**ML Challenge 2025: Smart Product Pricing Solution Template (Ensemble Model Approach)**

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**1. Executive Summary**

Our solution predicts product pricing using a multimodal ensemble approach, combining advanced text and image feature extraction with several machine learning models. Key innovations include robust feature engineering and stacking different architectures to leverage complementary strengths for improved price prediction accuracy.

**2. Methodology Overview**

**2.1 Problem Analysis**

We interpreted this challenge as a complex multimodal regression task, where price depends heavily on both catalog descriptions and product images, with missing data patterns also carrying significant signals. EDA revealed that longer text content and complete specifications are positively correlated with price, while missing values signal lower-priced items.

**Key Observations:**

* Text length and detail correlate with higher prices.
* Missing volume or pack-size features point to lower pricing.
* Text and image info capture distinct value aspects.

**2.2 Solution Strategy**

Our solution employs ensemble learning, stacking multiple models after extracting text and image features for maximal predictive capability.

**Approach Type:** Hybrid Ensemble Model  
**Core Innovation:** Feature fusion of BERT-based text embeddings and CNN-based image embeddings, followed by stacking regression models to optimize price estimates.

**3. Model Architecture**

**3.1 Architecture Overview**

Our pipeline is as follows:

**Raw Data → Feature Extraction (Text, Image) → Model Ensemble (Random Forest, XGBoost, Neural Net) → Price Prediction**

**3.2 Model Components**

**Text Processing Pipeline:**

* Preprocessing steps: Text cleaning, entity extraction, tokenization, TF-IDF + BERT embeddings
* Model type: Transformer-based embedding (BERT), Random Forest/XGBoost regression
* Key parameters: max\_text\_length, embedding\_dim, tree\_depth, n\_estimators

**Image Processing Pipeline:**

* Preprocessing steps: Robust image download, resizing, normalization
* Model type: CNN feature extractor (ResNet/EfficientNet, pre-trained and fine-tuned), regression head
* Key parameters: input\_shape, pretrained\_weights, dropout\_rate, learning\_rate

**Fusion & Ensemble:**

* Merge text and image features
* Feed to base regressors (CatBoost, XGBoost, LightGBM)
* Meta-learner (Ridge regression) blends predictions from all base models

**4. Model Performance**

**4.1 Validation Results**

* **SMAPE Score:** [Insert best validation SMAPE, e.g. 6.3%]
* **Other Metrics:** MAE: [xxxx], RMSE: [xxxx], R²: [xxxx]

**5. Conclusion**

Our ensemble model successfully fuses multimodal features from text and image data, capturing rich signals for price prediction. Stacking diverse models led to robust performance and low SMAPE, showing that combining multiple approaches yields superior results. Key takeaways include the power of feature engineering, ensemble learning, and treating missingness indicators as features.

**Appendix**

**A. Code artefacts**

[Include drive link for your complete code directory]

**B. Additional Results**

A diagram of a distribution of content

AI-generated content may be incorrect.

A graph of a graph

AI-generated content may be incorrect.

**Note:** This template highlights the ensemble approach clearly, showing how text and image modalities are processed, fused, and fed into multiple complementary models for robust product price prediction. Each section is concise but covers technical depth, ready for further adaptation to your team's specific implementation.