Unlocking Retail Potential: Utilizing Demand Sensing Techniques for Optimized Product Placement

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BUSINESS PROBLEM

Today's competitive retail environment thrives on delivering a **positive shopping experience** and implementing effective **product placement tools**, like **planograms** to enhance **Availability, Visibility, & Accessibility (AVA)** for sustainable business growth.

> Can we have an Interactive Solution to **Visually Analyze Product Placement** & make strategic decisions accordingly?

> Can visual displays be effectively integrated with **Demand Forecasts** to enhance Shopper Experience?

Our industry partner aims to improve product placement and reduce out of stock instances by shifting away from **manual processes.**

We aim to address this challenge by integrating visualization and analytical tools for planogramming and sales prediction.

Who Benefits?

RETAIL EXECUTIVES
- Improved Inventory Management
- Reduced OOS
- Reduced Expiry

BUSINESS PARTNERS
- Effective Budget Utilization
- Optimize limited Shelf Space
- Increased Sales

SHOPPERS
- Positive Shopping Experience
- Lesser Switch overs due to OOS

ANALYTICS IN RETAIL

Pain Points
- Stockout Rate
- Inventory turnover ratio
- Fill Rate
- Out of stock duration
- Foregone Sales
- Customer NPS

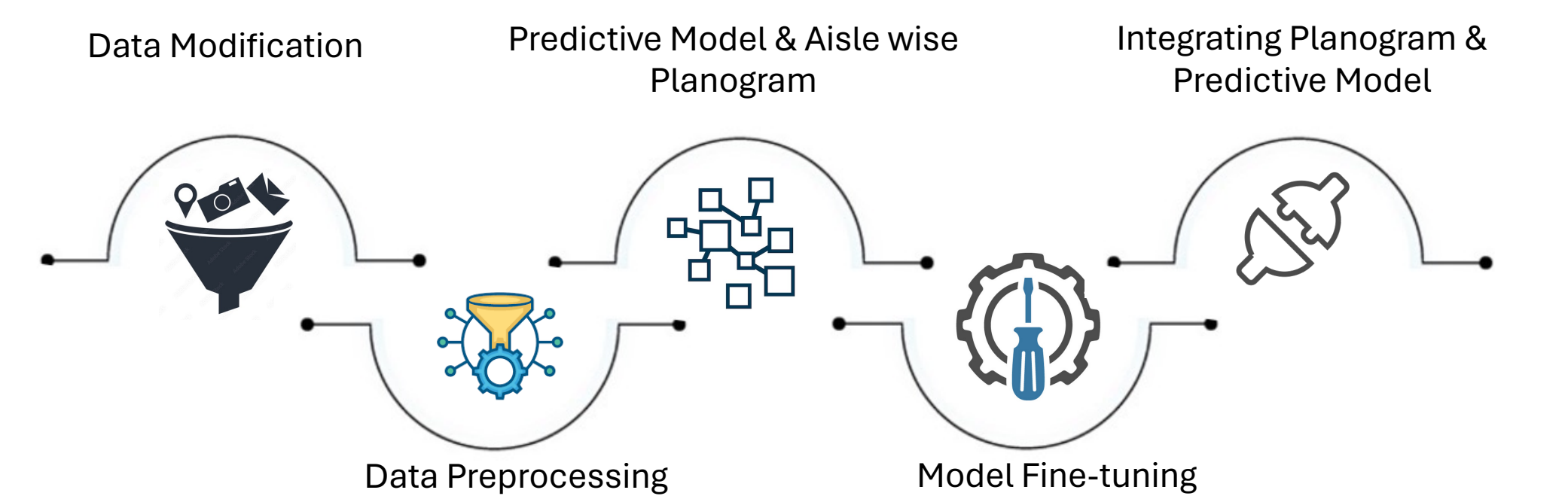**Analytical Framework**

Predictive Modeling

Output

In retail, managing inventory, minimizing out-of-stock (OOS) occurrences, and capitalizing on sales opportunities are significant challenges. By integrating comprehensive data and visual analytics, strategic decision-making becomes more efficient, with the goal of minimizing lost sales and improving the shopping experience through optimized product placement and inventory control.

We developed a **first in class** solution utilizing a unique blend of planogramming and data visualization tools, overlayed with prediction models.

Success Metrics

- Demand Prediction Accuracy
- Improved Inventory Control
- Reduced OOS

METHODOLOGY

- Data Modification
- Predictive Model & Aisle wise Planogram
- Integrating Planogram & Predictive Model
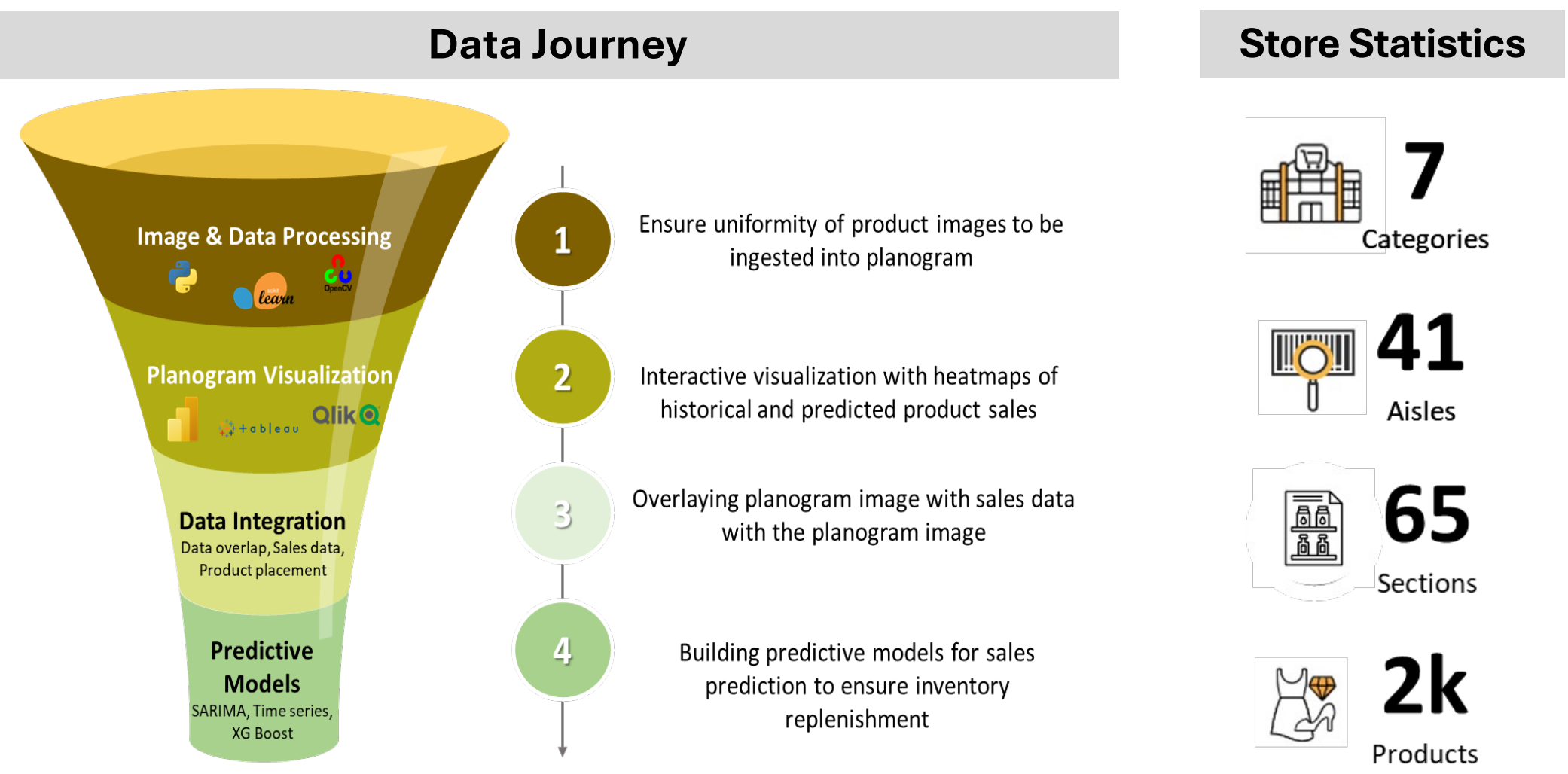- Data Preprocessing
- Model Fine-tuning

Our approach involves an **integrated digital planogram** tailored to our partner's superstore. By enhancing product images through **Python's** OpenCV library, we constructed an interactive planogram on **PowerBI**.

Our solution integrates daily sales data, empowering retail staff and managers to address product or category demand by not only **forecasting future sales** but also highlighting high-selling items, facilitating **optimized retail performance**. Product heat map can be viewed in the same dashboard based on the probability of OOS and inventory levels

Image Processing + **Sales Forecasting** = **Integrated Planogram**

OpenCV
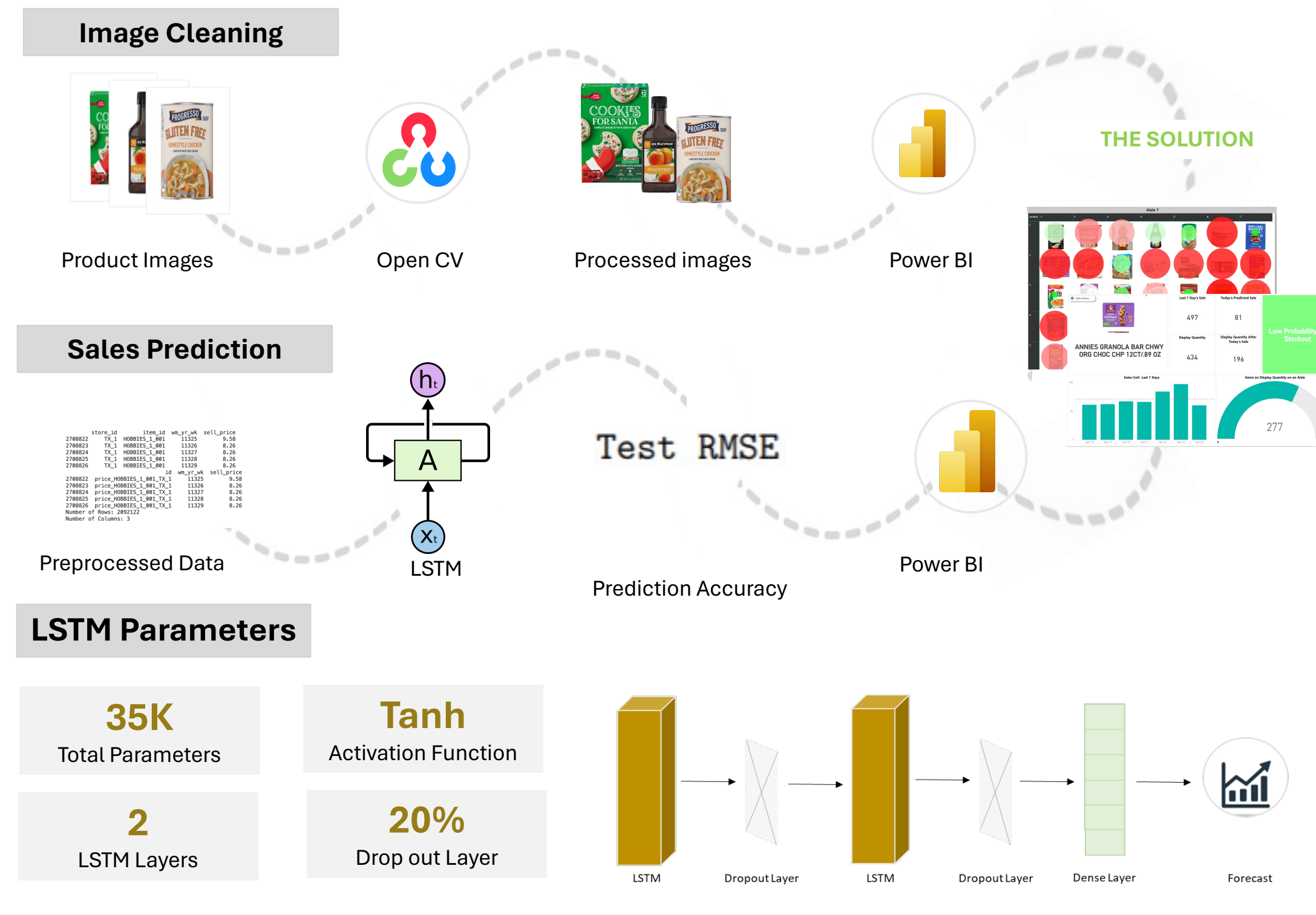python
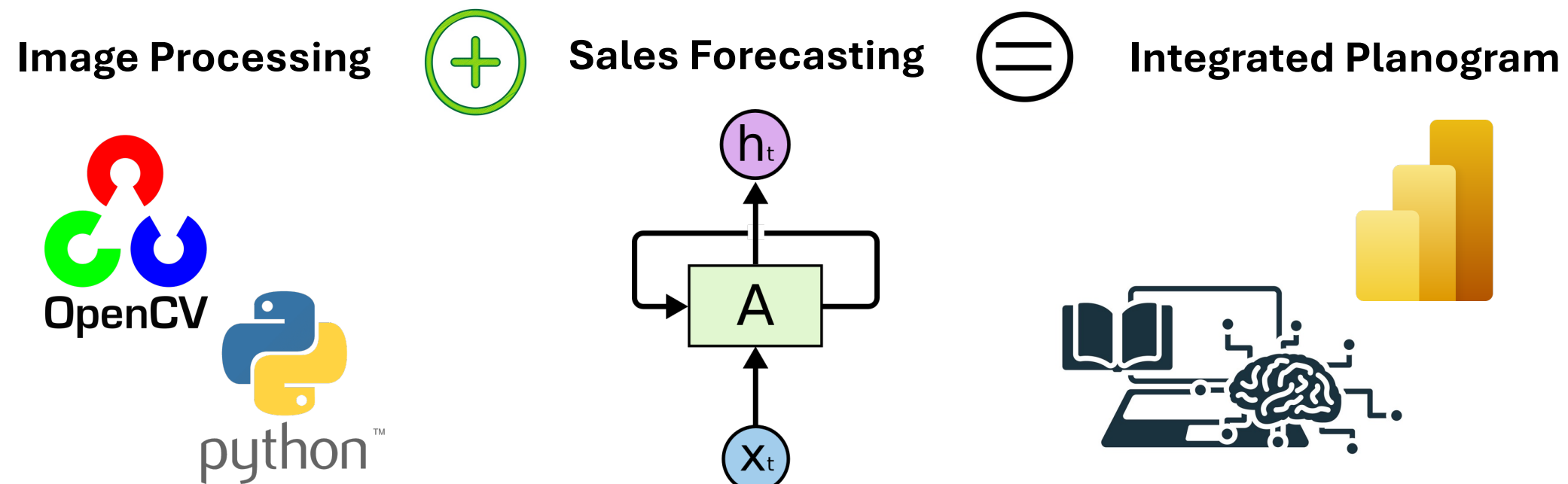
DATA COLLECTION & PROCESSING

Leveraging **product images**, **product placement** and **display quantity** data, we engineered an interactive planogram. In parallel, **historical sales data for 10K** products along with their **selling prices** for regular days and around events were used for predictive modeling

To enhance reliability, we engineered features as data preprocessing. 7-day and 14-day moving averages were taken to improve training and test data performance. Label Encoding was done to assign unique values to categorical variables like 'event type'.

Data Journey

- **Image & Data Processing** — 1. Ensure uniformity of product images to be ingested into planogram
- **Planogram Visualization** — 2. Interactive visualization with heatmaps of historical and predicted product sales
- **Data Integration** (Data overlap, Sales data, Product placement) — 3. Overlaying planogram image with sales data with the planogram image
- **Predictive Models** (SARIMA, Time series, XG Boost) — 4. Building predictive models for sales prediction to ensure inventory replenishment

Store Statistics

- **7** Categories
- **41** Aisles
- **65** Sections
- **2k** Products

MODEL BUILDING

First, to create a **planogram, +2K grocery product images** were standardized using **OpenCV** by removing backgrounds. Image URLs were created for automated product placements on the dashboard. Aisle wise planograms were then created on Power BI.

In parallel, multiple **sales prediction** models **Random forest, XG Boost, DNN, SARIMA** and **Time Series** forecasting were tested for our prediction problem. **LSTM** was eventually used due to its higher accuracy

Image Cleaning

Product Images → Open CV → Processed images → Power BI

THE SOLUTION

Sales Prediction

Preprocessed Data → LSTM → Test RMSE → Prediction Accuracy → Power BI

LSTM Parameters

35K Total Parameters	Tanh Activation Function
2 LSTM Layers	20% Drop out Layer

LSTM → Dropout Layer → LSTM → Dropout Layer → Dense Layer → Forecast

MODEL EVALUATION

To evaluate the success of the solution, we first evaluated the sales prediction model *accuracy*, and then created an integrated solution

1. Sales Prediction Model:

The output has **product-wise prediction** of **four-weeks daily sales**. Validation loss was **1.3%** but this rose to **1.5%** on test data. **Root mean squared error** and **mean squared error** performed best out of all models tested.

0.013 MSE

0.114 RMSE

2. Interactive Dashboard and Planogram:

Separate **qualitative** and **quantitative** metrics were used to evaluate *user-friendliness*, and *performance* after combining the prediction model and planogram:

100% Data Accuracy
- ✓ 100% data summaries & graph accuracy
- ✓ Accurate OOS calculation

Clarity & Intractability
- ✓ Buttons + navigation
- ✓ 100% image and text visibility

Scalability

DEPLOYMENT & LIFECYCLE MANAGEMENT

To **deploy** the model and dashboard, the following steps will be followed.

- **Internal Testing** — For model & dashboard deployment, we first tested them with a **subset of data** and evaluated performance based on **evaluation metrics**
- **Model Deployment + Live Dashboard** — The model was **trained and deployed** before integration with dashboard. The dashboard was then published with **scheduled data refresh**
- **Expanding products, categories, stores** — After deployment for one store for a single category (grocery), **expand the data** to include more grocery items, other categories (clothes etc.) and eventually to other store locations
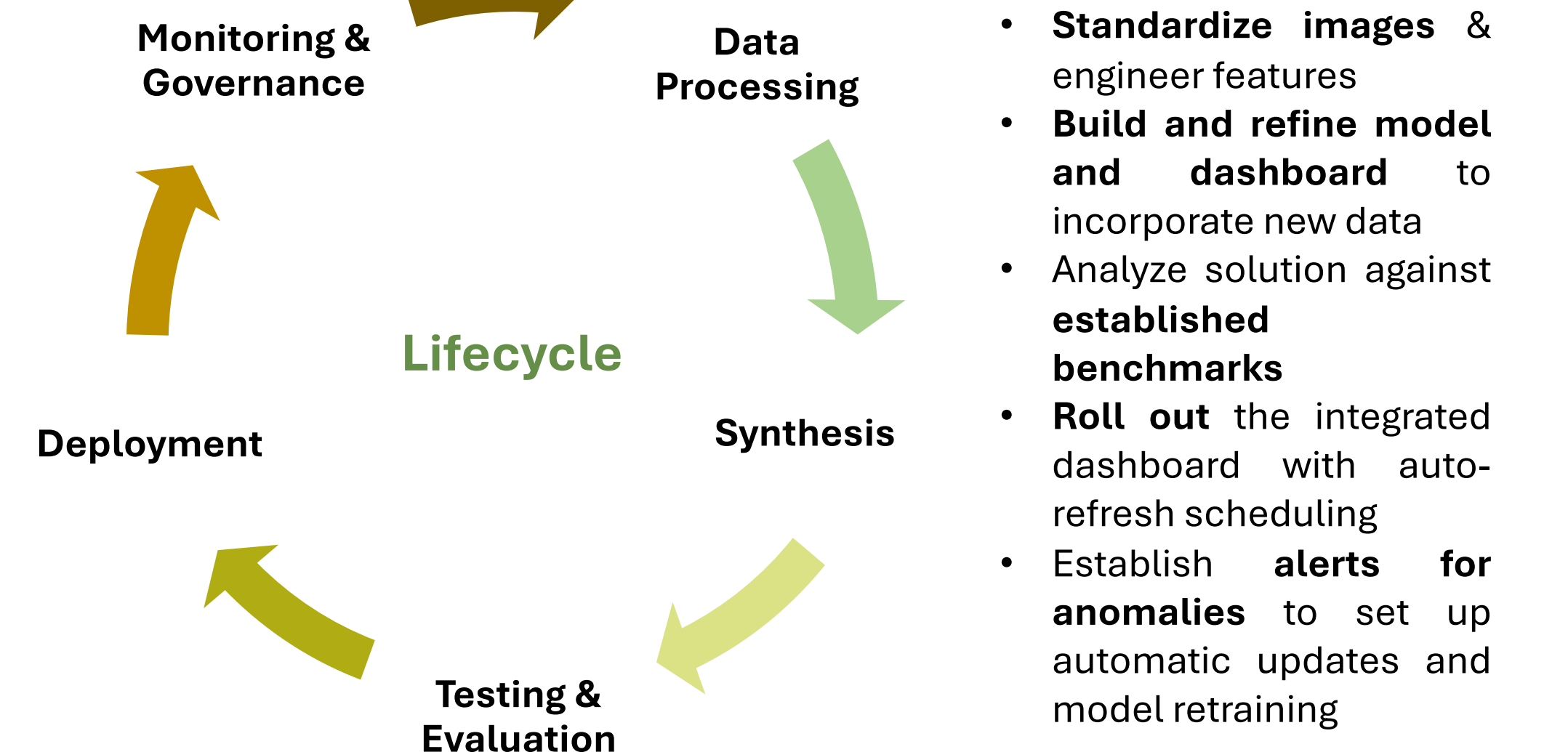- **Real-time Data Integration** — Integrating it with real-time data captured through **live aisle images** via store cameras along with update in prediction model to consider other models such as CNN
- **Set OOS Alerts** — Real value of this project lies in setting up **out of stock alerts** to merchandisers and store managers for **timely product replenishment**

To **manage** the model and dashboard, the below **lifecycle management loop** will be iterated

Lifecycle: Monitoring & Governance → Data Processing → Synthesis → Testing & Evaluation → Deployment → (loop)

- **Standardize images** & engineer features
- **Build and refine model and dashboard** to incorporate new data
- Analyze solution against **established benchmarks**
- **Roll out** the integrated dashboard with auto-refresh scheduling
- Establish **alerts for anomalies** to set up automatic updates and model retraining

OUR TEAM

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