Technical Overview

Agilent OpenLab

# Agilent AI Peak Integration for MassHunter

## A tool to optimize GC-MS Phthalate Test Quantitative Analysis


### Authors

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## Abstract

Agilent AI Peak Integration for MassHunter is a software tool designed to mimic the role of analytical chemists doing GC/MSD manual integration. AI peak integration improves the precision of test results, acting as an invaluable aid in quantitative concentration determination. It does this by advancing automatic peak integration to a new degree of accuracy, drastically reducing manual reintegration. AI peak integration reduces human error, resulting in enhanced consistency and analysis accuracy.

MassHunter was extended with an AI plug-in software tool initially tailored for the analysis of phthalates, but is expected to be applicable for the analysis of other compounds as development evolves. A machine learning model facilitates peak detection and identification and seamlessly integrates with the existing MassHunter user interface and customer workflow. Consequently, it significantly reduces the training required for users.

This technical overview serves as a comprehensive guide for Agilent GC/MS users conducting phthalate analysis to demonstrate the process of training and utilizing the AI peak integration model effectively.


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## Introduction

Testing laboratories face increasing pressure to consistently deliver fast and accurate analyses. The convergence of stringent regulations, customer expectations, and industry demand for quick turnaround times creates a bottleneck within labs. Sometimes, the nature of analytes also plays a role. In the case of phthalate analysis in consumer products, isomeric compounds such as diisononyl phthalate (DINP) and diisodecyl phthalate (DIDP), result in broader peaks and irregular peak shape which usually require additional manual integration. Introducing smart technology to streamline manual processes offers a solution to optimize the performance of analytical instrumentation in the laboratory.

## Key Features of AI Peak Integration

AI peak integration supports the following features when incorporated into the quantitative data analysis process:

1. **Continuous Learning:** AI peak integration continually enhances peak detection and integration accuracy by evaluating new data submitted to the system. As more diverse data are processed, the model becomes increasingly adept at identifying peaks. Users can train the model to adapt to their lab's specific peak integration protocols and patterns. Editing of inference results is allowed by technicians and all variables changed are recorded and fed back to training pipeline infrastructure to continuously enhancing the model. The model's performance can be monitored within the GC/MS data processing software, ensuring that predefined thresholds are met. The system also includes safety checks to prevent accuracy degradation if input data characteristics change over time.
2. **Model Adaptation:** AI peak integration adjusts to the quantitation method employed by a specific site or user. The software supports the creation of custom-trained models that can be defined based on user preferences, location, or specific customer requirements. This adaptability ensures a tailored approach to quantitative analysis.
3. **Reproducibility:** AI peak integration enables the re-evaluation of previously analyzed samples. This feature proves invaluable when conducting retrospective analyses or when there is a need to validate previous results. This is because all raw data can be associated to the relevant model version used for analysis at the time, therefore providing an auditable trail.
4. **Version Control:** The Model Registry component is a centralized model store and tool set to manage the full lifecycle of a model within the system. It provides and tracks the models uniquely along with information related to model versioning, stage transitions (for example when a model is promoted from staging to production), and annotations.
5. **Consistency:** AI peak integration provides analytical consistency between technicians and multiple lab locations due to the reproducibility, ensuring quality and consistency within an organization.
6. **Cloud Based:** AI peak integration operates as a cloud-based SaaS solution, allowing for effortless scalability and flexible feature updates. This ensures that users can access the latest advancements & improvements in Agilent AI algorithms and learning models without any disruption to their workflow.
7. **Seamless Incorporation:** AI peak integration seamlessly integrates with MassHunter Quantitative Analysis and aligns to support a customer's existing Standard Operating Procedures (SOP). The installation process is simple and electronically delivered, facilitating smooth adoption, and minimizing any potential disruptions.

## Designing the Agilent AI Peak Integration Tool

The development and training of the AI peak integration algorithm followed a comprehensive methodology that encompassed several key steps to ensure its accuracy and effectiveness. This section provides an overview of the methodology employed in creating the tool.

1. **Interviews with GC/MS Practitioners:** The initial step involved conducting interviews with experienced GC/MS practitioners testing consumer products. These interviews aimed to gain insight into their needs, challenges, and practices regarding manual peak integration of chromatographic peaks and compound identification.
2. **Data Collection:** Based on the insights gathered from the interviews, a dataset was collected primarily focused on a specific class of compounds, known as phthalates, which are commonly monitored in testing laboratories. A plug-in was developed and integrated into the existing MassHunter Quant analysis software to facilitate the collection and annotation of data for training the AI model. The plug-in allowed practitioners to perform manual integrations as they would normally using the MassHunter software, while capturing relevant chromatographic information, raw chromatograms, and corresponding peak integration results from the MassHunter Quant parameter-less peak integrator from several experts. This dataset provided a comprehensive range of integration scenarios and served as the foundation for training and evaluating the AI model. The inclusion of both automatic and manual peak integrations enabled the model to learn from the expertise of human analysts and the performance of existing algorithms.
3. **Feature Selection:** Relevant features such as chromatographic method settings, retention time, peak areas, peak shapes, and spectral patterns, were extracted from the collected data using the integrated plug-in. These features served as the input variables for the machine learning algorithm and played a crucial role in the iterative learning process and algorithm optimization. The feature selection process was guided by both expert knowledge from the GC/MS practitioners and data-driven insights.
4. **Machine Learning Development:** The development of the AI peak integration model followed standard best practices in the machine-learning and deep-learning community (Smith, 2017) (Zinkevich) (Brett Wujek, 2016). where state-of-the-art algorithms and models previously proved themselves robust in computer vision and biomedical signal analysis. These algorithms and models were adapted and tailored to the specific task of peak integration in GC/MS analysis. The development process incorporated established frameworks and libraries, ensuring robustness, reproducibility, scalability, and data safety.
5. **Training and Validation:** The dataset, comprised of annotated data collected using the MassHunter plug-in, was split into training, validation, and test subsets following the standard machine-learning methodology. The training subset was used to teach the model to follow the manual integration practices established in the partner laboratories. The validation subset was utilized to fine-tune the model's hyperparameters and assess its performance during the iterative training process. The validation subset served as an independent evaluation to measure the final accuracy and reliability of AI peak integration model.
6. **Model Optimization and Performance Metrics:** Iterative optimization techniques were applied to enhance the performance of the AI model. This involved establishing the optimal model training regime, cleaning the dataset, handling the outliers, and incorporating feedback from domain experts. Performance metrics (see the "*Model Quality Control*" section below for more details), such as accuracy and correctness metrics, were utilized to constantly monitor and improve the model. A comparison was made between the AI model's performance, the MassHunter default parameter-less integrator, and manual integrations, performed by practitioners to establish the optimal in-production prediction mode.

## Machine Learning Model

The Agilent AI Peak Integration includes a pretrained machine learning model. While this model provides a foundation for the phthalate analysis, it requires further fine-tuning to ensure optimal performance with customer-specific data.

The machine learning model gradually takes over the automatic integration process from the MassHunter default parameter-less integrator with demonstrated superior performance. This transition occurs when the model surpasses the performance threshold set by the MassHunter default parameter-less integrator.

To achieve the highest level of accuracy, the training of the machine learning model takes place in the secure Agilent cloud infrastructure. The current version of the cloud-based training utilizes powerful parallelized graphic processing units (GPUs), which are scalable and currently not feasible to deploy on customer premises. Using GPUs allows for more efficient parallel scaling improving performance with large datasets due to available computational bandwidth. In addition, this ensures end user performance without the requirement for costly continual onsite hardware upgrades as these resources are scaled up and down on demand.

The current production and previous model versions are securely stored in an online version management system, providing the capability to return to earlier training iterations if necessary. Version control for model management provides an important auditability function in addition to quality assurance to end users.

## AI Learning Model Quality Control

The accuracy of the Agilent AI Peak Integration machine learning model is influenced by the size and quality of the data it receives. As users submit more manual integrations, the model's accuracy improves. Several safeguards have been implemented to ensure the integrity of the system.

Outliers and incomplete data points are automatically excluded from the analysis. Additionally, data normalization procedures are applied to ensure consistency in naming conventions across all data points. This is also a process coupled with statistical measures to ensure consistency of the data output.

Automated data curation steps are integrated into the training pipeline to prevent statistical data leakage. Measures are also taken to enhance the statistical diversity of user-submitted training samples, thereby improving the overall robustness of the model.

The accuracy of the machine learning model is assessed by comparing it to the accuracy of the MassHunter default parameter-less integrator using a range of statistical quality metrics. Throughout the training process and during the prediction (inference) mode, the model's quality is monitored to prevent metrics degradation.

For each target compound, accuracy is measured independently. Based on the results, the prediction functionality is enabled only for those compounds where the accuracy surpasses predefined thresholds and outperforms the MassHunter default parameter-less integrator.

## Quantitation Accuracy

The quantitation accuracy refers to the degree of agreement between the machine learning-predicted peak area and the manually integrated peak area. Several accuracy metrics are employed to evaluate this agreement:

1. **Mean Error:** The average of the percentage difference between the manual integration area and the machine learning-predicted area.
2. **Median Error:** The middle value of the percentage difference between the manual integration area and the machine learning-predicted area.
3. **Maximum Error:** The highest value of the percentage difference observed between the manual integration area and the machine learning-predicted area.
4. **Error Standard Deviation:** A measure of the dispersion of the percentage differences between the manual integration area and the machine learning-predicted area.

## Peak Screening Correctness Metrics

The enhancement of the AI peak integration model is demonstrated through a positive trend in the Peak Screening Correctness Metrics (see Figure 1). The following metrics are utilized for the positive/negative peak classification task:

1. **Critical Success Index (CSI):** Calculated as the number of true positives divided by the sum of the number of all positives and the number of false negatives. It measures the overall success rate of correctly identified positive peaks. Maximum is 1, the larger is better.
2. **Positive Predictive Value (PPV):** Calculated as the number of true positives divided by the total number of all positives. It quantifies the proportion of correctly identified positive peaks out of all predicted positive peaks. Maximum is 1, the larger is better.
3. **Negative Predictive Value (NPV):** Calculated as the number of true negatives divided by the total number of negatives. It assesses the accuracy of correctly identified negative peaks. Maximum is 1, the larger is better.

The definition of the terms used in these metrics are as follows:

- **True positive:** A positive peak that is correctly identified.
- **False positive:** A negative peak that is incorrectly identified as positive.
- **True negative:** A negative peak that is correctly identified as negative.
- **False negative:** A positive peak that is incorrectly identified as negative.

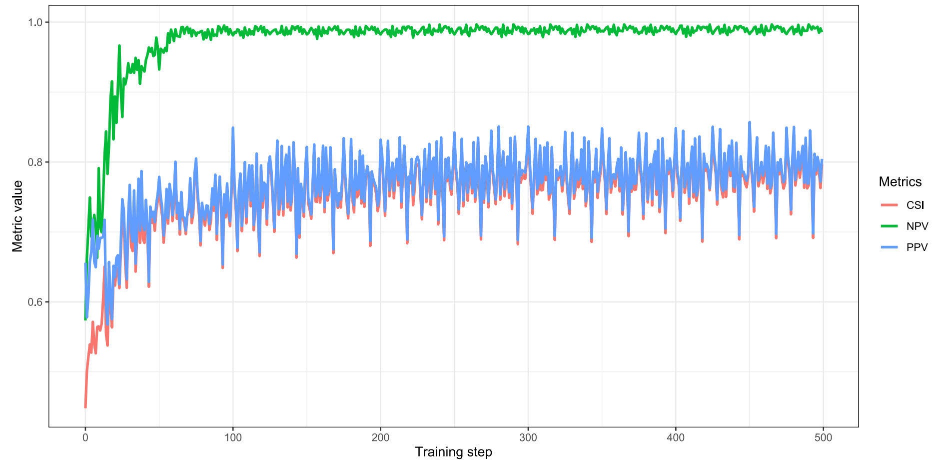


**Figure 1.** The positive trend in the Peak Screening Correctness Metrics is seen during the model training. All metrics were measured on the validation subset of data. The practical value of machine learning models lies in their ability to deliver effective performance, provide speed improvements, and outperform non-ML systems. When the model performs well enough for the intended tasks, it offers efficiency gains and outshines non-ML alternatives. When users focus on the practical benefits and advantages of machine learning, its power to enhance productivity and achieve real-world results become clear.

## References

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To learn more about AI Peak Integration for MassHunter, visit:

**www.agilent.com/mass-spec/ai-peak-integration**

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