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Memowee: Face Recognition System for Dementia Patient Care

Project Documentation

A Final Project

Presented to Mr. John Christopher Mateo

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West Visayas State University

La Paz, Iloilo City

In Partial Fulfillment

of the Requirements for the Course

CCS 248: Artificial Neural Networks

By

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Problem

Dementia is a progressive neurological disorder that impairs cognitive function, including memory loss and difficulty recognizing familiar people. Patients with dementia often struggle to identify family members, caregivers, and close friends, creating emotional distress for both the patient and their loved ones.

Memowee addresses this challenge by developing a face recognition system that allows dementia patients (or their caregivers) to pre-register known persons with their facial profiles and automatically identify them when they appear. The system displays contextual information (name, relationship, description) to help patients reconnect with their loved ones.

Dataset Preparation

The project uses a **subset of the VGGFace2** dataset (from Kaggle), which contains a large-scale collection of face images with variations in pose, age, lighting, and expression.[3] The subset was extracted and organized into train/validation folders, then renamed as **MEMOWEE_DATASET** for project convenience.

1. **MEMOWEE_DATASET Statistics**
   - Training Samples: 18,400 face image pairs
   - Validation Samples: 2,400 face image pairs
   - Total identities: Multiple persons across various demographic groups
   - Image format: JPEG, resized to 128×128 pixels
2. **Data Preprocessing**
   1. Image Loading: Images are loaded using OpenCV and converted from BGR to RGB color space.
   2. Resizing: All images are resized to 128×128 pixels to match the model input.
   3. Normalization: Pixel values are normalized to [0, 1] by dividing by 255.
   4. Augmentation (during training):
      a. Random Horizontal Lines
      b. Random Rotations (±10%)
      c. Random Zoom (±10%)

Data Validation and Quality Checks

1. **Bias Assessment:**

VGGFace2 is a well-established benchmark dataset with diverse identities, ages, and ethnicities, reducing demographic bias. [3]

2. **Privacy Considerations:**
    - VGGFace2 is properly licensed for academic research use.
    - The system stores 128-dimensional face embeddings (not raw images), reducing privacy exposure.
    - Patient profiles are stored locally and access-controlled.

Chosen Deep Neural Network

Siamese Neural Network with Contrastive Learning is chosen because:

- Face verification is inherently a similarity-learning task requiring the network to determine if two faces belong to the same person.[4]
- Siamese networks excel at one-shot and few-shot learning, suitable for scenarios where patients may register only a few photos per person.
- Contrastive loss directly optimizes learned embeddings: same-person pairs are close, different-person pairs are far apart.

Network Architecture

Embedding Model (Shared between Siamese inputs):

Layer	Output Shape	Parameters	Details
Input	(128, 128, 3)	0	RGB Images
Random Flip	(128, 128, 3)	0	Horizontal flip augmentation
RandomRotation	(128, 128, 3)	0	±10° rotation augmentation
RandomZoom	(128, 128, 3)	0	±10% zoom augmentation
Conv2D Block 1	(128, 128, 32)	896	32 filters, 3×3 kernel, ReLU, L2 regularizer (1e-4)
MaxPooling2D 1	(64, 64, 32)	0	2×2 pooling
Dropout 1	(64, 64, 32)	0	0.25 dropout
Conv2D Block 2	(64, 64, 64)	18,496	64 filters, 3×3 kernel, ReLU, L2 regularizer (1e-4)
MaxPooling2D 2	(32, 32, 64)	0	2×2 pooling
Dropout 2	(32, 32, 64)	0	0.25 dropout
Conv2D Block 3	(32, 32, 128)	73,856	128 filters, 3×3 kernel, ReLU, L2 regularizer (1e-4)
MaxPooling2D 3	(16, 16, 128)	0	2×2 pooling
Dropout 3	(16, 16, 128)	0	0.25 dropout
Flatten	(32,768)	0	Flattens spatial dimensions
Dense	(128)	4,194,432	128 units, ReLU, L2 regularizer (1e-4)
L2 Normalization	(128)	0	Unit-norm embedding output

Total Parameters: 4,287,680 (16.36 MB)

Trainable Parameters: 4,287,680

Non-Trainable Parameters: 0

Training Configuration

Loss Function:

Contrastive Loss is used to train the Siamese network

$$L = y \cdot d^2 + (1 - y) \cdot \max(margin - d, 0)^2$$

Where:

- $y = 1$ for same-person pairs (positive pairs)
- $y = 0$ for different-person pairs (negative pairs)
- d = Euclidean distance between embeddings
- $margin = 1.0$

This loss encourages small distances for same-person pairs and large distances for different-person pairs.

Optimizer and Learning Rate Strategy

Parameter	Value
Optimizer	Adam
Initial Learning Rate	0.001
Learning Rate Schedule	ReduceLROnPlateau
LR Reduction Factor	0.5 (reduce by 50% when val_loss plateaus)
Patience	3 epochs without improvement
Minimum Learning Rate	1e-6
Loss Monitor	val_loss (validation loss)

Adam is chosen for its adaptive learning rates and efficiency. ReduceLROnPlateau dynamically adjusts the learning rate based on validation performance, improving convergence.

Training Configuration Summary

Parameter	Value
Batch Size	32
Number of Epochs	30
Image Size	128×128 pixels
Data Generator	Custom SiameseDataGenerator (online pair generation)
Training Pairs	18,400
Validation Pairs	2,400
Pair Generation	For each anchor image: 1 positive pair + 1 negative pair per batch

Hyper Parameter Tuning Records

The model was trained for 30 epochs with continuous monitoring of training and validation metrics. Key epochs are recorded below:

```
Epoch 1/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 604s 1s/step - contrastive_accuracy_metric: 0.5440 - loss: 0.2696 - val_contrastive_accuracy_metric: 0.5819 - val_loss: 0.2394 - learning_rate: 0.0010
Epoch 2/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 602s 1s/step - contrastive_accuracy_metric: 0.5811 - loss: 0.2406 - val_contrastive_accuracy_metric: 0.6110 - val_loss: 0.2282 - learning_rate: 0.0010
Epoch 3/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 604s 1s/step - contrastive_accuracy_metric: 0.5953 - loss: 0.2327 - val_contrastive_accuracy_metric: 0.6027 - val_loss: 0.2244 - learning_rate: 0.0010
Epoch 4/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 600s 1s/step - contrastive_accuracy_metric: 0.6022 - loss: 0.2303 - val_contrastive_accuracy_metric: 0.6285 - val_loss: 0.2217 - learning_rate: 0.0010
Epoch 5/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 571s 993ms/step - contrastive_accuracy_metric: 0.6098 - loss: 0.2268 - val_contrastive_accuracy_metric: 0.6510 - val_loss: 0.2139 - learning_rate: 0.0010
Epoch 6/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 505s 878ms/step - contrastive_accuracy_metric: 0.6191 - loss: 0.2249 - val_contrastive_accuracy_metric: 0.6438 - val_loss: 0.2108 - learning_rate: 0.0010
Epoch 7/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 504s 876ms/step - contrastive_accuracy_metric: 0.6224 - loss: 0.2231 - val_contrastive_accuracy_metric: 0.6708 - val_loss: 0.2142 - learning_rate: 0.0010
Epoch 8/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 501s 871ms/step - contrastive_accuracy_metric: 0.6299 - loss: 0.2196 - val_contrastive_accuracy_metric: 0.6596 - val_loss: 0.2058 - learning_rate: 0.0010
Epoch 9/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 501s 871ms/step - contrastive_accuracy_metric: 0.6380 - loss: 0.2164 - val_contrastive_accuracy_metric: 0.6706 - val_loss: 0.2070 - learning_rate: 0.0010
Epoch 10/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 494s 860ms/step - contrastive_accuracy_metric: 0.6401 - loss: 0.2155 - val_contrastive_accuracy_metric: 0.6777 - val_loss: 0.2031 - learning_rate: 0.0010
Epoch 11/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 493s 857ms/step - contrastive_accuracy_metric: 0.6530 - loss: 0.2127 - val_contrastive_accuracy_metric: 0.6715 - val_loss: 0.2100 - learning_rate: 0.0010
Epoch 12/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 500s 870ms/step - contrastive_accuracy_metric: 0.6496 - loss: 0.2123 - val_contrastive_accuracy_metric: 0.6719 - val_loss: 0.2003 - learning_rate: 0.0010
Epoch 13/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 499s 867ms/step - contrastive_accuracy_metric: 0.6588 - loss: 0.2100 - val_contrastive_accuracy_metric: 0.6908 - val_loss: 0.1982 - learning_rate: 0.0010
Epoch 14/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 506s 880ms/step - contrastive_accuracy_metric: 0.6609 - loss: 0.2084 - val_contrastive_accuracy_metric: 0.6800 - val_loss: 0.1974 - learning_rate: 0.0010
Epoch 15/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 480s 835ms/step - contrastive_accuracy_metric: 0.6638 - loss: 0.2068 - val_contrastive_accuracy_metric: 0.7079 - val_loss: 0.1959 - learning_rate: 0.0010
Epoch 16/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 467s 813ms/step - contrastive_accuracy_metric: 0.6691 - loss: 0.2046 - val_contrastive_accuracy_metric: 0.7198 - val_loss: 0.1941 - learning_rate: 0.0010
Epoch 17/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 500s 870ms/step - contrastive_accuracy_metric: 0.6670 - loss: 0.2074 - val_contrastive_accuracy_metric: 0.6956 - val_loss: 0.1958 - learning_rate: 0.0010
Epoch 18/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 474s 825ms/step - contrastive_accuracy_metric: 0.6717 - loss: 0.2048 - val_contrastive_accuracy_metric: 0.6975 - val_loss: 0.1971 - learning_rate: 0.0010
Epoch 19/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 500s 870ms/step - contrastive_accuracy_metric: 0.6723 - loss: 0.2044 - val_contrastive_accuracy_metric: 0.7100 - val_loss: 0.1934 - learning_rate: 0.0010
Epoch 20/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 509s 886ms/step - contrastive_accuracy_metric: 0.6777 - loss: 0.2029 - val_contrastive_accuracy_metric: 0.7069 - val_loss: 0.1901 - learning_rate: 0.0010
Epoch 21/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 476s 828ms/step - contrastive_accuracy_metric: 0.6798 - loss: 0.2023 - val_contrastive_accuracy_metric: 0.7144 - val_loss: 0.1887 - learning_rate: 0.0010
Epoch 22/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 492s 856ms/step - contrastive_accuracy_metric: 0.6787 - loss: 0.2025 - val_contrastive_accuracy_metric: 0.6910 - val_loss: 0.1960 - learning_rate: 0.0010
Epoch 23/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 487s 847ms/step - contrastive_accuracy_metric: 0.6801 - loss: 0.2013 - val_contrastive_accuracy_metric: 0.7050 - val_loss: 0.1927 - learning_rate: 0.0010
Epoch 24/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 0s 805ms/step - contrastive_accuracy_metric: 0.6808 - loss: 0.2014
Epoch 24: ReduceLROnPlateau reducing learning rate to 0.0005000000237487257.
575/575 ━━━━━━━━━━━━━━━━━━━━ 479s 833ms/step - contrastive_accuracy_metric: 0.6804 - loss: 0.2017 - val_contrastive_accuracy_metric: 0.6823 - val_loss: 0.1980 - learning_rate: 0.0010
Epoch 25/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 478s 831ms/step - contrastive_accuracy_metric: 0.6911 - loss: 0.1961 - val_contrastive_accuracy_metric: 0.7319 - val_loss: 0.1831 - learning_rate: 5.0000e-04
Epoch 26/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 476s 828ms/step - contrastive_accuracy_metric: 0.6948 - loss: 0.1930 - val_contrastive_accuracy_metric: 0.7260 - val_loss: 0.1821 - learning_rate: 5.0000e-04
Epoch 27/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 478s 831ms/step - contrastive_accuracy_metric: 0.6952 - loss: 0.1922 - val_contrastive_accuracy_metric: 0.7260 - val_loss: 0.1798 - learning_rate: 5.0000e-04
Epoch 28/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 479s 833ms/step - contrastive_accuracy_metric: 0.6961 - loss: 0.1910 - val_contrastive_accuracy_metric: 0.7219 - val_loss: 0.1789 - learning_rate: 5.0000e-04
Epoch 29/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 481s 836ms/step - contrastive_accuracy_metric: 0.6980 - loss: 0.1898 - val_contrastive_accuracy_metric: 0.7229 - val_loss: 0.1823 - learning_rate: 5.0000e-04
Epoch 30/30
575/575 ━━━━━━━━━━━━━━━━━━━━ 498s 866ms/step - contrastive_accuracy_metric: 0.6997 - loss: 0.1897 - val_contrastive_accuracy_metric: 0.7306 - val_loss: 0.1806 - learning_rate: 5.0000e-04
```

Results and Evaluation

Metric	Value
Final Training Accuracy	69.97%
Final Validation Accuracy	73.06%
Final Training Loss	0.1897
Final Validation Loss	0.1806

Interpretation

- **Above Requirement**: The project requirement is ≥50–60% accuracy. This model achieves 73.06% validation accuracy, well exceeding the baseline.
- **Good generalization**: Validation accuracy slightly exceeds training accuracy, indicating the model generalizes well without overfitting.
- **Steady convergence**: Both losses decrease monotonically, confirming effective learning throughout training.
- **Learning rate adjustment**: The ReduceLROnPlateau callback reduced the learning rate at epoch 20, contributing to final convergence.

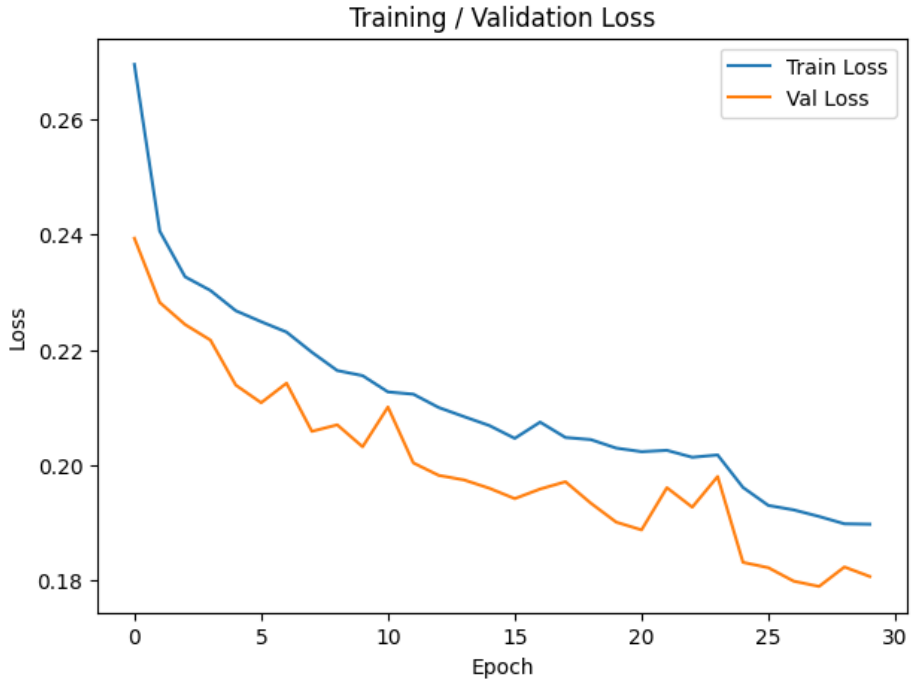

Fig 1. Training and Validation Loss

6. Application Overview

Memowee's Process Flow

- Registration Phase
  1. A caregiver enters the known person's name, relationship (e.g., "daughter"), and a personal note.
  2. A face image is captured or uploaded.
  3. The backend extracts a 128-dimensional embedding using the trained CNN.
  4. The embedding and profile are stored in a secure database.

- Identificaton Phase
  1. When the person appears before the patient, an image is captured.
  2. The system extracts the embedding and compares it to all registered profiles.
  3. If a match is found (distance < threshold), the person's name, relationship, and note are displayed.
  4. If no match is found, the system returns "unknown."

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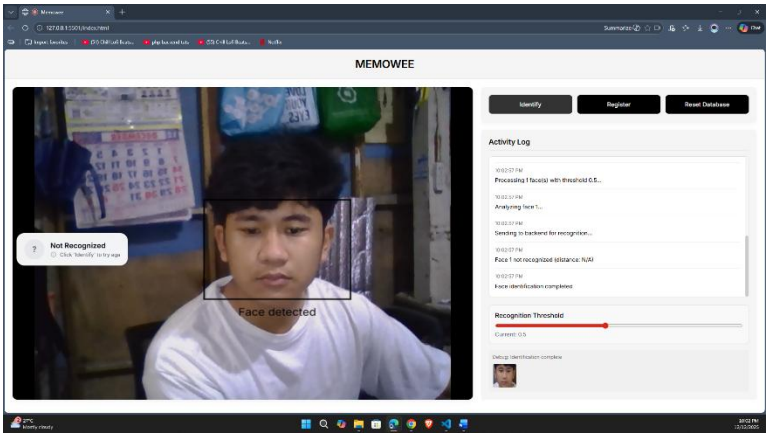
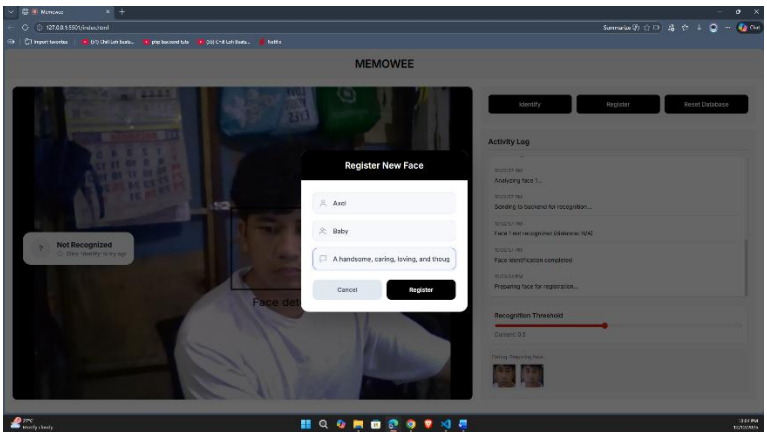
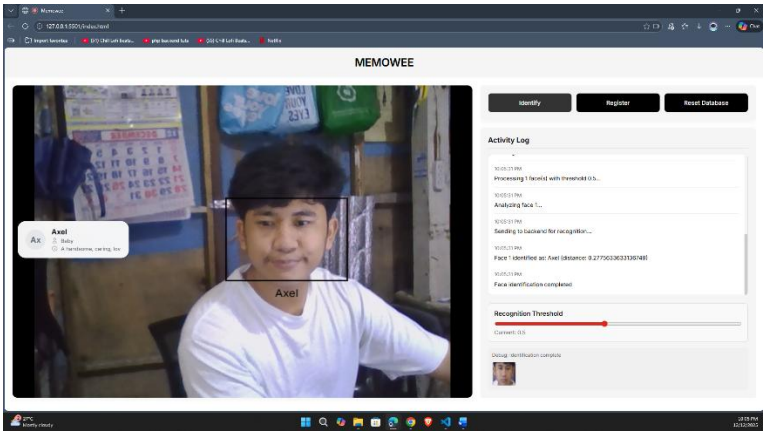
Screenshots

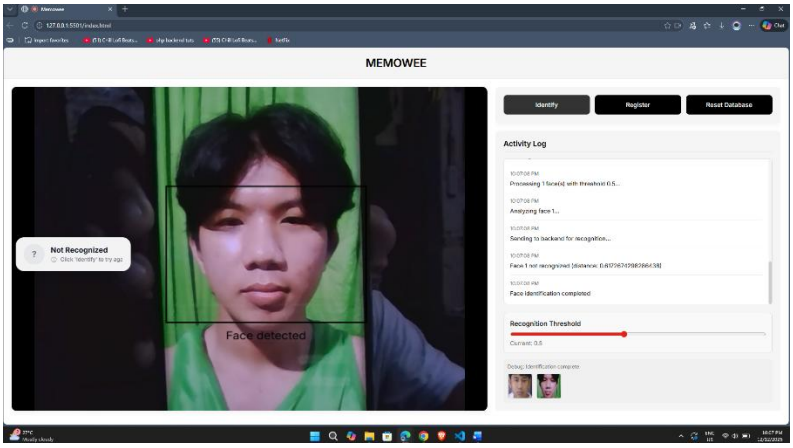
1. Axel

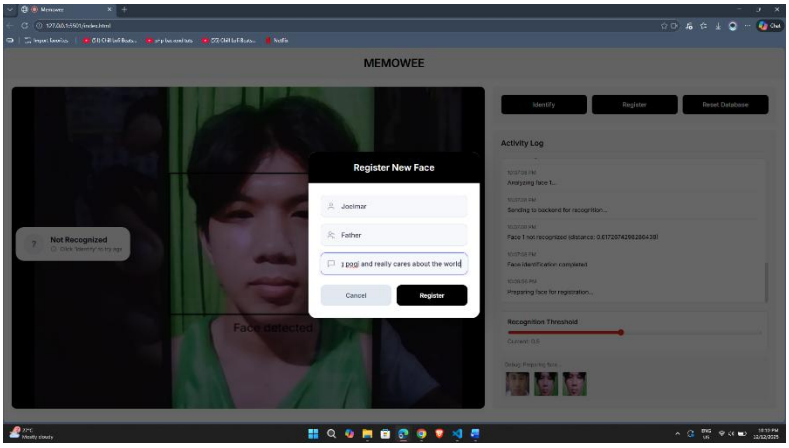


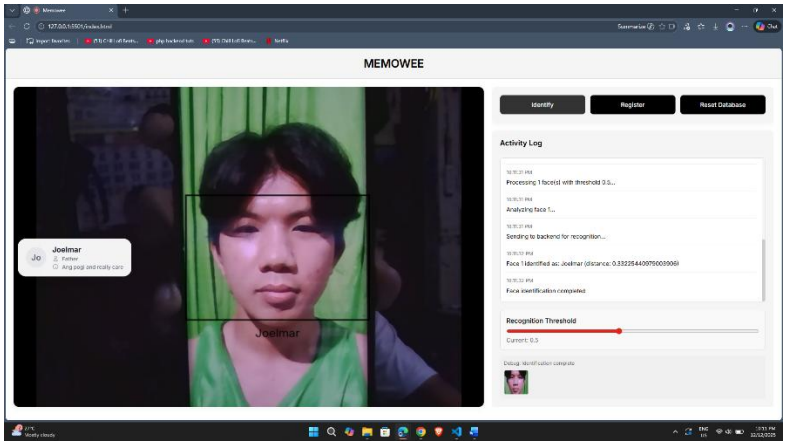




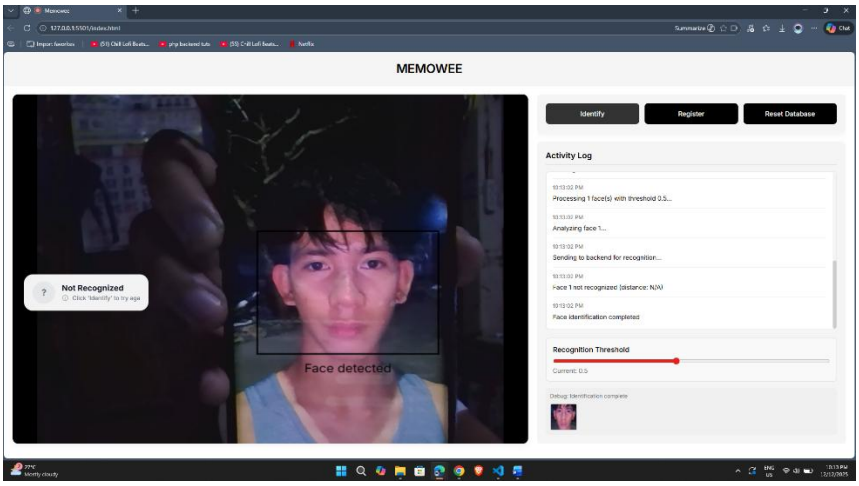
2. **Joelmar**

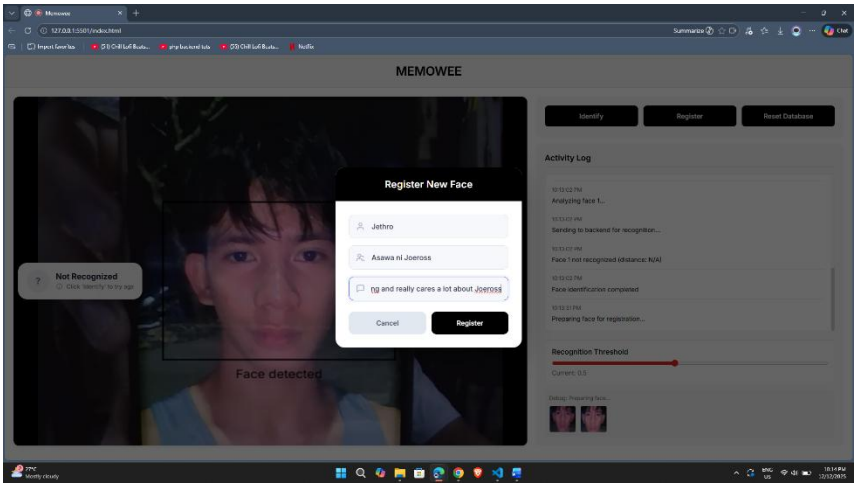

MEMOWEE
Identify
Register
Reset Database
Activity Log
Not Recognized
Face detected
Recognition Threshold

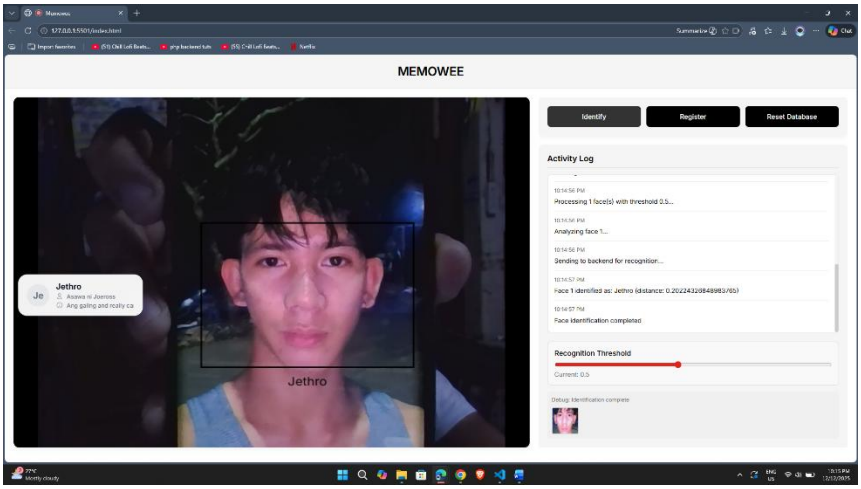

MEMOWEE
Register New Face
Joelmar
Father
Cancel
Register
Not Recognized
Face detected


MEMOWEE
Identify
Register
Reset Database
Activity Log
Joelmar
Recognition Threshold

3. **Jethro**


MEMOWEE
Identify
Register
Reset Database
Activity Log
Not Recognized
Face detected
Recognition Threshold


MEMOWEE
Register New Face
Jethro
Asawa ni Joeross
Cancel
Register
Not Recognized
Face detected
Activity Log
Recognition Threshold


MEMOWEE
Identify
Register
Reset Database
Activity Log
Jethro
Jethro
Recognition Threshold