2025 NTU Computer Vision Final Project

IRIS RECOGNITION CHALLENGE

Presented by **Trams**

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From Separate Components to Unified Pipeline

Traditional Pipeline:

Image → Mixed features and rules → Complex matching

Our Hybrid Pipeline:

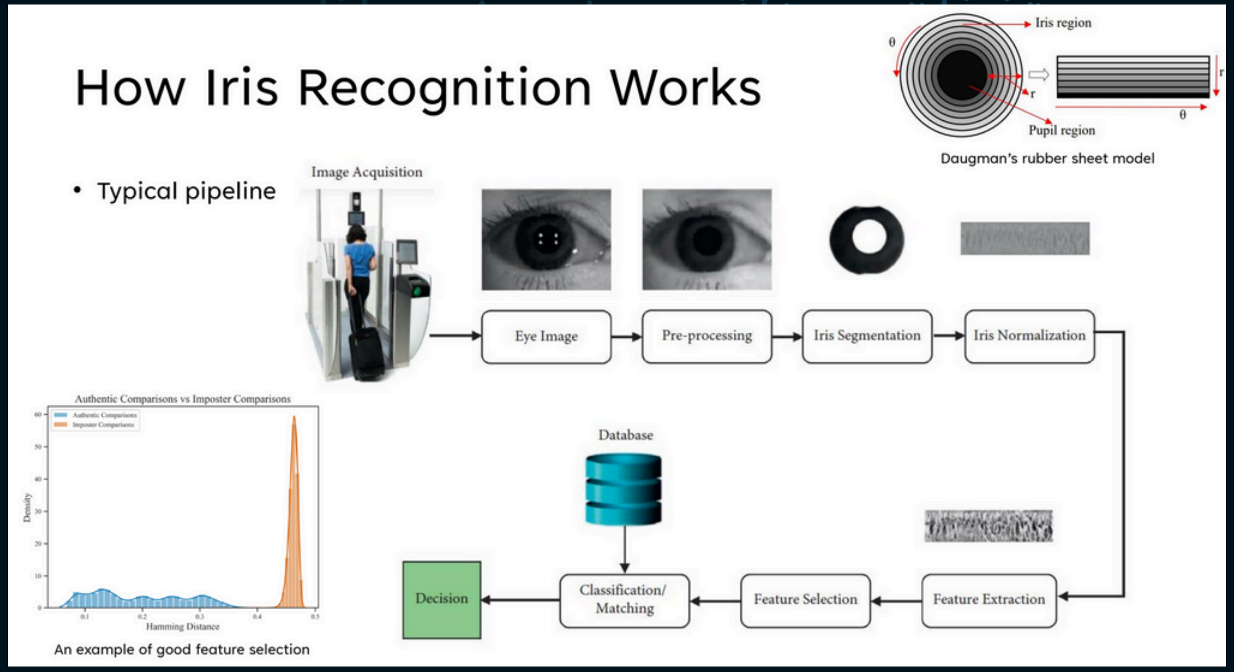
Image → Neural segmentation → Neural detection → Neural features → Calibrated matching

Quick Context:

- **HDBIF:** Binary encoding method using human-designed filters (traditional binary features)
- **TripletNN:** Neural network approach for iris feature extraction (modern neural features)

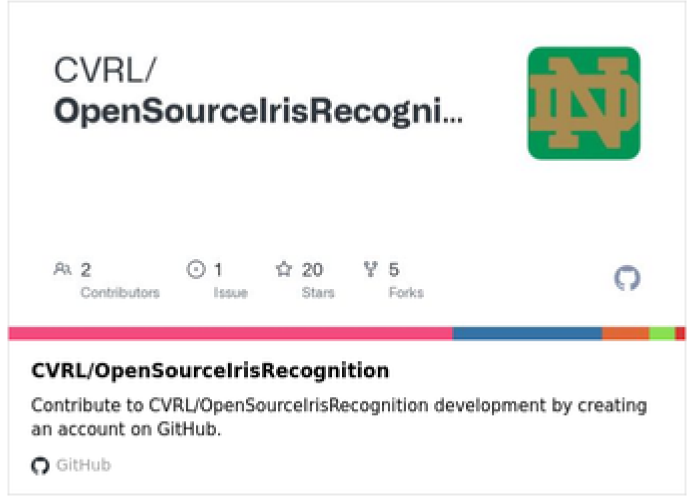
Key Innovation:

Unified pre-trained neural models from HDBIF and TripletNN with sigmoid probability calibration



Iris Recognition Methods: Original vs Our Hybrid Approach

Our integration is based on models from:



Original HDBIF Method

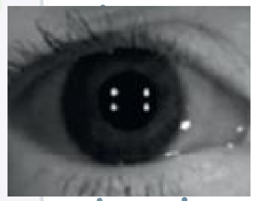
- Eye Image
- Segmentation — *NestedSharedAtrousResUNet*
- Circle Detection — *Hough Transform*
- Polar Transform — *Unwrap iris*
- Apply BSIF Filters — *17 human-driven filters*
- Binary Code — *e.g., 10110101...*
- Hamming Distance — *With normalization*

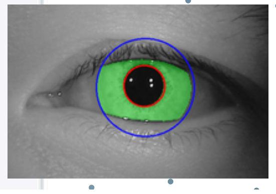
Original TripletNN Method

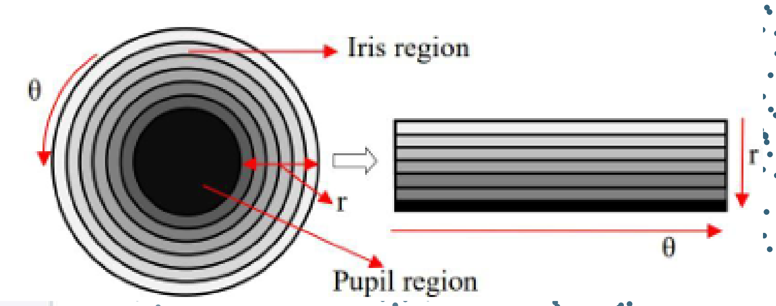
- Eye Image
- Circle Detection — *ResNet18*
- Polar Transform — *Unwrap iris*
- ConvNeXt-tiny — *Triplet loss trained*
- Feature Vector — *2048 dimensions*
- Euclidean Distance — *Raw distance value*

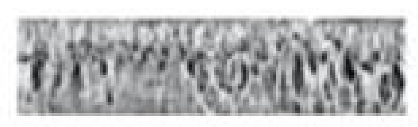
Our Hybrid Method

- Eye Image
- Segmentation — *NestedSharedAtrousResUNet*
- Circle Detection — *ResNet18*
- Polar Transform — *Bilinear interpolation*
- ConvNeXt-tiny — *Feature extraction*
- Feature Vector — *2048 dimensions*
- Sigmoid Distance — *α=1.3, threshold=13.773*









From HDBIF Method | From TripletNN Method | Our Custom Addition

Component Selection & Rationale

Segmentation

NestedSharedAtrousResUNet (from HDBIF)

- Used pre-trained weights
- Proven effectiveness for iris segmentation

Circle detection

ResNet18 (From TripleNN)

- Pre-trained model for pupil/iris localization

Feature Extraction

ConvNeXt-tiny (from TripletNN)

- Modern CNN architecture
- 2048-dimensional feature vectors

Score Normalization Method

Problem: ConvNeXt outputs raw Euclidean distances (0 to ∞) - not suitable for thresholding

Our Solution - Sigmoid Normalization:

- score = 1 / (1 + exp(-α * (distance - τ)))
- α = 1.3 (controls transition steepness)
- τ = 13.773 (decision boundary)

(These values determined on a data subset through trial and error)

- Converts any distance to [0,1] range
- Same threshold works across all datasets
- Easy Interpretation: 0 = match, 1 = non-match

Quantitative Performance

Statistical Significance:

What d' Scores Mean:

Measures separation between genuine and impostor matches

d' > 5 = Good discrimination

d' > 10 = Excellent discrimination

Participant	Entries	Date	ID	d'score (Total)	d'score (Lamp)	d'score (Thousand)	d'score (Gaze)
trams	1	2025-05-27 00:55	298706	**25.38**	12.67	6.98	5.74

12	1105_team	1	2025-06-01 23:45	302406	n/a	n/a	n/a	n/a
13	房組名	1	2025-06-01 23:19	302386	**860.76**	4.67	3.58	852.51
14	志齊77	1	2025-05-27 21:31	299262	**37.01**	6.55	4.95	25.51
15	trams	1	2025-05-27 00:55	298706	**25.38**	12.67	6.98	5.74
16	r13921104	1	2025-05-30 14:38	301061	**16.68**	3.14	3.64	9.9
17	EyeDentity Matrix	1	2025-05-30 17:43	301189	**14.73**	1.39	1.28	12.06
18	踩地雷	1	2025-06-01 16:08	302105	**9.94**	3.08	2.57	4.29

Key Observations:

Best performance on controlled data (Lamp & Thousand)

Consistent method across all datasets (no tuning)

Room for improvement on challenging conditions (Gaze)

Our Simple Yet Effective Approach

What We Did :

- Combined existing pre-trained models
- Added sigmoid normalization
- Kept same parameters across all datasets

Why It Works:

- Proven components = reliable performance
- Deep Learning features > binary encoding
- Universal parameters = true generalizability

Conclusion

What We Achieved:

- Successfully integrated HDBIF segmentation with TripletNN features
- Implemented sigmoid score normalization and found best performance at (α=1.3, τ=13.773)
- Maintained consistent parameters across datasets

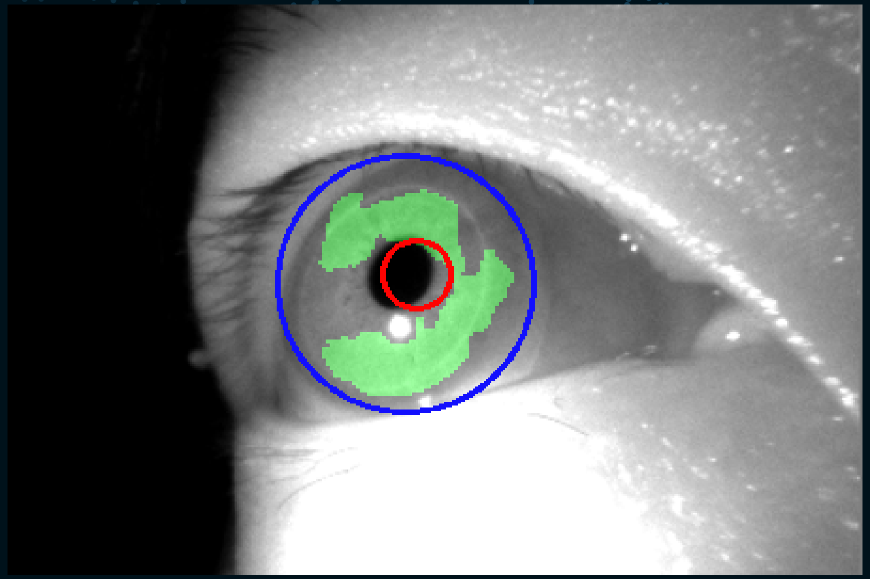
Results:

- d' scores: 12.67 (CASIA-Thousand), 6.98 (CASIA-Lamp), 5.74 (Ganzin-Gaze)
- Demonstrated practical integration approach

Future Work:

- Maintained consistent parameters across datasets
- Optimize for Ganzin-Gaze Dataset using enhances segmentation
- Test with dataset-specific parameters

Ganzin-Gaze Dataset



THANKS FOR LISTENING!

Q&A