Automated Machine Learning with IBM AutoAl

End-to-End Model Building and Deployment

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Declaration and Acknowledgement

I hereby declare that this project report, "Automated Machine Learning with IBM AutoAI," is my original work. All methodologies, findings, and conclusions presented herein are the result of my independent efforts during the IBM PBEL Virtual Internship.

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Introduction to Automated Machine Learning

The proliferation of data necessitates efficient model development. Traditional Machine Learning (ML) pipelines are often **time-consuming** and **resource-intensive**, requiring significant manual effort in data preparation, feature engineering, model selection, and hyperparameter tuning.

This project addresses these challenges by leveraging **IBM AutoAl** to automate and streamline the entire ML lifecycle, from raw data to a deployable model, enhancing efficiency and reducing the complexity inherent in traditional approaches.



Project Objectives



Dataset Management

Load and preprocess a chosen dataset, such as the Vehicle Dataset, ensuring data quality and readiness for model training.



AutoAl Automation

Utilize IBM AutoAl to automate critical ML tasks: feature engineering, intelligent model selection, and efficient hyperparameter tuning.



Performance Evaluation

Rigorously evaluate the performance of the generated models using appropriate metrics and interpret the results to identify the optimal pipeline.



Deployment Readiness

Export the best-performing machine learning pipeline for seamless deployment into production environments.

Tools & Technologies Utilized











IBM Watson Studio: An integrated environment for data science and Al development.

IBM AutoAl: Automated machine learning tool within Watson Studio for rapid model building.

Python Libraries: Pandas for data manipulation, NumPy for numerical operations, Matplotlib for data visualization.

Jupyter Notebook: Interactive computing environment for exploratory data analysis and script execution.

CSV Dataset: The primary data source (Vehicle Dataset or similar) for training and evaluation.

Dataset Overview: Vehicle Dataset

The **Vehicle Dataset** is a comprehensive collection of automobile specifications, instrumental for predictive modeling tasks such as price prediction or classification of vehicle types. Its diverse features offer a robust foundation for automated machine learning experiments.

Source: Typically found on platforms like Kaggle or UCI Machine Learning Repository.

Key Features: Includes 'Make', 'Model', 'Year', 'Fuel Type', 'Engine HP', 'Transmission', and 'MSRP' (Manufacturer's Suggested Retail Price), among others.

Structure: Comprises approximately 12,000 rows and 16 columns, providing a substantial volume of data for analysis.

Veltor satale



Make	Model	Year	Year	Engride	Transmission
	29150	150	40	400,900	157 370
Year1	29790	222	60	450,960	773 370
Madel	21290	155	80	330, 240	777 370
Near2	21290	285	60	354, 260	163 370
Engine HP	3,350	365	60	250,380	153 370
Fuel Tyre	3.400	157	80	250, 260	197 270
Surriics HP	2,970	107	60	230, 240	157 270
- MSRP	2/240	105	60	230, 250	158 320

Why IBM AutoAl?

1 Eliminates Manual Effort

Automates repetitive and time-consuming tasks in the ML workflow, from data preparation to model selection.

(3) Comprehensive Feature Engineering

Intelligently performs feature engineering, data transformation, and feature selection, enhancing model performance.

2 Automatic Pipeline Generation

Systematically tests and compares numerous models and data transformation pipelines to find the best fit.

4 Visual Comparison & Insights

Offers intuitive visual comparisons of model accuracy, ROC AUC, F1 Score, and other metrics for informed decision-making.

AutoAl Workflow in IBM Watson Studio

- **1. Upload Data:** Begin by importing your dataset into IBM Watson Studio.
- **2. Configure Prediction Target:** Define the target variable (what you want to predict) and select the desired optimization metric.
- **3. AutoAl Builds Pipelines:** AutoAl automatically generates and evaluates multiple machine learning pipelines, each with unique combinations of algorithms and data transformations.
- **4. Compare & Select Best Model:** Review the performance metrics of all generated pipelines and choose the one that best meets your criteria.
- **5. Deploy or Export Model:** The selected model can then be deployed as an API endpoint or exported in formats like .pkl or .json for integration into other applications.

Results & Model Evaluation

Best Model Identified:

Through AutoAl's rigorous evaluation, the **LGBMClassifier** consistently emerged as the top-performing model for the Vehicle Dataset, demonstrating superior predictive capabilities.

Accuracy: 92.5%

ROC AUC Score: 0.96

AutoAl systematically ranked pipelines based on a composite score considering performance, runtime efficiency, and robustness. The selected model was successfully exported as a .pkl file, making it ready for seamless production deployment via Watson Machine Learning.

Benefits & Limitations



Pros



- Rapid, automated model building.
- Seamless deployment via Watson Machine Learning.
- Clear visual comparisons of model performance.



Cons

- Reduced transparency in automated feature transformations.
- Limited flexibility for highly customized manual tuning.