DRT

precisionFDA Automated Machine Learning (AutoML) App-a-thon: Democratizing and Demystifying Artificial Intelligence (AI)

Executive Summary

While automated machine learning (AutoML) has shown significant potential in transforming healthcare by automating complex data tasks, improving diagnostic accuracy, and accelerating medical discoveries, its adoption in healthcare has lagged behind other industries. This slower growth is primarily due to the lack of transparency and the "black-box" nature of many AutoML tools. To address these challenges, the U.S. Food and Drug Administration (FDA) has called on innovators to explore the potential applications of AutoML in healthcare through the precisionFDA platform. In collaboration with CloudLeap Technologies, DRT Strategies developed a solution to evaluate the efficacy of AutoML, bridge the gap in AI/ML adoption, and promote the broader integration of ML-driven solutions in medical practice and research. The FDA recognized DRT's solution as one of the top performers.

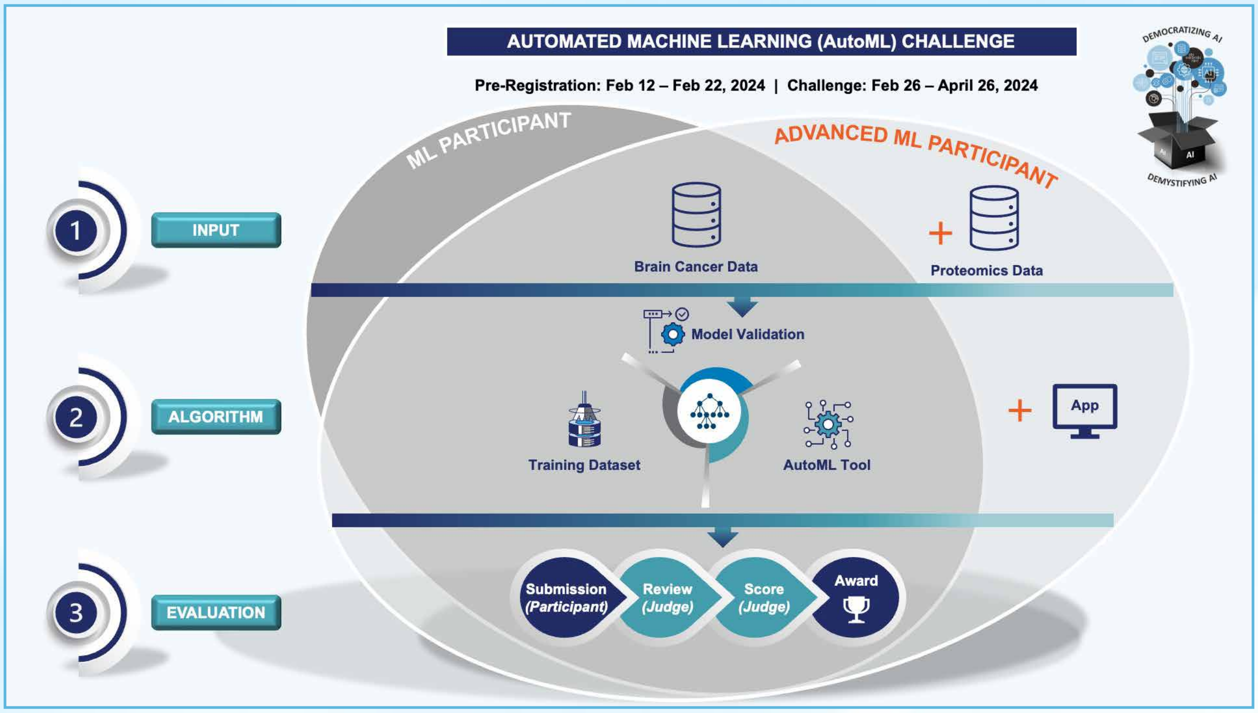
What was the challenge?

Despite of the widespread acknowledgement of Artificial Intelligence (AI) and Machine Learning (ML) as transformative tools across the industries, adoption in healthcare and medicine remains limited with only 15% of hospitals actively embracing this technology .

One challenge for the large-scale adoption of AI/ML in healthcare and medicine is the steep technical barrier and the lack of transparency of these tools. AutoML tools and platforms may be considered as "black box" systems because they may provide little to no insight on techniques used for data preprocessing, algorithm selection, or hyperparameter tuning. Transparency and Explainability are crucial because they are necessary for a larger user community to understand how a model achieved its results to ensure that the model did not train and learn any bias. Additionally, the stakes to develop a great ML model are much higher in healthcare sectors compared to other sectors like ecommerce because patient quality care is of highest priority.

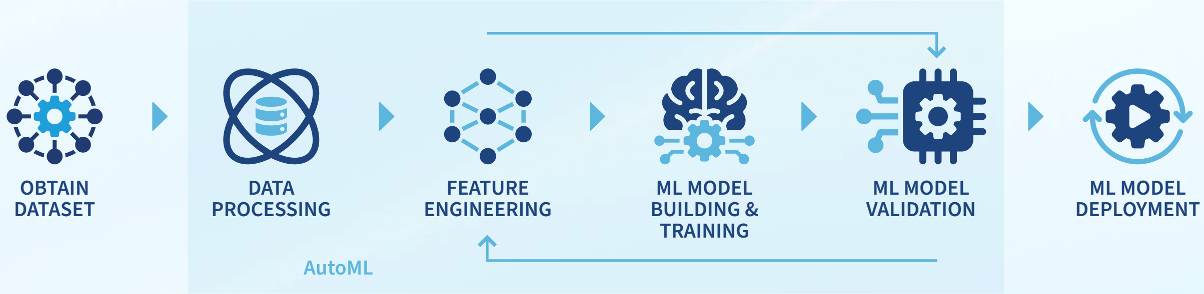
Developing an ML model is a time-consuming and iterative process. However, AutoML offers an automated solution to build ML models with high efficiency, scalability, and productivity while maintaining model quality. In addition, the open-source AutoML tools particularly can help improve transparency and lower technical barriers for AutoML adoption for their open-source libraries.

FDA is challenging the scientific and analytic communities to use open-source AutoML tools on biomedical datasets to help assess whether AutoML can match or improve the performance of previously developed traditional ML models. FDA provided Brain cancer gene expression data and wanted participants to use open-source AutoML tools to evaluate the effectiveness of AutoML when applied to biomedical datasets with the goal to unlock new insights to potential AI/ML applications in healthcare and help FDA understand how to democratize and demystify Artificial Intelligence (AI).



What was the approach?

The DRT Team's approach started with a rigorous assessment of the brain cancer training dataset through criteria such as data volume, data quality, completeness, balance, and bias. Biomedical and genomic datasets are complex and may contain many features such as gene proteins and other clinical data points for each sample. Different AutoML tools have very different capabilities in terms of how they pre-process and clean the ingested datasets. We conducted pre-processing steps including normalizing data, detecting outliers, fixing class imbalances, reducing dimensionality, transposing data, and transforming categorical variables into numeric values. To improve accuracy of the model, we also attempted to apply clustering for samples with missing features to align them to the known gene expressions. Since the outcome was not significant, we decided to exclude this approach in the development of our models.



We selected three open-source AutoML tools (PyCaret, H2O, Auto-SKLearn) based on the enhanced features and user simplicity they provide. Our team leveraged the Google Collaboratory platform (aka Google Colab) for development as it enables team collaboration and provides powerful computing resources, including Graphics Processing Units (GPUs) and Tensor Processing Units (TPUs).

Some common issues encountered in training ML models for medical applications include biased datasets, especially in recognizing adverse outcomes like patient mortality. For instance, a dataset may have more examples of patients who did not survive than those who did. To address this issue, we compared the three AutoML tools and discovered that the model producing the highest accuracy rate may not be the most appropriate model for the high-bias survivability data. These results support the notion that a balanced option with good performance is preferrable for highly biased datasets.

What was our recommendation?

AutoML tools can automate the often time-consuming tasks in ML model development and reduce the time needed to train, test, and select models allowing organizations to iterate more rapidly. AutoML demonstrates proven benefits including:

- ✓ Decreased Complexity – Manages multi-dimensional biomedical datasets and improves model performance.
- ✓ Improved Accuracy – Improves accuracy by automatically selecting the best fitting model.
- ✓ Time Efficiency – Enables citizen data scientists to streamline and automate iterative tasks, like data preprocessing, model selection, and hyperparameter tuning.
- ✓ Increased Optimization – Optimizes performance metrics such as accuracy, sensitivity, specificity, or area under the curve (AUC), which are crucial for biomedical applications.

We provided the following three recommendations to FDA:

Improve the Training Dataset

To mitigate bias, we recommend better input data quality control measures to minimize missing and unknown data values and using a larger training dataset to significantly improve prediction accuracy.

Democratize AutoML Tools

It is feasible to improve transparency and lower technical barriers of AutoML adoption to citizen data scientists. We suggest the use of open-source tools and libraries to promote visibility, encourage user feedback, and allow transparency on algorithms and methods through improved documentation.

Leverage FDA Governance and Collaboration

It is still important to keep human oversight of AI/ML a top priority despite its great potential in healthcare. We recommend FDA continue to leverage the AI Governance and Advisory Board to oversee AI usage in mission support and increase awareness, transparency, and cross-agency collaboration, which is key to harnessing the power of AI.

In conclusion, AutoML presents numerous opportunities for the FDA. It can accelerate clinical trial data analysis, expediting drug approval while upholding the FDAs rigorous standards. It can efficiently detect safety concerns in adverse events reporting and aid in regulatory compliance. AutoML can enable real-time health data surveillance and automate tasks, enhancing the overall efficiency for FDA personnel.

Please use the QR code below to view the recording for details: *https://youtu.be/qA3o2-sNviY*

precisionFDA Automated Machine Learning (AutoML) App-a-thon Video Presentation

Previously to this AutoML challenge, DRT participated in another precisionFDA challenge, Making Sense of Electronic Health Record (EHR) Race and Ethnicity Data. The purpose of this challenge was to seek technological solutions that would automate the summarization of race and ethnicity data in EHRs in conformance with OMB standards. DRT was selected as one of the top performers and featured in a Top Performers Webinar.

Please use the QR code below to view the recording for details: *https://youtu.be/QcYZYfNfPMg*

Making Sense of Electronic Health Record (EHR) Race and Ethnicity Data Top Performers Webinar

© 2024 DRT Strategies, Inc.