Support Vector Machine Kernel Model Calibration for Optimal Accuracy in Automatic Pineapple Slices Classification

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Abstract - **Sorting pineapple can be automated with use of computer vision. The unique challenge with the pineapple slices is variability of the fruit slices color, ripeness and texture due to varying environmental parameters and fruit types. The most common types of pineapple fruit are smooth Caen and MD2. Currently the pineapple industries sort the slices manually using casual workers. Before commencement of a typical production shift, there is start-up shift where machine are cleaned, prepared and calibrated for the production. Fruit slices are also sampled and processed to simulated actual production. A mock sorting is done to help guide the worker for the expected sorting for the five categories i.e: fancy ¾, fancy ½, choice, broken and reject. To achieve a fully automated sorting process there is a need to calibrate machine model and capture the day to day variability of fruit color, ripeness and texture. In this paper we propose to use an analytical method to calibrate the Support Vector Machine (SVM) with Gaussian radial basis function (RBF) for optimal sigma and box constraint (C). A compelling feature of the proposed algorithm is that it does not require an optimization search, making the selection process simpler and more computationally efficient. The proposed algorithm achieves the highest accuracy when used with the Gaussian multiclass SVM, as demonstrated by experimental results on three real-world datasets.**

Keywords: Gaussian Radial Basis Function, Sigma, Support Vector Machine, Class Separability, Computer Vision, Box Constraint.

I. DEFINITIONS

Notation	Meaning
C	Box contraint/ regularization parameter in SVM
ω	the weight vector in two dimensions for W and B
$\kappa(x_i, x_j)$	the kernel function
$\Phi(x_i)$	the kernel-space instance
W, B	separability within and between classes, accordingly
W', B'	The mean distance inside and between classes, respectively.
σ	Sigma parameter for kernel function

II. INTRODUCTION

Calibration is the process of configuring an instrument to produce acceptable results for a sample. Fundamental to the design of instruments is the elimination or minimization of factors that lead to inaccurate measurements. The purpose of pineapple classifier calibration is to reduce classification error by ensuring the precision of test equipment. Calibration quantifies and controls classification process errors and uncertainties to an acceptable level.

A human operator sorts the sample of pineapple slices into five categories i.e. fancy ¾, fancy ½, choice, broken and reject. The sample size holds at least 50 slices of each category. The samples are then passed into a machine to capture the day's pineapple slices variability. The machine is designed to accept the first 50 slices as the fancy ¾, the second 50 slices as fancy ½, then choice, broken and reject in that order. The machines then run the proposed algorithm to determine the optimal sigma and regularization parameters for the day. Here we describe how to develop the calibration algorithm.

The evaluation of SVM performance is a crucial step in ML design: precision, CPU time, and consistency. The kernel parameter is crucial for maintaining the SVM's high performance. Since's domain of definition ranges from zero to infinity, exhaustive search for parameter selection of is intractable. For instance, if the parameter is close to zero, SVM tends to over fit because all training instances are used as support vectors. Under-fitting occurs in SVM if the parameter tends toward infinity because all training instances are treated as a single instance. The vast majority of prior research on this topic is based on optimization search algorithms that result in a high computational load and are extremely slow. A simple but effective analytical algorithm is proposed for locating a good value of σ.

In the field of machine learning, the support vector machine (SVM) is a critical technique for supervised learning. SVM utilizes the principle of structural risk minimization to

locate an optimal hyper plane in which training instances of distinct classes are linearly separable. Due to its numerous desirable properties and promising empirical performance [i, ii], SVM quickly gained attention from researchers who applied it to a variety of fields, including science and engineering, such as condition monitoring and fault diagnosis [iii,iv]. Among the kernels available in SVM, the RBF kernel is the most widely used due to its attractive properties [1, 2], *e.g.* the property of structure-preserving. The Gaussian RBF kernel has a structure similar to that of $k(X_i, X_j) = \exp(-\frac{\|X_i - X_j\|^2}{2\sigma^2})$ where σ is the only parameter named by width of features.

We propose an algorithm for determining the optimal σ based on the maximization of between-class separability and minimization of within-class separability, and calibrate our classifier for optimal pineapple classification. An attractive feature of the proposed algorithm is that it does not require an optimization search, making the selection procedure simpler and more computationally efficient. Since the maximizer can be derived analytically, the proposed method avoids the optimization search process, resulting in a significant improvement in computation load for parameter selection. After the optimal σ has been determined, searching for the box constraint parameter is a simple iterative process. The experimental results on three real-world datasets indicate that the proposed algorithm provides the highest accuracy for the Gaussian multiclass SVM.

III. REPORTED WORK

3.1 Manufacturing Calibration

Manufacturing calibration ensures the precision and consistency of measuring/classification instruments by comparing them to reference calibrating equipment and making any necessary adjustments. The primary significance of calibration is that it preserves classification precision, standardization, and repeatability, thereby ensuring the reliability of benchmarks and results.

Without regular calibration, equipment can deviate from specifications, provide inaccurate classification, and jeopardize quality, safety, and longevity[v]

In terms of the quality and performance of a procedure or finished product, manufacturing precision is a crucial metric.

If the pineapple slices are not classified to the customer's required specifications, which are determined by the product's intended use, there will likely be negative consequences.

The significance of precision in manufacturing highlights the significance of calibration, as manufacturing equipment

must be properly calibrated to meet specifications. Without properly calibrated equipment, it is impossible to meet ISO quality standards and achieve the required level of accuracy.

The quality and safety of the finished product is the most essential reason why precision is a crucial manufacturing standard. Inaccurate components, or those that fall outside of the required tolerance, cannot be used because their likelihood of functioning properly is extremely low.

Calibration plays a significant role in preventing the production of inaccurate products; therefore, the benefits of calibrating your machinery and measuring equipment cannot be overstated.

There are numerous facets of calibration in the manufacturing industry, but calibration is generally significant in these two key areas:

- Calibration of classification equipment ensures that your quality control processes are precise and that you do not accept defective slices.
- Calibration creates a more efficient manufacturing process by ensuring that equipment is operating as expected. Inadequately calibrated equipment will lead to unpredictable manufacturing outcomes and inaccurate slices classification.

Here the SVM classifier is a virtual machine, developed to sort pineapple slices into five categories. The two parameters of Gaussian kernel required to be calibrated are sigma and regularization parameter. In this paper we propose to use method that entirely uses derived formulae to arrive to optimal parameter without rigorous iterative process.

3.2 Gaussian radial basis function (RBF) kernel

Without knowing the mapping function Φ explicitly, kernel methods map data from the feature space to the kernel space.

Using the kernel method, SVM can locate a hyper plane in the kernel space, resulting in a non-linear separation of features in the feature space.

The Gaussian radial basis function (RBF) kernel is one of the most widely used kernels in SVM due to its attractive characteristics, such as the structure-preserving property. The kernel of the Gaussian RBF has the form $k(X_i, X_j) = \exp(-\frac{\|X_i - X_j\|^2}{2\sigma^2})$ where σ is the only specified parameter by width of features. Sigma (σ) is determined by a default value, such as $\sigma=1$. It has been reported, however, that is crucial for the robust performance of SVM, whereas an arbitrary value of

σ cannot guarantee performance. Grid search is a simple and intuitive method. By defining a finite set, grid search applies a criterion to each possible solution (node) within the set. As the optimal value of σ, the node with the highest score on the criterion is selected. The grid search strategy is adopted, and the Support Vector Machine's (SVM) classification accuracy is typically used as the selection criterion. Grid search has two shortcomings;

1. CPU time increases exponentially with the number of nodes in the set, making it a time-consuming operation;
2. The optimal σ cannot be determined if the set is improperly defined.

This could occur due to a lack of prior knowledge. To determine the optimal value σ of, intelligent optimization techniques such as simulated annealing algorithm[vi], genetic algorithm [vii],gradient descent algorithm[viii]and particles warm optimization algorithm were utilized[ix]. Typically, classification accuracy is regarded as the objective function. However, the classification accuracy of SVM is affected by other parameters, such as the regularization parameter, in addition to σ. Li's method [x] identifies the optimal σ using gradient search. Using intelligent optimization search algorithms, the reviewed parameter selection methods may require less computation time than grid search. Nevertheless, they increase the complexity of selection algorithms, which is likely why the parameter σ in numerous applications is frequently set to a default value. To improve the efficiency of the selection procedure, a simple but effective analytical algorithm for determining a good value σ of is proposed in the present work. Introducing both within-class and between-class separability, we define the objective function of class separability. This class separability measure is in fact a function with respect to the parameter σ [xi].

3.3 Max Wins Voting (MWV) SVM

Initially, SVMs were designed for binary classification. Numerous methods for multi-class SVMs have been proposed, the most prevalent of which is to divide the multiclass problem into multiple binary classification problems [xii]. Three types of methods are frequently used: Winner-Takes-All (WTA) SVM, Max-Wins-Voting (MWV) SVM, and Directed Acyclic Graph (DAG) SVM. MWV has the highest accuracy in image classification among the three methods [xiii] and we select this method to optimize its accuracy.

Classification is accomplished using a strategy for the one versus one method in max wins voting (MWV). After constructing a binary SVM for each pair of classes, one will obtain C(C-1)/2 binary SVMs in total. When applied to new test data, each SVM assigns one vote to the winning class, and the test data is labeled with the class with the most labels. If there are two identical votes, MWV chooses the class with the smallest index. The following is the mathematical formula. The ijth (i= 1,2, …, C-1, j = i+ 1, …, C) individual binary SVM is trained with all data in the ith class with +1 label plus all data of the jth class with −1 label, so as to distinguish ith class from jth class. The decision function of ijth SVM is:

$$f_{ij}(x) = \sum_{n=1}^{N_1+N_j} y_n^{ij} \alpha_n^{ij} k(x_n^{ij}, x) - b_{ij}, i = 1,2, …, C - 1, j$$
$$= i + 1, i + 2, …, C$$
$$y_n^{ij} = \begin{cases} +1 & x_n^{ij} \in ith\ class \\ -1 & x_n^{ij} \in jth\ class \end{cases}$$

WhereN_i and N_j denotes the total number of ith class and jth class, respectively.$y_n^{ij} \in \{+1, -1\}$ depends on the class label of x_n^{ij}. If x_n^{ij} belongs to$i$th class, $y_n^{ij} = +1$; otherwise x_n^{ij} belongs to jth class, $y_n^{ij} = -1$. α_n^{ij} is the Lagrange coefficient; and b_{ij} is the bias term. α_n^{ij} and b_{ij} are obtained by training the ijth individual SVM. The output of ijth SVM is the sign function of its decision function, namely:

$$O_{ij}(x) = sgn\left(f_{ij}(x)\right)$$

if $f_{ij}(x) > 0$, then the output $O_{ij}(x)$ $is + 1$, denoting x belongs to ith class; otherwise output is -1, denoting $x$belongs to jth class.

IV. METHODOLOGY

To develop an analytical algorithm to determine the optimal σ and C and achieve the best calibration accuracy for Gaussian m-SVM, the following steps are used:

- Define the objective function, which is a class separability function with respect to the parameter σ.
- Analytically define the maximizer of the objective function
- Select the weight vector through intuitive and simple method.
- Develop a MATLAB algorithm implementing the maximizer function with selected weights.
- Test the code on three real world datasets and evaluate their prediction performance through 5-fold cross validation

4.1 Defining the objective function

Gramian matrix (also known as kernel matrix) is a matrix that contains all the dot product values of a training subset. SVM training relies on the dot product. In other words, the Gramian matrix contains all information that the SVM can learn about training instances, along with the label information.

Given a data set U and a kernel function, the Gramian matrix is denoted by

$$G = \begin{bmatrix} K_{11} \dots K_{1L} \\ \vdots \quad \ddots \quad \vdots \\ K_{L1} \dots K_{LL} \end{bmatrix} = \exp\left(-\frac{12}{\sigma^2}D\right), D = \begin{bmatrix} K'_{11} \dots K'_{1L} \\ \vdots \quad \ddots \quad \vdots \\ K'_{L1} \dots K'_{LL} \end{bmatrix}$$

D is known as the Euclidean distance matrix. The Gramian matrix has a relationship with both σ and D. Since D is fixed for a dataset, the only parameter that can be modified is σ. Class separability is a traditional concept for describing the scattering of instances in the feature space. Class separability takes the following two principles into account:

1. *Principle I*: Instances of the same class ought to be as comparable as possible;
2. *Principle II*: Different class instances should be as dissimilar as possible.

Typically, the within class separability (W) and the between-class separability (B) are used to evaluate adherence to these two principles. We first define two distance-based scalars to estimate W and B in the feature space. The relationship between the distance similarity in the feature space and that in the kernel space is depicted in the following equation [7].

$$\|\Phi(X_i) - \Phi(X_j)\|^2 = 2 - 2\exp\left(-\frac{\|X_i - X_j\|^2}{2\sigma^2}\right)$$

Given this relationship, two corresponding scalars are derived to estimate W and B in the kernel space. The optimal σ is the one that simultaneously minimizes W and maximizes B in the kernel space. It is assumed that datasets are Gaussian distributed so that the mean distance can be used to accurately estimate class separability. The following relationship exists between the within-class mean distance (W'), the between-class mean distance (B'), and the total mean distance (T') in the feature space:

$$T' = \left(\sum_{i=1}^{L} N_i^2/N^2\right)W' + \left(1 - \sum_{i=1}^{L} N_i^2/N^2\right)B'$$

W and *B* in the kernel space can be estimated respectively using:

$$W = 2 - 2\exp\left(-\frac{12}{\sigma^2}W'\right)$$

$$B = 2 - 2\exp\left(-\frac{12}{\sigma^2}B'\right)$$

The objective function of class separability is established by

$$J(\sigma) = \omega^T \begin{bmatrix} -W \\ B \end{bmatrix}$$

$$= \omega_w \left(2\exp\left(-\frac{12}{\sigma^2}W'\right) - 2\right)$$

$$+ \omega_B \left(2 - 2exp\left(-\frac{12}{\sigma^2}B'\right)\right)$$

Where ω, ω = $[\omega_W, \omega_B]^T$, is the weight vector with a constraint of $\omega_W + \omega_B = 1$. And we consider cases of W' < B' to be distinguishable while the other case is not.

4.2 Defining the maximizer of objective function

The optimal is the one that maximizes class separability, or the maximizer of the objective function that is twice differentiable. If the first derivative of J(σ) is equal to zero and the second derivative is negative, the maximizer is determined. The stationary point in the following equation is the maximizer and optimal σ we are seeking.

$$\sigma^* = \sqrt{\frac{B' - W'}{2 \times log(\omega_B B'/\omega_W W')}}$$

4.3 Selecting the weight vector

The proposed method proposes that the Gramian matrix is obtained by transforming the Euclidean matrix. A dataset's Euclidean matrix is fixed. The only factor that determines this transformation is the parameter σ. The selection of weight ω depends on the situation.

In this section, we provide two simple and intuitive options for selecting the weight vector. First, we must identify the constraints of ω in maximize Eq. Because of the application condition of W'< B', the denominator in the square root must be positive. In addition to the constraint $\omega_W + \omega_B = 1$, the constraints for two elements ω of are as follows:

$$0 < \omega_w < \frac{B'}{B'+W'} \qquad \frac{B'}{B'+W'} < \omega_b < 1$$

If we choose $\omega_W = \omega_B = 0.5$, it is clear that the two conditions hold. Under this selection, the optimal σ is calculated by:

$$\sigma_1^* = \sqrt{\frac{B' - W'}{2 \times log(B'/W')}}$$

If we choose $\omega_W = W'/(W' + B')$ and $\omega_B = B'/(W' + B')$, the two conditions are also satisfied. The optimal σ is calculated by:

$$\sigma_2^* = \sqrt{\frac{B' - W'}{4 \times log\left(\frac{B'}{W'}\right)}}$$

4.4 Developing a MATLAB algorithm

The algorithm was developed on the MATLAB 2018a (The Mathworks ©) platform. A function is coded using Euclidean Matrix Sum to return as follows:

function [optSigma, B_bar, W_bar] =OptimalSigma(feaVal,species,method)

The code is then tested on three real world datasets and evaluate their prediction performance through 5-fold cross validation to get optimal values for calibrating the classifier.

Optimal parameters are extracted with following steps:

Our first step on optimal accuracy selection is to select the database and load it in to the memory. There are three dataset to select: Ionosphere, Fisher iris and Pineapple Slices. The database details i.e. Number of classes, number of features and numbers of instances are displayed.

Our second step is to selected method of approach. Chose mode between default, proposed method 1 and proposed method 2. The method chosen is displayed on the text box.

Our third step is to run the objective function and generate the optimal parameters. These are sigma, between class separability (B), within class separability (W) and ration of B/W which supposed to be above one if classes are separable.

Our final step is to test for accuracy where test and training accuracy are evaluated through 5 fold cross validation and the best box constraint evaluated. The algorithm also output confusion matrix for the best class that yielded optimal box constraint using the optimal sigma.

The last step is to click Exit command or run for another database where from first to final steps.

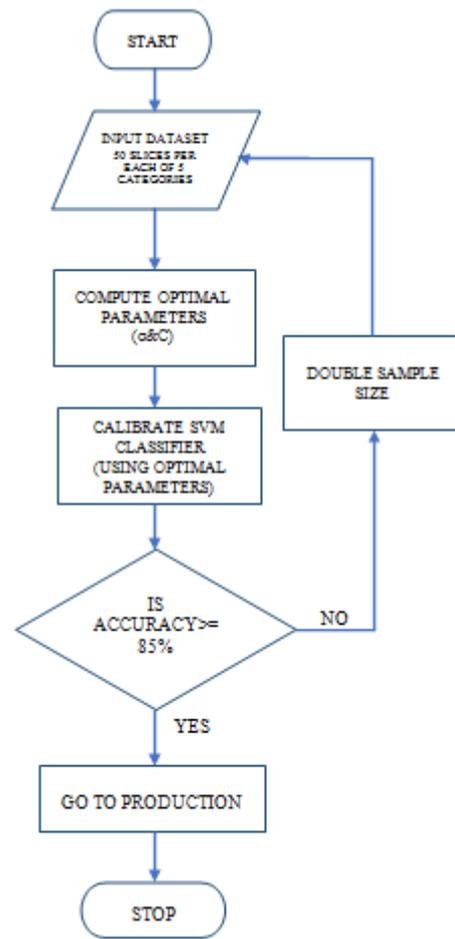After obtaining optimal parameter, the figure 1 below shows system overview.

Figure 1: System flow diagram

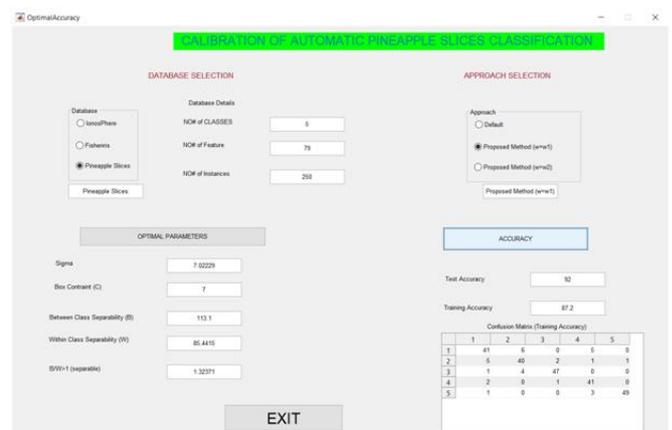The figure 2 below is the Graphical User Interface (GUI) of the experiment.

Figure 2: The Experiment GUI

V. RESULT AND DISCUSSION

This section compares the classification accuracy of two selection methods, the default and proposed method. Following is a description of the two approaches. The first method specifies σ and C with their default values, σ= C = 1. The

proposed method represents the second strategy. Using two distinct subsets, we assess the proposed method of ω: ω1 = [0.5, 0.5]^T; ω2 = [W'/(W' +B'), B'/(W' + B')]^T. A SVM classifier is used to evaluate the performance of the two approaches. Three real-world datasets were used to evaluate the two approaches.

Table 1: Summary of the three Datasets

No	Dataset	Number of Classes	Number of Features	Number of Instances
1	Ionosphere	2	34	351
2	Fisheriris	3	4	150
3	Pineapple Slices	5	79	250

The classification accuracy is used to compare the performance of the two approaches. The classification accuracy is defined as Nc/(Nc+Nf)100%, where Nc represents the number of instances correctly classified and Nf represents the number of instances incorrectly classified. The most important performance indicator is accuracy. Due to the fact that the parameter C (box constraint) affects classification accuracy, it is necessary to select C in order to evaluate the two approaches accurately. In the first approach, the default value C is specified.

The second method for C selection combines grid search with σ selection. Table 2 summarizes the selected values of σ and C.

Table 2: Selected parameters for three datasets

Dataset	Approach		σ	C	B'	W'	B'/W'
Ionosphere	Default		1	1	78.1863	55.2614	1.41484
	The proposed Method	$\omega = \omega_1$	5.74727	10			
		$\omega = \omega_2$	4.06393	10			
Fisheriris	Default		1	1	10.8171	2.20571	4.90416
	The proposed Method	$\omega = \omega_1$	1.64556	1			
		$\omega = \omega_2$	1.16358	1			
Pineapple Slices	Default		1	1	90.0723	67.9907	1.32477
	The proposed Method	$\omega = \omega_1$	6.26557	7			
		$\omega = \omega_2$	4.43043	10			

Once the optimal values for σ and C have been determined, the SVM model is trained on the training subset and hence calibrated for optimal performance. Each dataset is subjected to twenty independent iterations of each methodology. Using K-fold cross-validation (K = 5), the training and test accuracy for every run is estimated. The results are provided in Table 3.

Table 3: Experimental results of the three Dataset

Dataset	Method		Test Accuracy	Training Accuracy
Ionosphere	Default		68.5714	77.1429
	The proposed Method	$\omega = \omega_1$	94.2857	94.4857
		$\omega = \omega_2$	87.1429	94.8857
Fisheriris	Default		93.3333	95.3333
	The proposed Method	$\omega = \omega_1$	93.333	96
		$\omega = \omega_2$	100	96
Pineapple Slices	Default		50	53.6
	The proposed Method	$\omega = \omega_1$	88	88.6857
		$\omega = \omega_2$	88	89.08

As demonstrated in Table 3, training accuracy is typically higher than test accuracy for two approaches. This demonstrates that both approaches are effective at empirically minimizing risk in SVM.

We must evaluate the test accuracy generalizability of the two approaches. The first method, which utilizes default values for C and σ, is the least efficient of the three. In other words, the first method is often associated with low test accuracy. The second strategy has the potential to significantly improve test accuracy for the vast majority of datasets. The test accuracy of the first approach varies substantially across

datasets, indicating a lack of generalization ability. Only when the optimal value of σ is close to the default value of σ, as is the case with the Fisheriris dataset, is the first method comparable to the others.

The ionosphere dataset demonstrates that the first approach's test accuracy suffers significantly and even tends toward over fitting otherwise. As a result, it is strongly advised that the Gaussian SVM not be executed with the default value of σ.

The proposed method has a high degree of generalization, allowing it to achieve a high level of test precision and best

calibration parameters. On the pineapple slices dataset, the approach performs slightly worse than the default method. This is primarily due to the fact that when training with a small sample size, class separability is underestimated.

VI. CONCLUSIONS

The algorithm developed was used to calibrate the SVM classifier and the result from the three dataset showed higher accuracy in proposed calibration method than using default method. The accuracy achieved in the three dataset used were above 85% which is suitable for an online classification implementation as it exceed human accuracy based on 75%.

The analytical method developed in the paper is shown to be a fast, consistent and robust in parameter selection for calibrating the Gaussian radial basis kernel. The method resulted to test and training accuracies above the default. This will ensure the slices classification achieves optimal accuracy every time and capture the daily fruits variability in terms of color, ripeness and texture.

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