Automated Tuning of a Vision-based Inspection System for Industrial Food Manufacturing

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***Abstract*—Quality control in industrial food manufacturing can be reliably performed with computer vision systems that operate at high speed. However, most of these inspection stations need to be tuned manually and only perform well on a specific product. This research integrates machine learning techniques in the process to automate the initial tuning of real-time vision-based inspection systems for bakery products. The combination of feature selection techniques with machine learning is assessed in terms of classification performance. A formal automated tuning methodology is introduced and evaluated experimentally with data from industrial inspection stations. The work demonstrates that an inspection system automatically tuned with the proposed technique can systematically achieve 98% correct classification when compared with the classification generated with a manually tuned system.**

Keywords-Food inspection, quality control, machine vision, machine learning, feature selection, automated tuning.

I. Introduction

For several years, the food industry has adopted automated vision-based inspection systems in an attempt to reduce operation costs and increase product quality control. Vision-based inspection systems reduce human interaction with the inspected goods, classify generally faster than human beings, and tend to be more consistent in their product classification. Food industries where a large part of the quality attributes of a product are related to its visual appearance have taken advantage of vision-based inspection systems for quality control of products such as meat, fruits and vegetables, bakery products, and prepared consumer foods [1-3]. Such inspection systems extract and analyze a large number of features and automatically reject products that do not satisfy the set quality standards. In the majority of cases, the configuration of the inspection system requires an in depth knowledge of the product under inspection and of the inspection apparatus. It is therefore subjective, and based on a trial and error approach. With the objective of reducing the need for human expertise in the tuning of vision-based food inspection systems, this work experiments with several machine learning techniques that make the machine select and set the optimal parameters by itself over a training period. This strategy also allows performance improvement, which is beneficial to real-time quality control in high-volume industrial manufacturing. The influence of formal feature selection approaches when combined with machine learning techniques is also assessed.

Section II describes three fundamentally different machine learning schemes that were considered in the experiments with a vision-based food inspection system. Section III proposes a formal approach for automatically tuning an industrial inspection system. Section IV depicts the experimental vision-based inspection system and samples of bakery products considered. Section V reports the results of experimental training with the inspection system. Finally, Section VI validates the proposed procedure by tuning the best performing learned models into an industrial inspection system and evaluating its performance.

II. Machine Learning Schemes

This section portrays three classical but different learning approaches, namely Bayesian learning, decision tree learning, and neural networks. These models have been evaluated for automated tuning of an inspection station for bakery products.

A. Bayesian Learning

Bayesian learning builds on probability theory (Bayes' theorem) to represent uncertainty about a relationship being learned. During the learning phase, Bayesian learners build a set of probability distributions from training samples in an attempt to represent the relationships between the data input and the desired corresponding output. Those probability distributions can be viewed as the knowledge acquired during the learning phase over a training subset of data. When a sample of real data needs to be evaluated, the Bayesian learner computes a set of a posteriori probabilities that it combines with its prior knowledge such that the probability of an inconsistent hypothesis is minimized.

Bayesian learning offers high flexibility as it extracts a priori knowledge from training data to get the a posteriori probability of a hypothesis. It is therefore possible in theory to figure out the most probable hypothesis according to the training data. Bayesian learning algorithms deal explicitly with issues of uncertainty and noise [4]. Bayesian classifiers have been used for several purposes such as medical diagnosis [4-6] and have shown to be competitive with much more sophisticated induction algorithms [7]. The Naïve Bayes algorithm can be viewed as the simplest yet powerful Bayesian classifier and has been widely used in classification problems [8-11]. This work evaluates Naïve Bayes as a classifier running over vision-based food inspection systems.

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B. Decision Tree Learning

Decision trees offer an alternative tuning method. A decision tree is a predictive model which maps observations about an item to conclusions about the item's target value. Such tree models are commonly referred to as *classification trees* when their outcome is discrete, and as *regression trees* when their outcome is analog. In such tree structures, leaves map classifications and branches represent conjunctions of features that lead to those classifications. Decision tree learning induces a decision tree from data. Decision trees are widely used for classification purposes, for instance in equipment or medical diagnosis, or for credit risk analysis [5].

Because decision tree inducers typically form their decision tree from a subset of the available attributes, they can also be seen as feature selectors. C4.5 is a decision tree inducer which builds its decision tree top-down by recursively finding the best single feature test to conduct at the root node of the tree [12]. C4.5 has also proven itself to be one of the most competitive decision tree inducers in the world of machine learning for various domains of application [8-9]. For this reason, the C4.5 framework is also investigated for classifying products inspected with vision-based quality control systems.

C. Artificial Neural Networks

An artificial neural network (NN) is a mathematical model that tries to imitate the structural and functional aspects of biological neural networks with a network of interconnected artificial neurons [13]. The biological functional aspects simulated by such networks are the flow of information through the network and the processing of information by the artificial neurons. The adaption characteristic offered by the majority of neural networks allows them to modify their structure during the learning phase according to the information circulating through the network. They can be used to model complex relationships between inputs and outputs or to find patterns in data. Artificial neural networks have been widely used in image processing, robotics, data mining, and more recently for food products inspection [2, 14-18]. In most machine learning tasks involving numerical attributes, the multi-layer perceptron (MLP) has attracted attention due to its ability to capture complex nonlinear input-output relationships. Given its flexibility and simplicity, the MLP is also selected as a potential candidate to automatically tune the internal parameters of food inspection systems.

III. PROPOSED AUTOMATED TUNING APPROACH

The proposed methodology for automatically tuning a quality control system based on the visual appearance of a product builds on the assumption that a dataset of N training samples of the inspected product is available, which is realistic in most industrial setups. For every sample the dataset should contain the respective values of M features of interest to be monitored. Fig. 1 details the proposed approach.

The first step of the automated tuning process is feature selection. Machine vision systems used for inspecting processed food tend to extract a large number of features, such as their size, height, circularity, color, etc. This often results in close to one hundred different measurements collected on every inspected item. Such a high dimensionality slows down the rate of production and complicates the learning process for classification of each item as “accepted” or “rejected”. Consequently, performing an objective feature selection, based on inter-correlation between the features, becomes particularly attractive to reduce the redundancy between the parameters. This procedure has the potential to improve learning performance, and increase production and inspection rates. Four different feature selection techniques have been previously evaluated for this task: correlation-based feature selection (CFS) [9, 19], consistency-based feature selection [20], RELIEF feature selection [21-23], and the wrapper feature selection [8]. The conclusions of the study on feature selection are presented in [24]. As it was observed that feature selection performs better when the training data is discretized, data discretization [25] is performed prior to feature selection. However, data discretization is performed only for feature selection purpose. Once a feature selection technique selects a subset of the M initial features as relevant, training of the machine learning schemes shall be performed on the non-discretized training data to enable a more accurate learning.

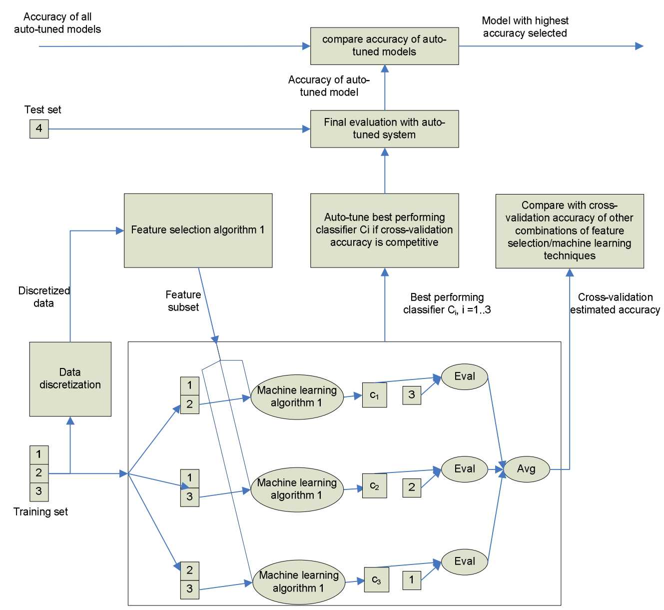

Fig. 1. Proposed automated tuning methodology.

Training is performed using 10 repetitions of 10-fold cross-validation as suggested in [26], with $N=3287$ training samples. In t-fold cross-validation, where t is a positive integer, the data is randomly split into t mutually exclusive subsets (the folds) of approximately equal size. The learner is trained and tested t times, each time with (t-1) training folds. The remaining one stands as the test fold. 3-fold cross-validation is depicted in the process illustrated in Fig. 1. The accuracy of the cross-validation is then compared for all combinations of feature selectors with machine learning algorithms (including the case where no feature selection is previously applied). Because the test for cross-validation is performed on product samples that were not presented in the training phase, the average accuracy provides an indication on the capability of each classifier, c_i, to generalize to new samples. The standard deviation of the accuracy also indicates how close the estimated accuracies of the 100 classifiers built during the 10 repetitions of 10-fold cross-validation are consistent with the average.

After comparing the cross-validation performance of the different combinations of feature selection and learning models, the most competitive models (i.e. those with highest rate of correct "accept" or "reject" decisions) are implemented into the inspection system, as candidate solutions for its automated tuning. For each of the competitive combinations of feature selection and machine learning techniques, the internal parameters of the classifier which achieved the highest classification performance during training are selected and tuned in the system for further validation.

The next step runs on new samples of products that were not part of the training phase (test set 4 in Fig. 1). The inspection system is then successively tuned with each of the retained classifiers and its performance is evaluated over those new samples for each model. The final step compares the accuracy of the classification achieved with each classifier and selects the one that exhibits the best performance as the final setting for the inspection station.

IV. Experimental Setup

A. Experimental Food Inspection System

The vision-based food inspection system used for the experiments is a technology designed to automate visual identification and classification of bakery products such as buns, cookies, tortillas, pizzas, croissants, etc. Fig. 2 shows the actual system on which experiments were conducted.

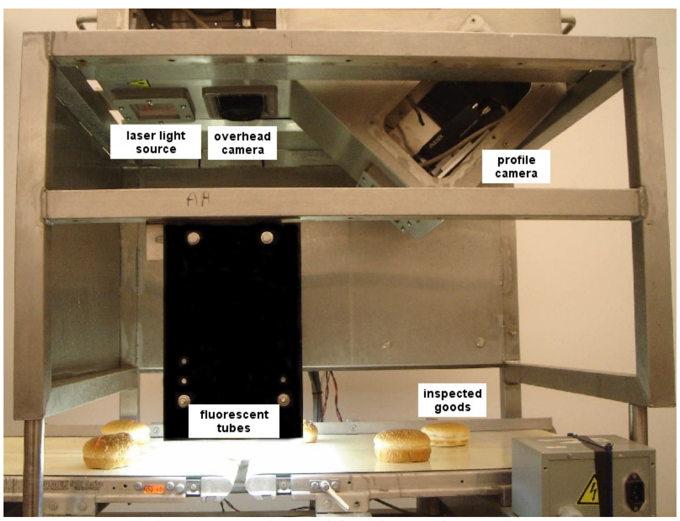

Fig. 2. Experimental food inspection station.

The system is equipped with a conveyor belt which moves the bakery products on an industrial production line, typically between the oven and the rejection or packaging systems. One line scan camera is mounted above the conveyor belt (overhead camera) and produces real-time images of the top view of products as they pass under fluorescent lamps that continuously illuminate the field of view of the overhead camera. A laser light stripe is also projected vertically on the conveyor belt and an extra profile camera, sensitive to the laser light wavelength, images in diagonal to generate 3D information about every item. For each food product item inspected, the vision-based inspection system extracts $M = 82$ continuous features related to the geometrical shape and the color characteristics of the product, plus one boolean feature representing the decision to either accept or reject the item.

B. Experimental Datasets

To validate the proposed methodology, experiments were conducted on common products handled by food inspection systems, including burger buns and tortillas, shown in Fig. 3.

(a) Seeded bun (b) Tortilla

Fig. 3. Seeded bun and a tortilla samples used for validation.

In order to perform the experimental evaluation on a representative set of product samples, videos of the overhead and profile cameras were captured by equivalent versions of the vision-based food inspection system installed in two different industrial bakeries (one manufacturing seeded buns, another for tortillas). The corresponding system's setting files, which were previously manually configured to achieve satisfactory classification, were also saved. The latter allowed to reproduce the generation of the exact sets of 82 parameters for every item using the inspection station depicted in Fig. 2 on which the video were loaded, therefore mimicking the operation of the actual inspection stations. The classification generated by the original classifier manually configured in the inspection station was recorded for each item to provide a ground truth comparison basis on the decision process. The two datasets coming from industrial bakeries served as a reference for measuring the reliability of the proposed automated tuning approach.

V. Learning a Model for Automated Tuning

As detailed in section III, the vision-based food inspection system measures a fairly large number of features (82) from each sample of the product. These parameters are first fed into a feature selection program to reduce the dimensionality of the parametric representation that is used by machine learning algorithms [24]. The goal of the resulting models is to preserve high classification accuracy. This section analyzes the results of the learning phase which involved datasets of tortillas and seeded buns containing $N = 3287$ items each, and compares between classifier models and settings.

A. Feature Selection Performance

For both the tortillas and seeded buns datasets, all feature selectors except RELIEF consistently judged more than 85% of the 82 initially extracted features to be irrelevant or redundant to proper classification of the bakery products. The lower reduction in dimensionality achieved with RELIEF was expected. Indeed Kohavi and John [8] demonstrated that RELIEF feature selection tends to keep most of the relevant features of a dataset even if they are redundant and even though only a fraction of them is necessary for the correct description of the concept. On the other hand, feature selection results also showed the wrapper approach to generally retain fewer features compared to correlation-based, consistency-based, and RELIEF feature selection. For instance, the wrapper feature selection retained less than 3% of the 82 features of seeded buns when trained to work with a C4.5 decision tree. A complete analysis of feature selection performance for tortillas and seeded buns is available in [24].

B. *Machine Learning Performance*

Fig. 4 and Fig. 5 show the accuracy estimation on the correct class prediction ("accept" or "reject") with different feature selection and machine learning techniques for the tortillas and the seeded buns datasets respectively. The accuracy is evaluated when each feature selector is combined with one of the three learning schemes selected previously: that is Naïve Bayes, C4.5, and MLP. The accuracy presented on these figures represents an average from ten repetitions of the 10-fold cross-validation as explained in section III. The vertical lines at the edge of the bars of Fig. 4 and Fig. 5 represent the standard deviation. On Fig. 4, "Full" represents the original entire dataset collected on tortillas that did not undergo any feature selection, and similarly on Fig. 5 for the seeded buns dataset. 100 % accuracy of classification corresponds to the classification for each item produced by the original classifier which was manually set by an expert on the industrial food inspection system. It is considered as the "ground truth".

Cross-validation accuracy estimation tests conducted on the tortillas and the seeded buns datasets show that for all of the considered feature selectors, the C4.5 learning scheme globally gives the highest classification accuracy and the lowest standard deviation. It is followed closely by the MLP learner and far behind by the Naïve Bayes learner. As 100 instances of a classifier are computed for each model, a low standard deviation indicates that the classification accuracies among the instances tend to be very consistent.

In the case of tortillas, the results of the cross-validation for the C4.5 learning scheme point out that learning with the full original dataset reaches an accuracy of 99.39% with a standard deviation of 0.47%. This is very close to the ground truth classification achieved with manual setting of the machine. Consistency-based feature selection combined with the C4.5 learner even gives a slightly higher accuracy (99.44%). A combination of C4.5 with the RELIEF feature selector reaches the same accuracy estimation as with the full dataset, followed by the C4.5 wrapper and the correlation-based feature selector (CFS) with an accuracy of respectively 0.03% and 0.04% below that of the full dataset. The standard deviation for the C4.5 decision tree inducer is consistently low and varies between 0.42% and 0.47% only.

Similar results are obtained over seeded buns classification when considering the C4.5 learning scheme. Learning with the original full-size feature dataset reaches an accuracy of 99.78% with a standard deviation of 0.27%. None of the reduced dataset achieves a higher accuracy. However, the consistency-based feature selection and the wrapper combined with the C4.5 learner closely follow by achieving an estimated accuracy only 0.55% inferior to that of the full dataset. RELIEF and CFS follow closely with accuracy less than 2% lower than that achieved with the full seeded buns dataset. Such levels of accuracy predict for great performance for an inspection station that will be configured with machine learning techniques rather than through human intervention.

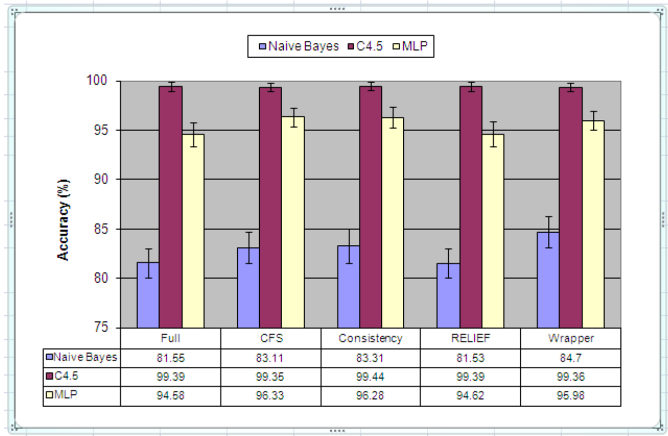

Fig. 4. Average accuracy on classification over 10 repetitions of the 10-fold cross-validation accuracy estimation for the tortillas dataset.

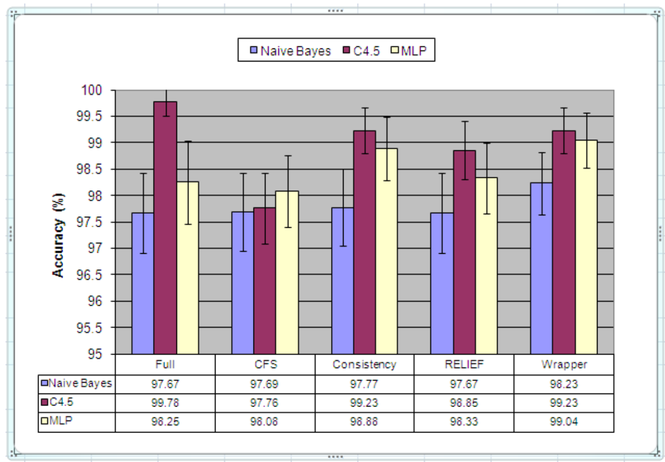

Fig. 5. Average accuracy on classification over 10 repetitions of the 10-fold cross-validation accuracy estimation for the seeded buns dataset.

VI. PERFORMANCE OF AUTOMATICALLY TUNED SYSTEM

The evaluation of performance of three learning algorithms demonstrated that the C4.5 decision tree clearly achieves the highest predicted accuracy. Therefore, C4.5 was retained as the best candidate for the classification model to be implemented on the inspection station. The parameters of the five variations of the C4.5 decision tree, with and without prior feature selection, were transferred into the system to mimic automated tuning. These correspond respectively to the C4.5 decision tree induced from the full set of features, and the C4.5 decision tree induced from the set of features reduced with CFS, consistency-based, RELIEF, or wrapper.

A. Tortillas

To evaluate the performance of the automatically tuned inspection station, 500 new samples of the large industrial tortillas dataset were used. These samples, which contain products of acceptable visual appearance and products to be rejected, were first analyzed by the classifier manually tuned by the bakery personnel to obtain the correct classification (in the sense of the bakery's expectations). The "ground truth" corresponding to 100% accuracy is represented by the classification produced by the manually set classifier.

Second, the same 500 tortilla samples were presented to each of the five automatically set models resulting from the learning phase. For every item that is inspected with the automatically tuned model, its classification is considered accurate if it matches the classification ("accept" or "reject") obtained from the manually set classifier, and inaccurate otherwise. Since those 500 samples were not used during the learning phase and cross-validation, this test measures the capability of generalization of the automatically tuned system and its ability to operate on new products to be inspected.

Fig. 6 presents the real accuracy achieved by the automatically tuned system against the accuracy predicted in Section V at the end of the learning phase by cross-validation for the tortillas. As before, "Full" represents the entire set of features without any feature selection. For all of the considered models, the real accuracy achieved is slightly lower than the accuracy predicted by cross-validation. However, in the worst case, the real accuracy is only 4.59% inferior to the prediction. It is achieved when the C4.5 decision tree model is generated from the full set of features, or equivalently, with the C4.5 model induced from the reduced set of features selected by RELIEF, which happens to be the feature selector removing the least attributes. The C4.5 decision tree induced after consistency-based feature selection offers similar performance. On the other hand, the decision tree based on CFS achieves an accuracy that is only 2.15% under the prediction. The C4.5 tree combined with wrapper feature selection performs as well, its accuracy being 2.16% under the prediction. Therefore, the C4.5 decision tree combined with wrapper or CFS feature reduction provides the best performance.

It is interesting to observe that, on one hand the different feature selectors combined with C4.5 decision tree learning provide slightly reduced performance as automated tuning solutions when compared to the theoretical predicted performance estimated by 10-fold cross-validation. On the other hand, experimental results show that all of the C4.5 models generated after feature selection, of any type, achieve accuracy greater or equal to when the full set of features is considered. Feature space dimensionality reduction therefore leads to slight increase in classification accuracy on the real inspection station, while reducing the number of parameters to process, which can afford for higher inspection rates.

B. Seeded Buns

In order to tune a classification model for the seeded buns, the same methodology was followed. The experiment also involved 500 new samples of seeded buns that have not been used during the model learning phase and performance prediction with cross-validation. Fig. 7 presents a comparison between the predicted accuracy performance of the five variations of the C4.5 decision tree and their real performance measured when the system is actually configured with the parameters of the corresponding C4.5 decision trees.

The results shown in Fig. 7 demonstrate that the accuracy achieved with the automatically tuned vision-based food inspection system over the 500 new samples differs less than 1% from the accuracy predicted using cross-validation. The same performance is observed independently from the use or not of feature reduction in this case. The full set of features achieves the best performance as was predicted by cross-validation (98.8% of the samples were correctly classified compared to the predicted 99.78%). The C4.5 decision tree learning scheme combined with the wrapper feature selector offers the same performance. These facts demonstrate that using a substantially reduced set of features (C4.5 wrapper selected less than 3 % of the 82 extracted features as mentioned in section V) still allows achieving the same performance as with the full set of features. This can support higher inspection rates. The decision tree generated after consistency-based feature selection achieves 98.4% correct classification, which is only 0.83% less than the predicted accuracy. In this case, any of the combinations of the C4.5 learner with feature selectors offers very good performance.

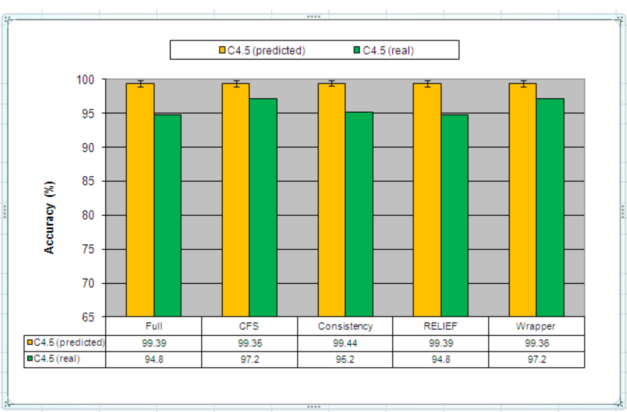

Fig. 6. Classification accuracy achieved by auto-tuned system with C4.5 learning versus predicted accuracy (tortillas).

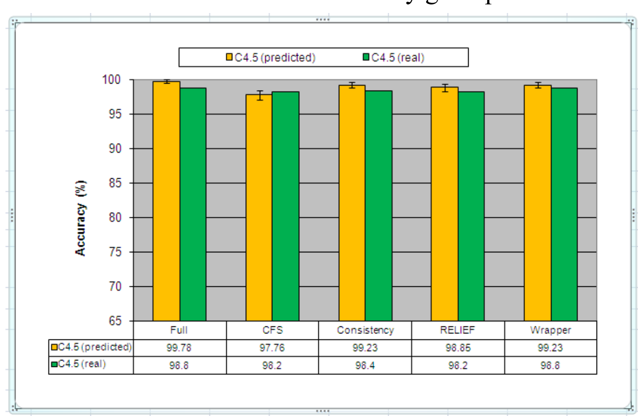

Fig. 7. Classification accuracy achieved by auto-tuned system with C4.5 learning versus predicted accuracy (seeded buns).

C. Summary of Experimental Validation

The results of the experiments on tortillas and seeded buns globally demonstrate that the accuracy of the inspection system automatically tuned with a model obtained from machine learning is generally comparable to the accuracy predicted by cross-validation for the same model. The correctness of the classification also compares advantageously with the ground truth reference that is obtained when the same system is tuned with lengthy and costly manual procedures. As a matter of fact, provided that the training samples are available, manually tuning the inspection system can easily take an entire day or more depending on the expertise of the operator, whereas the automated tuning proposed in this work can be performed within one to two hours.

VII. Conclusion

This paper presented a formal evaluation of three machine learning algorithms for the calibration of vision-based food inspection systems. A specific procedure to automatically set the internal parameters of an inspection station is proposed, starting from a sample of product items. The proposed solution distinguishes itself from other vision-based food inspection systems configuration techniques by providing an explicit predicted performance for several candidate machine learning techniques that automatically adapt to the product to be inspected. As such, means of anticipating the performance of an inspection station are made available. A validation step challenges the predictions by tuning the most promising classifier from different models into the inspection station and testing with new real samples to refine the final selection.

The experimental validation confirmed that the accuracy predicted using cross-validation is very close to the real performance observed once the system is tuned with the best classifier identified. Results obtained on different bakery products clearly demonstrated that among three evaluated machine learning techniques, the C4.5 learning scheme is the most suited for industrial vision-based quality inspection of typical bakery products. It reveals that an inspection system automatically tuned with the proposed technique can systematically achieve about 98% correct classification when compared with ground truth classification, obtained with manual tuning. Given the variations that are omnipresent in any human based decisions regarding the visual appearance of a product, the proposed approach achieves comparable performance. The technique competes advantageously with manual tuning which requires extensive expertise with the inspection system, depends on individuals' abilities, and often results in time-consuming and expensive procedures.

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