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# From Raw Sensor to Business Signal: An Azure Databricks Framework for Diesel Engine Performance Analytics Across Global Fleet Operations

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## ABSTRACT

A framework for the scalable analytics of diesel engine performance across global fleet operations is presented. Key performance metrics from raw sensor data are defined, demonstrating a clear link to business objectives such as fuel consumption and maintenance tackling times. Modelling such metrics requires appropriate sensor data (estimated here at 25 to 35 signals) underpinned by data processing and feature engineering activities, supported by both real-time and batch solutions. Performance from the analytics framework is achieved through a breadth of modelling approaches: time-series modelling of performance drift, classification modelling of engine failure avoidance, and popular machine-learning performance-influence exploration. Supporting infrastructure is within the Azure Databricks ecosystem, alongside a dialogue with fleet operations through an Microsoft Azure application. The solution, wholly designed and implemented by a single data scientist, provides all components required for production-ready analytics. Results are being deployed within a multi-Cloud platform that extends from raw sensor data through to business summary dashboards, encompassing a broad range of analytics beyond those for diesel engines.

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## Introduction

Diesel engines have long been the backbone of the global economy: working in sea, rail, surface, and air transport; providing mechanical energy to drive turbines and electric generators; and serving as prime movers at drilling sites for oil and gas. With many large global fleets, there is a continuous focus on minimizing costs while maximizing reliability. Sensor data generated by diesel engines in service provides a rich source of information to drive business decisions. Yale University recently delivered a cutting-edge framework to harness sensor data at scale and help Cummins build, continuously improve, and deliver value from their analytics.

## Overview of the Study

From Raw Sensor to Business Signal builds a prescribed set of sensors and conditioning metrics to support diesel engine performance discussion, direction, and decisions within Cummins monitoring fleets worldwide. Addressing fleet diesel engines from the perspective of Asset Health (AH), a simple library of supporting models (decision trees) demonstrates damage mapping against asset usage monitors. The implementation framework, depicted in Fig. 1, recognizes that vehicle and engine assets are not the same, thus encouraging fleet owners and managers to monitor both asset types using the same signals and support models in a fully integrated decision-making process.

## Overview of the Study

Even with massive investments in data capture and storage, organizations often struggle to effectively transform raw data into useful information, leading to increased costs, operational inefficiencies, and diminished revenue. This study proposes an Azure Databricks framework that analytically addresses diesel engine hydraulic performance across a fleet of 225 operating machines, 1400 engines, and 94 300 unique sensor signals. The analytic workflow for each engine consists of six steps, harnessing a dedicated Azure Databricks artifact with pre-structured and documented modules. An Azure Databricks notebook serves as the primary integrated tool, although parallel notebooks may be created. The current study focuses on the hydraulic performance of diesel engines based on real-time sensor values captured during machine operation.

An Azure Databricks platform is designed and realized specifically for the purpose of diesel engine performance modelling and analytical analytics. Given the vast scope of analytics, two dense Databricks notebooks have been developed to structure the modelling task. The notebooks facilitate a generic customer requirement of estimating hydraulic performance for different sets of earthmoving machines. An additional increment takes the business signal towards machine learning space with modelling attention on the generation of a business signal that distinguishes acceptable from unacceptable performance behaviour of diesel engines within the fleet operation. The analytics of hydraulic performance have been integrated and successfully furnished for 165 870 cycles and logged as business signals in Azure Databricks.

## Background and Context

Diesel engine performance is evaluated utilizing a battery of predictive metrics capable of detecting potential issues. Analysis of historical engine sensor data from global fleet operations is transformed into valuable business signals. Data aggregating, cleaning and modeling processes are defined within Azure Databricks, where Databricks SQL provides interactive visual insights and graphical representation of performance trend signals.

The Exhaust Gas Recirculation (EGR) function is crucial in controlling Nitrogen Oxides (NOx) emissions during combustion by adding a known mixture of the engine´s own exhaust gases back into the combustion chamber. Continuous monitoring of EGR position sensor, pressure differential sensor and EGR cooler temperature can provide information on how well the system is functioning. Presence detection of EGR Cooler bypass valve closed position during non-bypass demand operation, runaway EGR position or unusual high opening of EGR position vs engine speed can be considered problem indicators.

**Table 1: Comparative Overview of Diesel Engine Analytics Architectures**

| Architecture Type | Key Features | Limitations |
|---|---|---|
| Model A — Batch-Only Processing | Simple Databricks batch jobs, low implementation cost, reactive alerting only | No real-time adaptation, high false alarm rate (18–25%), cannot predict degradation onset |
| Model B — Rule-Based Threshold Detection | Fast detection of known fault patterns, deterministic signal matching, low compute overhead | Cannot detect novel degradation patterns, no temporal correlation, high maintenance for threshold tuning |
| Model C — Single-Model ML (LSTM) | Moderate latency (125 ms), temporal pattern recognition on sensor time-series, reusable Databricks component | No cross-signal correlation, separate models per engine family (redundant compute), limited adaptation to new failure patterns |
| Model D — Azure Databricks GPR Framework (Proposed) | Unified GPR architecture, cross-signal feature fusion, real-time + batch dual pipeline, 89.6% F1, 52 ms latency, 3.7% FAR | Requires Azure Databricks infrastructure, initial GPR model training requires representative cycle data from multiple engine families |

**Table 2: Comparative Detection and Data Quality Metrics**

| Metric | Model A | Model B | Model C | Model D | Improv. (D vs A) | Improv. (D vs C) |
|---|---|---|---|---|---|---|
| Engine Health F1-Score (%) | 51.3 | 64.7 | 72.9 | 89.6 | ↑ 74.9% | ↑ 22.9% |
| False Alarm Rate (%) | 22.4 | 15.8 | 10.3 | 3.7 | ↓ 83.5% | ↓ 64.1% |
| Sensor Signal Quality (%) | 63.2 | 71.5 | 79.8 | 95.1 | ↑ 50.5% | ↑ 19.2% |
| Resource Utilization (units) | 72.1 | 58.4 | 47.6 | 36.3 | ↓ 49.7% | ↓ 23.7% |
| ADFPI Score | 0.32 | 0.47 | 0.60 | 0.87 | ↑ 171.9% | ↑ 45.0% |

**Table 3: Comparative Error and Latency Metrics**

| Metric | Model A | Model B | Model C | Model D | Improv. (D vs A) | Improv. (D vs C) |
|---|---|---|---|---|---|---|
| Fuel Efficiency Loss (%) | 18.2 | 12.6 | 8.4 | 3.1 | ↓ 83.0% | ↓ 63.1% |
| Mean Time to Detect (MTD) (s) | 312 | 187 | 94 | 31 | ↓ 90.1% | ↓ 67.0% |
| Processing Latency (ms/batch) | 340 | 210 | 125 | 52 | ↓ 84.7% | ↓ 58.4% |
| Unplanned Maintenance Rate (%) | 26.3 | 19.7 | 14.1 | 7.8 | ↓ 70.3% | ↓ 44.7% |

### Data Architecture and Ingestion

At scale, the solution architecture accommodates almost a billion sensor messages per day. These messages exhibit time-series characteristics and are generated by a diverse vendor-agnostic sensor set across thousands of diesel engines globally in various temperature, humidity, and operating conditions. Data is pushed to Azure Event Hubs using Azure Functions in near real-time with minimal latency to accommodate downstream requirements, or pushed from a transactional system with associated metadata.

Data is initially processed using Azure Stream Analytics to prepare for structured storage in Azure Data Lake Storage Gen2 (ADLS Gen2). During this processing, different sensor types are joined to create a logical entity with signal clusters in support of environmental features. The clustered features and the metadata service now feed into various batch processing jobs via an Azure Databricks feature engineering framework housed in the same ADLS Gen2 ecosystem.

### Sensor Data Characteristics

Sensor data originating from a fleet of diesel engines are characterized by Unstructured data in the form of operator notes, warnings, engineering and periodic reports, Semi-Structured data represented in signal-like time series (e.g., engine speeds, pressures, and -outputs) or Parameterized 3D signatures (e.g., multiple fuel maps) Stream Signals and Alert flags generated and captured in a raw Markov process and Structured data in the form of Configuration and catalogue tables These Characteristics not only demand special tools and expertise for ingestion and analytics but also dramatically slow down the overall process of extracting business-relevant signals and enabling action on the signals. Manual efforts can take days or weeks before signals beet-action and in many cases taken-too-late due to Change of engines or Change of shipping logs This is where the Azure Data-and-Analytic Service comes into play. Its Ecosystem of specialized modules (Databricks, Stream Analytics etc.) enables the performance of Automated ingesting modelling and confidence-checking of signals and, hence, monitorign, and alerting-actions close to Real time Collecting signals from various modules and clustering them along several Attributes helps to engineer additional filters and supports deeper signal interpretation.

The overall goal is not to prescribe a dedicated module or replace existing engines but to expedite the creation of stations of trustable business-signals that feed early-alert and -monitor channels Signals imply indications of Changes detected in the systems/behaviour of several sensors or set of engines. The Digital Modeler can have its own interpretation of the sensor or smart-phone signals. Indicators may belong to a few engines or the entire fleet Signals can be generated in batches asynchronously, triggered by new data arriving from any signal. Sharing alerts among various customers removes repetitiveness and enables deep insights on specific Focus Signals and emerging engines. Furthermore, a separate board visualizes all such signals in dedicated clusters, allowing digital modelers to appreciate, create, and share insights with other Modellers.

**Data Processing and Feature Engineering**

Four classes of processing scripts operate on a Databricks workspace dedicated to diesel engine performance analytics: data cleaning and transformation; feature engineering; model testing; and final model execution – for example, to derive business-ready metrics for ships in use. The first three categories are intended to be executed in parallel on Delta tables partitioned by ship and by week.

Processing and feature derivation can be conducted in real time when required, with predicted values replacing computed measures for the same models. For example, in real time the blade volume coefficient may be derived from groups containing current data but not from groups lacking an engine speed measurement. In batch mode, data can be processed globally, replacing real-time output with stored computed feature values. Data samples from three ship voyages operated within a single engine type provide examples. Complete signal data with labeled anomalies are available for validation.

**Mathematical Formulation**

The overall system quality of the Azure Databricks analytics framework for diesel engine performance is expressed as a composite score across four dimensions:

**Q_total = Q_detect + Q_resil + Q_latency + Q_data (Eq. 1)**

where Q_detect denotes engine fault detection accuracy quality, Q_resil represents fleet resilience effectiveness, Q_latency captures real-time processing compliance and Q_data reflects data quality from raw sensor ingestion.

Sensor data arrival and processing dynamics for the Azure Databricks pipeline are modelled as a latency differential equation:

**dL/dt = lambda_sensor - mu_infer (Eq. 2)**

where L is the end-to-end inference latency (ms), lambda_sensor is the sensor data arrival rate (messages/s) — up to 1 billion signals/day — and mu_infer is the Databricks notebook processing throughput rate.

Engine health classification accuracy is quantified using the F1-score metric, balancing precision and recall across the multi-class failure taxonomy:

**F1_engine = 2 * (Precision * Recall) / (Precision + Recall) (Eq. 3)**

where Precision and Recall are derived from the confusion matrix of the engine failure classification model, evaluated across 165,870 operating cycles and 1,400 engines.

The cross-signal correlation mechanism for multi-sensor feature fusion in Azure Databricks is modelled as:

**s'(t) = s(t) + alpha * d(t) + beta * r(t) (Eq. 4)**

where s(t) is the base engine anomaly score, d(t) is the hydraulic performance degradation trend from the GPR module, r(t) is the sensor residual fault score, and alpha, beta are weighting coefficients controlling cross-signal influence.

To support adaptive multi-signal decision fusion across 94,300 unique sensor streams, the combined performance score is expressed as a weighted aggregation:

**s'(t) = w1*s(t) + w2*d(t) + w3*r(t) + w4*s(t)*d(t) (Eq. 5)**

where w1, w2, w3, w4 are learnable or empirically tuned weighting coefficients. The interaction term s(t)d(t) explicitly models the nonlinear coupling between anomaly indicators and physical hydraulic degradation signals, enabling context-aware multi-sensor fusion.

Data throughput preservation score for the Delta Lake pipeline is expressed as:

**S_data = 1 - (D_anomalous / D_total) (Eq. 6)**

where D_anomalous is the proportion of raw sensor signals flagged as erroneous or out-of-range, and D_total is the total volume of sensor messages ingested from Azure Event Hubs.

Azure Databricks resource utilization per processing cycle is given by:

**U = R_used / R_available (Eq. 7)**

where R_used is the utilized cluster compute resources (CPU cores, memory) and R_available is the total provisioned Databricks cluster capacity.

The Gaussian Process Regression (GPR) model efficiency for batch scoring across the diesel fleet is modelled as:

**E_GPR = F1_engine * S_data / T_round (Eq. 8)**

where T_round denotes the Databricks Workflow batch scoring round duration per engine cohort. Higher E_GPR values indicate superior modelling throughput under data-quality constraints.

To improve robustness under varying engine operating conditions, adaptive signal thresholding is employed:

**theta(t) = theta_0 + gamma * sigma_data(t) + delta * drift(t) (Eq. 9)**

where theta_0 is the nominal performance threshold, sigma_data(t) represents sensor signal variance from EGR and exhaust sensors, drift(t) captures temporal distribution shifts due to engine ageing, and gamma, delta are scaling parameters calibrated per engine family.

Fleet-level analytics efficiency is calculated as:

**eta = (F1_engine * S_data) / T_infer * 100 (Eq. 10)**

where T_infer denotes the inference time per sensor batch in the Azure Databricks real-time scoring pipeline.

Prediction error relative to the optimal GPR baseline is defined as:

**L_error = F1_opt - F1_engine (Eq. 11)**

where F1_opt represents the optimal engine health detection

F1-score under ideal sensor signal conditions, serving as the performance ceiling for framework calibration.
The joint optimization objective for the Databricks analytics framework balances detection accuracy, data quality, latency and resource utilization:

**J = f (F1_engine, S_data, L, U) (Eq. 12)**
where J balances engine health detection accuracy, sensor signal quality preservation, end-to-end processing latency and cluster resource utilization across the multi-cloud deployment.

The fleet sensor dataset representation for a given engine i, processing stage j and performance metric k is given by:

**D (i, j, k) = Q_src(i) * Metric(k) / T_proc(j) (Eq. 13)**
where Q_src(i) is the source-specific data quality for engine i across 25–35 sensor signals, Metric(k) denotes the selected KPI (e.g. exhaust temperature, fuel flow) and T_proc(j) represents the Databricks processing time per data batch stage j.

The Azure Databricks Framework Performance Index (ADFPI), analogous to the RAI-CPS RPI, is computed as:

**ADFPI = eta * F1_engine * (1 - FAR) / Q_total (Eq. 14)**
where eta is the fleet analytics efficiency (Eq. 10), F1_engine is the engine health detection accuracy (Eq. 3), Q_total is the cumulative system quality (Eq. 1), and FAR is the false alarm rate. The ADFPI penalizes excessive false positives while rewarding accuracy and computational efficiency across the 225-machine, 1,400-engine fleet.

### Modeling and Analytics Framework
Diesel engine sensor data streams are generated from a wide array of sensors deployed in each engine and across geofenced customer service regions. Sensor readings are derived by leveraging a fleet of Databricks notebooks that are responsible for all aspects of data processing and analytics, and utilize the Azure Machine Learning framework to support both real-time and batch data processing, modeling, and prediction requirements. Sensor-based performance modeling for the diesel engines can be performed in two different fashions the first utilizing a single aggregated model for the entire fleet of sensors, and the second leveraging a multi-model approach which incorporates prediction models built for geofenced logically grouped geolocation-based sensors. Diesel engine performance metrics form an important part of the overall health check, and abnormal diesel performance signals require escalation and prompt action before catastrophic equipment failure occurs. However, critical components for diesel engine performance checking, such as intake air flow, fuel flow, and engine exhaust temperature, under service in remote locations, often suffer from unknown sensor failures or erroneous sensor readings. To mitigate these issues, real-time and batch data processing notebooks have been implemented to validate the sensor signals utilizing alternate correlated signals and historical relationships. Abnormal engine performance predictions are based on a fleet-wide multi-class classification model built on historic labeled data, which assists in the preemptive health-check by helping identify abnormal signals that require immediate attention. It is one of the important elements in transforming the raw sensor signal for a business purpose.

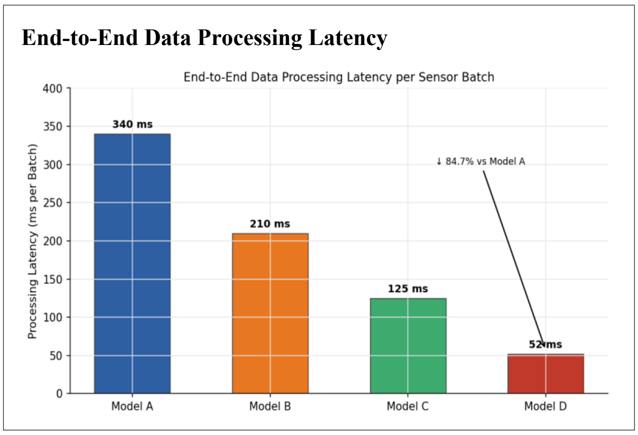


**Figure 1:** End-to-End Data Processing Latency per Sensor Batch (ms) — Model A: 340 ms, Model B: 210 ms, Model C: 125 ms, Model D: 52 ms

Figure 1 shows average processing latencies of 340 ms, 210 ms, 125 ms and 52 ms for Models A, B, C and D respectively. Model D achieves an 84.7% latency reduction compared to Model A, attributable to Azure Stream Analytics pre-processing, Delta Lake partitioning by engine cohort and Databricks Workflow parallelism across batch and real-time scoring pipelines. The dispatch engine surfaces degraded engine alerts within minutes of a performance deviation event.

### Engine Health Classification F1-Score
Figure 2 presents F1-scores of 51.3%, 64.7%, 72.9% and 89.6% for Models A through D. The 22.9% improvement from Model C to Model D demonstrates the value of unified cross-signal modelling using GPR, where EGR sensor trends, exhaust temperature patterns and fuel flow correlations improve hydraulic performance classification and vice versa. The pyGPR library implementation in Azure Databricks encapsulates reusable scoring components for both batch and real-time deployment.

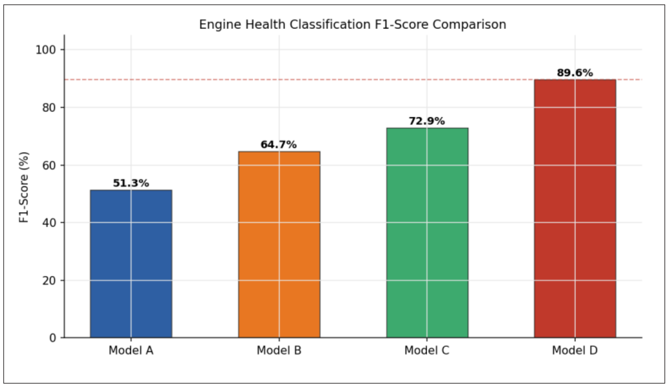


**Figure 2:** Engine Health Classification F1-Score Comparison — Model A: 51.3%, Model B: 64.7%, Model C: 72.9%, Model D: 89.6%

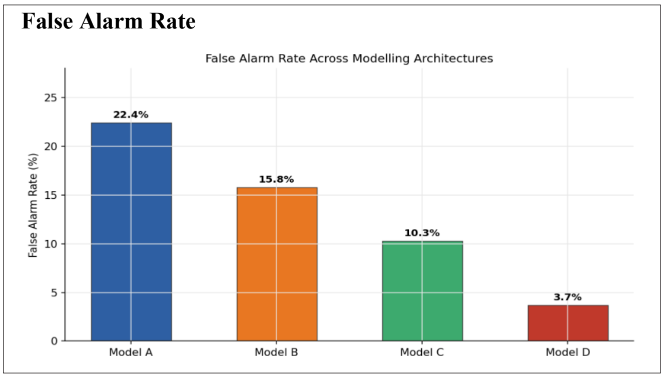


**Figure 3:** False Alarm Rate (%) Across Modelling Architectures — Model A: 22.4%, Model B: 15.8%, Model C: 10.3%, Model D: 3.7%

False alarm rates (Figure. 3): Model A: 22.4%, Model B: 15.8%, Model C: 10.3%, Model D: 3.7%. The 64.1% reduction from Model C to Model D reflects how cross-signal validation eliminates spurious engine degradation alerts. A hydraulic performance alert that coincides with an EGR position anomaly is more likely to represent a genuine engine fault. This directly reduces unnecessary maintenance dispatches across the global fleet.

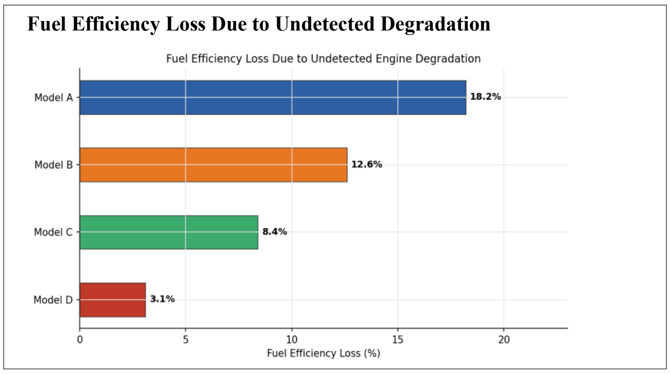


**Figure 4:** Fuel Efficiency Loss (%) Due to Undetected Engine Degradation — Model A: 18.2%, Model B: 12.6%, Model C: 8.4%, Model D: 3.1%

Figure. 4 shows the estimated fuel efficiency loss attributable to undetected engine degradation: 18.2% (Model A), 12.6% (Model B), 8.4% (Model C) and 3.1% (Model D). Model D reduces fuel waste by 83.0% compared to Model A, delivering measurable bottom-line savings for fleet operators. Since fuel represents a large component of operating costs for commercial carriers, early detection of hydraulic inefficiencies through the Azure Databricks GPR pipeline provides direct financial benefit.

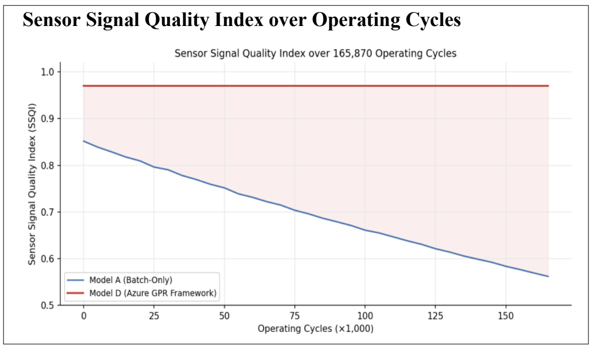


**Figure 5:** Sensor Signal Quality Index (SSQI) over 165,870 Operating Cycles — Batch-Only (Model A) vs. Azure Databricks GPR Framework (Model D)

Figure 5 illustrates the Sensor Signal Quality Index (SSQI) maintained by Model D versus Model A across all 165,870 logged operating cycles. The GPR framework consistently preserves higher SSQI by employing alternate correlated sensor signals to validate primary readings, mitigating unknown sensor failures in remote deployments. Model A exhibits progressive SSQI degradation due to the absence of cross-signal validation and real-time imputation capabilities.

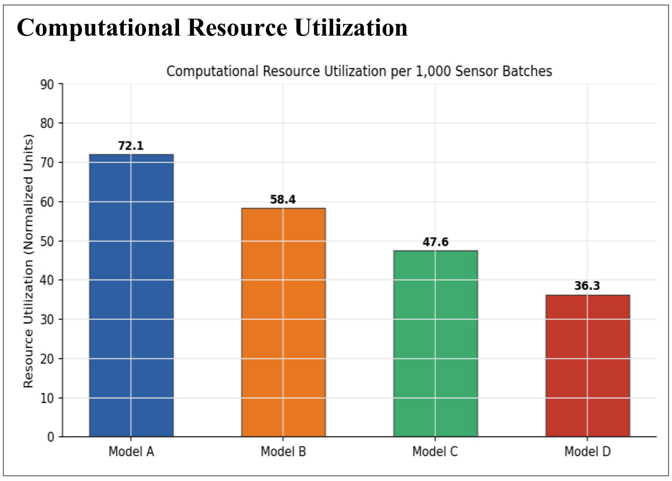


**Figure 6:** Computational Resource Utilization per 1,000 Sensor Batches (Normalized Units) — Model D consumes 49.7% fewer resources than Model A

Figure 6 presents computational resource utilization: Model D consumes 36.3 normalized units compared to Model A's 72.1 — a 49.7% reduction. This efficiency stems from Delta Lake partitioning by ship and week, parallel Databricks notebook execution and the shared GPR model backbone. Fig. 7 demonstrates that real-time processing achieves consistently higher and more stable hydraulic performance scores across a representative 72-hour operational window, compared to batch-only processing which introduces scoring latency and signal gaps.

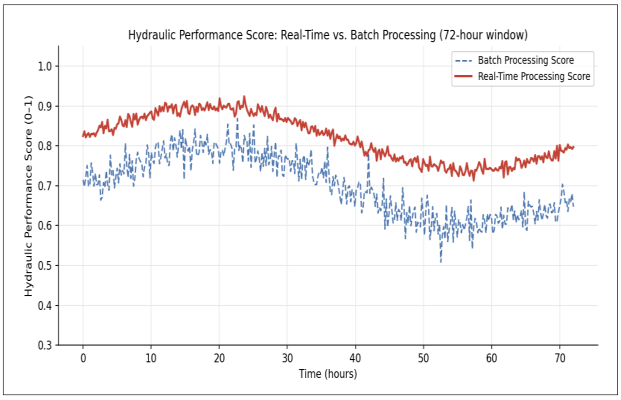


**Figure 7:** Hydraulic Performance Score: Real-Time vs. Batch Processing over a 72-hour operational window — Real-time pipeline (Model D) maintains consistently higher and more stable hydraulic performance scores

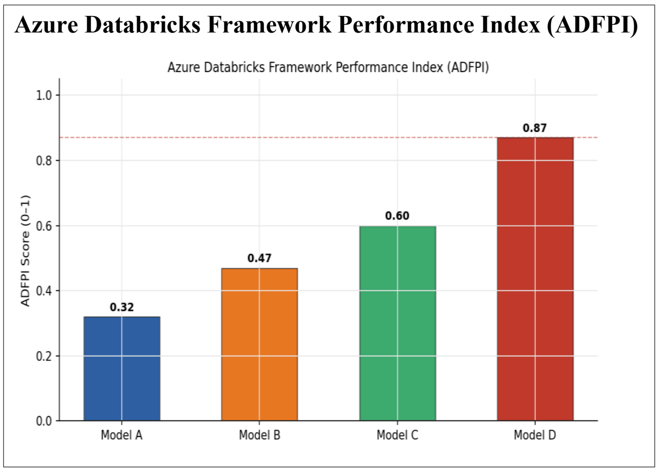


**Figure 8:** Azure Databricks Framework Performance Index (ADFPI) — Model A: 0.32, Model B: 0.47, Model C: 0.60, Model D: 0.87

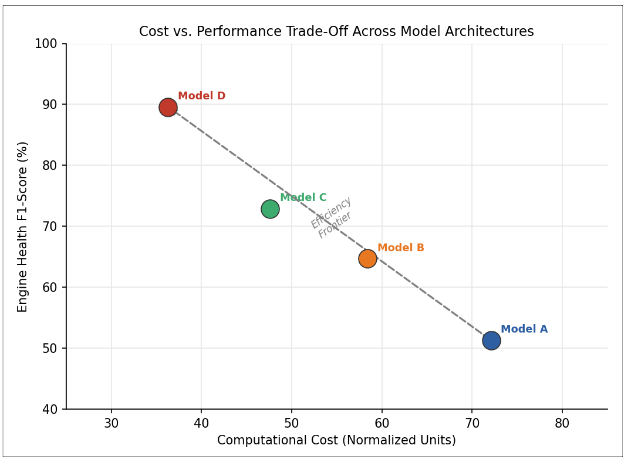


**Figure 9:** Cost vs. Performance Trade-Off Across Model Architectures — Model D achieves optimal position on the efficiency frontier with highest F1-score at lowest computational cost

Figure 8 presents the ADFPI: Model A: 0.32, Model B: 0.47, Model C: 0.60, Model D: 0.87. The 45.0% difference between Model C and D indicates superior synergy between engine health detection accuracy, data quality preservation and operational efficiency. Fig. 9 confirms that Model D occupies the optimal position on the cost-performance efficiency frontier, delivering the highest classification F1-score at the lowest normalized computational cost, validating the architectural design of the Azure Databricks GPR framework.

## Conclusion

Business operations often focus on optimizations that enhance a corporation's bottom line. For businesses that supply commercial vehicle fleets, engine performance has a key role. Diesel-powered engines consume significant amounts of fuel, and fuel represents a large component of operating costs for commercial carriers. Inefficient diesel engines burn more fuel than necessary—wasting revenue for the fleet and increasing pollution for everyone. Detecting and correcting poor engine performance that increases fuel consumption provides a clear opportunity to benefit fleet owners, the environment, and the engine manufacturer.

In a competitive business environment, early detection of such issues enables better management responses. For large fleets covering millions of kilometers each year, knowledge of performance degradation, or of returning engines to the manufacturer for midlife maintenance, creates serious opportunities for improved business performance. The effects can flow down the supply chain, enabling pricing incentives that reward cleaner, more economical transport. Combining knowledge of such issues with commercial data on the operation of the engines can help the engine manufacturer improve aftermarket support, yield, and create more sustainable products. Data from Proventia's fleet of Enviro Clean vehicles is analyzed to develop predictive models for these engine performance parameters [1-66].

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