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Multi-class Support Vector Machine Application in the Field of Agriculture and Poultry: A Review

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ABSTRACT

This paper discusses and surveys the implementation of multiclass support vector machine algorithms in the field of agriculture and poultry. It presents the most common algorithms that have been deployed in the context of farming, which is then described and categorised depending on their properties. We summarize the method used, their performance and accuracy to facilitate the process of choosing the best method for agriculture area, which involves other areas of interest.

Keywords: multiclass support vector machine, agriculture

1. Introduction

The agriculture and poultry sector plays a major role as a source of food and protein supplier especially in Malaysia. The development of this sector in Malaysia is influenced by the government policy and political views in Sahar and Chamhuri (2016). The authors delved deeper into the current role of Malaysia's agricultural sector by examining the National Agricultural Policy since 1992 till 2020. Therefore, in the effort to boost the agricultural and poultry industries in Malaysia, it is necessary to have a very systematic agriculture and poultry management system to produce a high grade of agriculture and livestock product. One of the possibilities includes an artificial intelligence agent to detect and classify quality meat, identify rotten vegetables and fruits, detect early birds disease in chicken poultry, and any signage of infection in livestock production. There are numerous scientific ways to classify, identify and detect the aforesaid problems such as neural network, Bayesian classifier, multiple layer perception, nearest neighbour, support vector machine, naÃ¯ve Bayesian classifier, decision tree and much more, which can be categorised as under supervised and unsupervised learning. However, this paper only focuses on support vector machine specific to multiclass support vector machine in the field of agriculture and poultry implementation.

Support vector machine, also known as SVM, has become more favorable choices as one of the classification methods in most of the research area. It is due to the class separation process, and the facilities of kernel space that makes SVM is a robust and powerful tool to do the classification in most of the applications (Hosseini and Ghassemian (1996)). SVM shows better performance when dealing with small amount of samples, because it has advantages in nonlinear and high-dimensional pattern recognition problems as well as good generalisation capability in Jiang et al. (2011). Although SVM is well verse known for its performance value, hence it is still very sensitive in term of choosing a good parameter and to configure it in Zhang et al. (2015). A multi-class classifier, however can be designed by either modifying the original SVM algorithm or combining several binary SVMs in Jiang et al. (2011). However, the major problem of multiclass support vector machine appears is when the current multiclass SVM classifiers are built either by converting the multiclass problems into a single optimization, in which may cost expensive computational or combining one or more binary SVM in which may perform moderately for some of the problematic classes (see Ping and Xiangsheng (2014)). For this reason, the multiclass SVM's performance may be disgraced than the multilayer perceptrons (MLPs). By SVM may be still acknowledged as the most powerful classifier that is replacing the Artificial Neural Network (ANN) which has gradually moved into one of the most significant mainstream classifiers. It is widely used in the research of texture classification in Prasad et al. (2012). In this paper, the SVM multiclass algorithm will be described, including the advantages and disadvantages of each algorithm and their implementation in the agricultural.

The organization of this paper is as follows: Section 2 elaborates on the advantages and disadvantages of each multiclass SVM algorithm, and Section 3 explains the implementation of multiclass SVM's algorithm in health and medical fields, aquaculture, surveillance, social media and road utilities. Section 4 specifically focuses on multiclass SVM algorithm in agriculture research area and finally the conclusion is provided in Section 5.

2. Multiple Classifier Techniques and Algorithm applied in applications: Advantages and Disadvantages

2.1 Introduction

In this section, the multiclass algorithm in SVM will be described in detail, including how each of these algorithms works, their advantages and disadvantages and how they are applied. The focus is only on one-against-all (OAA) which is also known as one-versus-all, one-against-one (OAO) algorithm, directed acyclic graph support vector machine known as DAGSVM algorithm, the binary tree algorithm and error correcting output code algorithm shorten by ECOC.

2.2 One-Against-All (OAA)

One-Against-All (OAA) algorithm is the earliest method approach in extending the SVM binary classification in Anthony et al. (2007). In OAA, the number of classes in sub-classifier is developed. Every i^{th} of each sub-classifier is trained to have ith samples of positive marking and the rest are marked with negative sample classes in Liu et al. (2010) and Wang et al. (2010). It constructs M binary SVM in which will fall under each category to solve a problem arise for M-class.

Each category SVM is trained to separate its data points from the data points of other classes. A new data point is classified to a class which binary SVM gives the largest value. It is the binary SVMs that train separately and naively combined (see Hwang et al. (2013), Rocha and Goldenstein (2014), Wang et al. (2012b)). The binary SVM classifiers are built and evaluated in which every classifier separates themselves from one into another combined classes. It means that every i^{th} classifier is trained with the training sample with positive labels and the rest samples associated with the negative labels. Within the sample x classification, the largest values of decision function will be applied in Yu et al. (2012) and Zhang and Wu (2012). This gives advantages in term of its short training time that only constructs a few sub-classifier, and the training of single sub-classifier becomes much simpler (see Liu et al. (2010)).

One of the disadvantages is that it may have unbalanced training sample points which influence the accuracy, and it may occur due to the large number of classes (see Liu et al. (2010), Wang et al. (2012a), Wang et al. (2010)), unclassified region (Liu et al. (2010)) and the optimal setup which heavily depends on the problems to be solved (Ping and Xiangsheng (2014)). Another drawbacks are the possibility of having an incorrect pair in the training samples between the positive and negative label and also the high training and evaluation time (see Yu et al. (2012)).

One way to improve this method is by introducing the multiclass multi-objective SVM. It finds weights of a combination of binary SVMs that maximises the geometric margins, which can reduce the computational resources. Other works and implementation based OAA are done by combining the binary SVMs on the basis of geometric margins measured by utilising the whole training data (see Wang et al. (2012b)), decision tree based OAA (see Hwang et al. (2013)), implementation of OVA SVMLight package, which involve the combination of two methods, OAA and OAO. All in One (AO) combines the strengths of both methods and partially avoids their sources of failure (see Hwang et al. (2013)). An improvement on the OAA algorithm had also being carried out by Liu et al. (2007) in which they claimed to use only $k-1$ hyper-planes instead k hyperplanes to classify the k classes without dividing each class from the others by only using one corresponsive hyper-plane.

2.3 One-Against-One (OAO)

OAO constructs the $\frac{c(c-1)}{2}$ sub-classifiers in which c is the number of classes or categories by using the voting method in Liu et al. (2010). A voting strategy is used after all the $\frac{c(c-1)}{2}$ classifiers are trained to make a final decision, and this strategy is called max-win strategy (see Arun Kumar and Gopal (2010)). For example, if there are c classes, then $\frac{c(c-1)}{2}$ SVM would be trained and evaluated to distinguish the samples of one class from the samples of another class. It is also known as 'pairwise classification'. The advantages are that OAO only needs less time than OAA because the binary SVMs of OAO is trained for two information classes and involves much fewer SVs (see Siuly and Li (2014)).

Nevertheless, the drawbacks of having OAO is that the optimal setup heavily depends on the problems to be solved (Ping and Xiangsheng, 2014). The performance of the individual binary SVM models may seriously degrade when applied to the multiclass problem, which may have unbalanced training sample points that could influence the accuracy by Liu et al. (2010). It also has an unclassified region (Liu et al. (2010)), lack of decision function construction, and incapability to serve different dataset in Ping and Xiangsheng (2014).

Hence, SVMGH (Support Vector Machine Geometry Hyperplane) is proposed to improve the methods. It is based on geometric properties of hyperspheres in Ping and Xiangsheng (2014), thus another way to improve it is through the combination of two methods, OAA and OAO. All and One (AO) combines the strengths of both methods and partially avoids their sources of failure in Arun Kumar and Gopal (2010). Finally, the LSVM for Multiclass Problem designed At Once (LSVMMPAC), includes works that have been done by researchers in Hwang et al. (2013). The further improvement of OAO algorithm continues by works that have been done by researchers from Korea. They introduced Diversified One-against-One (DOAO) method by constructing a multiclass classifier using the OAO approaches but with different classification algorithm (see Kang et al. (2015)). By running several experiments based on the benchmark dataset, it proves that the DOAO outperform the traditional OAO algorithm in terms of performance.

2.4 Error Correcting Output Code (ECOC)

ECOC encodes each class to construct a vector by facilitate between 0 and 1; the dimension that is equal to the number of sub-classifiers. For each of this vector has it owns category, whereby a sample point belongs to the class which vector is most similar to the output vector of the sub-classifiers in Liu et al. (2010). It is a special case from OAO and OAA which decomposes the multiclass problem into a pre-defined set of binary problems (Wang et al., 2010). According to Xiao-feng et al. (2010), Zhou et al. (2014), ECOC is used to reduce classification error by exploiting the redundancy of the coding scheme. It employs a set of binary classifiers assigned with code words such that the Hamming distance between each pair is far enough apart to enable proper error correction (Dubey and Jalal (2012)).

ECOC is one of the general frameworks to handle the multiclass problem. It is based on ECOC binary set with suitable coding rules to reach a nonlinear classification while reducing both bias and variance learned classification models in many applications in Arun Kumar and Gopal (2010). The approaches for multiclass from binary based on ECOC codes usually focus on designing a proper ECOC matrix responsible for pointing out, which classes need to be separated, finding good base learners for them and combining these base learners in the end in a process called decoding strategy in Muhammad (2015). The framework also acts as a classifier fusion block because of its efficiency in the reconstructing of a multiclass task from a set of binary classifiers. (as cited in Rutkowski et al. (2016)).

The advantages are that it only needs fewer sub-classifiers than OAA method in Liu et al. (2010). ECOC framework is justified to be simple but more effective than other multiclass extensions (Arun Kumar and Gopal (2010)) as it needs only a few classifier (Dubey and Jalal (2014)).

The disadvantages are that the classification accuracy which is influenced by vector codes, and high accuracy cannot be gained when the number of classes is more than 10 (Liu et al. (2010)) because it must construct a right ECOC matrix in Wang et al. (2010) and the output labels [0, 1] are always restricted by the output of SVM in Dubey and Jalal (2014).

Hence, to overcome the problem in ECOC, the Universal data-driven topology-preserving output code (TPOC) scheme is proposed by Zhang et al. (2013). Other works are suggested such as a probabilistic error-correcting output code by Wang et al. (2010), an improvement in creating ECOC matrix (Rocha et al. (2014)), and also a new approach of encoding method CMECOC in building the adaptive ECOC mainly based on the confusion matrix (see Wang et al. (2012b)).

2.5 Directed Acyclic Graph Support Vector Machines (DAGSVM)

This method also needs to construct $\frac{n\times(1)-n}{2}$ sub-classifiers where n is the number of classes, and then combines these sub-classifiers into a directed $n \times (1) - \frac{n}{2}$ acyclic graph, in which there are internal nodes and n leaves (Liu et al., 2010). It is an improvement method from the OAO approach in Wang et al. (2010). This method is introduced to overcome the problems that are faced in OAO and OAA methods, in which there is no bound on the generalisation error for the OAA SVM whereby the standard time needed to do the training linearly scales for N-classes. The voting method also does not have bounds on the generalisation error, and the number of the binary classifier may grow super-linearly with N-classes, thus it may be slow to handle a problem with large N-classes in Jiang et al. (2011).

The advantage is that this method only needs to calculate $n-1$ times when it makes a prediction and has no unclassifiable regions (Liu et al. (2010)). It also has less computational cost in Escalera et al. (2011). The DAGSVM scheme has been proven to have a theoretically defined generalisation error bound, and it is more efficient than other multiclass SVM schemes with respect to the training and computation time (see Xiao-feng et al. (2010)). Fast prediction of speed and fault tolerance is better than the OAO and OAA methods (Jiang et al. (2011)). This may be the factor why this method is chosen to classify infant crying research work by Chang et al. (2016).

The only disadvantage is that this method accumulates errors and the locations of sub-classifiers greatly influence the classification accuracy (see Liu et al. (2010), Taner Eskil and Benli (2014)). Thus, to overcome this problem, a research work has been done by Taner Eskil and Benli (2014) to introduce an improved method of calculating the distance between the classes, hence the distance formula is being used as the class measure in DAGSVM.

2.6 Binary Tree

In each node of the tree, a binary SVM is trained using two classes. All samples in the node are assigned to the two sub-nodes derived from the current node. This step is repeated at every node until each node contains only samples from one class, in such a way, until the leaves of the tree in Lee et al. (2015).

The advantages include less classification time, no unclassifiable regions, and is easier to determine the location of each sub-classifier to obtain better classification results (Liu et al. (2010)). The drawback is that it is heavily dependent on the sub-classifiers assignment of hierarchical structures of binary-tree (Li et al. (2016)).

A way to improve this method has been carried out in One-versus-All Tree (OVA Tree Multiclass) in which it combines the support vector machine algorithm with the binary tree algorithm (see Lee et al. (2015)). The accuracy and decision speed of the classifier are closely related to the structure of the binary tree which focuses on the separability of classes rather than samples (see Ouyang et al. (2013)). It claims to have a very structured and improved binary tree (Liu et al. (2010)).

3. Implementation of Multiclass SVM's Algorithm in Various Area and Fields

This section will describe the performance of multiclass SVM algorithm based on the research done previously in areas such as surveillance, aquaculture, health, medical and road utilities. Each research is categorize based on the area, the purpose, and the methods used. We also summarize their findings and results based on each algorithm. Table 1 summarises the implementation of multiclass SVM algorithm in various areas together with the findings.

Table 1: Summarization of multiclass SVM algorithm

Area	**Purpose**	**SVM Multiclass Algorithm**	**Findings**
Agriculture	To classify fruits automatically (Zhang and Wu (2012))	To One-against-one, One-against-all, Direct Acyclic Graph SVM	To One-against-one with linear kernel gives the best accuracy result compared to other multiclass algorithm
Health/ Medical	Automatic Parkinson a disorder classification (Fanany and Kumazawa (2007))	One-against-all, One-against-one	This paper compares the accuracy rate between binary and multiclass classification. It proves that multiclass classification gives higher accuracy result compared to the binary classification provided if the feature selection analysis is done before the classification process in order to produce meaningful information
Health/ Medical	EEG signal classification (Siuly and Li (2014))	Least squares SVM (LSVM) with one-against-one, One-against-all and ECOC	Optimum allocation based on LS-SVM beats the traditional method of classifying
Health/ Medical	Hypothyroid detection and classification (Chamasemani and Singh (2011))	One- Against-One, One-Against-All	One-Against-All with polynomial kernel gives better performance than other classifier methods

Area	Purpose	SVM Multiclass Algorithm	Findings
Health/ Medical	EEG beat classification (Saini et al. (2014))	Directed acyclic graph SVM	Multiclass DAGSVM emphasises on the development of optimal kernel function which yields better accuracy performance compared to OAO SVM, Least Squared SVM (LSSVM), ECOC SVM and Particle Swarm Optimization (PSO) based SVM.
Health/ Medical	Posture recognition-based fall detection system (Yu et al. (2012))	Directed acyclic graph SVM	Implementing the DAGSVM scheme for classification of posture. The performance accuracy highly depends on the preprocessing and also post processing of dataset.
Visual surveillance	Background subtraction (Zhou et al. (2014))	One-against-one	The novel approach of background subtraction using multiclass SVM using the OAO algorithm.
Aquaculture	Classification of fish (Robotham et al. (2011))	Decision tree method, One-against-all	One-against-all method performs better than the decision tree method.
Aquaculture	Fish species classification (Hu et al. (2012))	One-against-one, Directed acyclic graph SVM, Voting based SVM	The DAGMSVM is not only fast but also accurate; hence the DAGMSVM is the best choice for fish classification.
Audio Surveillance	Automatic sound recognition (Sharan and Moir (2015))	One-against-all, Decision directed acyclic graph (DDAG), Adaptive directed acyclic graph (ADAG)	OAA gives the best classification accuracy and it is also more robust to noise. However, the training time of this classification method is slightly longer than other multiclass SVM classification methods, and it also has a little longer evaluation time when compared to DDAG and ADAG classification methods.
Road Utilities	Classification of road sign (Azad et al. (2014))	One-against-one	The accuracy rates reach 98.66% and 100% for detection and recognition stage respectively.

Area	Purpose	SVM Multiclass Algorithm	Findings
Social Media	Tweet classification (Takemura and Tajima (2012))	ECOC	It is a classification of messages based on its value property at real-time time span. As compared to others, it proves that SVM with the probabilistic corrections algorithm yields the highest accuracy than others.
Cognitive-affective emotions	Comparing features extraction algorithm classified by multiclass SVM (Diana and Sabiq (2016))	One-against-all	By implementing the one-against-all algorithm in multiclass SVM together with the 10-fold cross validation gives higher accuracy rate compared to Holdout cross validation.

As being depicted in Table 1, multiclass SVM has been widely used in critical areas such as health and medical sector. It proves that the extension of binary classification of SVM gives a very significant impact on producing higher and more accurate classification result. In the next section, the multiclass SVM in agriculture and poultry field will be discussed.

4. Application of Multiclass Support Vector Machines in Agriculture and Poultry

The implementation of multiclass SVM in this area is still 'green' and 'fresh'. In Table 2, the multiclass SVM that had been applied in this area is shown. The findings and result are also summarised based on the research that has been conducted by the authors and how the authors blend the algorithm to perfectly suit each of the cases.

Table 2: Multiclass SVM in agriculture for the past three years

Purpose	Methods Used/ Comparison of Methods	Findings
To classify fruit and vegetables automatically (Dubey and Jalal (2012))	Standard multiclass SVM which uses OAA approach	The feature is extracted by using the proposed texture feature extraction before is classified using multiclass SVM. It is proven that by doing preliminary works in feature extraction could increase the robustness and accuracy of the classification
Dates fruits classification (Muhammad (2015))	One-against-all approach	The dates are extracted based on local texture descriptors such as color, shape and size. It is then being classified using multiclass SVM with 10 folds cross-validation with both the RBF kernel and the C parameter set automatically by using LibSVM
Categorized the fruit disease based on images (Dubey and Jalal (2014))	One-against-all approach	Combines the clustering techniques for disease segmentation and multiclass SVM as their classifier. It proves that by combining both methods the accuracy is increased
To classify fruits using computer vision and multiclass SVM (Zhang and Wu (2012))	Multiclass kernel support vector machine (kSVM)	Proposed a novel approach in classifying fruits by combining the color histogram, Unser's texture and shape feature before classifying it using three different multi-class SVM in the various kernel
Classification of Crop/ Weeds Using Shape/ Color Features (Wong et al. (2015))	Multiclass SVM Optimized with GA algorithm	Proposed methods for selecting the best parameters and features in multiclass SVM by applying the generic algorithm in feature selection processes.
Research on the missing data recovery of waste gas monitoring in animal building (Liu et al. (2015))	Multiclass SVM (OAA) with GA algorithm	By combining the GA algorithm inside the multiclass SVM approach, it enhances the complementarity between sensors which improves the reliability of the monitoring system.

Purpose	Methods Used/ Comparison of Methods	Findings
Classification lying hen and stress detection based on sound analysis (Lee et al. (2015))	Multiclass SVM with one-against-all algorithm	By implementing the SVM methods, it is proven that the stress detection accuracy is almost 97% which had been developed in a low-cost and non-invasive environment.
Strawberry disease identification (Ouyang et al. (2013))	Multiclass SVM (OAA)	As compared to Bayesian Propagation (BP) neural network, SVM shows higher accuracy in classifying the strawberry disease into normal, powdery mildew, shrink disease and uneven ripening. The most important part is image preprocessing analysis which gives a major contribution in reaching higher accuracy in the classification.
Soil type identification (Jiji and Nadar (2016))	Multiclass SVM with OAO approach	It introduces an indexing task process on extracted feature before doing the multiclass SVM classification for soil type. It improves the retrieval performance compared to the previous work.
Crops ripeness stages classification (Javanmardi et al. (2014))	Multiclass SVM with OAO approach	A classification comparison between SVM and random forest classifier. It proves that SVM performs better than Random Forest (RF).
Fruit and branch identification in natural scenes (Qiang et al. (2014))	Multiclass SVM with OAO strategy	In this paper, the author claims that multiclass SVM managed to classify the citrus fruits with more than 90% accuracy rate but for branch classification, it allows the diameter of more than 5 pixels only.

5. Conclusion

This review paper discusses the important role and contributions of multiclass Support Vector Machine (SVM) in various research areas and mostly in the agriculture and poultry industries. Most of the findings show the most important characteristic of multiclass SVM which is its ability to generalize well even with a small dataset. In most cases, the selection of the feature extraction method and preprocessing of the data provide a higher contribution in the classification result. We have also found out that there are not many types of research done that demonstrate SVM capabilities in classifying texture images with similar background and foreground color.

Future researchers may improve the existing model of multiclass SVM and utilise its properties including the optimisation methods by combining other classification methods and algorithm such as a genetic algorithm. It is also recommended to start focusing and implementing it in the agriculture area, especially for early disease detection for poultry industry based on texture images. This review paper discusses the important role and contributions of multiclass Support Vector Machine (SVM) in various research areas and mostly in the agriculture and poultry industries.

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