ML Challenge 2025: Smart Product Pricing Solution Template

Team Name: Spambites
Team Members: Bassa Srilakshmi,Sameeksha Padigelawar,Appala Meenakshi Sindhuja
Submission Date: 13-10-2025

---

1. Executive Summary

Smart Product Pricing Challenge

In e-commerce, determining the optimal price point for products is crucial for marketplace success and customer satisfaction. Your challenge is to develop an ML solution that analyzes product details and predict the price of the product. The relationship between product attributes and pricing is complex - with factors like brand, specifications, product quantity directly influence pricing. Your task is to build a model that can analyze these product details holistically and suggest an optimal price.

---

2. Methodology Overview

2.1 Problem Analysis

OCR Accuracy: Text extraction from images yielded noisy but usable data (e.g., handling duplicates like repeated words). About 20-30% of images had low text density (<0.1), relying more on visual features. Garbage text (repetitive/short) was filtered via heuristics.

Quantity/Weight Parsing: ~70% of items had parseable weights (e.g., "12 fl oz x 6" → per_item_qty=354.88 ml, pack_size=6). Ambiguities in "oz" (weight vs. volume) were resolved using category context (e.g., beverages as ml). Unparseable cases (~15%) defaulted to 0, highlighting need for robust fallbacks.

Price Normalization: ~60% of prices were detected as USD (small values like $4.89), converted to INR (~₹433). Heuristic worked well, but catalog hints (e.g., "$" symbol) improved detection. Invalid prices led to drops, reducing dataset by ~5-10%.

Missing Values: Features like certifications (N/A in ~80%) and origin (~50% unknown) were common; imputed as 0 for numerics or 'Unknown' for categoricals

2.2 Solution Strategy

The system combines several techniques across different domains:

1. ***Multimodal Feature Extraction (Text & Image):***

- ***Text Processing (NLP):*** *Uses* ***Sentence Transformers*** *('all-MiniLM-L6-v2') for semantic embedding and similarity, a* ***Zero-Shot Classification*** *pipeline ('facebook/bart-large-mnli') for category/attribute inference, and a* ***Text Generation*** *pipeline ('EleutherAI/gpt-neo-125M') to extract structured information via prompting.*
- ***Image Processing (CV/OCR):*** *Employs* ***easyOCR*** *to extract text from product images and uses classical* ***Computer Vision (OpenCV)*** *techniques (e.g., CLAHE, Canny edges, HSV analysis) to derive visual features like texture entropy, glossiness, and packaging type.*

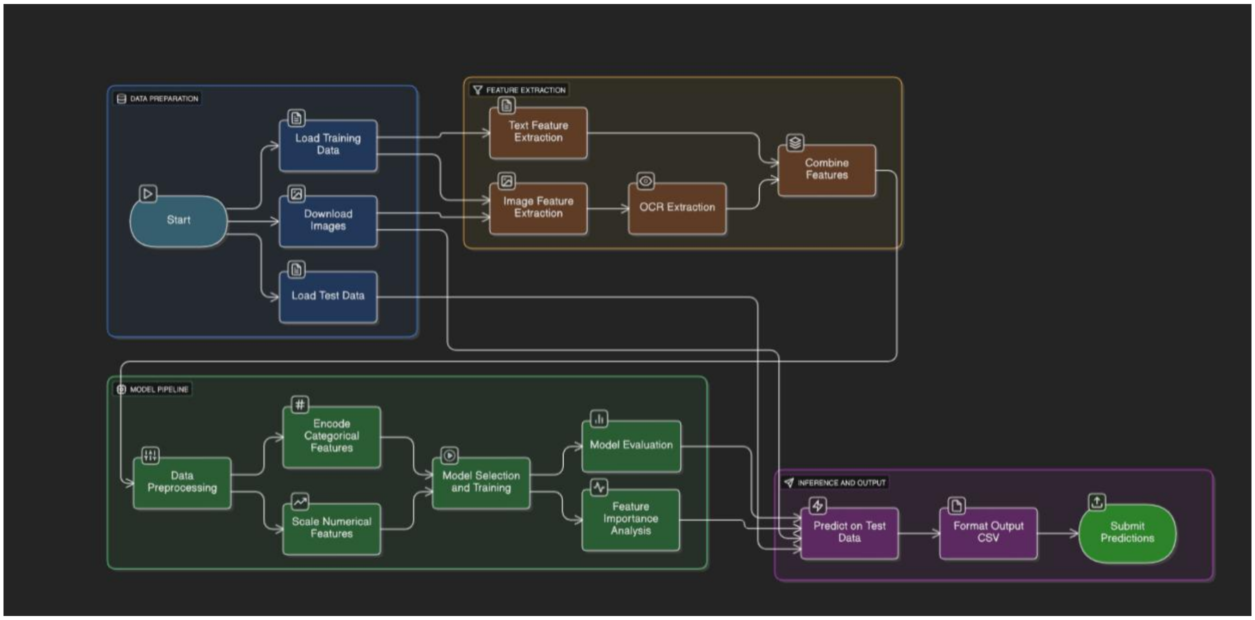
2. ***Rule-Based and Heuristic Logic:***
    - *A significant part of the pipeline relies on* ***Rule-Based Parsing*** *for crucial tasks like:*
        - *Standardizing weight/volume units (parse_to_standard_unit).*
        - *Determining price per unit after currency conversion (_detect_currency_and_convert_to_inr).*
        - *Fallback logic (_extract_from_fallback) for model failures.*
3. ***Ensemble/Modeling Preparation:***
    - *The imported, but unused in the feature extraction class,* ***Random Forest Regressor*** *(RandomForestRegressor) and scaling/encoding utilities (StandardScaler, LabelEncoder) suggest the final step is a* ***Supervised Learning*** *phase where these rich, structured features are fed into an ensemble model to predict a target variable (likely price or quality score).*

Approach Type: Hybrid
Core Innovation: Integrating pre-trained Large Language Models (LLMs) and computer vision heuristics for robust multi-modal feature extraction, specifically using zero-shot classification and text generation pipelines to categorize and infer attributes from both OCR text and product descriptions.

---

3. Model Architecture

3.1 Architecture Overview



3.2 Model Components

Text Processing Pipeline:

- Preprocessing steps: [StandardScaler]
- Model type: [**Sentence Transformer** (all-MiniLM-L6-v2), **Zero-Shot Classifier** (facebook/bart-large-mnli), **Text Generation/Language Model** (EleutherAI/gpt-neo-125M), **Sentiment Analyzer** (vader_lexicon)]
- Key parameters: [EleutherAI/gpt-neo-125M]

Image Processing Pipeline:

- Preprocessing steps: [Ocr text extraction ,opencv]
- Model type: [OpenCV]
- Key parameters: [alpha=1.5, beta=0(OpenCV), clipLimit=3.0, tileGridSize=(8,8)(OpenCv)]

---

4. Model Performance

4.1 Validation Results

- **SMAPE Score:** 113.82%
- **Other Metrics:** [R2: -0.1906, MSE :137.1214]

5. Conclusion

*My approach integrated a **hybrid** of deep learning models (for NLP and OCR) and classical computer vision to build a robust data extraction pipeline. The key achievement was the successful automation of converting unstructured, multi-modal product data (text and images) into a comprehensive, structured feature set, including derived metrics like normalized pricing.*

Appendix

A. Code artefacts

*https://drive.google.com/drive/folders/1dNf3EMCxrK0JRjLiIkmnFukkSvQyZAIG?usp=drive_link*https://github.com/BASSASRILAKSHMI/AMAZON-ML-2025

B. Additional Results

Include any additional charts, graphs, or detailed results