieved good results up to 96%, when applied to a number of test text documents for each sub-category of main categories.

Key Words

Rough Set Theory; Text Categorization; Text Mining.

I. INTRODUCTION

The enormous amount of information stored in unstructured texts cannot simply be used for further processing by computers, which typically handle text as simple sequences of character strings. Therefore, specific (pre-) processing methods and algorithms are required in order to extract useful patterns. Text mining refers generally to the process of extracting interesting information and knowledge from unstructured text [1].

The main goal of text mining is to enable users to extract information from textual resources and deals with the operations like, retrieval, categorization and summarization. The most important part of text mining is the text categorization [2].

Text Categorization (TC), also known as *text classification* or *topic spotting* [3], is the automatic classification of text documents under predefined categories. Information Retrieval (IR) and Machine Learning (ML) techniques are used to assign words which are also called (features, tokens, terms or attributes) to the documents which are also called (examples or instances) and classify them into specific categories. Machine learning helps to categorize the documents automatically. Information Retrieval helps to represent the text as a feature.

Manually organizing large document bases is extremely difficult, time consuming, error prone, expensive and is often not feasible, which results are dependent on variations experts judgments [4].

There are mainly two types of approaches to text categorization. One is the *rule-based approach*. In the rule-based approach, the classification rules are manually created usually by experts in the domain of the texts. Although the rule-based approach can achieve high accuracy, it is costly in terms of labor and time. The second approach involves *machine learning techniques*, in which classification rules are automatically created using information from labeled (already-categorized) texts. Machine learning is cost-saving because it requires only labeled texts [5].

Section two of this paper shows the related works and section three explains text categorization, while rough set theory is explained in section four. Section five presents the proposed system and section six presents the Abbreviations and Acronyms. Finally section seven shows the conclusions.

II. RELATED WORKS

1. In [6], **Nigam K.** demonstrated that supervised learning algorithms that use a small number of classified documents and many inexpensive unclassified documents can create high-accuracy text classifiers. Then an algorithm is introduced for learning from classified and unclassified documents based on the combination of Expectation-Maximization (EM) and a Naive Bayes probabilistic classifier.

2. In [3], **Ruiz M.** focused on the use of hierarchical classification structures, such as the Yahoo hierarchy of topics, to build and train machine learning algorithms for text categorization. For this purpose, Hierarchical Mixtures of Experts (HME) model is adapted for text categorization. HME based on the *"divide and conquer"* principle in which a large problem is divided into many smaller, easier to solve problems whose solutions can be combined to yield a solution to the complex problem. The HME model was also evaluated using neural networks, and linear classifiers (Rocchio, Widrow-Hoff (WH) and Exponentiated-Gradient (EG)) as the nodes of the hierarchy.

3. In [7], **Lee K.** describes the development of supervised and semi-supervised learning approaches to similarity-based text categorization systems. Supervised approaches to text categorization usually require a large number of training documents to achieve a high level of effectiveness. His goal was to develop a text categorization system that uses fewer classified documents for training to achieve a given level of performance. A new similarity-based learning algorithm which is called Keyword Association Network (KAN) and thresholding strategies (RinSCut variants) were described to achieve his goal. KAN was designed to give appropriate weights to features according to their semantic content and importance by using their co-occurrence information and the discriminating power values for similarity computation. RinSCut (rank-in-score) was designed to combine the strengths of two common thresholding strategies, rank-based (RCut) and score-based (SCut). The thresholding strategies can be applied to the similarity-based learning algorithms as well as similarity-based text processing tasks.

4. In [8], **Ifrim G.** proposed a model to text categorization that concentrates on the underlying meaning of words in their context (i.e., concentrates on learning the meaning of words, identifying and distinguishing between different contexts of word usage). This model can be summarized in the following steps:

- Map each word in a text document to explicit concepts.
- Learn classification rules using the newly acquired information.
- Interleave the two steps using a latent variable model.

The proposed model combines Natural Language Processing techniques such as word sense disambiguation, part of speech tagging, with statistical learning techniques such as Naïve Bayes in order to improve classification accuracy and to achieve robustness with respect to language variations.

5. In [9], **Radhi A.** designed a system which was achieved by the following steps:

- Extracting concepts from text printed in natural language using machine learning approach and finding the embedded relations between concepts using Inductive Logic Programming (ILP) to have a clear schema defining the entities and hierarchal relations in the interesting domain.

- Classifying a set of different documents based on machine learning techniques; a general inductive process automatically builds a classifier by learning from a set of pre-classified documents. The advantages of this approach are its very good effectiveness, considerable savings in terms of expert labor power and straightforward portability to different domains.

6. In [4], **Karamcheti A**. implemented two categorization engines for text categorization based on Naive Bayes and k-Nearest Neighbor methodology. Then he compared the effectiveness of these two engines by calculating standard precision and recall for a collection of documents. The compared results show that the k-Nearest Neighbor categorization engine is better than Naïve Bayes engine.

III. TEXT CATEGORIZATION

Text Categorization is the process of assigning a given text to one or more categories. This process is considered as a supervised classification technique, since a set of pre-classified documents is provided as a training set. The goal of TC is to assign a category to a new document.

TC can play an important role in a wide variety of areas such as information retrieval, word sense disambiguation, topic detection and tracking, web pages classification, as well as any application requiring document organization [10]. The following points represent the text categorization applications:

- Automatic Indexing.[11]
- Document Organization.[12]
- Document Filtering.[12] , [13]
- Word Sense Disambiguation.[8]
- Hierarchical Web Page Categorization.[14] , [15: pp. 66]

Text categorization has many types, the difference between these types are as follows.

A. Single-Label versus Multilabel Text Categorization

The case in which exactly one category is assigned to the input text is called single-label text categorization, whereas the case in which multiple categories can be assigned to the input text is called multi-label text categorization [15] , [16].

B. Document-Pivoted versus Category-Pivoted Categorization

Usually, the classifiers are used in the following way: Given a document, the classifier finds all categories to which the document belongs. This is called a document-pivoted categorization. Alternatively, the classifier finds all documents that should be filed under a given category. This is called a category-pivoted categorization [15].

C. Soft versus Hard Text Categorization

Hard categorization means a complete automated categorization system makes a binary decision on each document-category pair, while soft categorization which is also called ranking categorization means ranking the input documents or the output categories by the order of relevance, instead of making explicit assignment decision [15] , [12].

IV. ROUGH SET THEORY

Rough set theory was developed by Zdzislaw Pawlak, in the early 1980's. It deals with the classificatory analysis of data tables. The data can be acquired from measurements or from human experts. The main goal of the rough set analysis is to synthesize approximation of concepts from the acquired data [17].

The rough set approach seems to be of fundamental importance to artificial intelligence and cognitive sciences, especially in the areas of machine learning, knowledge acquisition, decision analysis, knowledge discovery from databases, expert systems, inductive reasoning and pattern recognition [18].

Rough set theory has close connections with many other theories such as fuzzy sets, statistic methods, genetic algorithms etc. Despite its connections with other theories, the rough set theory may be considered as an independent discipline [19].

The starting point of rough set theory which is based on data analysis is a data set which is represented as a table, where each row represents an object. Every column represents an attribute that can be measured for each object; this table is called an *information system*. More formally, it is a pair S = (U, A), where U is a nonempty finite set of *objects* called the *universe* and A is a nonempty finite set of *attributes* such that $a : U \rightarrow V_a$ for every $a \in A$. The set V_a is called the *value* set of a. then with any $B \subseteq A$ there is associated an equivalence relation $IND_A(B)$:

$$IND_A(B)=\{(x,y) \in U^2 \mid \forall\, a \in B \;\; a(x) = a(y)\} \quad (1)$$

$IND_A(B)$ is called the B-*indiscernibility relation*. If $(x, y) \in IND_A(B)$, then objects x and y are indiscernible from each other by attributes from B. The equivalence classes of the B-indiscernibility relation are denoted $[x]_B$ [17].

Assigning to every subset $X \subseteq U$ two sets $\underline{B}X$ and $\overline{B}X$ called the *B-lower* and the *B-upper approximations* of X, respectively, and defined as follows:

$$\underline{B}X = \{ x \mid [x]_B \subseteq X \} \quad (2)$$

$$\overline{B}X = \{ x \mid [x]_B \cap X \neq \emptyset \} \quad (3)$$

Hence, the B-*lower approximation* of a set is the union of all B-*granules* that are included in the

set, whereas the B-*upper approximation* of a set is the union of all B-*granules* that have a nonempty intersection with the set.

The set

$$BN_B(X) = \overline{B}X - \underline{B}X \quad (4)$$

will be referred to as the B-*boundary region* of X. If the boundary region of X is the empty set, i.e., $BN_B(X) = \emptyset$, then the set X is *crisp* (exact) with respect to B; in the opposite case, i.e., if $BN_B(X) \neq \emptyset$, the set X is referred to as *rough* (inexact) with respect to B [20].

A rough set X can be also characterized numerically by the following coefficient:

$$\alpha_B(X) = \frac{|\underline{B}X|}{|\overline{B}X|} \quad (5)$$

Called the *accuracy of approximation*, where |X| denotes the cardinality of $X \neq \phi$. Obviously $0 \leq \alpha_B(X) \leq 1$. If $\alpha_B(X) = 1$, X is crisp with respect to B (X is precise with respect to B), and otherwise, if $\alpha_B(X) < 1$, X is rough with respect to B (X is vague with respect to B) [19].

V. THE PROPOSED SYSTEM

The proposed system can be summarized in three main steps that are integrated to give accurate results: text document representation, classifier construction and performance evaluation. In the first step, after reading the input text document by the proposed system which divides that text document into features which are also called (tokens, words, terms or attributes), it represents that text document in a vector space as a vector whose components are that features and their weights which are computed by the frequency of each feature in that text document, thereafter it removes the non-informative features (stop words, numbers and special characters). The remaining features are next standardized by reducing them to their root using the stemming process.

In spite of the non-informative features removal and the stemming process, the dimensionality of the feature space may still be too high. So the proposed system applies specific thresholds to reduce the size of the feature space for each input text document based on the frequency of each feature in that text document.

In the second step, the proposed system performs the learning and testing processes. In the first process, the classifier is built by observing the features of sub-categories for each main category from the training set, this process can be done using one of the supervised categorization techniques that is called the rough set theory. In the second process, the classifier applies a pair of precise concepts from the rough set theory that are called the lower and upper approximations to classify the input text document from the test set into one or more of main categories and sub-categories.

In the final step, the performance of the proposed system can be measured by computing its efficiency and its effectiveness. The proposed system framework is shown in Figure1. The details of the main steps for the proposed system framework are in the following sections:

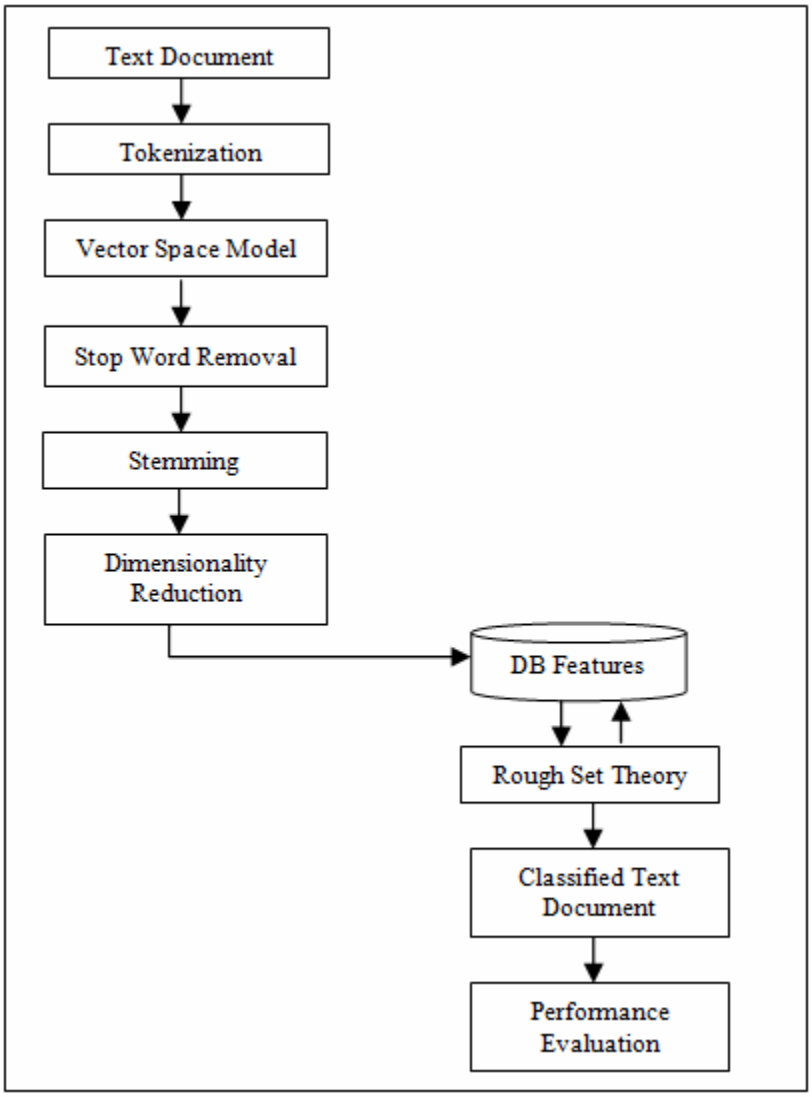

FIGURE 1. THE PROPOSED TEXT CATEGORIZATION SYSTEM FRAMEWORK.

A. Text Document

Text document collection is divided into two sets: Training set and Test set. The former indicates to pre-classified set of text documents which is used for training the classifier, while the latter determines the accuracy of the classifier based on the count of correct and incorrect classifications for each text document in that set which is classified by the classifier into suitable main categories and sub-categories.

The training set with 280 text documents was distributed in 3 main categories (Computer Science, Mathematics and Physics) and a number of sub-categories which belong to these main categories such as Computer Science includes 4 sub-categories (Artificial Intelligence, Database, Image Processing and Security), Mathematics includes 3 sub-categories (Algebra, Numerical Analysis and Statistics) and Physics includes 2 sub-categories (Laser and Materials).

B. Tokenization

Each input text document is partitioned into a list of features which are also called (tokens, words, terms or attributes).

C. Vector space model

Each input text document is represented as a vector in a vector space, each dimension of this space represents a single feature of that vector and its weight which is computed by the frequency of occurrence of each feature in that text document. This representation is called *vector space model*. In this step, each feature is given an initial weight equal to 1.

This weight may increase based on the frequency of each feature in the input text document (i.e., the similar features in size and characters are conflated under a single feature. The weight of a single feature results from summing the initial frequencies of the conflated features).

D. Stop Words Removal

A stop list is a list of commonly repeated features which appear in every text document. The common features such as pronouns he, she, it and conjunctions such as and, or, but etc. need to be removed because they do not have effect on the categorization process (i.e., each feature should be removed when it matches any feature in the stop words list). For the same reason, if the feature is a special character or a number then that feature should be removed.

E. Stemming

Stemming is the process of removing affixes (prefixes and suffixes) from features. This process is used to reduce the number of features in the feature space and improve the performance of the classifier when the different forms of features are stemmed into a single feature.

For example: (**convert, converts, converted, converting**)
From the above example, the set of features is conflated into a single feature by removal of the different suffixes -s, -ed, -ing to get the single feature **convert**.

There are different types of the stemming algorithms; some of them can produce incomplete stems which don't have meaning.

One of the most common stemming algorithms uses a set of rules to remove suffixes from features, this process continues until none of the rules apply. This algorithm has some drawbacks such as it is not limited to produce feature stems, for example, "revival" becomes "reviv". And it does not deal with prefixes completely, so "relevant" and "irrelevant" remain as unrelated features.

Another type of the stemming algorithms has a large set of suffixes. This type gives priority to the longest suffix which exists in the set of suffixes; the suffixes can be removed by applying a set of rules. The main drawbacks of this type are that it is time consuming, and many suffixes are not available in the set of suffixes.

The proposed system implements the stemming process by applying a set of rules in specific way. The rules of the stemming process are as follows:

- All prefixes are removed from features, if the prefix exists in features.
- The stemming process uses a lexicon to find the root for each irregular feature. Where the lexicon has four irregular tables (irregular verb, irregular noun, irregular adjective and irregular adverb), each table has some fields which represent conjugate of each feature such as the irregular verb table has (the verb root, past, past participle, present participle and plural) fields. If the feature matches any feature in the fields of the irregular tables then that feature should be converted to its stem (root) form which exists in the first field of each irregular table.
- When the only difference among the similar features in the first characters is (-s, -d, -es, -ed, -ly, -er, -ar, -ing, -ance, -ence, -tion, -sion or any other suffixes), then these features are conflated under the shortest one among them. The weight of the shortest feature results from summing the frequencies of the conflated features.

F. Dimensionality Reduction

Even after the non-informative features removal and the stemming process, the number of features in the feature space may still be too large. Among these features, some features may be unuseful to the categorization task and sometimes decrease accuracy. Such features can be removed without affecting the classifier performance.

The large number of features may affect the classifier learning because most machine learning algorithms which are implemented on text categorization cannot deal with this huge number of features.

Dimensionality reduction of the feature space can be done by feature selection and feature extraction.

Dimensionality reduction by feature selection deals with several methods for features selection.

These methods are applied to reduce the size of the full feature set. Most feature selection methods suffer from time-consuming which is considered a critical problem in text categorization system.

Dimensionality reduction by feature extraction is to create a small set of artificial features from original feature set. The main cause for using artificial features is the problems of polysemy, homonymy and synonymy; the words may not be the optimal features.

For the above reasons, the proposed system does not use the dimensionality reduction by feature selection or feature extraction; it uses specific thresholds (10%, 8%, 6% and 4%) to reduce the number of features in the feature space for each input text document (i.e., the features are selected from features that derived from the stemming process, whose frequencies equal or larger than 10%, 8%, 6% or 4% of the number of derived features from the stemming process) and in the learning process, it stores the resulted features which represent the input text document in one of the database tables which represent the sub-categories for each main category based on the sub-category for that text document and stores the weights of the resulted features under any frequency field (i.e., Freq. >= 10%, 8%, 6% or 4%) of that database table based on the frequency of these features in the input text document. But in the testing process, it stores the resulted features in a list which contains all features that represent the input text document.

G. The Learning \ Categorization Technique for Text Categorization - Rough Set Theory

A classifier can be built by learning the features which represent all the training text documents for each sub-category of main categories, after that the classifier becomes ready to classify any test text document into a suitable main category and sub-category based on the content of that text document.

Rough set theory has been successfully applied to machine learning. This theory is a supervised categorization technique, because the categories of the training text documents are already known in advance.

A pair of precise concepts from the rough set theory that are called the lower and upper approximations have been used to classify the test text documents into one or more of main categories and sub-categories. When the test text document is given to the trained classifier; it should predict the correct main category and sub-category for that text document.

The testing set with 100 text documents was categorized into 4 categories and a number of sub-categories which belong to the first three categories (Computer Science, Mathematics and Physics) such as Computer Science includes 4 sub-categories (Artificial Intelligence, Database, Image Processing, Security), Mathematics includes 3 sub-categories (Algebra, Numerical Analysis, Statistics) and Physics includes 2 sub-categories (Laser and Materials). The proposed system does not only deal with text documents in these categories, but it also deals with any text

document in any topic.

All the steps that were applied to the training text documents should be applied to the test text documents such as tokenization, vector space model, stop words removal, stemming and dimensionality reduction.

After applying all the previous steps to the test text documents, a set of distinct features which represents the test text document is obtained.

1. *Upper approximation:* It is the intersection between the features which represent the test text document and the features in any database table, that have a frequency under any frequency field (i.e., Freq. >= 10%, 8%, 6% or 4%) of that database table which represent the sub-category of main categories. The resulted features represent a set of upper approximation features.

2. *Lower Approximation:* It is the intersection between the features which represent the test text document and the features which appear in only one database table, that have a frequency under any frequency field (i.e., Freq. >= 10%, 8%, 6% or 4%) of that database table which represents the sub-category of main categories. The resulted features represent a set of lower approximation features.

The difference between the upper and lower approximations for the set of features is called the boundary region for that set.

The accuracy of approximation can be measured by computing the ratio between the lower and upper approximations for the set of features which represents the test text document, when the accuracy value equals to 1 then the above set of features is called **Crisp**, but when the accuracy value less than 1 then the above set of features is called **Rough**.

H. Classified Text Document

After applying all the steps to represent the test text documents (i.e., to convert the test text documents into compact representation of their contents) and implementing the lower and upper approximations concepts from the rough set theory to their representation, the trained classifier should predict the correct main categories and sub-categories for these text documents.

I. Performance Evaluation for a Classifier

The performance of the proposed system can be measured by calculating its efficiency (i.e. average time required to build a classifier from a set of the training text documents and average time required to classify any test text document by the classifier) and its effectiveness (i.e. the classifier ability to give the correct classification). The learning time for building the classifier is shown in Figure 2. The average of the testing time for classifying of the test text documents is shown in Figure 3.

There are many metrics to evaluate the effectiveness of the proposed system. The most common are accuracy, error rate, precision and recall [21]. The results of calculating Precision and Recall are shown in Table 1.

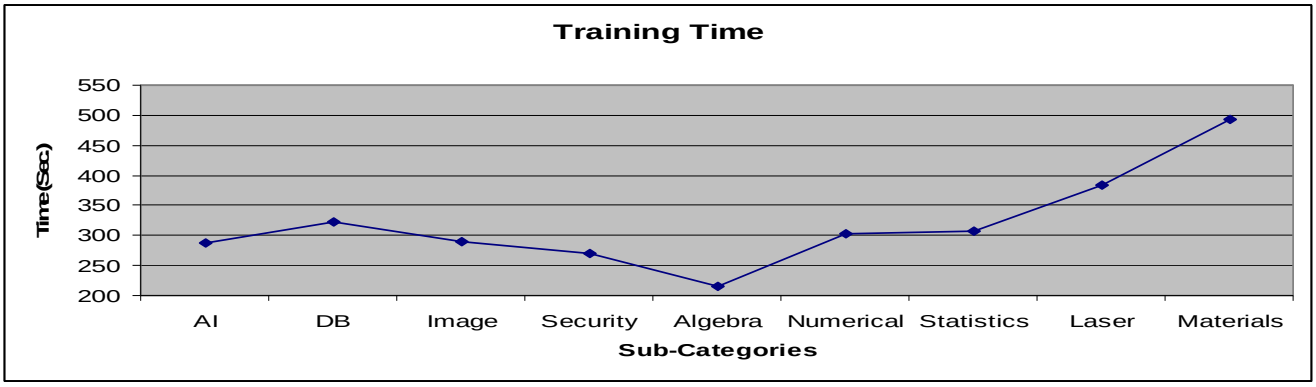

FIGURE 2: THE LEARNING TIME FOR BUILDING THE CLASSIFIER

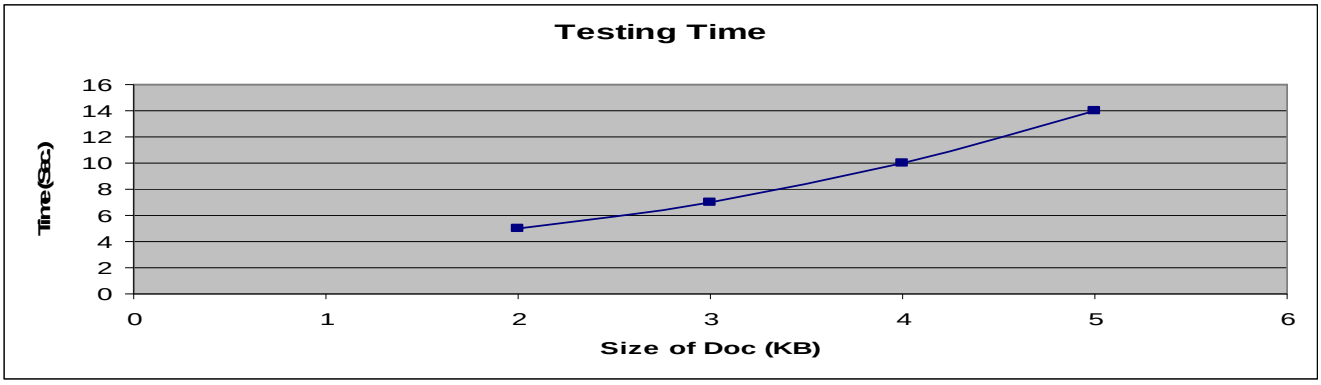

FIGURE 3: THE AVERAGE OF THE TESTING TIME FOR CLASSIFYING OF THE TEST TEXT DOCUMENTS

1. Accuracy (Ac): Is the ratio between the number of text documents which were correctly categorized and the total number of documents.

$$Ac_i = \frac{TP_i+TN_i}{TP_i+TN_i+FP_i+FN_i} \quad (6)$$

Where TPi (true positives) is the number of text documents correctly classified in category ci, TNi (true negatives) is the number of text documents correctly classified as not belonging to category ci, FPi (false positives) is the number of text documents incorrectly classified in category ci, and FNi (false negatives) is the number of text documents incorrectly classified as not belonging to category ci [21].

2. Error rate (E): Is the ratio between the number of text documents which were not correctly categorized and the total number of text documents.

$$E_i = 1 - Ac_i = \frac{FP_i+FN_i}{TP_i+TN_i+FP_i+FN_i} \quad (7)$$

3. Precision (P): Is the percentage of correctly categorized text documents among all text documents that were assigned to the category by the classifier.

$$P_i = \frac{TP_i}{TP_i+FP_i} \quad (8)$$

4. Recall (R): Is the percentage of correctly categorized text documents among all text documents belonging to that category.

$$R_i = \frac{TP_i}{TP_i+FN_i} \quad (9)$$

TABLE 1. THE RESULTS OF CALCULATING PRECISION & RECALL FOR THE PROPOSED SYSTEM.

Main Categories	Sub-categories	Precision	Recall
Computer Science	Artificial Intelligence (AI)	100%	100%
	Database (DB)	95.65%	100%
	Image Processing	100%	94.73%
	Security	83.33%	95.23%
Mathematics	Algebra	100%	100%
	Numerical Analysis	100%	100%
	Statistics	95.23%	90.90%
Physics	Laser	100%	100%
	Materials	100%	100%
Unknown		100%	100%

The performance evaluation for each category is shown in Figures 4, 5 and 6.

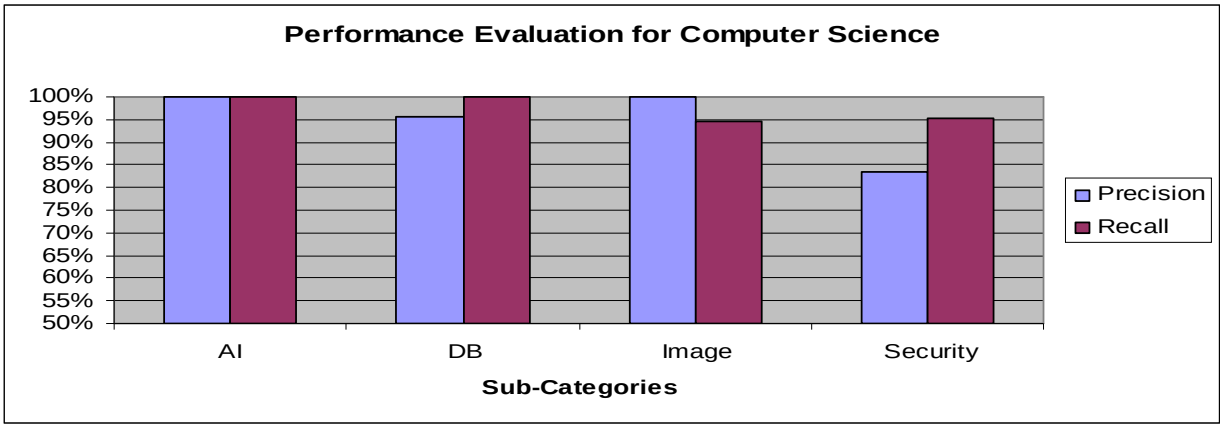

FIGURE 4. THE PERFORMANCE EVALUATION FOR COMPUTER SCIENCE CATEGORY.

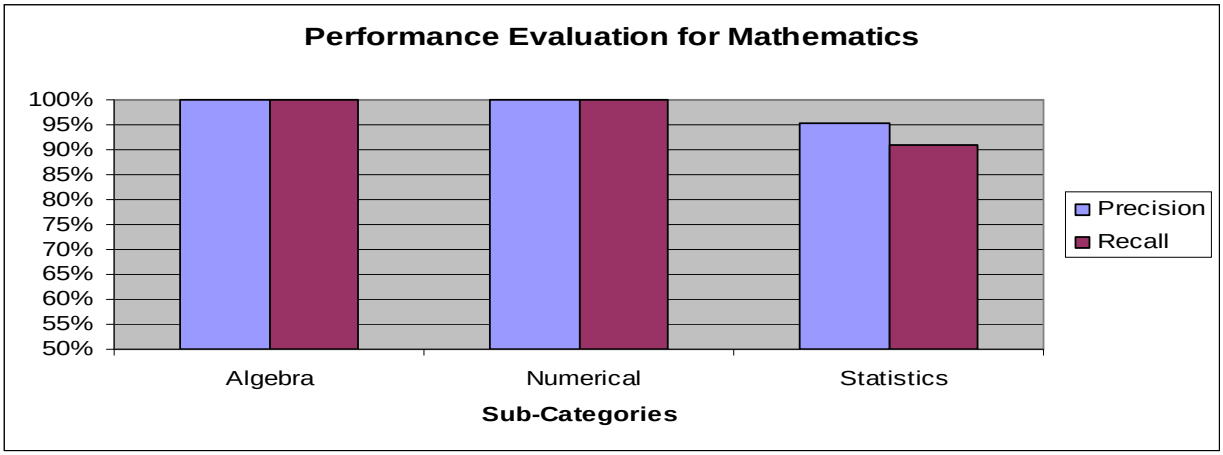

FIGURE 5. THE PERFORMANCE EVALUATION FOR MATHEMATICS CATEGORY.

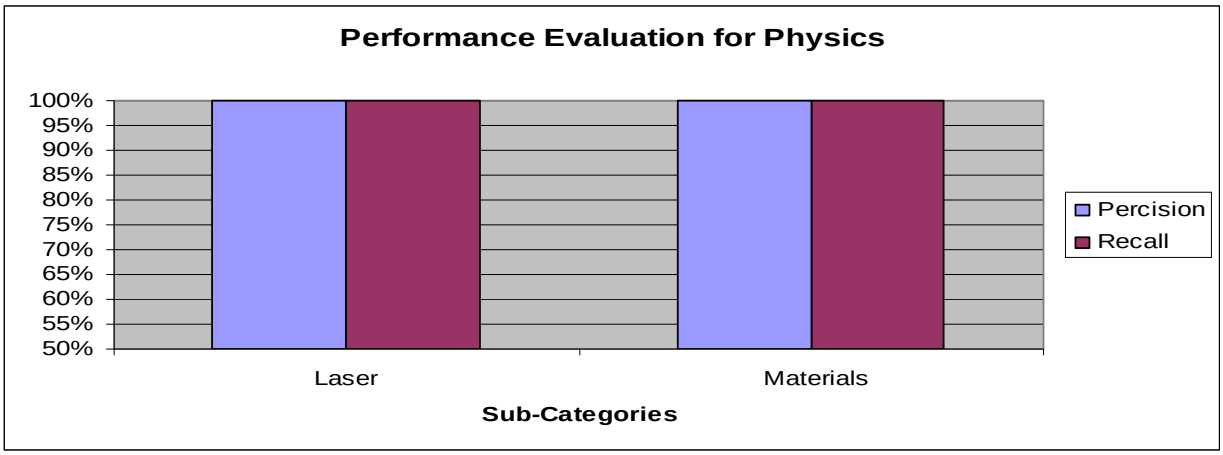

FIGURE 5. THE PERFORMANCE EVALUATION FOR MATHEMATICS CATEGORY.

The below Algorithm illustrates the main behavior of the proposed system.

Input: *$D_1, D_2,\ldots,D_m$ (Different Text Documents), $C_1, C_2,\ldots,C_n$ (specific categories)*

Output: *Classified Text Document*

Begin

For *each category C_i* ***Do***

For *each Text Document D_j for C_i* ***Do***

Split D_j into features $\Rightarrow F_j$

Remove stop words, number and special characters from $F_j \Rightarrow T_j$

Give frequency equal to 1 for $T_j \Rightarrow Ftr_j$, Ftr_freq_j

Make stemming and some morphology processing for Ftr_j and increase frequency for Ftr_freq_j $\Rightarrow Short\_Ftr_j$, $short\_Ftr\_Freq_j$

Make Dimensionality Reduction for $Short\_Ftr_j \Rightarrow DR_j$

Add DR_j in DB (database) for C_i

End For

Compute Upper Approximation for C_i using the following equation

$$\overline{B}X = \{ x \mid [x]_B \cap X \neq \emptyset \}$$

Compute Lower Approximation for C_i using the following equation

$$\underline{B}X = \{ x \mid [x]_B \subseteq X \}$$

Compute the Percentage between Upper Approximation for C_i and DR_j for D_j, the highest Percentage represent the correct category for D_j

Compute accuracy for C_i using the following equation

$$\alpha_B(X) = \frac{|\underline{B}X|}{|\overline{B}X|}$$

End For

End

VI. CONCLUSION

The categorization techniques cannot directly process the text documents in their original form, so each input text document should be converted into compact representation of its content by using the preprocessing steps which include (tokenization, vector space model, stop words removal, stemming and dimensionality reduction).

The stemming process can be implemented by applying a set of rules in specific way instead of chopping off the characters blindly and producing stems that don't have meaning. So the similar features are conflated under a single feature, thereafter when the only difference among the similar features in the first characters is (-s, -d, -es, -ed, -ly, -er, -ar, -ing, -ance, -ence, -tion, -sion or any other suffixes) then these features are conflated under the shortest one among them. The weights of the single feature and shortest feature result from summing the frequencies of the conflated features under them.

The size of the feature space is not reduced by implementing the feature selection methods such as (mutual information, information gain, etc.) because these methods reduce the size of the full feature set and are time consuming. So the proposed system implements specific thresholds (10%, 8%, 6% and 4%) to reduce the size of the feature space for each input text document based on the frequency of each feature in that text document, the resulted features represent that input text document.

The rough set theory is a supervised categorization technique; it is used for building the text categorization model by learning the properties of a set of pre-classified text documents for each sub-category of main categories. Thereafter, the model uses a pair of precise concepts from the rough set theory that are called the lower and upper approximations to classify any test text document into one or more of main categories and sub-categories, because the system deals not only with the main categories, but also with a number of sub-categories for each main category.

When the rough set theory concepts are used in the proposed system, the results of the system reach to 96% when it is applied to a number of test text documents for each sub-category of main categories.

The proposed system computes for each test text document in the set of the test text documents the testing time based on the size of each text document in that set. Thereafter, the average of that time is computed for all test text documents, which ranges from 5 to 14 Sec.

The proposed system computes for each sub-category from the training text documents the learning time based on the size of each text document in that sub-category. The above time ranges from 215 to 494 Sec. for all sub-categories.

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