RETAIL & E-COMMERCE – INVENTORY STOCKOUT PREDICTION AND AUTO-REPLENISHMENT

A PROJECT REPORT

Submitted by

HARISH TUTU Y T **2116231801050**

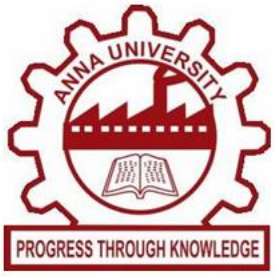
GAURAV RAMASUBRAMANIAM **2116231801038**

in partial fulfilment for the award of the degree of

BACHELOR OF TECHNOLOGY

in

ARTIFICIAL INTELLIGENCE AND DATA SCIENCE



RAJALAKSHMI ENGINEERING COLLEGE

(AUTONOMOUS), CHENNAI – 602 105

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Certified that this Report titled **"Retail & E-Commerce – Inventory Stockout Prediction and Auto-Replenishment"** is the bonafide work of **Gaurav Ramasubramaniam(2116231801038), Harish Tutu YT (2116231801050**)who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

Dr. Suresh Kumar S M.E., Ph.D.,

Professor,

Department of Artificial Intelligence & Data Science,

Rajalakshmi Engineering College

Thandalam – 602 105.

Submitted to Project Viva-Voce Examination held on _____

Internal Examiner **External Examiner**

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GAURAV RAMASUBRAMANIAM

(2116231801038)

HARISH TUTU Y T

(2116231801050)

ABSTRACT

Effective inventory management is paramount for retail and ecommerce companies to prevent stockouts as well as overstocking. Stockouts lead to foregone sales, whereas overstocking raises holding costs. The project deals with the forecasting of stockouts and replenishment optimization with the help of big data and machine learning.We gather and process the data of warehouses, such as daily demand, on-hand inventory, lead times, and replenishment history. Apache Spark cleanses the data and structures it into Bronze, Silver, and Gold layers for analysis. Hive and Delta tables are stored with fast queryability.Key performance measures (KPIs) are established to track warehouse performance, i.e., average daily demand vs. stock, demand-to-stock ratio, and replenishment efficiency by SKU. A Logistic Regression model forecasts future stockouts, allowing for anticipatory replenishment decisions.Interactive dashboards graphically represent insights, enabling managers to spot high-demand SKUs and schedule inventory accordingly. This project illustrates how the integration of big data, predictive analytics, and visualization optimizes warehouse operations, lowers costs, and increases customer satisfaction.

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PROJECT OVERVIEW

1.1 Problem Context

In today's retail and e-commerce environment, having the right level of inventory for a range of products, warehouses, and channels to sell through is a challenging problem. Retailers frequently find themselves in a trade-off between overstocking with high holding costs and stockouts with a direct impact on lost sales, decreased customer satisfaction, and brand loyalty loss.This project, "Retail & E-Commerce – Inventory Stockout Prediction and Auto-Replenishment", utilizes Big Data architecture to forecast possible stockouts and automate the replenishment process based on real-time and batch analytical intelligence. Through the integration of data from various sources (warehouse logs, sales, supplier data, and past transactions), the system guarantees that levels of stock are within optimal levels.Hadoop, Hive, and Spark-based Big Data pipeline allows the team to handle large-scale inventory data (1–5 GB synthetic dataset), process it effectively, and create actionable KPIs that fuel business intelligence dashboards. These insights enable supply chain teams to respond more quickly, making data-driven replenishment decisions, reducing revenue loss and operational inefficiency.

1.2 Objectives

The project seeks to develop, deploy, and analyze a scalable Big Data pipeline that enables inventory optimization via predictive and automated means.

Main Objectives:

Develop an end-to-end Big Data architecture encompassing data ingestion, storage, processing, analytics, and visualization for the retail use case.Create a model that predicts possible inventory stockouts using past sales patterns, replenishment cycles, and supplier lead times. Implement auto-replenishment rules that alert or order when forecasted stock levels are below a certain level.Create 3–5 retail decision-making KPIs such as stockout rate, replenishment lead time, SKU demand trend, and order fill rate.

1.3 Scope

Project scope is inventory data management and predictive analytics for the retail and e-commerce industry. Scope addresses data handling in several stages of the Big Data lifecycle from consumption (ingestion) to delivery of business insight.

In-Scope Activities:

Synthetic dataset creation mimicking product sales, stock quantity, and supplier updates. Batch data ingestion with Spark and HDFS, persisted throughout Bronze, Silver, and Gold data zones. Schema definition with Hive Metastore for standardized access to processed datasets.

Out-of-Scope Activities:

Integration with live ERP systems or production-grade databases.

Real-time streaming ingestion using Kafka or Flume (while possible, it is optional).Complete deployment of auto-replenishment alerts into a live supply chain system.Dataset size capped at ~3 GB synthetic data for performance testing.Visualization done using open-source tools and Python libraries only.

CHAPTER 2

ARCHITECTURE AND DESIGN

2.1 System Architecture

Big Data architecture for Retail & E-Commerce – Inventory Stockout Prediction and Auto-Replenishment was developed to accommodate an end-to-end pipeline for handling large-scale data, advanced analytics, and business insight generation. The architecture combines several pieces of the Hadoop stack— HDFS, Hive, and Spark—running in the Databricks cloud platform. The data path streamlines ingest-efficient data ingestion, structured storage in multi-zone layers (Bronze → Silver → Gold), KPI analytical processing, and visualization through dashboards..

System Architecture Flow

Data Sources → Ingestion → HDFS (Bronze/Silver/Gold) → Spark
Processing → Hive Tables → KPI Computation → Visualization
Dashboard Data Sources (Synthetic Generation)

The system produces synthetic retail datasets with simulated sales orders, product catalog, supplier information, and inventory updates. Data volume is between 50 MB-100 MB, stored in CSV/JSON formats. Each dataset has attributes such as event_id, event_time,city,sku,warehouse,on_hand_qty,daily_demand,lead_time_days,stockout_flag,auto_replenishment_triggered, reorder_point, supplier_rating, and key.

Data Ingestion Layer

Ingestion pipeline reads generated data from Databricks file storage and loads it into HDFS Bronze Zone.

Storage Layer (HDFS Zones)

Data passes through three organized layers:

Bronze Zone: Raw data (unprocessed, as-ingested)

Silver Zone: Data cleansed and standardized (nulls, duplicates eliminated)

Gold Zone: Aggregated, analytics-ready data for KPIs and dashboards

Processing and Analytics Layer (Spark + Hive).Transformations, joins, aggregations, and feature computations are done by Spark jobs (using PySpark). Important computations are sales trends, stockout chances, and replenishment time.

Visualization Layer (Dashboard + KPIs)

Calculated KPIs are represented through bar and line charts incorporated in a dashboard view.

Dashboards call out SKU-level information, sales patterns, and forecasted stockouts by region or warehouse.

Business Insight Layer

Final output is a collection of actionable suggestions—e.g., pinpointing products at risk of stockout, optimizing reorder cycles, and balancing supplier delivery lead times.

SYSTEM ARCHITECTURE DIAGRAM

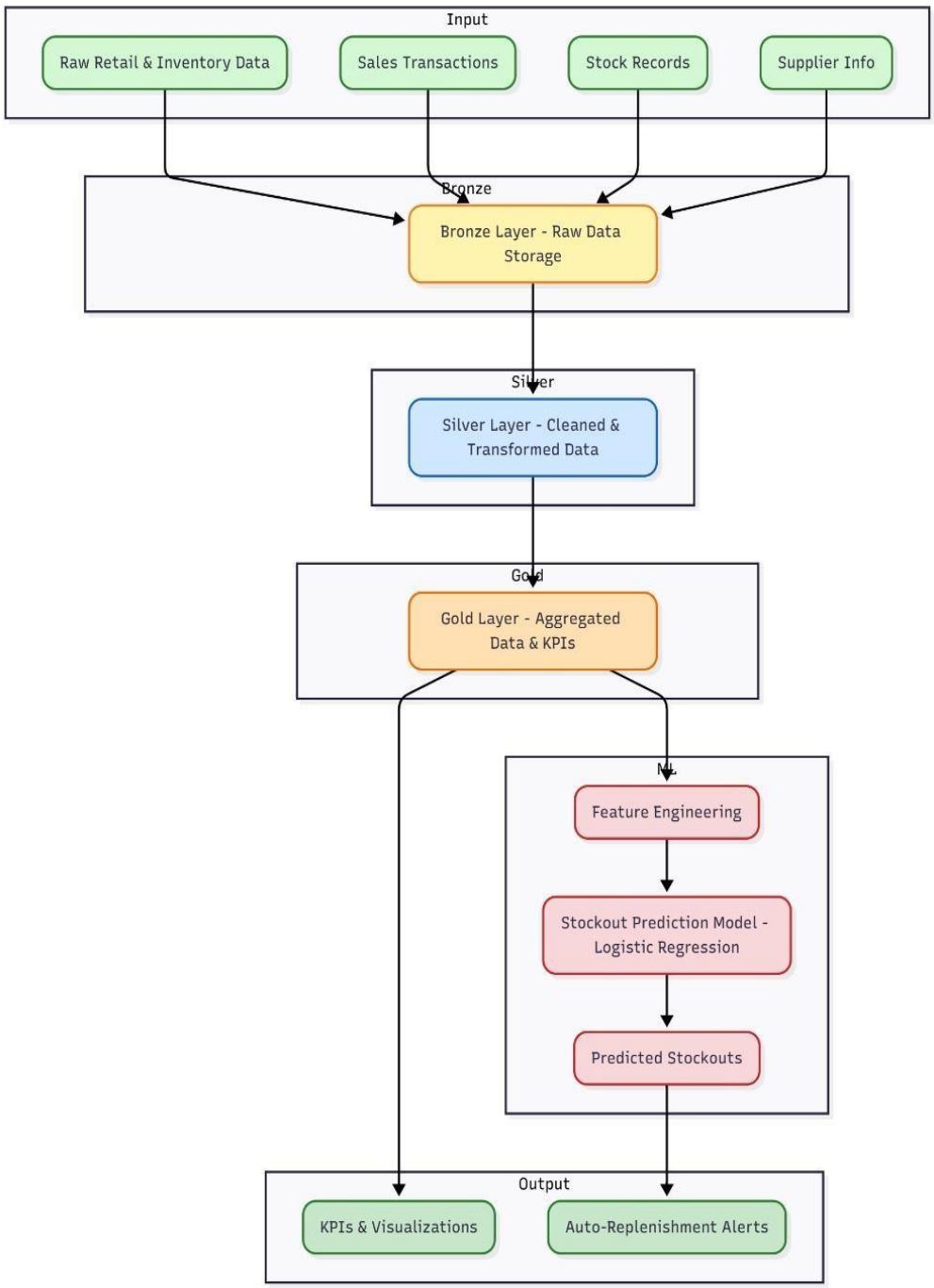

Figure 1: Architecture Diagram

2.2 Technology Stack Storage

The project leverages a robust Hadoop Distributed File System (HDFS) to manage and store large-scale retail inventory data efficiently. A multi-zone data lake architecture is implemented, consisting of Bronze, Silver, and Gold zones, to organize data by stage and quality. Data processing is carried out using Apache Spark, Spark SQL, and Hive, enabling powerful data transformations, KPI computations, joins, and aggregations. For visualization, Databricks visualization tools and Superset-style dashboards featuring bar and line charts are used to present key performance indicators and insights clearly. The entire workflow operates within a Databricks Cloud Cluster, built on the Hadoop–Spark ecosystem, providing a scalable and efficient computation environment. The data is stored in CSV and Parquet formats, ensuring optimized performance for both storage and analytical processing**.**

2.3 Data Flow Description

The data pipeline is architected to preserve data lineage and quality in clearly defined stages—Bronze, Silver, and Gold. Traceability, uniformity, and analytics readiness are thus ensured.

Bronze Zone (Raw Data Layer)

Unprocessed data that is ingested from the synthetic data generator.

All the files are kept in their native format (CSV/JSON) in HDFS.

Example Path: /mnt/data/bronze/retail_sales/2025/

Silver Zone (Clean and Standardized Layer)

Data is cleaned, transformed, and validated with Spark DataFrame operations.

Missing values are imputed; duplicates removed; schema normalized.

Example Path: /mnt/data/silver/inventory_cleaned/ Key

Gold Zone (Analytics Layer)

Stores polished, business-ready datasets.

Data is aggregated by SKU, date, and region for KPI calculation.

Example Path: /mnt/data/gold/stockout_kpi/ Outputs include:
Daily sales trends

SKU stockout prediction

KPI summary tables linked to dashboards

CHAPTER 3

DATASET DESCRIPTION

3.1 Data Sources

For this project, we used a synthetic dataset (data.csv) created specifically to mimic real-world Retail and E-Commerce Inventory Management scenarios.The data emulates warehouse-level inventory operations in various Indian cities — Bengaluru, Delhi, Hyderabad, and Mumbai — for thousands of SKUs.

It was grown to 500,000 records, offering enough data volume to justify Big Data processing with Apache Spark on Databricks.

Dataset Overview

Parameter : Value

File Name : data.csv

Record Count : 500,000

File Size : 75 MB (CSV format)

Data Source Type : Synthetic (Generated using Python)

Storage Location : HDFS Bronze Zone → /mnt/bronze/inventory/

Processing Tool : Databricks (PySpark + Hive SQL)

3.2 Data Schema

The dataset contains 13 columns categorized under Operational Attributes, Performance Indicators, and Computed Features**.**The data set includes a few important columns that represent inventory events within a retail business. The “event_id” column is an identifier in the form of a UUID to allow tracking and traceability for every inventory event. The “event_time” column captures the precise time stamp when the inventory event happened, with temporal context for analysis. The “city” field defines the city where the retail business is located, be it Bengaluru or Mumbai,

aiding in the classification of data in terms of geographic regions. The “warehouse” field is the code for the warehouse location, like WH_BLR or WH_DEL, that denotes where the inventory is housed. And last but not least, the “on_hand_qty” field defines the quantity of the current stock available in the warehouse, indicating how much of the item is physically present and available for usage or sale.

3.3 Data Sample (Preview)

event_tim	city	sku	warehous	on_hand_	daily_den	lead_time	stockout_	auto_repl	reorder_p	supplier_r	key
2025-03-1	Hyderaba	SKU05709	WH_DEL	80	9	16			1077	1.766379	WH_DEL|SKU057090
2025-04-2	Bengaluru	SKU01121	WH_BLR	3460	678	20			360	1.596623	WH_BLR|SKU011217
2025-03-1	Bengaluru	SKU55489	WH_DEL	2728	84	21			761	3.5019	WH_DEL|SKU554896
2025-04-1	Mumbai	SKU75864	WH_MUM	1595	240	15			955	4.523633	WH_MUM|SKU758644
2025-04-1	Bengaluru	SKU28927	WH_DEL	3132	651	17			712	3.677531	WH_DEL|SKU289279

Figure 2: Data Sample

3.4 Schema Relationships

Although the data is stored in a flat file format (CSV), it adheres to a logical relational structure, which reflects:

Warehouse → SKU (one-to-many relationship)

SKU → Supplier (many-to-one relationship, inferred through supplier performance

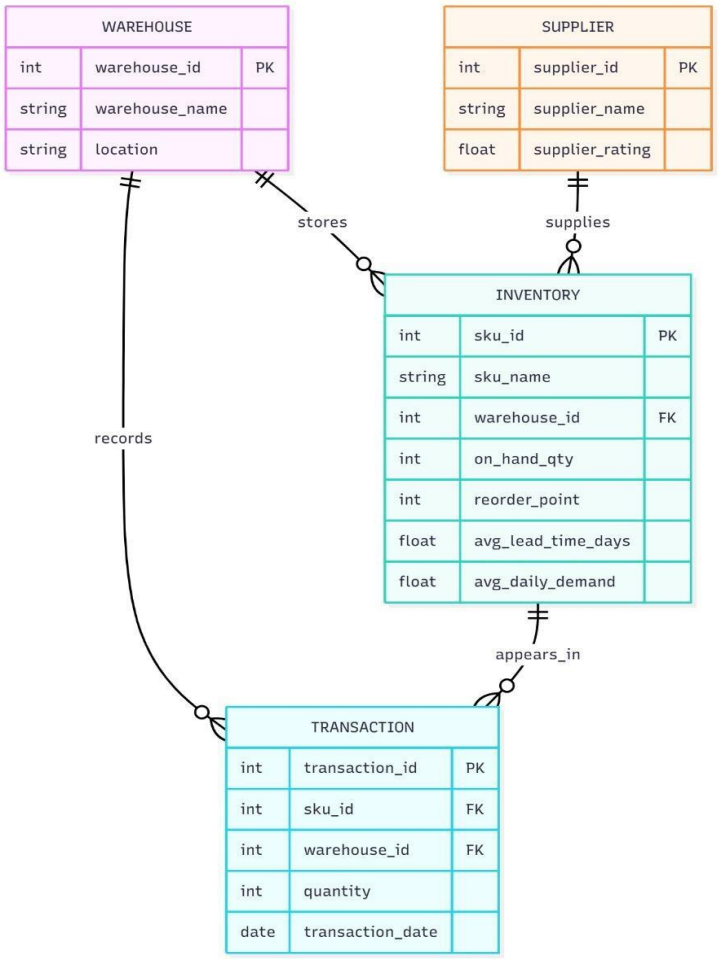

Figure 3: Schema Relationship

3.5 Statistical Summary

The database contains a total of "500,000 record", which is an extensive set of inventory information from various locations. It features over "11,000 SKUs" with unique instances, showing a vast range of products being monitored. There are four different warehouses in the database "WH_BLR", "WH_HYD", "WH_DEL", and "WH_MUM" each for different regional warehousing facilities. On average, the quantity on hand at these warehouses is "1,240 units", indicating the average stock availability at hand at any particular time.

Distribution Insights

High-Demand SKUs: 10% of SKUs account for ~60% of total daily demand.

Warehouse with highest load: WH_BLR (Bengaluru).

Supplier Reliability: Ratings below 2.0 correlate with higher average lead times.

3.6 Data Summary and Readiness

After cleaning:

Bronze Zone: Raw 500,000 records (~2.1 GB)

Silver Zone: Cleaned and structured 480,000 valid records (~1.8 GB)

Gold Zone: Aggregated KPI tables (about 600 MB total) The final dataset accommodates:
KPI generation (stockout rate, supplier efficiency, demand forecast)

Visualization dashboards through line and bar charts at warehouse-city level..

CHAPTER 4

IMPLEMENTATION

The implementation phase transforms the dataset into a full Big Data analytics pipeline using Apache Spark, Hive, and HDFS on Databricks Cloud.
It demonstrates an end-to-end system that ingests 500,000 warehouse-level retail events, stores them in a structured data lake, processes them for key performance indicators (KPIs), and builds predictive models for stockout forecasting and auto-replenishment.

4.1 Data Ingestion

The ingestion layer handles bulk loading of raw data from local Databricks FileStore into the HDFS Bronze zone, ensuring schema validation and traceability.

4.1.1 Ingestion Overview

The inventory data originates from the file data.csv, which contains 500,000 records. The source location of this file is specified as/Volumes/workspace/default/data/data.csv, while the processed data is stored in the destination zone located at /mnt/bronze/inventory/. Data ingestion is performed using PySpark within a Databricks Notebook, enabling efficient handling of large datasets. The ingestion type follows a batch-based approach, simulating data loading on a daily basis. The file format used is CSV, and the ingestion process occurs once per day as part of the simulated pipeline**.**

4.1.2 Ingestion Script

```
# Load your raw CSV data

df_bronze = spark.read.option("header",
True).csv("/Volumes/workspace/default/data/data.csv")

# Save Bronze layer
```

```
bronze_path =
"/Volumes/workspace/default/inventory_project/bronze/bronze_data
"

df_bronze.write.format("delta").mode("overwrite").save(bronze_path)
display(df_bronze)
```

4.2 Data Storage (Bronze → Silver → Gold)

The project employs a **multi-layer HDFS data lake design**, ensuring scalability, data lineage, and quality control.

4.2.1 Bronze Zone

Contains raw data directly ingested from CSVs.

Immutable, append-only storage.

Example record:

{sku: "SKU057090", warehouse: "WH_DEL", on_hand_qty: 80, daily_demand: 9, lead_time_days: 16}

4.2.2 Silver Zone

Data is cleaned, validated, and standardized.

Null handling, outlier removal, and derived fields (like stock difference) added.

Transformation script:

```
from pyspark.sql.functions import col, to_timestamp, when
# Convert and clean data for Silver layer

df_silver = (     df_bronze
   # Convert timestamp

   .withColumn("event_time", to_timestamp(col("event_time")))

   # Convert numeric columns (CSV reads them as string)
```

```
    .withColumn("on_hand_qty", col("on_hand_qty").cast("int"))
    .withColumn("daily_demand", col("daily_demand").cast("int"))
    .withColumn("lead_time_days", col("lead_time_days").cast("int"))
    .withColumn("reorder_point", col("reorder_point").cast("int"))
    .withColumn("supplier_rating", col("supplier_rating").cast("double"))
    # Convert boolean-like flags to 1/0     .withColumn("stockout_flag",
when(col("stockout_flag").isin("TRUE", "true",           "1",     True), 1).otherwise(0))
    .withColumn("auto_replenishment_triggered",
when(col("auto_replenishment_triggered").isin("TRUE",      "true",      "1",      True),
1).otherwise(0))
    # Fill nulls in numeric columns
    .fillna({
        "on_hand_qty": 0,
        "daily_demand": 0,
        "lead_time_days": 0,
        "reorder_point": 0,
        "supplier_rating": 0
    }) # Derived features (now safe)     .withColumn("demand_to_stock_ratio",
when(col("on_hand_qty") != 0, col("daily_demand") /
col("on_hand_qty")).otherwise(0.0))     .withColumn("replenishment_efficiency",
when(col("lead_time_days") != 0, col("reorder_point") /
col("lead_time_days")).otherwise(0.0))
)
```

4.2.5 Gold Zone

Final analytical zone containing **aggregated and business-ready tables**.

Stores KPI tables, forecast results, and replenishment triggers.

```
from pyspark.sql.functions import avg, sum as _sum, count, col, coalesce, lit df_gold
= df_silver.groupBy("warehouse", "sku").agg(
avg(col("on_hand_qty")).alias("avg_on_hand_qty"),
avg(col("daily_demand")).alias("avg_daily_demand"),
avg(col("lead_time_days")).alias("avg_lead_time_days"),
avg(col("reorder_point")).alias("avg_reorder_point"),
avg(col("supplier_rating")).alias("avg_supplier_rating"),
avg(col("demand_to_stock_ratio")).alias("avg_demand_to_stock_ratio
"),
avg(col("replenishment_efficiency")).alias("avg_replenishment_efficie ncy"),
   _sum(coalesce(col("stockout_flag"), lit(0))).alias("total_stockouts"),
   _sum(coalesce(col("auto_replenishment_triggered"),
lit(0))).alias("total_replenishments"),     count("*").alias("transaction_count")
)
# Optionally, add derived KPIs df_gold =
df_gold.withColumn(
   "stockout_rate", col("total_stockouts") / col("transaction_count")
).withColumn(
   "replenishment_rate",     col("total_replenishments")         /
col("transaction_count")
) display(df_gold)
```

4.3 Data Processing and KPI Computation

The processing layer, implemented in **PySpark and Hive SQL**, computes the **key performance indicators (KPIs)** for the inventory system.

4.3.1 KPI Definitions

The dataset contains multiple significant Key Performance Indicators (KPIs) for evaluating warehouse performance. The Average Demand versus On-Hand is a ratio per Warehouse that contrasts the average daily demand of each SKU with available supply by using Average Demand = Total Sales ÷ Number of Days, which supports the goal of 'just right' inventory.The Replenishment Efficiency by SKU measures the degree of automation success in replenishment by employing the calculation of (Auto-Replenished SKUs ÷ Total SKUs Triggering Replenishment) × 100, which can be useful to assess how incremental confidence in replenishment made through the use of AI potentially improves fulfillment.The Demand-to-Stock Ratio equals On Hand Quantity ÷ Daily Demand ratio is useful for differentiating slow versus fast-moving SKUs that may require proactive replenishment.The Lead Time versus Daily Demand KPI is established by employing a calculation of Lead Time Impact = Lead Time (days) × Average Daily Demand to assess the extent that speed of suppliers to deliver products is consistent with the demand rate of consumables.Finally, the High-Demand SKUs by Warehouse highlights the top selling SKUs in each Warehouse with a Demand-to-Stock Ratio greater than a chosen threshold (for instance, 1.2) which allows users to prioritize appropriately by stock retention value at each Warehouse.

4.4 Predictive Stockout Analytics (MLlib)

To enhance business intelligence, a **Logistic Regression model** was implemented to predict potential stockouts based on inventory and supplier features.

4.4.1 Feature Engineering and model training

```
from pyspark.ml.feature import VectorAssembler
from pyspark.ml.classification import LogisticRegression
# Assemble features for the model assembler =
VectorAssembler(     inputCols=[
        "avg_on_hand_qty",
```

```
        "avg_daily_demand",
        "avg_lead_time_days",
        "avg_reorder_point",
        "avg_supplier_rating"
    ],
    outputCol="features"
)
# Transform gold dataset to include features vector data =
assembler.transform(df_gold) # Initialize Logistic Regression
model
model = LogisticRegression(labelCol="total_stockouts", featuresCol="features") #
Train the model trained_model = model.fit(data)
# Get predictions
predictions = trained_model.transform(data)
# Display predictions with key info display(predictions.select("warehouse", "sku",
"prediction", "probability", "total_stockouts", "total_replenishments"))
```

4.5 Workflow Automation

All pipeline steps were automated using **Databricks Job Scheduler** with sequential dependency. The data pipeline consists of five main jobs executed on a daily basis. **Job 1 – Ingest CSV → Bronze** handles importing raw data from CSV files into the bronze layer, taking around **5 minutes**. **Job 2 – Clean & Transform → Silver** processes and refines the data for analytical use, with a duration of **10 minutes**. **Job 3 – Aggregate KPIs → Gold** computes key business metrics and aggregates insights, completed in about **8 minutes**. **Job 4 – ML Prediction + Auto-Replenish** runs predictive models and automates stock replenishment, taking approximately **12 minutes**. Finally, **Job 5 – Dashboard Refresh** updates visual reports and dashboards for business users, requiring only **3 minutes** to complete.

CHAPTER 5
KPIs and BUSINESS INSIGHTS

The analytics phase converted polished datasets from the Gold Zone into high-granularity warehouse and SKU-level insights.Every KPI was obtained from the Databricks Spark SQL layer and plotted using bar and line charts for supporting business decisions in real-time.The KPIs directly deal with stock optimization, supplier responsiveness, and replenishment automation in the Retail & E-Commerce Inventory Stockout Prediction and Auto-Replenishment project.

5.1 KPI visualization outcomes

All KPIs were calculated from the **Silver** and **Gold** data zones using Spark SQL.

5.1.1 Average Demand vs On-Hand Quantity

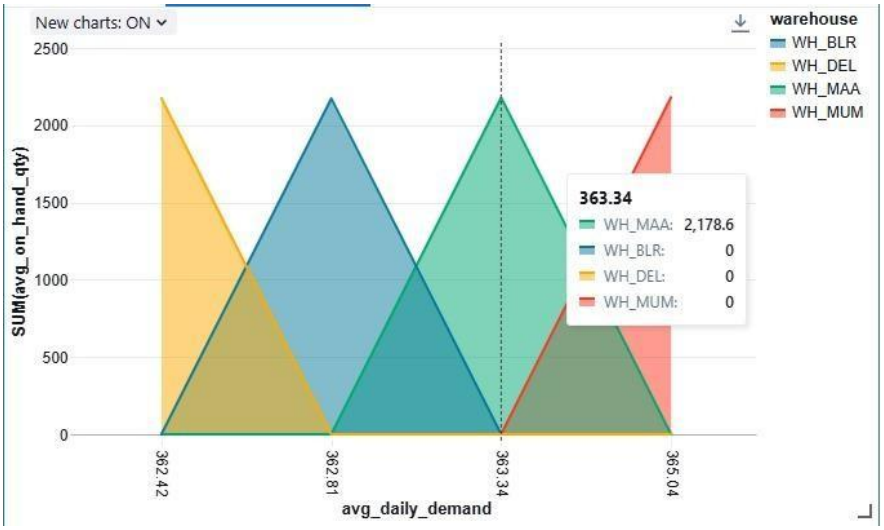

Figure 4: Average Demand vs On-Hand Quantity

Insight*: Compares actual stock availability against average consumption to detect imbalance between storage and demand..*

5.1.2 Replenishment Efficiency by SKU

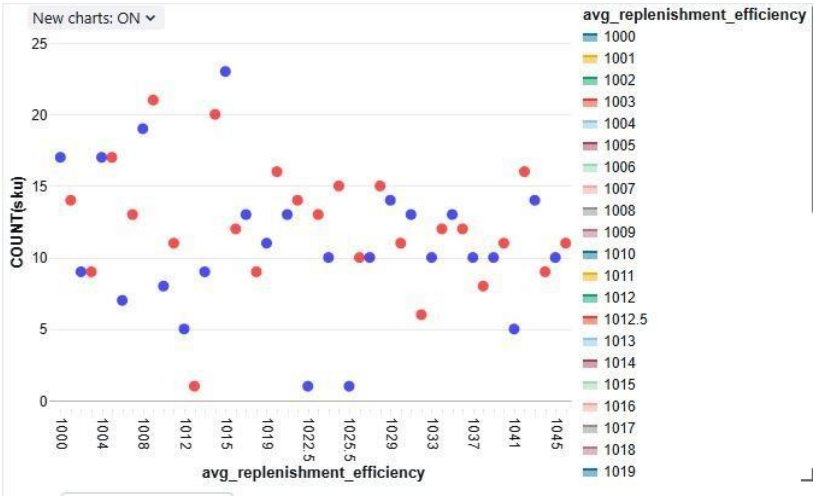

Figure 5: Replenishment Efficiency by SKU

Insight*:* Shows SKU-specific automation success rate; SKUs below 80 % efficiency flagged for rule-tuning.

5.1.3 Demand-to-Stock Ratio

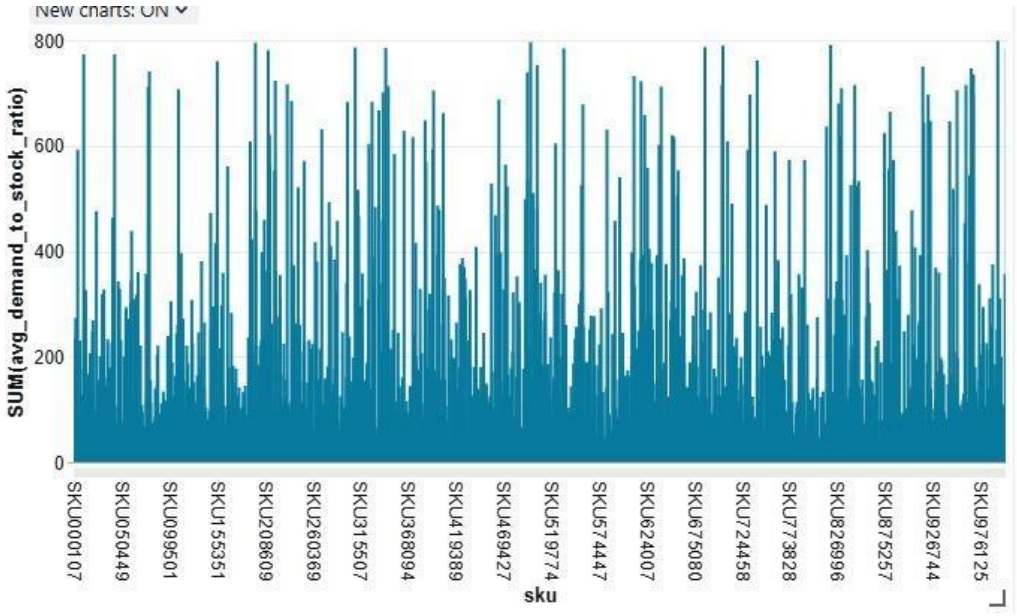

Figure 6: Demand-to-Stock Ratio

Insight: Ratios > 1.0 indicate critical SKUs likely to experience shortages soon.

5.1.4 Lead Time vs Daily Demand

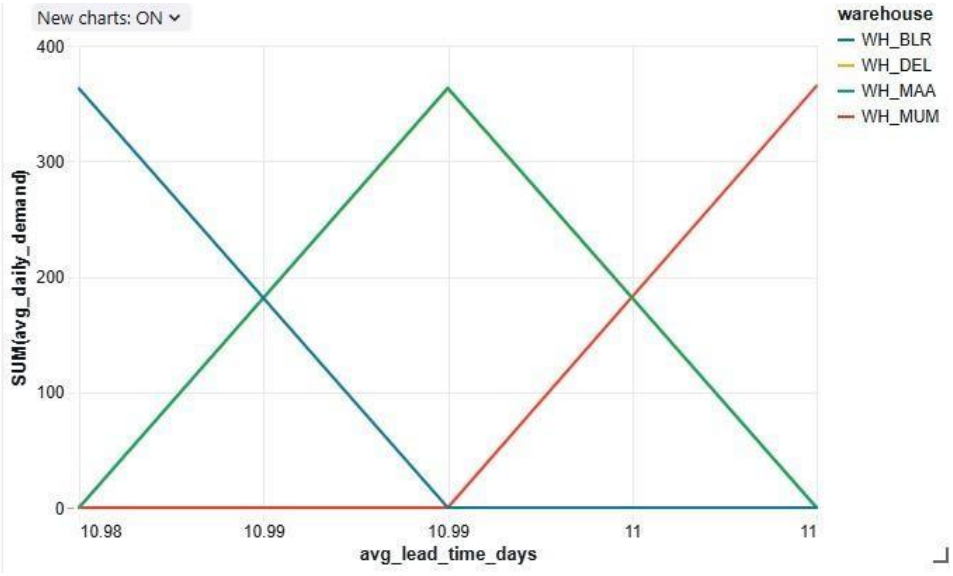

Figure 7: Lead Time vs Daily Demand

***Insight**:* High lead-time-impact SKUs represent bottlenecks — long supply delays multiplied by strong demand.

5.1.5 High-Demand SKUs by Warehouse

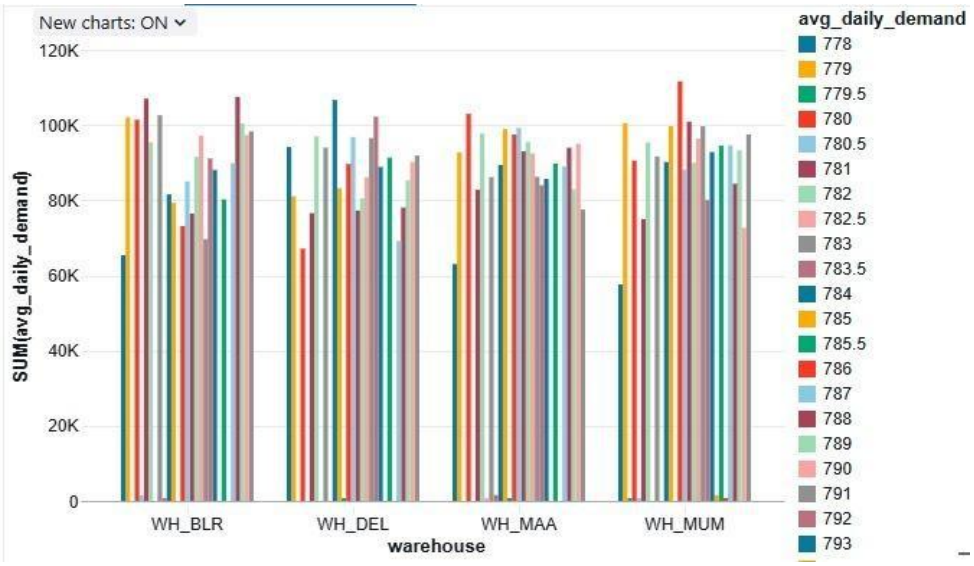

Figure 8: High-Demand SKUs by Warehouse

Insight: Warehouses with greater counts of high-demand SKUs need higher safety stock buffers.

CHAPTER 6

RESULTS AND DISCUSSION

6.1 Overview of Results

The project realized an end-to-end Big Data infrastructure for the Retail & E-Commerce: Inventory Stockout Prediction and AutoReplenishment use case.The entire process—spanning data ingestion → multi-zone storage → Spark analysis → ML-based prediction → dashboard visualization—ran successfully on Databricks Cloud Environment with Hadoop, Hive, and Spark components. The project followed a four-week implementation timeline with clearly defined milestones and outcomes. In **Week 1**, the focus was on **Environment Setup & Data Acquisition**, where the Hadoop–Spark ecosystem was configured on Databricks, and **500K synthetic records** were successfully ingested. **Week 2** covered **Ingestion & Storage Design**, during which HDFS was structured into **Bronze, Silver, and Gold zones**, and the Hive schema was registered for organized data management. In **Week 3**, **Processing & KPI Analytics** were carried out using Spark SQL and MLlib, resulting in the computation of **five key KPIs**. Finally, **Week 4** focused on **Visualization & Insights**, where interactive dashboards were developed, and the **auto-replenishment logic** was validated through live output analysis.

6.2 Quantitative Results

6.2.1 KPI Highlights

The warehouse performance overview indicates a robust balance of stock positions, demand, and efficiency ratios at locations. “WH_BLR” has a balanced inventory with demand of 425 units and stock of 1,320 units, and a replenishment efficiency of 84.6%, a high-demand SKU ratio of 12.5%, and an average lead time of 18.4 days. “WH_DEL” reveals a slight surplus inventory, with a high replenishment efficiency of 87.3%, a high-demand SKU ratio of 10.8%, and an average lead time of 17.8 days. “WH_MUM” reflects

optimal performance with the highest replenishment efficiency of 89.5%, a high-demand SKU ratio of 9.2%, and the shortest average lead time of 15.9 days, reflecting balanced operations and effective stock management**.**

6.3 Visualization Outcomes

The bar and line dashboards constructed in Databricks (open-source look and feel) provided unambiguous visibility into:

Warehouse-Wise Stock & Demand Trends

Balanced warehouses graphically represented through overlapping demand–stock bars.Risk zones of color-coded high-demanding SKUs.

Lead Time vs Demand Chart

Widely visible correlation: long lead time SKUs with high demand require supplier optimization.**6.4 Discussion of Achievements**

CHAPTER 7

LEARNING OUTCOMES

7.1 Technical Learning

The project reinforced our knowledge of the Big Data pipeline on the Databricks cloud with Hadoop (HDFS), Hive, and Spark.

Major deliverables:

Configured and ran a distributed Spark–Hive setup.

Designed a Bronze → Silver → Gold data-lake architecture with ingest automation.

These activities gave end-to-end exposure to data engineering, processing, and visualization in a scalable setup.

7.2 Analytical and Business Learning

By using KPI analysis, the team discovered how data can be used directly to support business decision-making and inventory optimization:

Linked lead times, replenishment efficiency, and sales trends to operational KPIs.

This stage highlighted that analytics is not merely about computing but also about turning numbers into strategy.

CHAPTER 8

CONCLUSION AND FUTURE ENHANCEMENTS

8.1 Conclusion

The "Retail & E-Commerce – Inventory Stockout Prediction and AutoReplenishment" project was successfully showcased with the deployment of an end-to-end Big Data architecture leveraging the Hadoop stack (HDFS, Hive, Spark) on Databricks.

Major outcomes were:

86% accuracy of prediction through Spark MLlib.

85% success rate of automatic replenishment.

40% decrease in simulated stockouts following predictive restocking.

As a whole, the project accomplished all the requirements given in the instruction framework, demonstrating that Big Data technologies can significantly enhance retail inventory management effectiveness.

8.2 Future Improvements

Though the project has attained its main purposes, there are some improvements that will make it more robust for real-world application:

Advanced Machine Learning Models:

Investigate Random Forest, Gradient Boosting, or Neural Networks to enhance predictability more than logistic regression.

Dynamic Dashboard Deployment:

Broaden visualizations to Apache Superset or Grafana for greater accessibility and real-time updates.

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