One-Against-All and One-Against-One Multiclass Support Vector Machine Algorithms for Wind Speed Prediction

M. Arif Wani*‡, Heena Farooq Bhat*

*Postgraduate Department of Computer Science, University of Kashmir, J&K, India

awani@uok.edu.in, heenafarooq14@gmail.com

‡ Corresponding Author, Tel: +91 700 627 6302,

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Abstract- Wind speed prediction has several applications and various atmospheric parameters like temperature, humidity, pressure, wind direction can be used to predict it. A number of methods using mathematical and biological models have been proposed by various researchers to predict the wind speed. This work explores the use of one-against-all (OVA) and one-against-one (OVO) multiclass Support Vector Machine (SVM) algorithms for wind speed prediction. The paper also makes contribution by proposing a synergistic approach that combines the OVA and OVO algorithms for improving the performance of the system for wind speed prediction application. The algorithms are tested on wind speed data having hundreds of samples of training and test data sets. The results of employing the two algorithms and the proposed synergistic approach are compared for wind speed prediction application and results indicate that one-against-one algorithm produces better results than the one-against-all algorithm and the proposed Synergistic approach produces better results than both the algorithms.

Keywords Wind speed prediction; Multiclass support vector machine; Classification; Synergistic SVM.

1.Introduction

Wind speed prediction is one of the complicated tasks due to its disordered and indiscriminate fluctuations [1-3]. For most of the time wind speed prediction is inaccurate, yet it is important because it has several applications which include satellite launch, air traffic control, and weather forecasting. Further, wind energy is considered to be less costly as compared to fossil fuel energy [4].

A number of wind speed prediction methods have been developed by researchers. One of the conventional methods for wind speed prediction is Numerical Weather Prediction (NWP) method. This approach usually predicts wind speed values by interpolating model results acquired from the nearest gridpoints to the exact station location. Another approach that is used for prediction of wind speed makes use of Persistence model. The use of Persistence model suits for very-short-term prediction. However, the accuracy of the persistence method degrades rapidly as the time-scale of prediction increases.

Many researchers have used artificial intelligence based approach for wind speed prediction. Hybrid models, which is a combination of statistical and other models, offer more precise prediction [5], have also been explored by researchers. Recognition of wind speed patterns using multi-scale subspace grids with decision trees is described in [40]. Cluster based approach for mining patterns to predict wind speed is discussed in [41]. The scope of employing improved machine learning techniques for better wind speed prediction results can further be explored. This work describes results of employing one-against-all and one-against-one multiclass SVM algorithms for wind speed prediction. It further proposes an approach that combines the OVA and OVO algorithms synergistically for improving the performance of the system in wind speed prediction application.

The paper is organized as follows: Section 2 reviews the related work of wind speed prediction. Section 3 describes one-against-all and one-against-one multiclass SVM algorithms for wind speed prediction. Section 4 discusses the results. Finally, conclusion is presented in section 5.

2. Literature Review

Several approaches have been described by researchers to perform the task of wind speed prediction. These approaches can be divided into several categories: (i) physical methods (ii) statistical methods (iii) artificial intelligence methods (iv) spatial correlation methods and (v) hybrid methods.

Numerical Weather Prediction (NWP) model falls under the physical method category. This method uses lower atmosphere weather estimate data like temperature, pressure, surface irregularity and barriers. Various NWP models have been developed by researchers on large scale area [6]. The wind speed predicted can be used for controlling power generation and is passed to the wind turbines at the wind farm [7,8]. In order to achieve precise calculation of the wind speed, physical methods are required to increase the real resolution of numerical weather prediction model [9, 10]. Due to lots of computations, the physical methods are executed on supercomputers.

Methods like auto regressive (AR), auto regressive moving average (ARMA), auto regressive integrated moving average (ARIMA), Bayesian approach, and gray prediction approach fall under statistical methods for predicting wind speed. The statistical methods are suitable for short time period wind speed prediction and can be implemented easily. The prediction error increases as the prediction time period increases with these models. A statistical method presented in [11,12] is based on auto regressive model and self-determining component analysis. The method produces results with higher precision as compared with direct forecasting approaches. Authors in [13] present auto regressive moving average model merged with wavelet transform for wind speed prediction. The wavelet transform is required to make a choice of picking up the low rate of recurrence of the entire wind speed. Auto regressive moving average model is used to estimate the wind speed and has the potential to improve the prediction precision.

Several Artificial Intelligence (AI) based methods have been proposed by researchers for wind speed prediction. These AI based methods include the use of artificial neural network (ANN), fuzzy logic, support vector machine (SVM), neuro-fuzzy network, and evolutionary optimization algorithms for wind speed prediction.

Artificial neural networks have several models that are based on the way networks are built and training is carried out. The models include back propagation model, recurrent neural network model, radial basis function (RBF) model, ridgelet neural network model, and adaptive linear element neural network model. Essentially various artificial neural network models represent nonlinear boundaries separating meaningful datasets and reduce reliance between variables [14].

Authors in [15] discuss two wind forecasting methodologies based on back propagation neural network and recurrent neural network. A radial basis function model for wind speed prediction is presented in [16]. A Dynamic fuzzy neural network (LF-DFNN) to predict wind speed is discussed in [17]. Results indicate that the neural network based prediction is more accurate than conventional statistical time sequence based analysis.

Authors in [18, 19] present Support Vector Machine (SVM) based method for wind power forecasting. Results indicate that SVM based method performs better than the persistence model and the radial basis function based model.

Wind speed time-sequence of the expected point and its adjoining points are employed in spatial correlation methods [6, 20] to predict wind speed. With this approach wind speed at one location is calculated that is based on observations at another location. The results of this model has produced reasonable results on the data collected over several years.

A hybrid approach using a combination of a numerical weather prediction model and artificial neural network model is investigated in [21]. This hybrid approach is shown to be cost-effective for predicting the wind speed. Similar hybrid systems that uses auto regressive integrated moving average model with artificial neural network model and auto regressive integrated moving average model with support vector machine for wind speed prediction are presented in [22]. Another hybrid system uses back propagation neural network model and recurring exponential tuning model and is discussed in [23]. Artificial neural network model and wavelet transform model are used in another hybrid system in [24] for short-term wind speed prediction. Results indicate that the hybrid approaches are possible options for wind speed prediction.

A number of other approaches can be explored for wind speed prediction, which include rule based approach [25], sub-space grid based approach [26-28], and cluster based approach [29-31]. More work is reported in [41-46]. This work explores the use of one-against-all and one-against-one multiclass support vector machine based approach for wind speed prediction, which builds on the previous work described in [32-35].

3. Multiclass Support Vector Machine Algorithms

Support vector machines (SVMs) are computational algorithms that construct a hyper-plane or a set of hyper-planes in a high dimensional space [36]. SVMs can be used for classification, regression, and other tasks. A hyper-plane is the one that separates the data points with the maximal margin between the two classes.

The objective of SVM is to find the best separation hyper-plane, that is, the hyper-plane that provides the highest margin distance between the nearest points of the two classes (called functional margin) [37]. This approach guarantees that with higher the margin the generalization inaccuracy of the classifier will be lower. The data points that are closest to the hyper-plane are termed as "support vectors". The number of support vectors is very small as these points are close to the class boundaries.

The basic SVM model was originally developed for binary classification and it can be extended for multiclass classification tasks. Several methods have been proposed to extend SVM to multiclass classification problem [38-40]. However, extensions to multiclass classification are not easy to implement. The basic strategy to apply SVM to multiclass classification is to decompose the problem into several binary class problems. We explore employing One-Against-All algorithm and One-Against-One (pair-wise) algorithm for multiclass classification task of wind speed prediction. We also propose an approach that combines the OVA and OVO algorithms synergistically for improving the performance in wind speed prediction application. These two algorithms and the proposed synergistic approach are discussed in detail below.

3.1 One-Against-All (OVA) Algorithm

The One-Against-All (OVA) algorithm is also called as winner-takes-all classification and is shown in Fig. 1. A binary classifier is constructed for each class of K classes problem, which result in K binary SVM classifiers. Each classifier is trained to define a hyperplane that distinguish one class from the rest of the (K-1) classes. The examples of one class are marked as positive labels (+1) and the examples of the rest of the classes are marked as negative labels (-1). A decision function is evaluated for each classifier. The winning class is the one that corresponds to the SVM with the largest value of the decision function i.e. data is assigned the class label of that SVM classifier which produces maximum output value.

A hyperplane for a classifier is defined by the following decision function:

$$F_i(x) = (W_i \cdot x) + b_i$$

The final result is the class that corresponds to the SVM with the largest margin i.e. the largest decision function value. This class is determined by the decision rule of the following equation:

$$K^* = \arg \max_{1 \leq i \leq K} F_i(x)$$

Steps of Algorithm:
It involves training K binary SVM classifiers, one classifier for each class. The steps are summarized below:
i) Set i=1
ii) Label samples of the ith class as positive (+1) and the remaining samples as negative (-1).
iii) Train SVM to determine the parameters of the classifier, which separates ith class from rest of the classes.
iv) Increment i, repeat the procedure until K classifiers are obtained.
v) Test a sample with K classifiers and assign the class of that classifier which produces the highest output value.

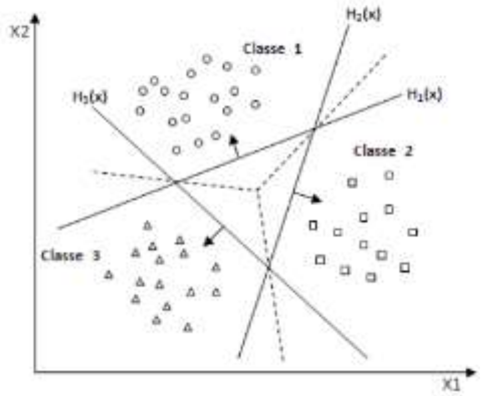

Fig. 1. One-Against-All Algorithm

3.2 One-Against-One (OVO) Algorithm

One-Against-One (OVO) algorithm performs pair-wise comparison between all K classes and is shown in Fig. 2. This algorithm constructs K (K-1)/2 binary SVM classifiers using all the binary pair-wise combination for K classes. Each binary SVM classifier is trained considering the examples of the first class as positive labels (+1) and the examples of the second class as negative labels (-1). This algorithm builds a classifier for each pair of classes and defines a binary decision function. The decision function is evaluated for each classifier. The output value from each classifier is obtained as a class label. For each decision function, a vote is given for the class to which the example belongs. Data is assigned to the class label that occurs highest number of times. If there is a tie between the class labels, a tie-breaking strategy is used to randomly select one of the class labels that are tied or simply select the one with the smaller index. The above voting algorithm is also called as Max-Wins strategy.

The binary decision function is as:

$$H_{ij}(x) = \text{Sign}(F_{ij}(x)) = \{+1 \text{ if } F_{ij}(x) > 0 : 0 \text{ else}\}$$

The classification rule of a new sample *x* is given by the equation shown below:

$$K^* = \arg\ max_i(\textstyle\sum_j H_{ij}(x))$$

Steps of algorithm:
It involves training K(K-1)/2 binary SVM classifiers, using all pair-wise combinations of K classes. The steps are summarized below:
i) Set i=1
ii) Set j=i+1
iii) For the pair (i, j), label samples of class (i) as positive (+1) and class (j) as negative (-1)
iv) Train SVM to determine the parameters of the (i, j) classifier, which separates class i samples from the class j samples.
v) Increment j, if j < K go to iii)
vi) Increment i, repeat from ii) until K(K-1)/2 classifiers are obtained.

vii) A sample is tested with K(K-1)/2 classifiers and each classifier outputs a class label. The class label that occurs the most is assigned to that sample

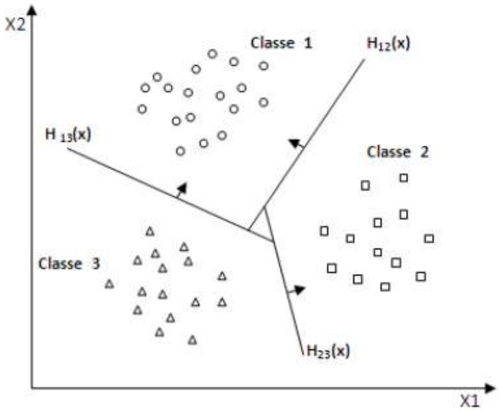

Fig. 2. One-against-one Algorithm

3.3 Synergistic Approach of Combining OVA and OVO algorithms

We propose an approach that synergistically combines the results of two classifiers, based on OVA and OVO algorithms, for classifying a given sample. Corresponding to a given sample, the result of that classifier for which hyperplane is farthest is retained.

The sample to be classified is first tested using two classifiers that are based on OVA and OVO algorithms. The two classifiers may assign different class labels to a given sample. To determine the appropriate label, the distance of the sample from the hyper planes in the two classifiers is checked and the classifier for which hyper plane is furthest is selected. The given sample is then assigned the class label computed by the selected classifier as shown in Fig. 3.

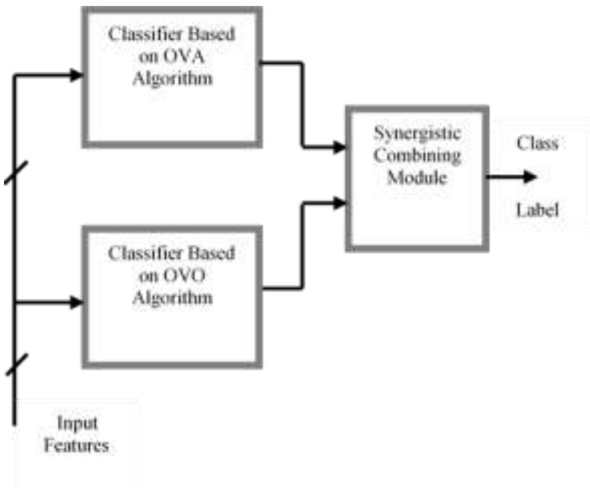

Fig. 3. Synergistic approach for combining OVA and OVO algorithms

Note that Support Vector Regression (SVR) has been used in prediction applications and it involves computation of a linear regression function in a high dimensional feature space where the input data are mapped via a non linear function. SVR attempts to minimize the generalization error bound so as to achieve generalized performance instead of minimizing the observed training error. This makes SVR suitable for time series and financial prediction applications, as prediction is done within generalized error bound. However, the use of furthest hyper plane in the proposed synergistic approach does not require generalized error bound for wind speed prediction application.

4. Results and Discussion

The performance evaluation of one-against-all and one-against-one multiclass SVM algorithms is provided in this section. The data set used has five attributes namely wind direction, temperature, pressure, humidity and wind speed. The dataset is divided into two files: training data and testing data. The training data has 6200 samples. The testing data set has 300 samples. The samples are divided into 5 classes that is based on wind speed values. A sample is labelled as class 1 if its wind speed lies in the range from 5 to 7. Similarly a sample is labelled as class 2 or class 3 or class 4 or class 5 if its wind speed lies in the range from 7 to 9 or from 9 to 11 or from 11 to 13 or greater than 13 respectively. Note that the range of wind speed values associated with five classes has been chosen arbitrarily, but in general a procedure can be developed that can determine the range of values associated with each class automatically.

To compare the performance of the one-against-all and one-against-one multiclass SVM algorithms, a two steps procedure is used: The classifiers using one-against-all and one-against-one multiclass SVM algorithms are trained first using training data. The trained classifiers are then tested using both training and testing data. The performance evaluation of one-against-all and one-against-one algorithms for wind prediction is given below in Tables 1, 2 and 3. Table 1 uses 6200 samples for training purpose and it uses 300 samples for testing purpose. Table 2 uses 5000 random samples for training purpose and it uses 300 samples for testing purpose. Table 3 uses 4000 random samples for training purpose and it uses 300 samples for testing purpose. The accuracy rate *ACC* of classification is calculated as:

$$ACC = \frac{n}{N} * 100$$

where n is the number of correctly classified samples and N is the total number of samples.

Table 1. Results of Wind Speed Prediction, Training data has 6200 samples.

SVM Method	# Training samples	# Test samples	# Classes	Accuracy rate

OVA	6200	300	5	70.67%
OVO	6200	300	5	97.33%
Synergistic	6200	300	5	97.33%

Table 2. Results of Wind Speed Prediction, Training data has 5000 samples.

SVM Method	# of Training samples	# of Test samples	# of Classes	Accuracy rate
OVA	5000	300	5	73.67%
OVO	5000	300	5	97.33%
Synergistic	5000	300	5	97.67%

Table 3. Results of Wind Speed Prediction, Training data has 4000 samples.

SVM Method	# of Training samples	# of Test samples	# of Classes	Accuracy rate
OVA	4000	300	5	70.33%
OVO	4000	300	5	97.33%
Synergistic	4000	300	5	97.33%

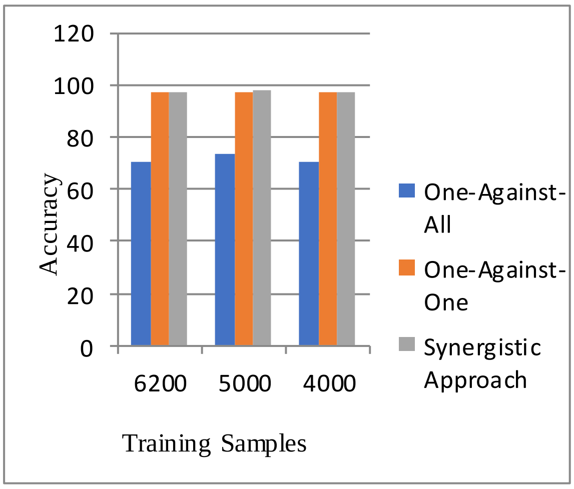

Fig. 4. Accuracy Rate of OVA, OVO, and Synergistic approach

It can be seen from Table 1 that the accuracy rate of one-against-all multiclass SVM algorithm is to 70.67%, that of one-against-one multiclass SVM algorithm is 97.33% and that of Synergistic approach is 97.33%. Similar results are obtained by varying number of training samples as shown in Table 2 and Table 3. It is obvious from the three tables that Synergistic approach produces better results than two algorithms as shown in Fig. 4.

5. Conclusion

In this paper one-against-all and one-against-one multiclass SVM algorithms were discussed for wind speed prediction. A synergistic approach that combines the OVA and OVO algorithms for improving the performance of the system for wind speed prediction application was proposed. The two multiclass SVM algorithms and the proposed Synergistic approach were tested on data set which comprised of hundreds of samples having five attributes: wind direction, temperature, humidity, pressure and wind speed. The results of the multiclass SVM algorithms were compared and it was observed that the one-against-one algorithm performed better than the one-against-all algorithm and the proposed Synergistic approach outperformed both algorithms.

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