Quality Assurance using Active Learning

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Abstract

This research addresses the problem of quality control in the food industry through the utilization of AI-powered classification systems. The current reliance on human inspection poses challenges, including subjectivity and labor-intensive processes. Our investigation aims to introduce an innovative solution that leverages computer vision, along with an AI agent employing active learning and specialized querys.

Key Concepts:
Active-Learning, Computer Vision, Quality-Control, Industry 4.0

1 Introduction

Quality control is a vital aspect of the food industry [Duong *et al.*, 2020], as it ensures the safety, consistency and customer satisfaction of the products. However, the traditional methods of quality control rely heavily on human inspection, which can be subjective, inconsistent and prone to errors. Moreover, human inspection is a labor-intensive and costly process that requires extensive training and supervision. Therefore, there is a need for more efficient and reliable methods of quality control that can cope with the increasing demand and complexity of the food industry [Chandani, 2020].

One promising approach to improve quality control is to use artificial intelligence (AI) powered classification systems that can automatically detect and classify defects or anomalies in food products. These systems can use computer vision techniques to analyze images of food products and compare them with predefined standards or criteria. By using AI, these systems can learn from data and improve their performance over time, as well as adapt to different scenarios and environments.

This way of approaching the problem is very niche and there are not a lot of solutions out there yet, never the less, the most notable one we could found is Clarifruit [Southey, 2021], an automated, end-to-end quality control as a service (QCaaS) solution that facilitates fast, objective, and consistent fruit and vegetable fresh produce quality control and management. The solution uses computer vision, machine learning, and cloud computing to analyze real-time data about the external and internal attributes of fresh produce.

However, developing and deploying AI-powered classification systems for quality control is not a trivial task. There are several challenges that need to be addressed, such as:

1. How to acquire sufficient and representative data for training and testing the AI models?
2. How to ensure the accuracy and robustness of the AI models in different settings and conditions?
3. How to handle the uncertainty and variability of the data and the AI models?
4. How to incorporate human feedback and domain knowledge into the AI models?
5. How to evaluate and validate the performance and impact of the AI models?

In this paper, we propose an innovative solution that tackles these challenges by leveraging computer vision, along with an AI agent employing both active and incremental learning. Active learning is a technique that allows the AI agent to select the most informative data points for labeling by human experts, thus reducing the data acquisition cost and improving the data quality. Specialized queries are questions that the AI agent can ask the human experts to obtain additional information or guidance, such as clarifying ambiguous cases, requesting explanations or confirming predictions. By using active learning and specialized queries, we aim to enhance the efficiency and reliability of the AI-powered classification systems for quality control, as well as to facilitate the collaboration and communication between the AI agent and the human experts.

The main contributions of this paper are:

- We present a novel framework for quality control in the food industry using computer vision, active learning and a deploy method for the real world.
- We propose and evaluate different strategies for active learning and specialized queries that can optimize the data acquisition process and improve the performance of the AI model.
- We conduct experiments on real-world datasets of food products to demonstrate the effectiveness and applicability of our proposed solution.

The remainder of this paper is structured as follows: Section 2 reviews the related work on quality control in the food industry using AI techniques. Section 3 describes the proposed system architecture and components. Section 4 describes the techniques and the way we used AI. Section 5 will be about the different experiments we did and how we did them. Section 6 will analyse the results obtained and finally section 7 will be the conclusion of the project and will talk about how we can improve on your work.

2 State of Art

In the field of food quality control, AI-powered classification systems have been proposed to improve efficiency, accuracy, and reliability. These systems leverage computer vision techniques to analyze images of food products and compare them with predefined standards or criteria. Active learning techniques, such as sequential minimal optimization (SMO), decision tree (DT), random forests (RFs), and neural networks (NN), have been incorporated to reduce data acquisition costs and improve data quality.

A study on incorporating active learning into machine learning techniques for sensory evaluation of food quality [Huynh, 2020] used active learning to improve the classification performance of food products. The study found that active learning techniques could significantly reduce the number of labeled samples required for training, compared to passive learning approaches.

Another approach to improve data efficiency in food quality control is the use of semi-supervised learning (SSL) [Zhang, 2022]. SSL combines active learning with machine learning techniques to leverage both labeled and unlabeled data, further reducing the need for manual labeling of images.

In the context of food safety applications, spectroscopy approaches have been used to analyze food quality, safety, and nutritional properties. Machine learning, particularly SSL and active learning, has shown great potential in improving the classification performance of these applications.

The proposed innovative solution in this paper shares similarities with these published works in terms of leveraging active learning techniques for data acquisition and model improvement. The approach differs in its focus on a deploy method for the real world, aiming to enhance the efficiency and reliability of AI-powered classification systems for quality control, as well as facilitate collaboration and communication between the AI agent and human experts.

In comparison to existing solutions like Clarifruit [Clarifruit, 20223], the proposed approach focuses on active and incremental learning for data acquisition and model improvement, setting it apart from other approaches in the field. The approach is evaluated on real-world datasets of food products to demonstrate its effectiveness and applicability in the food industry.

3 Materials

In order to ensure that the model is trained and tested with images that are focused on a specific fruit, we have decided to use an autonomous cropping tool that uses computer vision. After some research, we verified that many of YOLO (you-only-look-once) implementations are extremely accurate and trustworthy in detecting numerous types of objects. We decided to use an implementation that allowed us to realize the cropping. Basically, this module of the project receives an image that may contain one or more pieces of fruit and saves all the croppings in a directory. Since this process requieres to have a lot of images to crop, we worked on a dataset with already croped images [SRIRAM REDDY KALLURI,].

To build the second module, we decided to use keras, a high-level, deep learning API developed by Google. That allowed us to build the neural nets and train them in an easy and comprehensive way. It is important to note that there were no pre-built modules to perform active-learning, we will explain more about our implementation in the methods section.

4 Methodologies

The architecture used for the deep learning network is what we found during our research to be the default good neural net for image classification. We use a Convolutional Neural Network architecture with two convolutional layers and max pooling, which allows the learning of hierarchical features, dense layers capture high-level information, and soft-max activation facilitates multi-class classification. Compiled with the Adam optimizer and categorical cross entropy loss, this architecture is known to be effective for diverse image data sets, offering a balance between complexity and computational efficiency.

The main focus of our project is the active learning module. We decided to implement a system that evaluates batches of 100 images. The model will pick the 20 it is more insecure about when classifying by using one of the implemented query strategies: least confident, smallest margin and entropy based. All these queries have associated thresholds of confidence that will determine what action we will perform with the image that the system has analyzed. There are 3 possible actions: asking the expert for a label, do nothing or label the image by itself. If it does nothing, those images stay in the directory, while if they are labelled by the expert or by the model, they are removed.

We begin the active learning process with a pre-trained model because at the start the model is uncertain about all data, therefore the use of the expert is not that valuable since finding the most uncertain data in the first iterations does not add a lot more worth than just using a random pool of images.

We choose to split the images in groups of 100, because we came rapidly to the conclusion that in a real world scenario, we want to use the data recently gathered as fast as possible, but since we don't want to force the expert to have to label more than 20% of the images in a batch we chose that the machine will only be allowed to, in cases of maximum uncertainty 20 images to the expert.

5 Experiments

When doing the fine tuning of our active learning model we decided that the parameters that we would be tweaking with would be the query strategies, the confidence thresholds in the different query strategies, the size of the batches, the number of epochs in the pretraining and the number of epochs in the increments.

To make sure that the results do not depend on the data set used we created an experimental data set that was used on all experiments. The only luck factor involved in the experiments is the initialization of the weights that is performed randomly.

The results of the different experiments will be evaluated by quantitative values such as the accuracy that the module obtained, the data that was used to get that accuracy and the amount of wrongly labeled images by the machine.

1. Experiment: Understand how many pre-trained examples are needed in each class. In order to understand this we trained models with different amounts of images and measured the performance they obtained.
2. Experiment: Test how many iterations will be needed until the model's performance stagnates. For this one we trained several models, and saw the progression curve in the accuracy domain. We used the Query Least Confidence and a confidence tresh-hold of 95%.
3. Experiment: Test the different Query Strategies, this one was difficult to measure since for the different Query Strategies, the tresh-hold of confidence means different things, still we used a 95% confidence on all the query's.
4. Experiment: Understand the effects of the epochs on each increment and find the best computational effort result relation. For this one we used the Query Strategy smallest margin and the confidence was 95%.
5. Experiment: Find the optimal value of confidence threshold for the best query strategy. This one comes has a following of the experiment 3 were we try the different confidence thresholds and see the effects. This one will be measured on both amount of data machine labeled, accuracy on the data labeled by the machine, and accuracy.
6. Experiment: Compare the passive Learning model and the active learning model for similar amounts of data. This one is meant to show how active learning data has a higher value than random data, and will prove that active learning reduces the labeled data requirements.

The results of these experiments will be presented on the next section and will be accompanied by an explanation of why do we get those results.

6 Results

6.1 Amount of images used in pre-train

Images of each class	20	35	50
Accuracy (%)	68	72	74

Table 1: Pre-trained Data and Accuracy

By looking at the Table 1, we observe that for an augment of 75% of the data used (20 - 35), the model only gained 4% of accuracy, and that for a augment of 150% (20 -50), the model gets 6% accuracy. This makes sense, since not the accuracy progression and the amount of data used follows a logarithmic curve. Based on those results we decided that in order to reduce the demand of pre-labeled data we will start on a model that only uses 20 images of each.

6.2 Iterations until the model ready

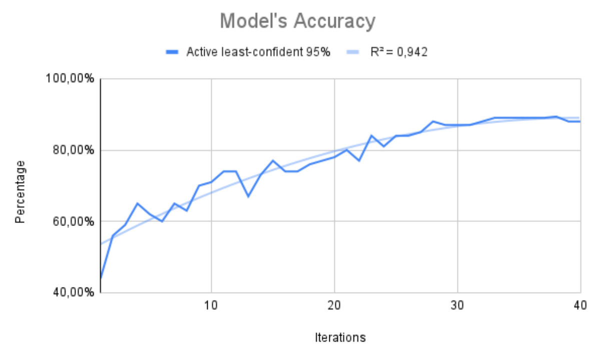

Figure 1: Progression curve

By looking at the Figure1, we can conclude that the model tends to stop progressing at a pace that is relevant around the iteration 35, nevertheless due to the fact that there is some variance we decided that from this experiment we will stop our experiments at the iteration 40.

6.3 Results of the different query's

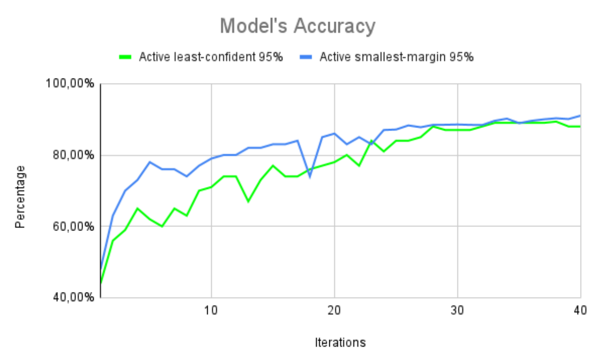

Figure 2: Leas Confidence vs Smallest Margin

This result was one of the most unexpected, we found that there is a very significant difference in performance augmentation on the early phases between both query strategies. And that implies that there is also a great comeback from the least confidence query. The results of this experiment leads us to believe that the most optimal query strategies would not be only one but instead the combination of multiple ones. Still we saw that the upper limit of each query strategy is greater on the smallest margin, that made us believe that is was the better query strategy for this problem. Also, when the machine was labeling images, it made less errors using smallest margin.

6.4 Epochs on the incremental training

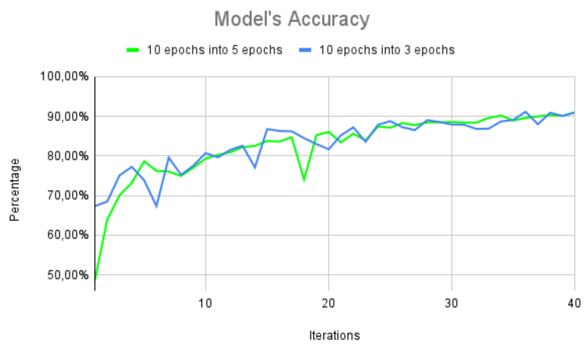

Figure 3: 5 epochs vs 3 epochs

We did this experiment with the goal of reducing the computational power that is demanded on each iteration, and we managed to reduce the number of 5 epochs to 3. As it is expected, in the early phases it is under fitting, but as the iterations progress, it will catch-up and unlike the 5 epochs one it will not be over fitting. This once again allowed us to push the upper limit of the curve higher and at the same time reduce the number of epochs by 40% per iteration.

6.5 Testing confidence thresholds

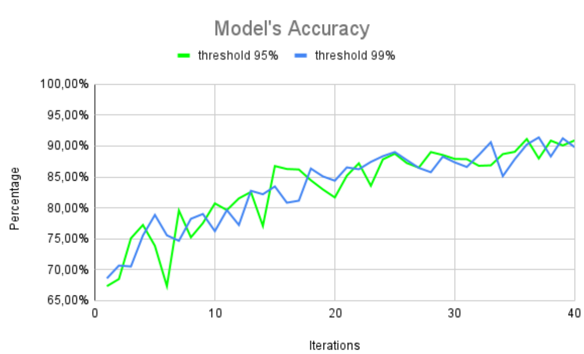

Figure 4: 0.99 confidence vs 0.95 confidence Accuracy

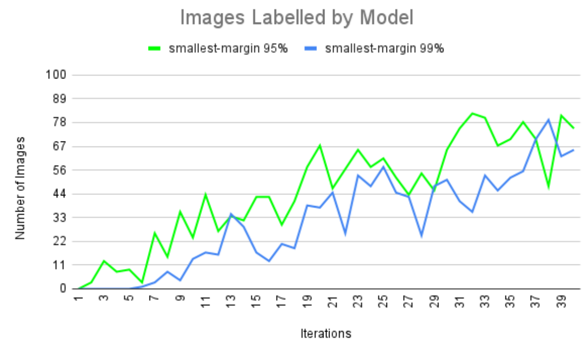

Figure 5: 0.99 confidence vs 0.95 confidence Lables

By looking at both Figures 4 and 5, we can observe that the higher the threshold of confidence is to accept an image as machine labelled, the least images we will be accepting on an early phase, but as iterations progress, the machine labels even out and we will be labelling as many as on the lower confidence one. The biggest difference between both of these is the among of wrong labels that the machine does, since on the 99% the machine starts labeling on a later phase it only obtains a 1.85% of wrong labels on the other hand the 95% obtains 4.3%. Even thug this does not seem to highly impact the accuracy of the model it is relevant to have the confidence threshold in mind if the goal is to label the data Set.

6.6 Passive vs Active Learning

Total of images	600	1800	2000	3000
Passive (%)	68	87	/	90
Active (%)	86.7	89	91	/
Expert-Data Only (%)	88	/	/	/

Table 2: ActiveLearning vs PassiveLearning

We concluded our experiments demonstrating that the goal of using less data and outperforming passive learning was achieved, as expected the data that is used in passive learning is more relevant, and therefore allows to obtain better results. Even tough the expert data is the most important one, the way active learning allows to cover more data by self labeling, makes it possible to gather a big data set for training and not lose the value of the examples labeled by the expert.

7 Conclusion

The research presented in this paper introduces a novel approach to quality assurance in the food industry using AI-powered classification systems. The proposed solution leverages computer vision, active learning, and specialized queries to improve the efficiency and reliability of quality control processes. After the analysis of the results, we believe that we were successful in our approach, we designed a system capable of reaching an accuracy of 98% on 70% of the data set, those who pass the confidence threshold in our best model were accurately classified 98% of the time, while the others who don't reach the threshold still obtain a satisfactory accuracy of 75%. So we can conclude that if our system was deployed in real world scenario, we could cut 80% of the manual labor that is used to perform this task. Results might be even better on a controlled environment such as a fabric since our data sets had multiple backgrounds and we worked on several fruits at the same time.

A part of the possible future work that we think it would be interesting to explore is the removal of the background of the cropped image, since it would eliminate any influence of it in the model's performance. Also, we think that it would be interesting to explore the possibility of cleaning the labelled data from time to time, removing all images that the model is more in doubt about (for example, all images that the current model's labeling certainty is lower than 70%). We would also like to explore mixing query strategies on the different stages of the training since as we saw on experiment 3, different query's perform better on different phases of the training.

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