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HYBRID CLASSIFICATION ALGORITHMS FOR TERRORISM PREDICTION in Middle East and North Africa

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Abstract

Machine learning methods used for prediction and decision support are of great concern nowadays. Methods for learning implicit, non-symbolic knowledge provide better predictive accuracy. But Methods for learning explicit, symbolic knowledge produce more comprehensible models. Hybrid machine learning models combine strengths of both knowledge representation of model types. In this research we compare predictive accuracy and comprehensibility of explicit, implicit, and hybrid machine learning models. This research based on predicting terrorist groups responsible of attacks in Middle East and North Africa from year 2009 up to 2013 by comparing various standard, ensemble, hybrid, and hybrid ensemble machine learning methods namely; Naïve Bayes, K-nearest neighbours, Decision Tree, Support Vector Machine; Hybrid Hoeffding Tree, Functional Tree, Hybrid Naïve Bayes with Decision Table, Classification via Clustering; Random Forests; and Stacking classifiers. Afterwards compare the results obtained from conducting the experiments according to four different performance measures. Experiments were carried out using real world data represented by Global terrorism Database (GTD) from National Consortium for the study of terrorism and Responses of Terrorism (START).

Keywords: Hybrid Models, Machine Learning, Predictive Accuracy, Supervised Learning.

1.Introduction

Machine learning (ML) is the process of estimating unknown dependencies or structures in a system using a limited number of observations [1]. ML algorithms are used in data mining applications to retrieve hidden information and used in decision-making [1]. Machine learning methods are rote learning, learning by being told, learning by analogy, and inductive learning, which includes methods of learning by examples and learning by experimentation and discovery [1], [2].

Numerous machine learning methods and different knowledge representation models can be used to support decision making methods [3]. For example, classification, and regression methods can be used for learning decision trees, rules, Bayes networks, artificial neural networks and support vector machines.

The concept of combing classifiers is proposed as a new direction for the improvement of the performance of individual machine learning algorithms.

Hybrid and ensemble methods in machine learning have attracted a great attention of the scientific community over the last years [1]. Multiple, ensemble learning models have been theoretically and empirically shown to provide significantly better performance than single weak learners, especially while dealing with high dimensional, complex regression and classification problems [2]. Adaptive hybrid systems has become essential in computational intelligence and soft computing, a main reason for being popular is the high complementary of its components.

The integration of the basic technologies into hybrid machine learning solutions [4] facilitate more intelligent search and reasoning methods that match various domain knowledge with empirical data to solve advanced and complex problems [5]. Both ensemble models and hybrid methods make use of the information fusion concept but in slightly different way. In case of ensemble classifiers, multiple but homogeneous, weak models are combined [6], typically at the level of their individual output, using various merging methods, which can be grouped into fixed (e.g., majority voting), and trained combiners (e.g., decision templates) [7]. Hybrid ML systems combine, and integrate different machine learning, heterogeneous machine learning [8],[9] and decision making models, they are, however, may considerably improve quality of reasoning and boost adaptivity of the entire solutions. For that reason, ensemble and hybrid methods have found application in numerous real word problems ranging from person recognition, through medical diagnosis, bioinformatics, recommender systems and text/music classification to financial forecasting [8], [10], medical studies, weather prediction as well as terrorism prediction in our research.

In our research study a real world data set of Middle East and North Africa is used for terrorism prediction based on hybrid machine learning algorithms with the help of WEKA as one of important machine learning software written in JAVA [11], and a detailed comparison is performed among the used hybrid methods and other standard, and ensemble models.

The organization of this paper is as follows; Section 1 covers the literature review about the previous and present work on hybrid machine learning algorithms. Section 2 illustrates the machine learning concept as well as machine supervised learning methods for learning classification. Section 3 explains hybrid machine learning models and methods. Section 4 studies in details the experimental methods, dataset and used software, results and analysis; illustrated with figures and tables. Finally, section 5 covers conclusions and future work.

2.LITERATURE REVIEW

According to M. Wozniak [12] and J. Gama [13], there are a lot of machine hybrid methods developed in the past such as Model Trees- multivariate trees with linear or some other functional models at the leaves [14], [15], [16]. Perception Trees- combination of a decision tree and a linear threshold unit are presented by P. E. Utgoff [17]. The authors B.Konoenko and R.Kohavi proposed a new algorithm, NBTree, which induces a hybrid Decision Tree and Naïve Bayes Classifiers where the decision tree nodes contain univariate splits as regular decision-trees, but the leaves contain Naïve Bayes classifiers [18], [19]. Functional trees- an extension of multivariate and model trees [12]. Model Class Selection- a hybrid algorithm that combines, in a single tree, nodes that are univariate tests, or multivariate tests generated by linear machines or instance-based learners [20]. In Meta decision tress- Lj. Todorovski, S. Dzeroski combined different classifiers with meta Decisoin Trees where leaves predict which classifier should be used to obtain a prediction [21]. Stacked generalized hybrid ensembles which are constructed from different base learning methods [22]. In Hybrid Hoeffding Trees - several hybrid variants of the basic method using naïve bayes, functions and ensemble methods are presented by S. B. Kotsiantis, I. D. Zaharakis [23]. Piotr Sobolewski and Michał Woźniak faced with concept drift that means the problem of significant changes in statistical properties of the target variables is usually caused by some hidden and unknown features making the classification models less accurate over course of time. Detection of concept drift is very important in real dynamic environments since it may be a hint to trigger classification model reconstruction, and they focus on detection of virtual concept drift using unsupervised learning based on knowledge about the possible data distributions that may occur in the data stream; without any knowledge about real class labels. A priori distribution patters are treated as the known concepts, among which changes are being detected. The authors have developed their own method called simulated recurrence based on majority voting ensembles on results of statistical tests for distributions of known features. As an additional benefit, the concept detection makes the selection of the right classification model easier since a separate model may be pre-assigned to each concept.

Javier Torres Niño et al. extended fundamental classification method – decision trees by combination unsupervised and supervised machine learning, i.e. clustering and classification. Additionally, they utilize a third component, which goal is to adjust clustering parameters. First, the predicted class attribute is removed before clustering and the number of instances in the majority class is calculated and compared with a given threshold to determine whether the instances in the entire cluster are treated as classified or not. The instances from the non-classified cluster are used to learn the decision tree [24].

Tomasz Kajdanowicz and Przemysław Kazienko [25] provided a new method for the complex machine learning problem – multi-label classification, in which every instance can be independently assigned with many class labels simultaneously. The problem becomes especially demanding in case of larger output space – with many possible subsets of the class label set. The method is derived from the general boosting concept adapted to the multi-label environment.

Chun-Wei Lin et al. [26] proposed a new integrated MFFP- tree algorithm to extract fuzzy association rules, its main feature is its ability to process and integrate multiple sources, local databases. It has been achieved by means of integration of many local fuzzy regions and tree branches into one coherent multiple fuzzy frequent pattern tree (MFFP-tree). It enables the authors to generate more complete global association rules, also preserving their local equivalences.

3. MACHINE LEARNING METHODS

3.1Machine Learning

Machine learning (ML) is defined as the process of estimating unknown dependencies or structures in a system using a limited number of observations [1]. The goal of ML is to devise learning algorithms that do the learning automatically without human intervention or assistance. Machine learning tasks are classification, regression and clustering. Machine learning methods are rote learning, learning by being told, learning by analogy, and inductive learning, which include different methods of learning by examples, learning by experimentation, and discovery [1], [2]. There are several applications for ML, the most significant of which is predictive data mining [23]. Every instance in any dataset used by ML algorithms is represented using the same set of features. The features may be continuous, categorical, or binary.

If instances are given with known labels then learning is called supervised,

in contract with unsupervised learning, where instances are unlabeled [27]. Numerous ML applications involve tasks that can be set up as supervised. In our research we have concentrated with machine learning of classifications which is an important branch of study. A system learns to classify new cases to predefined discrete problem classes. Classification is a special kind of regression, ML of classification performs an estimation of an unknown dependence between input (data) and output of the considered system (classification) [3].

The main goal of our research is to learn the possibility of combining classifiers which is usually better than any of its elements; with other words utilize the strengths of one classifier to complement the weaknesses of another.

3.2.Machine Learning Methods for Learning Classifications

3.2.1Methods for learning comprehensible Knowledge

Methods for learning comprehensible, human readable knowledge are especially appropriate in building knowledge based decision support systems/expert systems. Well known and famous methods are Decision Tree (DT), and rule Learning(RL), as well as Hoeffding Tree or Very Fast Decision Tree(VFDT), which is a new method introduced for incremental machine learning from data streams [25]. It stores a data stream only once and after that updates the tree.

3.2.2. Methods for Learning Implicit Knowledge

Implicit or distributed knowledge is subjective, empirical, hard to formalize, and not understandable for humans [3]. It can be represented in forms of bayes or neural networks, support vectors or using the similarity function and learning examples by itself. The most used methods of this type are K-Nearest Neighbours (KNN), Bayes Networks, Artificial Neural Networks (ANN), and Support Vector Machine (SVM).
SVM is a very successful method of machine learning from examples [26], which is based on mapping of learning examples from input space to a new high dimensional, potentially infinite dimensional feature space in which examples are linearly separable. The method then finds an optimal hyperplane.

3.3.3.Redundant Knowledge Machine Learning

Methods of learning and combining redundant classifiers or ensembles are one approach for increasing prediction accuracy models on unseen examples, which is the most important generalization property. The most famous methods in that regard are Random Forests Method [30], which simultaneously uses two sources of diversity of its elements: (1) resampling of learning data and (2) resampling the attribute set as part of the induction process, the other method called CART [31].

4.HYBRID MACHINE LEARNING METHODS

Supervised learning is the machine learning task of inferring a function from supervised training data [3]. This function is called a classifier; with other words, the supervised learning problem is to find an approximation to unknown function given a set of previously labeled examples. Different methods explore different hypothesis spaces, use different search strategies and are appropriate for different types of problems. The training data consist of a set of training examples. In supervised learning, each example is a pair consisting of an input object (typically a vector) and a desired output value (also called the supervisory signal).
A supervised learning algorithm analyzes the training data and produces an inferred function, which is called a classifier (if the output is discrete, so we deal with classification) or a regression function (if the output is continuous, so it is a regression). The inferred function should predict the correct output value for any valid input object.

5.EXPERIMENTS

This research paper investigates applicability of selected basic and hybrid machine learning methods to predict the terrorist groups that responsible of attacks in Middle East & North Africa from year 2009 up to year 2013.

5.1 Methods

Selected standard and hybrid machine learning methods are compared, together with ensemble and hybrid ensemble methods:

- **Standard Methods:** Naïve Bayes (NB), K-nearest neighbours (KNN), Decision Tree(C 4.5), Support Vector Machine (SVM);
- **Hybrid Methods:** Hybrid Hoeffding Tree (HHT), Functional Tree (FT), Hybrid Naïve Bayes with Decision Table (DTNB), Classification via Clustering(C via C);
- **Ensemble Methods:** Random Forests (RFs);
- **Hybrid Ensemble methods (Meta):** Stacking

5.2 Data Set

The data set used in our research study is a real world data about terrorist events occurred in Middle East & North Africa in the period from 2009 till 2013, which consists of a total of 43335 terrorist events (instances), and 45 attributes, the attribute terrorist group is consisting of 120 diverse terrorist groups.
The main steps in our research study are explained in the following flow diagram.

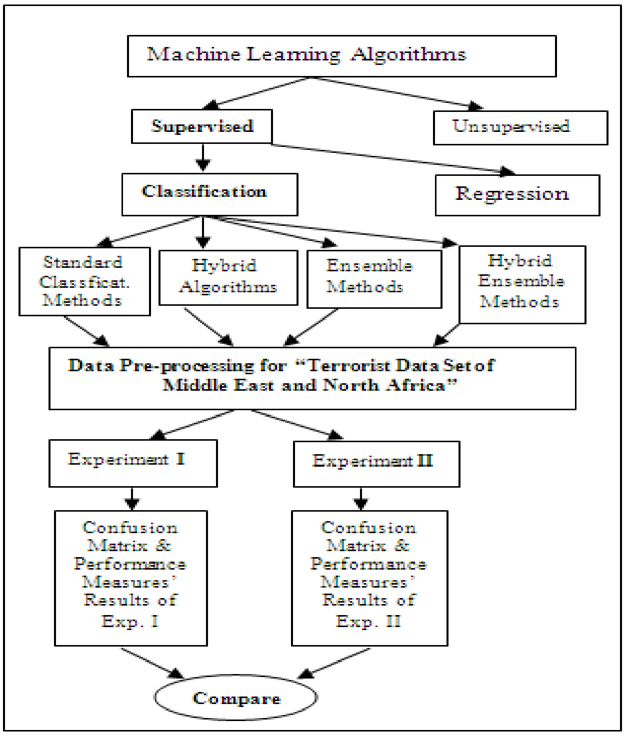

Figure 1 Flow Diagram of Main Steps in the Research Study

Before applying different standard and hybrid classification algorithms usually some pre-processing is performed on the data set. In order to perform data processing, it is essential to improve the data quality [29]. There are a few number of techniques used for the purpose of data pre-processing [30] as data aggregation, data sampling, dimension reduction, feature creation, data discretization, variable transformation, and dealing with missing values. It is necessary in our research to apply the following steps for data preparation and data pre-processing:

5.2.1First Step

Data reduction is performed on the terrorism data by selecting the most informative attributes that are highly correlated to our predicted attribute (Terrorist Group Name) without lose any critical information for classification and so 10 attributes are selected to be included in our experiment, The selected attributes are year, month, country, region, provstate, city, attack-type, target-type, weapon-type, and group-name. These selected attributes are highly related to the predicted attribute (Terrorist Group).

Instance selection is not used to handle noise but to cope up with the infeasibility of learning from very large data sets; instance selection in our data set is an optimization problem that attempts to maintain the mining quality while minimizing the sample size [34]. It reduces data and enables a data mining algorithm to function and work effectively with very large data sets. There are a variety of procedures for sampling instances from a large data set. The most well known are [32] random sampling and stratified sampling.

In our data set we applied stratified sampling as a supervised filter instance method which is applicable when the class values are not uniformly distributed in the training sets, instances of the minority class (es) are selected with greater frequency in order to even out the distribution.

5.2.2 Second Step

For the missing data values, there are three approaches to handle missing data elements: removal, imputation, and special coding [33], [37]. In our research we applied the approach of Litwise Deletion or data removal for the unknown and missing data instances in order to produce the new data, and then we will conduct our experiments by applying the selected classification algorithms on new data set and compare between them via the classification accuracy and other three different performance measures namely; precision, recall, and f-measure.

5.2.3Third Step

Conducting the experiments to perform different classification algorithms on the research data set by using WEKA as one of important tools available for implementing data mining algorithms to train the base classifiers then the evaluation of the implemented classifiers is performed by using the testing data set.

5.3Software used

The Machine learning classification algorithms in this research are implemented based on WEKA. Waikato Environment for Knowledge Analysis (WEKA) is open source software written in JAVA, a public collection of machine learning algorithms allows the researcher to mine his own data for trends and patterns. The algorithms can either be applied directly to a dataset or called from the researcher own JAVA code [33]. WEKA contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization.

In our experiment we performed different ML classification algorithms on the Terrorism data of Middle East & North Africa from 2009 to 2013, by using Litwise deletion of missing and unknown instances, and a stratified supervised instance reduction method with the help of WEKA Software. During experiment, and after pre-processing steps, the huge data set size became 2002 instances (records), and then the data file is converted to .ARFF file to be used by WEKA environment.

5.4Experimental Methods

5.4.1.Experiment I

The experiment is conducted by using the whole data set as testing data set and the results are illustrated in Table 1.

5.4.2.Experiment II

The experiment is conducted by using 10 Fold cross validation as testing option and the results are shown in Table 2. The results of the applied standard, and hybrid classifiers from the experiments will be evaluated according to four performance measures which are defined bellow:

- **The Classification Accuracy:** is the percentage number of correctly classified instances (the number of correct predictions from all predictions made)
- **Precision:** is a measure of classifier exactness (used as a measure for the search effectiveness)
- **Recall:** is a measure of classifier completeness.
- **F-Measure:** also called F-Score, it conveys the balance between the precision and the recall.

5.5.Results and Analysis

5.5.1.Experiment I

Table1 shows the classification accuracy and other performance measures results from conducting experiment I of applying the selected standard, hybrid, ensemble, and hybrid ensemble methods as follow:

- In Standard classification methods; KNN is superiors in accuracy where it could classify all the instances correctly, and so it has the highest measures. SVM can be consider as a good classifier too in which it succeed to classify correctly about 95% of the training data as well as it has high precision, recall, and f-measure results.

- In Hybrid algorithms; it is obvious that FT is very accurate and outperformed other hybrid classifier, it classified correctly about 99% of the training data as well as it has the highest performance measures. We can notice that classification via clustering is not accurate to be applied on our data set as it could not classify correctly more than 25% of the whole training data.
- In Ensemble Method(s); Random Forests (RFs) method is very accurate where it classify correctly about 99% of the data; its precision, recall, and f-measure are high as well.
- In hybrid Ensemble classifiers; Stacking classifier performs badly where the classifier accuracy is only 20%.

The overall results in Table1 show that hybrid machine learning classifiers demonstrate good and proved obvious improvement in predictive accuracy over some standard comprehensible and ensemble methods.

TABLE 1: Performance Measures Results of Experiment I

Method	Accuracy & Performance Measures				
	Corre. Class.	Incorr. Class.	Precision	Recall	F-Measure
C 4.5	80.198%	19.802%	0.752	0.802	0.762
KNN	100%	0%	1	1	1
SVM	95.0495%	4.9505%	0.941	0.950	0.944
NB	91.0891%	8.9109%	0.895	0.911	0.889
HHT	82.6733%	17.3267%	0.820	0.827	0.813
FT	99.0099%	0.9901%	0.990	0.990	0.990
DTNB	74.2574%	25.7426%	0.654	0.743	0.689
C Via C	25.7426%	74.2574%	0.104	0.257	0.144
RFs	99.009%	0.9901%	0.985	0.990	0.988
Stacking	20.7921%	79.2079%	0.043	0.208	0.072

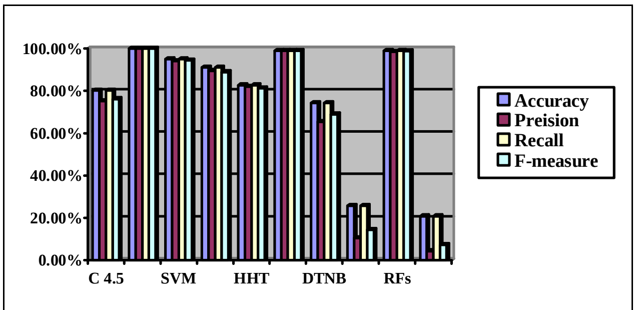

Figure 2 Accuracy and Performance Measures of ML Standard, Hybrid, and Ensemble Hybrid Methods of Experiment I

5.5.2 Experiment II

Table 2 shows the ML classification accuracy and other performance measures results from conducting experiment II of applying the selected standard, hybrid, ensemble, and hybrid ensemble methods as follow:

- In Standard classification methods; C45 classifier performs almost good as it classified correctly about 67% of the whole data, obvious that NB classifier performs well as C45. The researcher can notice that SVM and KNN are fairly good in their results.
- In Hybrid algorithms; FT and DTNB hybrid machine classifiers perform well as they near to classify correctly about 65%, and 63% from the data set as well as they have high recall values. It is obvious that HHT and classification via clustering hybrid classifiers are not accurate as they could not classify more than 32% and 37% from the training data as they also have bad precision and f-measure results.
- In Ensemble Method(s); Random Forests (RFs) classifier is fairly accurate as it could classify about 52% of the data, and it has a good recall result too.
- In hybrid Ensemble classifier(s); Stacking classifier performs badly and it is not accurate; as it could not classify correctly more than 21% from the whole data.

The overall accuracy and performance measures in Table 2 show that hybrid machine learning classifiers perform well and in some cases it could outperformed the single classifiers with some enhancement, but ensemble methods are more accurate and outperformed the hybrid ensemble methods in their prediction results.

TABLE 2: Performance Measures Results of Experiment II

Method	Accuracy & Performance Measures				
	Corre. Class.	Incorr. Class.	Precision	Recal	F-Measure
C 4.5	67.3267%	32.6733%	0.624	0.673	0.645
KNN	54.4554%	45.5446%	0.501	0.545	0.521
SVM	56.9307%	43.0693%	0.518	0.569	0.540
NB	64.8515%	35.1485%	0.555	0.649	0.585
HHT	31.6832%	68.3168%	0.328	0.317	0.282
FT	64.8515%	35.1485%	0.562	0.649	0.602
DTNB	62.8713%	37.1287%	0.494	0.629	0.544
C Via C	37.1287%	62.8713%	0.148	0.371	0.211
RFs	51.9802%	48.0198%	0.471	0.520	0.479
Stacking	20.7921%	79.2079%	0.043	0.208	0.072

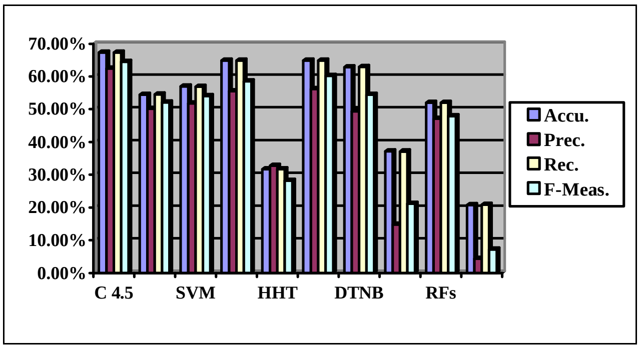

Figure 3 Accuracy and Performance Measures of ML Standard, Hybrid, and Ensemble Hybrid Methods of Experiment II

6.CONCLUSION AND FUTURE WORK

A supervised standard, ensemble, and hybrid machine learning classification algorithms and models are introduced in this research paper for prediction of the terrorist groups responsible of terrorist attacks in Middle East and North Africa from year 2009 up to 2013, by conducting different experiments, the data used in our experimental study is based on real data represented by Global terrorism Database (GTD) from National Consortium for the study of terrorism and Responses of Terrorism (START). To achieve the goal of this research; two different experiments are conducted on the used data, as well as using Litwise deletion approach to handle the missing data and provide a detailed comparative study of the used classification algorithms between different 10 different classifiers which categorize into four main types namely; standard classification algorithms, hybrid classifiers, ensemble classifiers, and ensemble hybrid classifiers. We based on using popular software in that area of study called WEKA software and evaluate the obtained results via two different test options which are; evaluation on training set, the other option is 10 fold cross-validation during the experiments. The results from the first experiment that conducted using the whole training data showed that KNN and SVM are outperformed the other standard classifiers, FT is very accurate and outperformed other hybrid classifier, In Ensemble Method(s); Random Forests (RFs) method is very accurate. In hybrid Ensemble classifiers; Stacking classifier performs badly and not accurate.

The overall results show that hybrid machine learning classifiers demonstrate good and proved obvious improvement in predictive accuracy over some standard comprehensible and ensemble methods.

The results obtained from the second experiment which based on using 10 fold cross validation showed that: C45 and NB standard classifier are almost good; FT and DTNB hybrid classifiers are good ML hybrid classifiers. And so the overall performance of the different types of classifiers used proved that hybrid machine learning classifiers perform accurate and in some cases it could outperformed the single classifiers with some enhancement, but ensemble methods are more accurate and outperformed the hybrid ensemble methods in their prediction of terrorist groups' attacks results.

For Future research, there is a plan to make further combinations of different ML classification algorithms with Genetic Algorithms, and Neural Networks to improve the performance of hybrid classifiers.

Some researchers may perform a modification for this research by using different methods for handling missing data instances, and make a comparison. Others may use different test options to test the performance of the classification algorithms.

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