ECOMATCH AI: AN AUTOMATED PRODUCT INQUIRY RESPONSE SYSTEM FOR LIGHT RECYCLING

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BACKGROUND AND PURPOSE

The Product Care Association (PCA) plays a crucial role in diverting post-consumer lighting products from landfills through recycling programs across multiple Canadian provinces. However, the current product inquiry process—determining whether a product qualifies for recycling and identifying its product category—is largely manual, leading to inefficiencies, inconsistent decision-making, and operational delays. This research aims to develop an AI-powered Product Inquiry Response System to enhance efficiency by leveraging machine learning (ML).

RESEARCH QUESTION

How can I design and implement an end-to-end AI-powered system that effectively integrates text and image data to enhance matching accuracy and minimize response times in the current product inquiry process?

METHODOLOGY

1. WEB PORTAL DEVELOPMENT

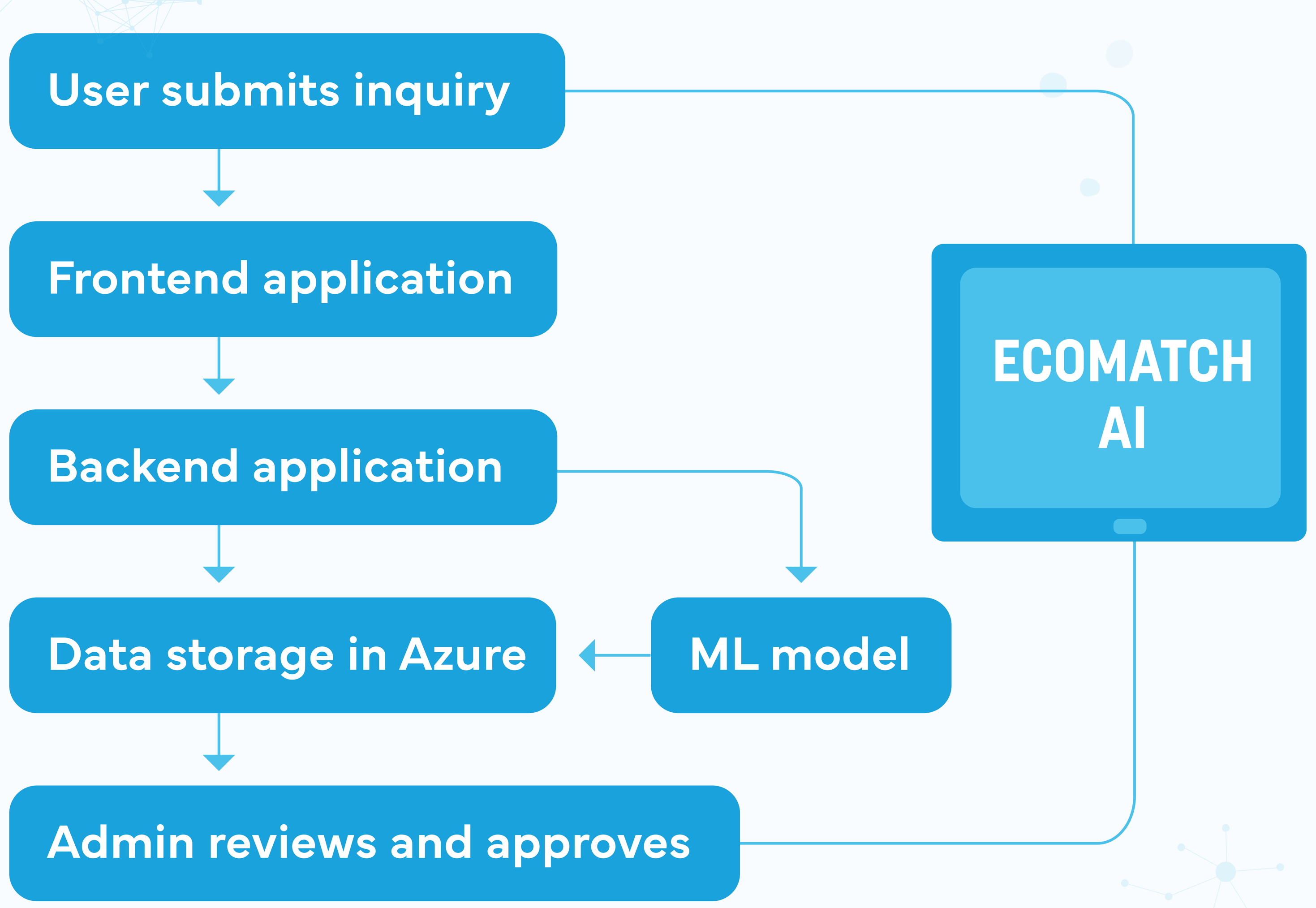
Frontend: Built using Python Flask and Bootstrap for responsive user interface.

Backend: Manages API calls and integrates ML models using Python Flask.

Data Storage: Inquiry text is stored in Azure Table Storage; images in Azure Blob Storage.

User Roles:
- Member: Submits and views inquiries.
- Admin: Reviews ML-recommended categories, approves or overrides them.

Typical Flow: A member submits a product inquiry. The system stores data and triggers the ML model to recommend a category. The admin reviews and finalizes the recommended category.



2. ML MODEL FOR TEXT SIMILARITY

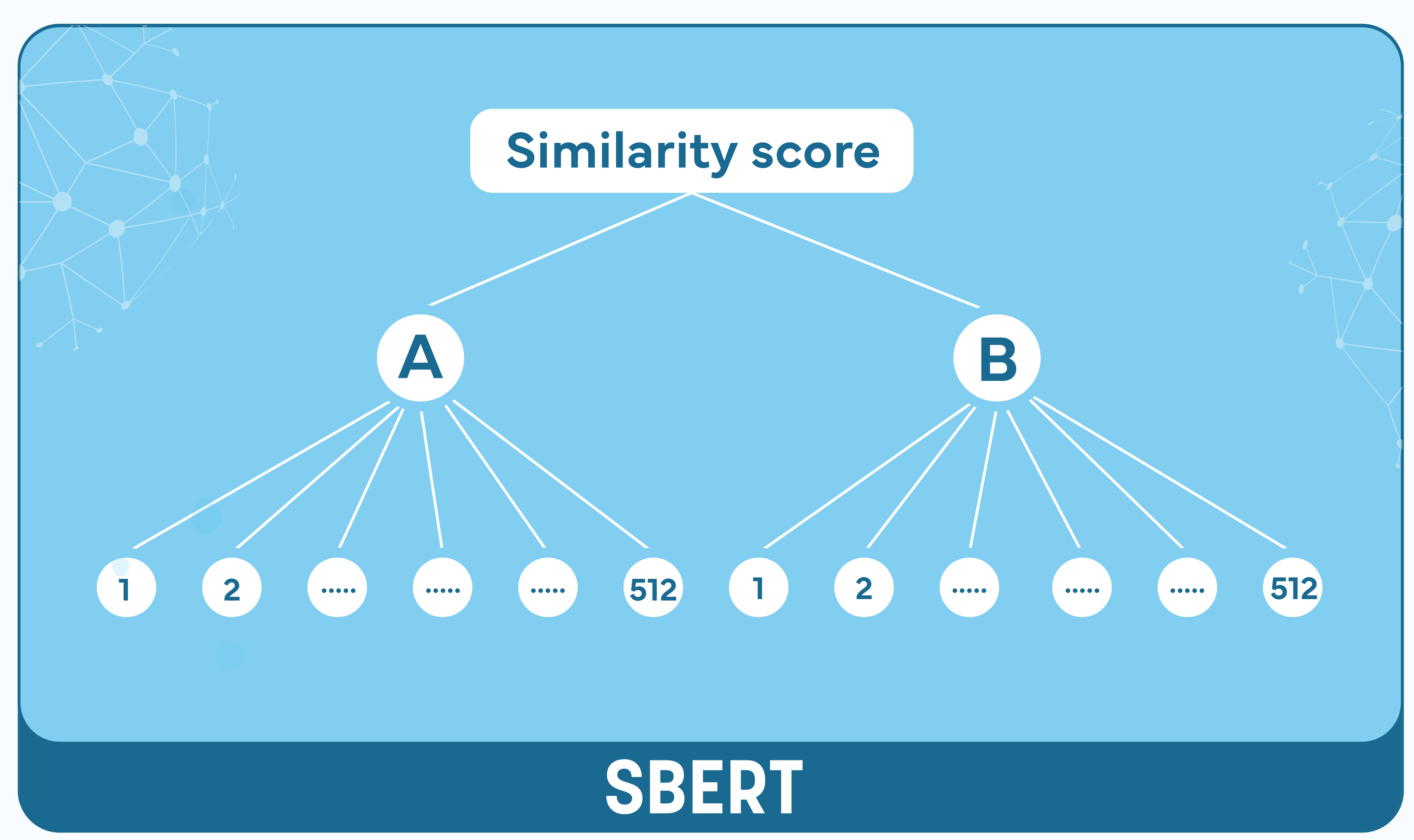
Objective: Accurately compare name and description of the submitted product to existing product descriptions.

Technique: Sentence-BERT (SBERT), a fine-tuned transformer for semantic similarity. SBERT converts sentences into dense vector embeddings to measure how semantically similar two texts are.

Platform: Hugging Face's SentenceTransformer library.

Model Evaluation: Multiple SBERT models—including all-mpnet-base-v2, roberta-large-nli-stsb-mean-tokens, bert-large-nli-stsb-mean-tokens, all-MiniLM-L12-v2, all-MiniLM-L6-v2, roberta-base-nli-stsb-mean-tokens, paraphrase-multilingual-MiniLM-L12-v2, bert-base-nli-mean-tokens, and distilbert-base-nli-stsb-mean-tokens—were evaluated using Mean Reciprocal Rank (MRR) and Top-K Accuracy to determine their effectiveness in semantic text similarity tasks.

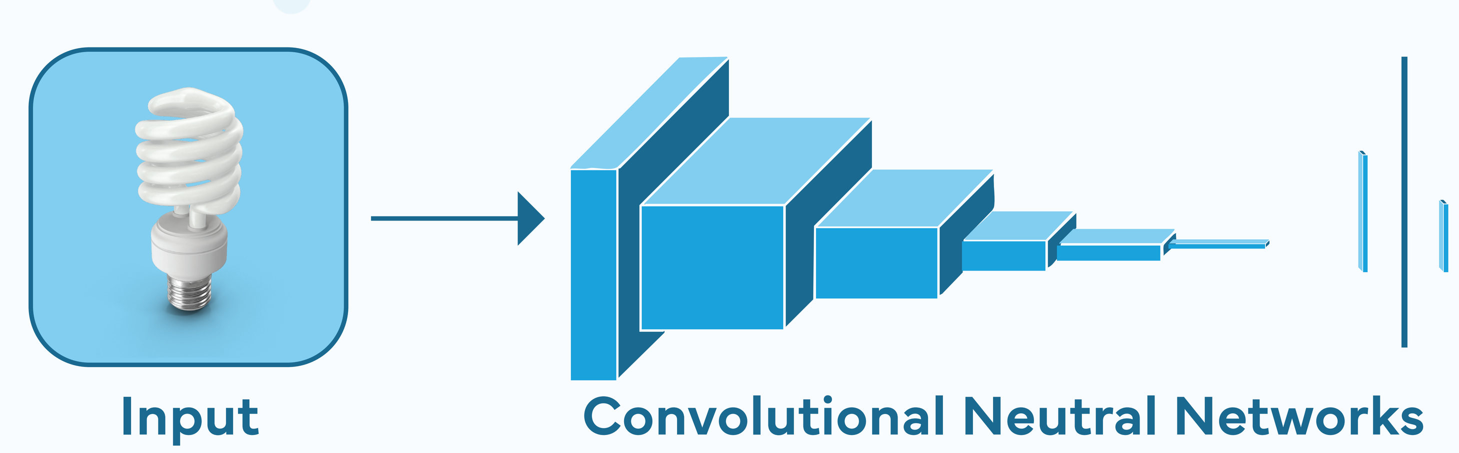
Best Performers:
- Short text: all-mpnet-base-v2 — balances accuracy and performance.
- Long text: bert-large-nli-stsb-mean-tokens — handles detailed descriptions well.



3. ML MODEL FOR IMAGE SIMILARITY

Objective: Identify visually similar products in the product guide.

Technique: Convolutional Neural Networks (CNN) based feature extraction. CNN extracts visual features from images to identify patterns and compare visual similarity between different images.



Model Evaluation: Multiple CNN models—including ResNet50, VGG16 / VGG19, InceptionV3, DenseNet, EfficientNet, MobileNetV2—were evaluated.

Best Performer: ResNet50 — due to its deep residual learning architecture and proven performance in feature extraction.

4. ENSEMBLE METHOD

Combines text and image similarity scores using a weighted approach, resulting in more accurate and robust product matches. This method ensures that both visual and descriptive cues influence the final match.

FINDINGS

- Top Text Models: all-mpnet-base-v2, bert-large-nli-stsb-mean-tokens
- Top Image Model: ResNet50
- The ensemble model showed improved accuracy and consistency across varied product categories.

LIMITATIONS

- Limited training and fine-tuning due to insufficient labeled data for machine learning models.
- System performance depends heavily on the accuracy and completeness of product details submitted by members.

IMPLICATIONS

- Establishes a scalable AI framework that can be extended to other recycling categories beyond lighting products. (examples: Paint, Smoke Alarms, etc.)
- Demonstrates potential for significant cost savings and operational efficiency through AI-driven automation within circular economy initiatives.

CONCLUSION

The AI-powered system significantly enhances the current manual process by reducing response time by approximately 80% and improving matching accuracy, leading to greater operational efficiency and consistency in decision-making.

REFERENCES

Please contact the researcher for the complete reference list.

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