Vietnam National University – HCM International University

University of the West of England

UFCFFC-30-3 – Information Technology Project

DEFENSE PRESENTATION

MOBILE APPLICATION FOR FOOD RECOMMENDATION BASED ON USER’S MOOD USING AI MODELS

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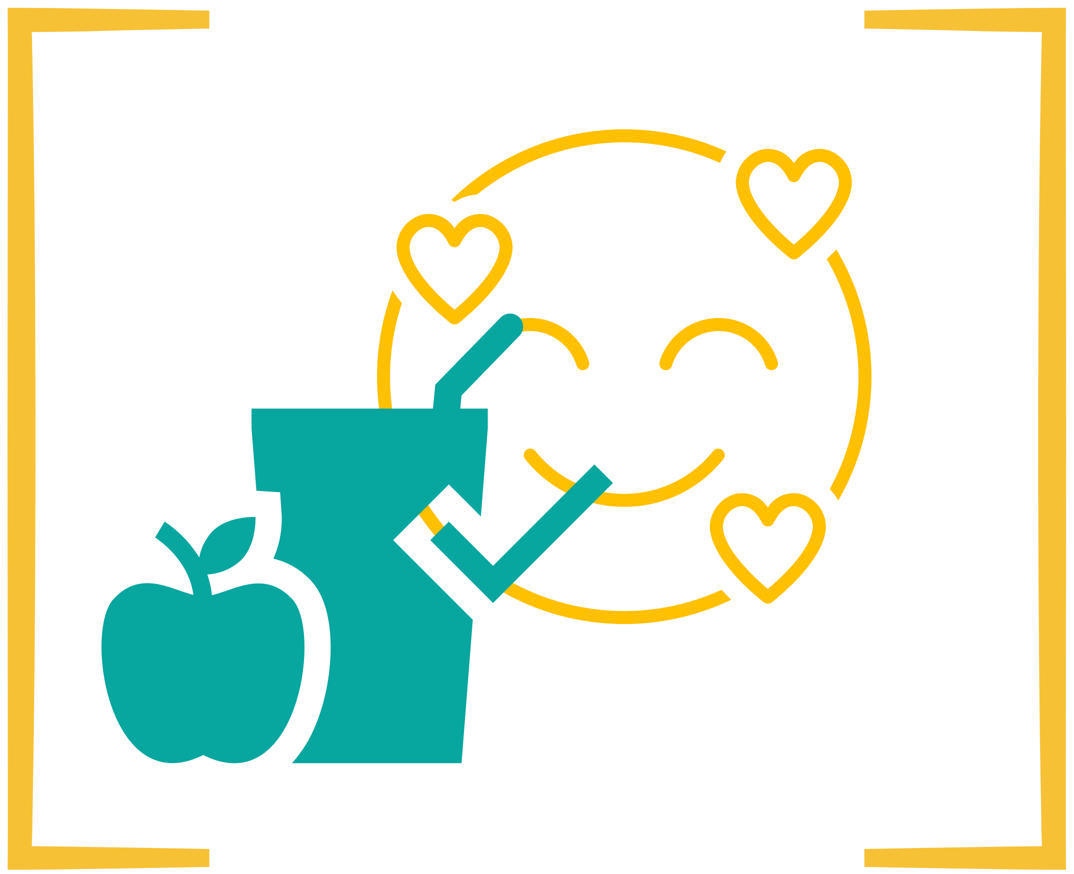
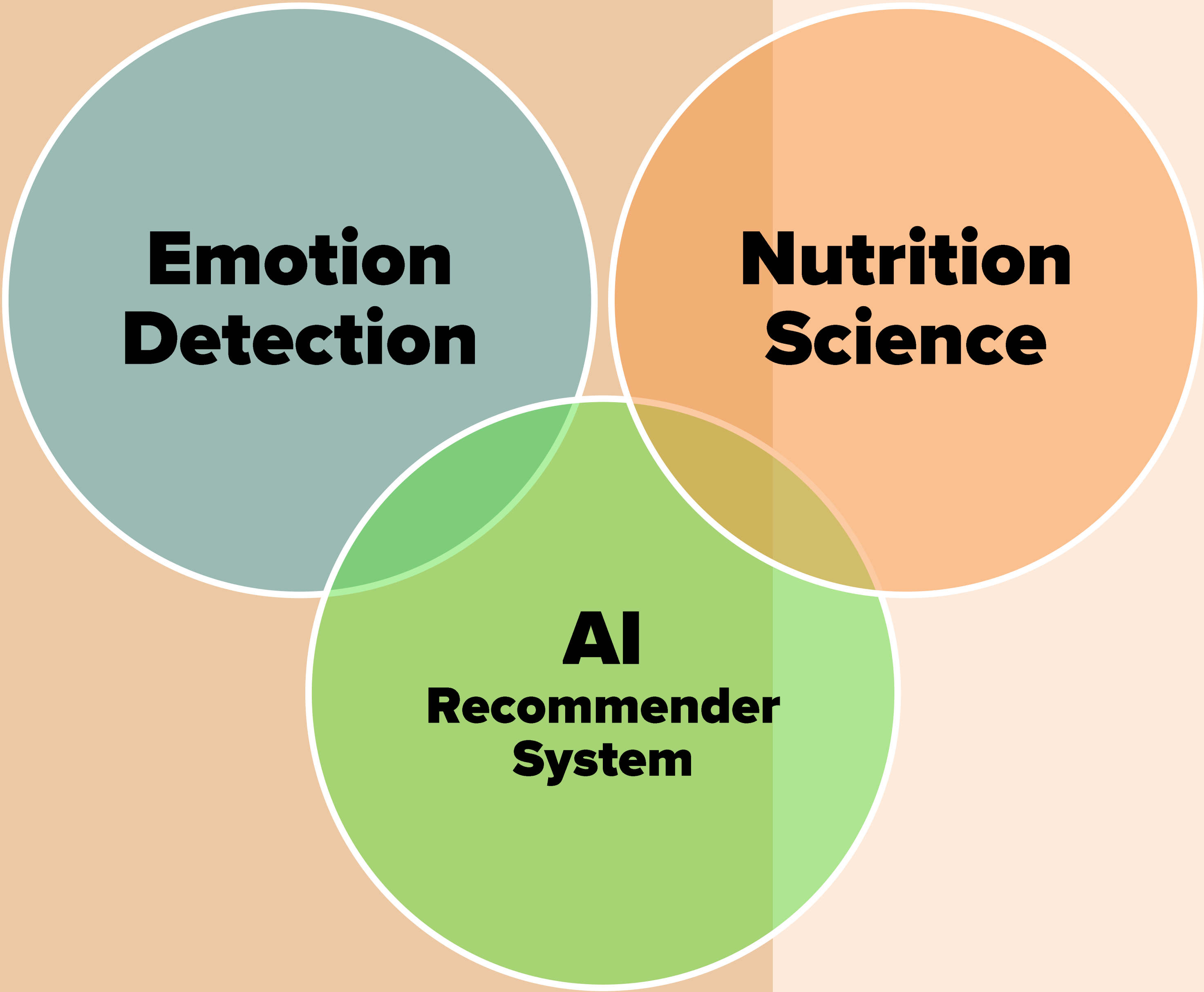


Presentation Roadmap

1. Problem & Objectives
2. Emotion Detection
3. Nutritional Science & Compatibility Scoring
4. Model Design & Training
5. Model Evaluation
6. Mobile Application
7. Demonstration
8. Limitations & Future Work
9. Q&A

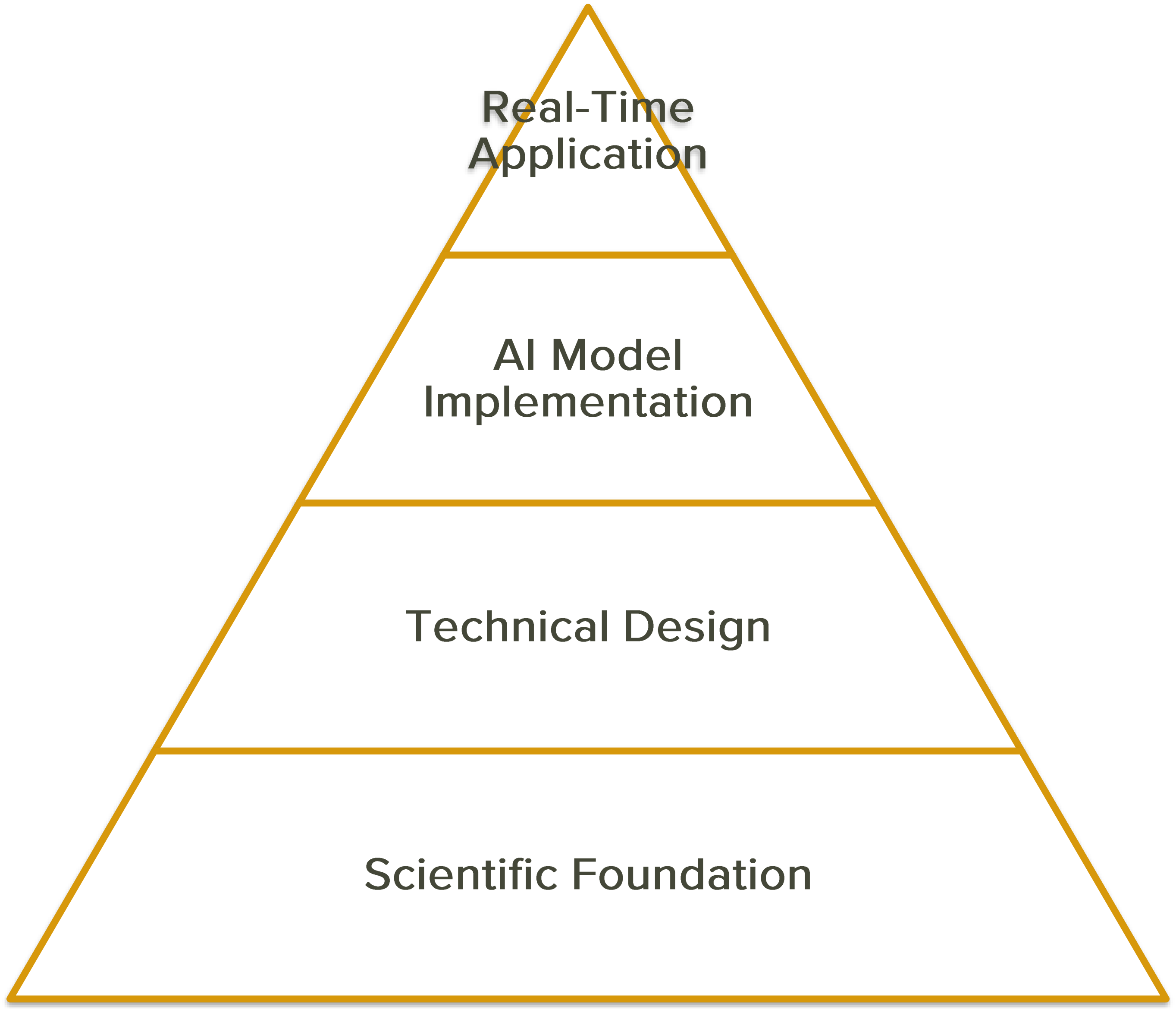
Problem & Research Gap



- Emotion drives food choices.
- Most food recommendation apps use static input. (BMI, allergies), ignore mood influence.
- **Challenge**: Combine emotion & nutrition in AI.

Research Objective

- Map psychological moods to nutrient needs
- Develop a Compatibility Scoring method
- Train a modular multi-model AI system
- Deploy a cross-platform mobile application



Emotion Detection Evolution

MFQ
(Mood and Feelings Questionnaire)

Strengths	Limitations
• Easy to implement	• Only detects negative states • No real-time detection

Pre-trained facial emotion recognition model
(Hugging Face)

Strengths	Limitations
• Fast, non-invasive • Suitable for mobile	• Depends on training quality and data bias from the pretrained model

Nutritional Science: Emotion–Nutrient Relationship

- Emotional states influence neurotransmitter and hormonal balance.
- Each mood requires specific nutrients to support emotional regulation.
- Nutrient mapping is based on psychological and nutritional studies.
- This table forms the **foundation for the scoring model** in the next stage.

TABLE I
Priority Nutrients by Emotions

Emotion	Top Priority Nutrients	Primary Functions
Sad	Polyunsaturated Fats, Vitamin D, Protein, Vitamin B6, Vitamin B12, Magnesium, Zinc	Supports serotonin production, reduces inflammation, and improves depressive symptoms
Angry	Magnesium, Vitamin C	Regulates GABA and adrenal function, helping reduce stress and emotional reactivity
Fear	Magnesium, Polyunsaturated Fats, Vitamin B6, Vitamin B12, Vitamin C	Calms the HPA axis and oxidative stress response, supporting emotional balance under fear
Disgust	Dietary Fiber, Magnesium, Zinc, Vitamin B6	Restores gut-brain balance, relieves visceral tension, and promotes mucosal healing
Neutral	Carbohydrates, Protein, Vitamin B1, B2, B5, B6, B12, Magnesium, Zinc, Iron	Maintains energy, cognitive clarity, and neurotransmitter synthesis
Happy	Protein, Carbohydrates, Vitamin D, Polyunsaturated Fats, Magnesium	Enhances serotonin synthesis and sustains emotional well-being
Surprise	Carbohydrates, Vitamin B1, B2, B3, B5, B6, B12, Protein	Boosts alertness and cognitive performance through stress adaptation and dopamine support

Compatibility Scoring Formula

1. Standardization

Normalize each nutrient value by comparing it with age-based recommended intake (actual_i / ideal_i).

2. Suitability Factor Calculation

Calculates a score (0–1) for each nutrient based on 3 cases:

- Overdose penalty (if > 2× ideal): score drops
- Underdose penalty (if < 10% ideal): score drops
- Ideal zone: score close to 1

3. Final Compatibility Score

Sum weighted suitability scores and normalize to a 0–10 scale:

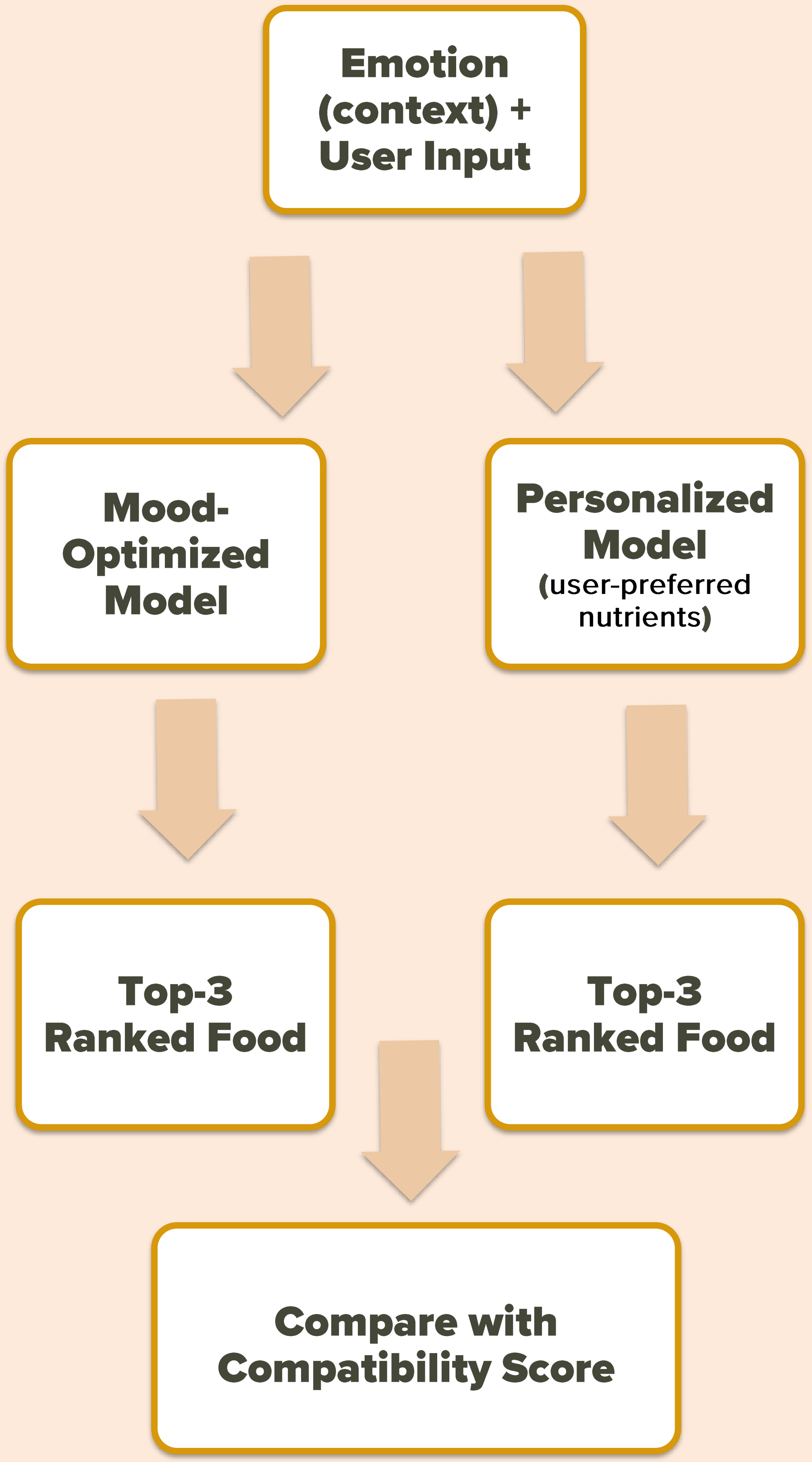
$$\text{score} = \sum_{i=1}^{n} (\text{normalized\_weight}_i \times \text{factor}_i) \times 10$$

Note: The final score ranges from 0 to 10 and reflects how well a food item fits the prioritized nutritional profile for a given emotional state.

Why Random Forest?

- Handles non-linear tabular
- Shows feature importance → interpretable
- Works without complex preprocessing
- Resistant to outliers & correlated variables
- Faster & more stable for small-to-mid datasets

Experiment A:



Objective: Train **two separate models** simultaneously:

- Model 1 ➔ recommends food compatibility based on **emotional nutrient priorities**
- Model 2 ➔ recommends foods containing user-selected nutrients

Dataset:

- 2,395 food items ➔ filtered to 230 café-style items

2 synthetic datasets:

- 4,000 mood-based samples
- 2,720 personalized samples

Issue:

- Personalized model → **overfitting**, inconsistent
- Emotion model → stable but lacks generalization

=> Led to modular integration strategy in Experiment B

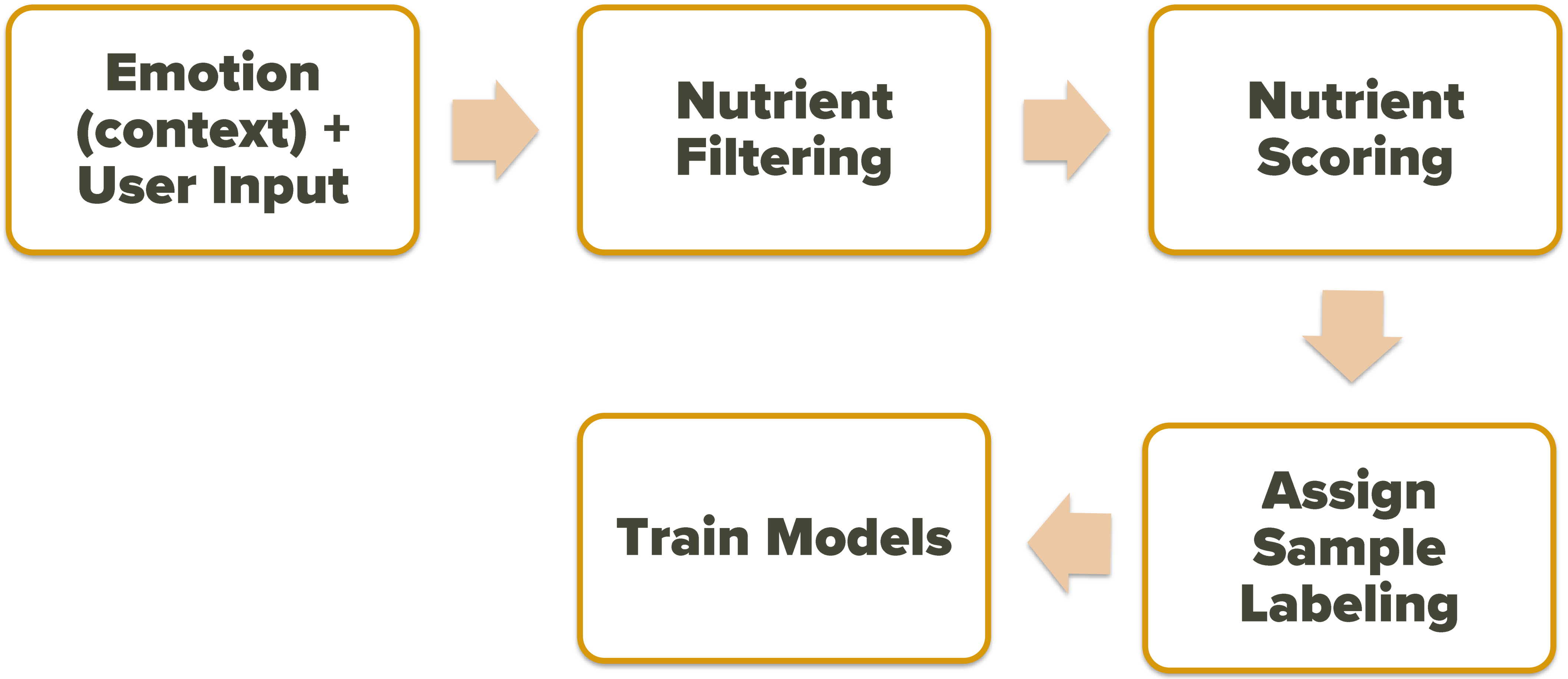
Experiment B: Overview

- **Objective:** Train **three separate models**
- **Algorithm:** Random Forest
- **Simultaneously:**
  - Regression → learn Compatibility Score directly
  - Ranking → learn relative order of foods
  - Binary classification → predict Good vs Bad match
- Each model focuses on a distinct task but shares the same underlying emotion–nutrient logic
- Final recommendation is **not based on just one model**, but through consensus and scoring integration

Experiment B: Data Generation & Features

1. Synthetic Training Dataset:

- Generate 5,000+ scenarios (each = 10 food options per user context), simulating: User IDs, Age Group, Meal Types, Food Types
- Filtered for nutritional suitability using nutrient limit thresholds
- Every sample labeling includes:
  - Compatibility scores calculated per emotion
  - Binary label: Good/Bad match
  - Ranking index

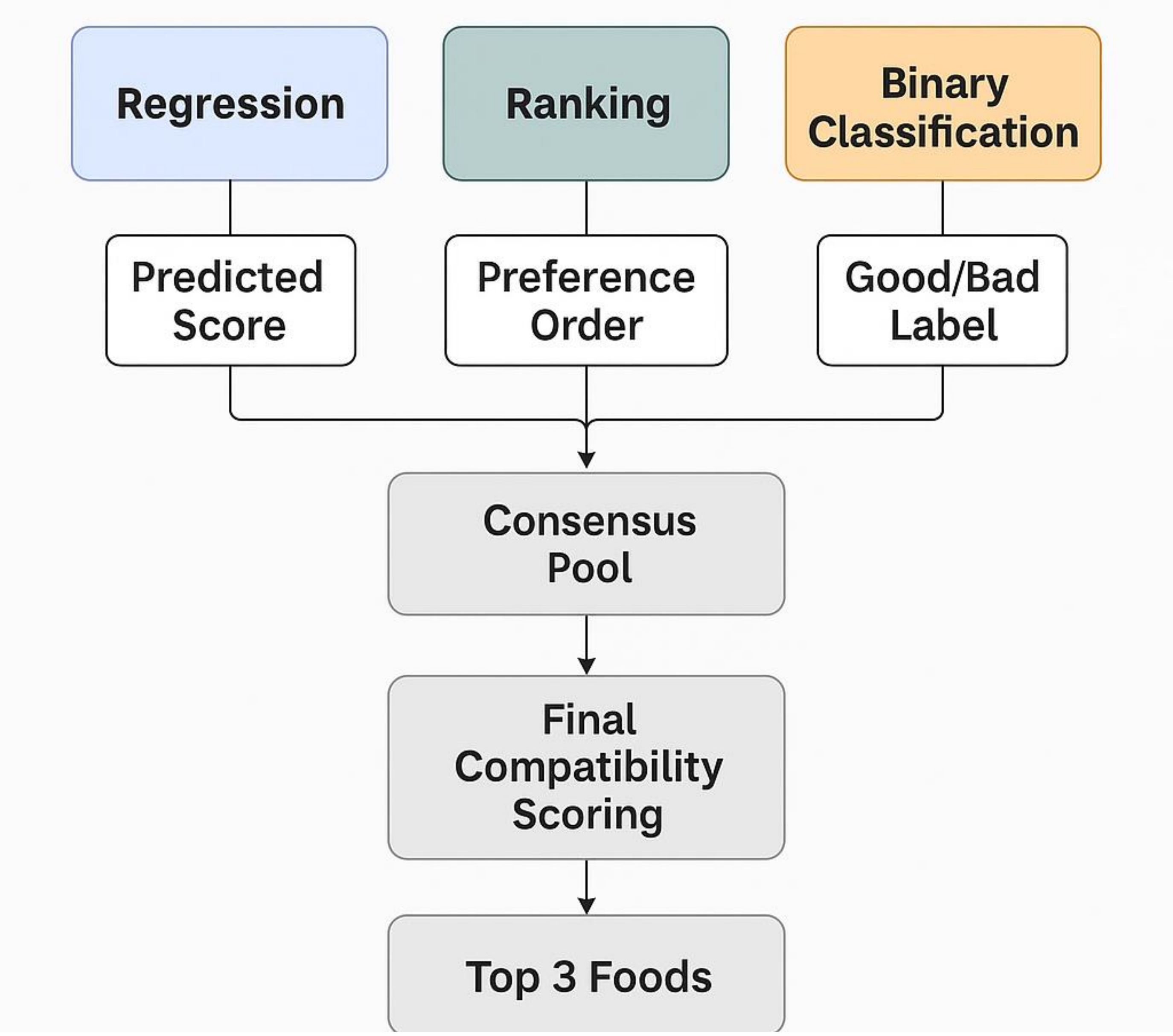


Experiment B: Data Generation & Features

2. Feature Engineering:

- Nutrient Features : All priority nutrients normalized by StandardScaler()
- Interaction Features: Emotion × Nutrient cross-terms (e.g., interaction_sad_Vitamin_B6)
- User Preference Features: User History Matrix Features (e.g. user_food_matrix)
- Contextual Features: One-hot Encoding for Meal Type, Season

Experiment B: Model Training & Integration



Training Process:

- Regression ➜ predict Compatibility Score (regression)
- Ranking ➜ learns relative preference order
- Binary classification ➜ outputs Good/Bad label
- Random Forest used due to robustness, interpretability, and resistance to outliers
- All models share same feature space engineered in previous step

Final Output:

- Top 3 recommendations per context
- Compared against ground truth (Compatibility Score Top 1 / Top 3 match)

Evaluation: Learning Curve Comparison

Evaluation Metrics:

- Random Forest Regressor: MSE and R^2
- Random Forest Classifier: confusion matrix, precision, recall, F1 Score, Accuracy

Purpose:

- Evaluate model behavior and diagnose overfitting or underfitting via 5-fold cross-validation.

Model	MSE (Train)	MSE (Test)	R^2 (Train)	R^2 (Test)	Train-Test Gap
Ranking	0.2093	0.2436	0.9748	0.9699	0.225
Regression	0.0242	0.0276	0.9935	0.9930	0.013

Model	Accuracy	Precision	Recall	F1 Score	CV Score	Train-Test Gap
Binary Classification	0.999	0.998	1.000	0.999	0.999	0.009

Evaluation: Accuracy vs. Performance

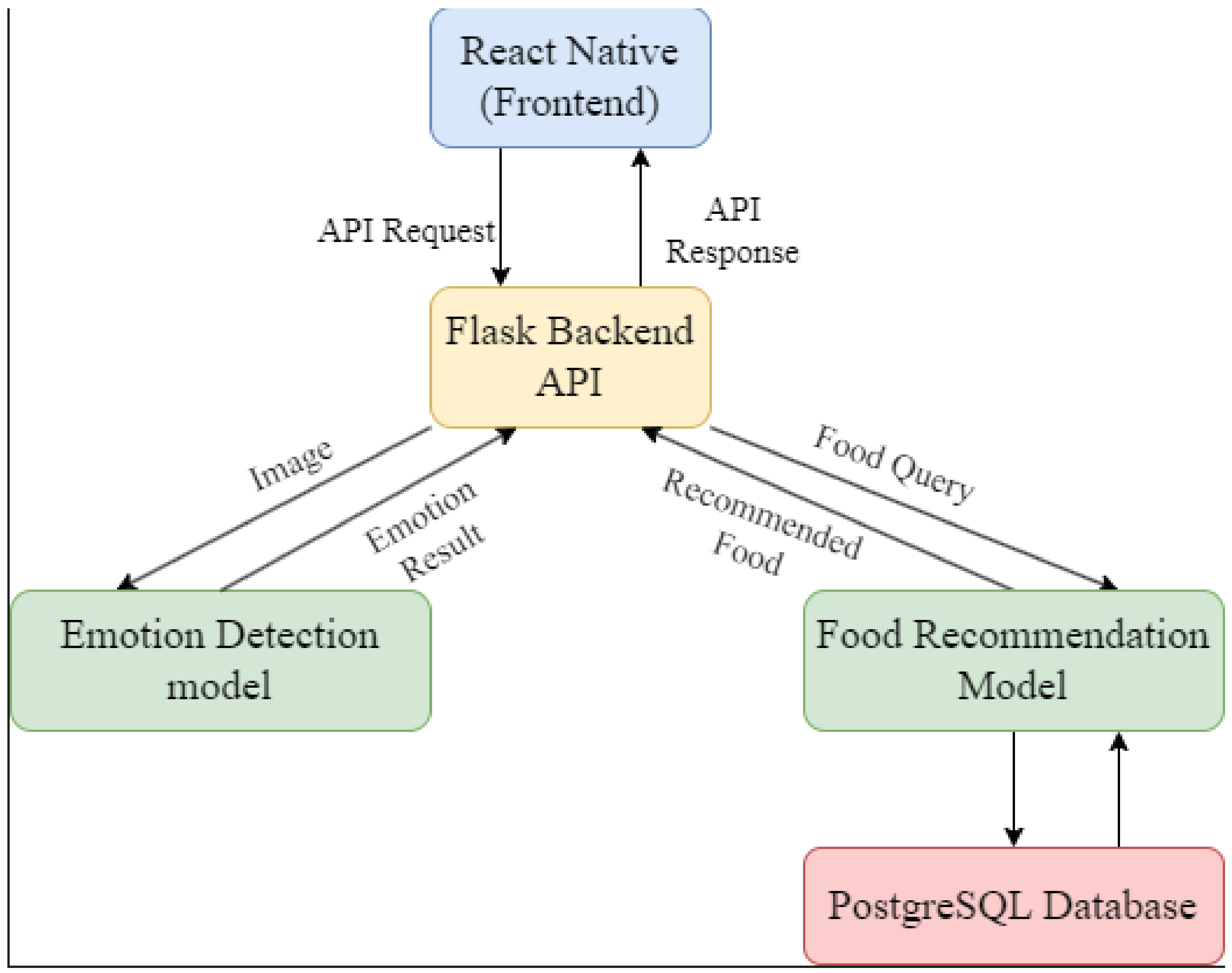
Metrics Used:

- Top-1 Accuracy – How often the top model suggestion matches the correct one.
- Top-3 Overlap – % of overlap between top-3 predictions and compatibility score ranking
- Average Processing Time – Speed per recommendation
- Evaluated on 294 input conditions:
  - Full dataset (1,157 foods)
  - Reduced dataset (147 foods for mobile testing with 21 foods for each type)

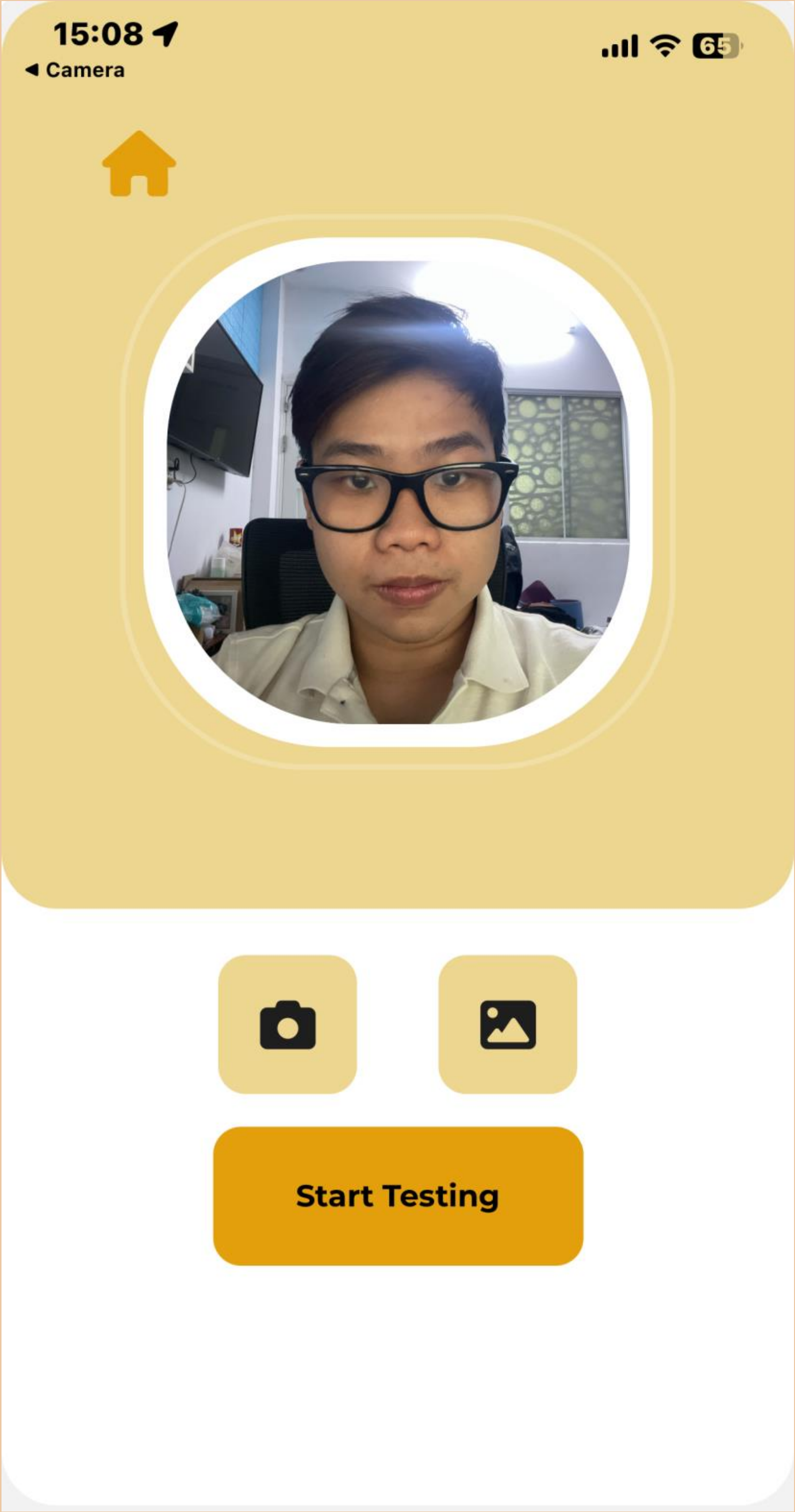
Dataset	Top-1 Accuracy	Top-3 Overlap	Avg. Time (sec)
Full (1157 items)	87.07%	74.72%	4.93
Reduced (147 items)	94.90%	86.05%	0.85

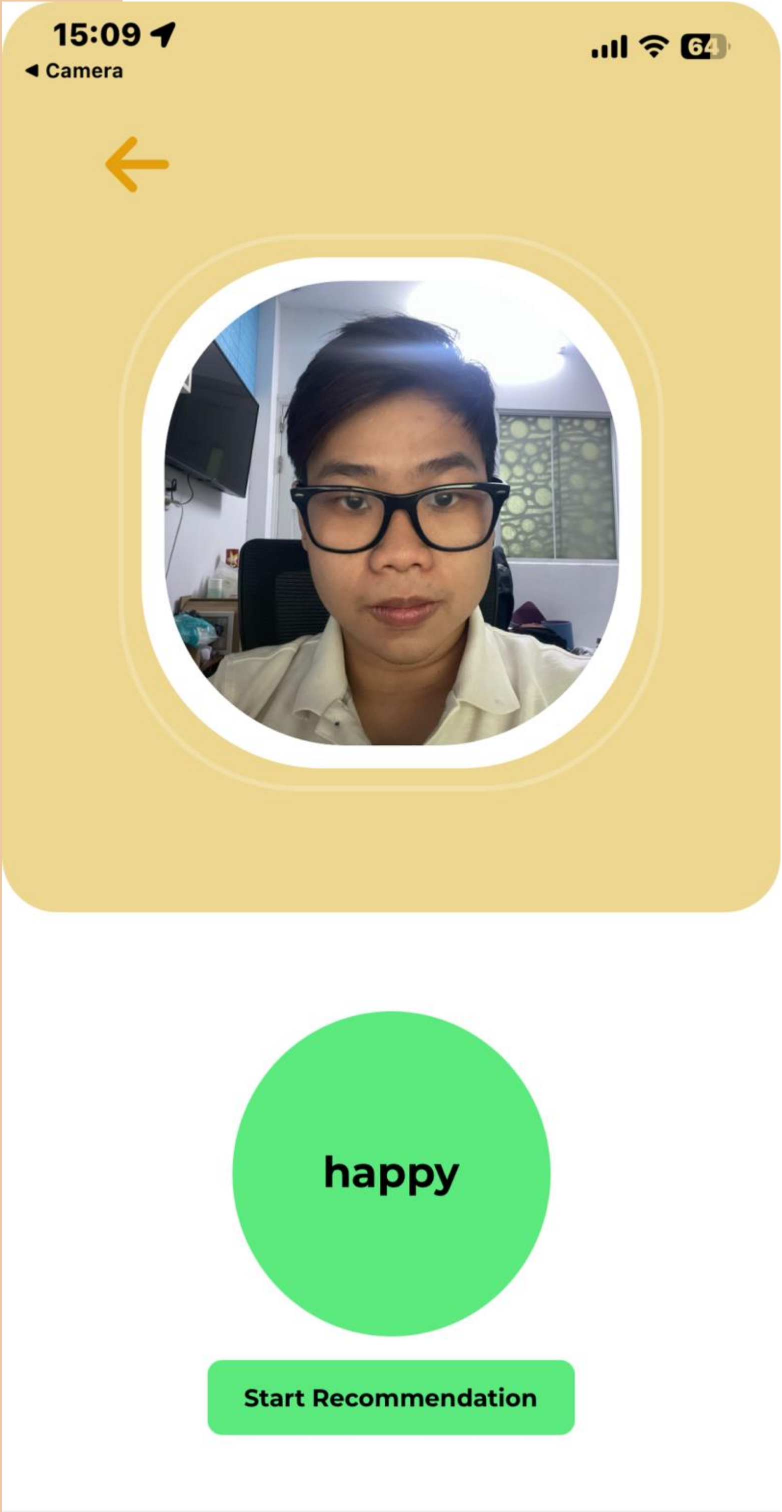
Mobile App Architecture

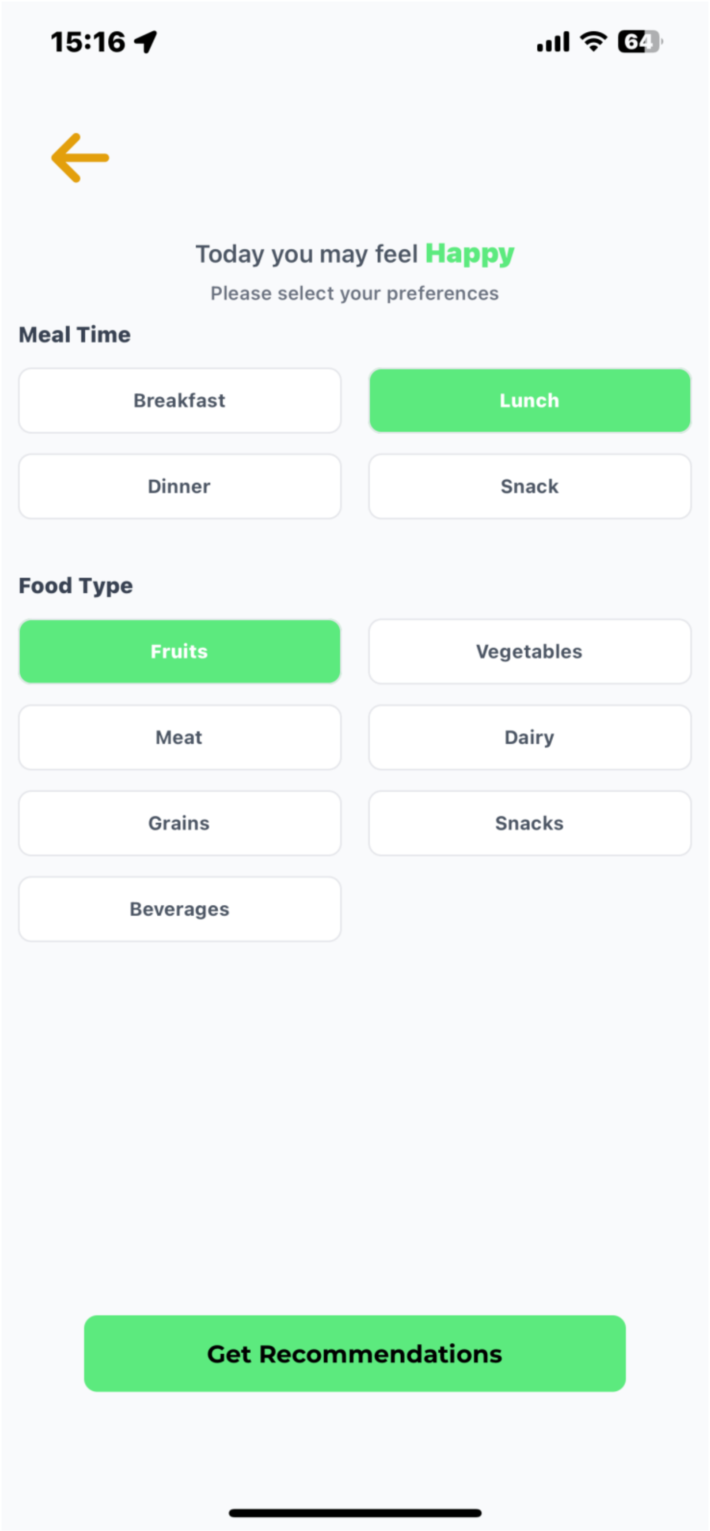
- **Frontend:** React Native + Expo Go (cross-platform, mobile-optimized)
- **Backend:** Python Flask API
- **Database:**
  - PostgreSQL (user info, history, nutrition scores)
  - CSV (static food list, image, display name)
- **AI Model:** Deployed as REST API endpoint

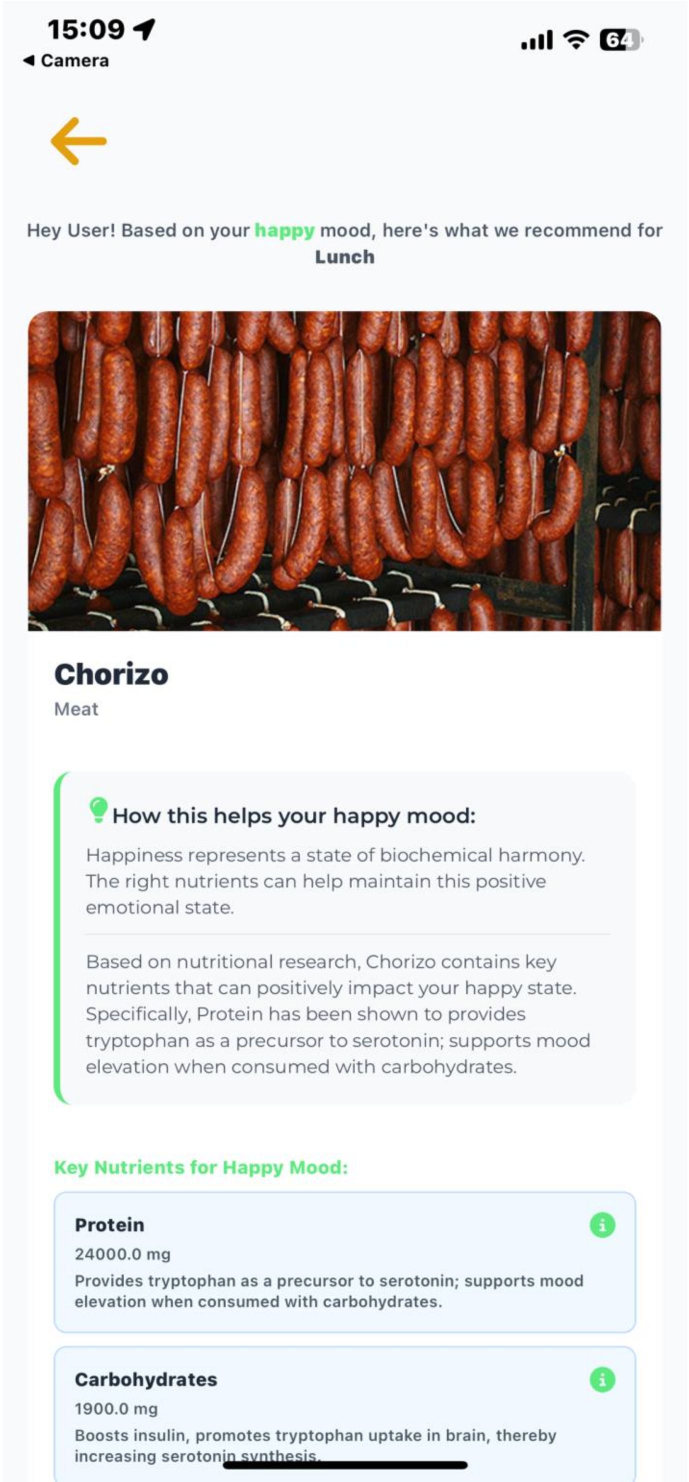


Mobile App Feature









Demonstration

Limitation

- **No real user testing yet ➔** Current evaluation is technical, using synthetic and simulated data
- **Lack of expert consultation in nutrition and psychology ➔** Nutrient-emotion mappings were derived from literature, but not clinically validated by professionals

Future Work

- **Conduct real-world user testing➔** Evaluate emotional outcomes, not just accuracy
- **Integrate multimodal emotion input➔** e.g., facial + text + voice for richer mood detection
- Paper submitted to CICET 2025 (awaiting result on May 27) – based on this thesis work

Q&A