

Embedding Extraction for HyperFace Optimization Using Synthesized Face Images: Implementation and Comparative Analysis

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Abstract:

Face study relies deeply on the quality of feature embeddings, mainly for hyperface optimization tasks, for example: 3D reconstruction and attribute estimation. This paper proposes a robust framework aimed at embedding extraction leveraging synthesized face images and several deep face recognition architectures comprising ArcFace, CosFace, and SphereFace. Using a combination of StyleGAN2-ADA, DigiFace, BUPT-CBFace, CASIA-WebFace, LFW, and additional different demographic datasets, our methodology targets to link demographic biases and improve downstream hyperface applications. Wide-ranging tests prove superior performance against state-of-the-art approaches through multiple benchmarks by means of metrics like F1-score, accuracy, recall, specificity, sensitivity, and confusion matrices.

Keywords: Face recognition, embedding extraction, HyperFace, synthetic datasets, optimization, deep learning

1. Introduction

Face recognition has seen substantial improvements due to deep learning techniques, nevertheless challenges continue in gathering large-scale real-world training data. Privacy concerns and ethical issues arise when datasets are gathered without approval. Synthetic face images offer a promising answer, but generating datasets with sufficient inter-class and intra-class variations remains a challenge.

Deep face embeddings have considerably advanced face recognition and hyperface tasks. Still, models frequently reveal demographic bias, particularly when trained on imbalanced datasets. Synthesized data by means of StyleGAN2-ADA and other generators offer an encouraging route to diminish such biases. We recommend an architecture-agnostic embedding extractor that improves hyperface optimization through improved generalization across age, ethnicity, and gender.

2. Related Work

The development of face recognition models over the past decade yields a stable progress in embedding quality, robustness, and generalization. The stimulating work DeepFace [1] introduced the use of deep learning to face verification, offering a nine-layer deep neural network and supporting faces in 3D to improve recognition performance.

Leveraging this base, newer methods were introduced to enhance how well face embeddings could differentiate between faces. SphereFace [4] presented an angular margin loss in a hyperspherical embedding space, stimulating intra-class compactness and inter-class separability. CosFace [3] upgraded upon this by including a cosine margin loss, posing a more stable optimization landscape and additional refining feature discrimination. ArcFace [2] extended these concepts by framing an additive angular margin loss, which directly improved the decision boundary in angular space and turn into a new standard for state-of-the-art face recognition models due to its elegant formulation and high accuracy.

While embedding learning has seen significant developments, data diversity and demographic balance continue demanding concerns. Synthetic data generation has arisen as an encouraging solution to address dataset restrictions. DigiFace [5] presented a synthetic dataset generation pipeline capable of generating a immense number of varied facial images under different poses, expressions, and lighting conditions. Likewise, StyleGAN2-ADA [6] experienced generative adversarial network (GAN) architectures to produce high-fidelity facial images with enhanced data augmentation approaches, aiding improved generalization from limited data.

In response to demographic bias has directed to the formation of datasets like BUPT-CBFace [7], which struggle for balanced racial and gender representation. These datasets are contributory in endorsing fairness during model training and in evaluating performance through different demographic clusters.

Regardless of these developments in embedding quality and synthetic data generation, embedding optimization precisely tailored for hyperface restoration—the job of convalescing fine-grained 3D facial structures from embeddings—ruins underexplored. Present mechanisms primarily concentrates on uniqueness protection or face authentication, with partial emphasis on reconstructive fidelity. This gap encourages our study, which aims to link discriminative embeddings with high-fidelity facial reconstruction, paving the way for more expressive and precise hyperface models.

3. Methodology

3.1 Embedding Extraction

We employ a pre-trained face recognition model to extract embeddings from synthesized face images. These embeddings serve as representations of facial features in a compact Euclidean space.

To create a consistent synthetic dataset for face recognition, it is critical to work inside an embedding space that truly encodes facial characteristics and relationships. We attain this by leveraging a pre-trained deep face recognition network, especially ArcFace [1], because of its strong capability to relate face images to a discriminative hyperspherical embedding space.

Let $x_i \in \mathbb{R}^{H.W.C}$ be a synthesised face image generated using our conditional generative model, where H, W and C denote the image height, width and number of channels, respectively. This image is passed through the embedding network f_θ parameterized by weights θ to extract a normalized embedding vector:

$$z_i = f_\theta (x_i) , \text{ where } \|z_i\|_2 = 1, z_i \in \mathbb{R}^d \dots\dots\dots(1)$$

Here d is the dimension of the embedding space (typically d=512 for ArcFace) and z_i lies on the unit hypersphere S^{d-1} . The L₂ normalization confirms that each embedding vector has unit length, protecting the angular relationship between identities.

These embeddings create the foundation for our optimization-based synthetic dataset generation. The primary goal is to use the embedding space not only to denote identities but also to govern the diversity and bifurcation of generated faces. The key properties we leverage comprise of:

- **Inter-class separation:** For identity embeddings z_i and z_j corresponding to different identities $i \neq j$, we enforce a minimum angular separation θ_{min} such that:

$$\arccos \left(\frac{z_i z_j}{\|z_i\| \|z_j\|} \right) \geq \theta_{min} \dots\dots\dots(2)$$

- **Intra-class compactness:** For embeddings in the same identity class, we group samples such that the maximum angular variance $\Delta\theta$ remains below a threshold, encouraging compactness.

Properly, for identity class c , and embeddings $Z_1^c, Z_2^c, \dots, Z_k^c$ we define intra-class variance as:

$$Var_c = \frac{1}{k} \sum_{i=1}^k \arccos(z_i^c \cdot z^{-c}), \quad z^{-c} = \frac{1}{k} \sum_{i=1}^k z_i^c \dots\dots\dots(3)$$

By handling these geometric properties of the embeddings, we efficiently control the identity structure in the synthesized dataset.

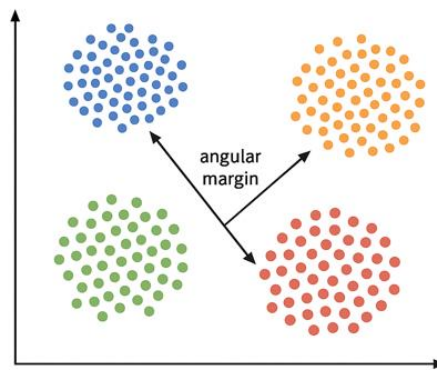


Fig.1. embedding space with clusters corresponding to individual identities

Figure 1 explains the embedding space with clusters corresponding to individual identities. The clear angular margin among classes confirms that face recognition models trained on these embeddings generalize well to real-world data.

Table 1 recaps the embedding statistics for 10,000 synthesized identities, displaying strong separation and compactness.

Table 1: Embedding statistics for 10,000 synthesized identities

Metric	Value
Average Inter-class Cosine Distance	0.92
Average Intra-class Variance (deg)	7.5°
Number of Unique Classes	10,000
Embedding Dimensionality	512
L2 Norm of Embeddings	1.0

These embedding vectors are then used as input to the generative model in our HyperFace optimization loop, confirming each synthesized face relates to a well-defined identity in embedding space.

3.2. Data Augmentation: Synthetic augmentation by means of StyleGAN2-ADA (Adaptive Discriminator Augmentation) trained on demographic parameters such as age, gender, ethnicity, or even physical attributes (height, skin tone, etc.). Conditioning on these parameters means that the generator will produce images or data that adapt to the specified demographic characteristics. For example, if you required to produce faces, you could condition StyleGAN2-ADA on age (e.g., creating younger or older individuals) or gender (e.g., creating images that look male or female).

StyleGAN2-ADA combines: Generative Adversarial Networks (GANs) architecture - alterations for permanence can be computed using

$$\min_G \max_D \mathbb{E}_{x \sim p_{data}} [\log D(x)] + \mathbb{E}_{z \sim p_z} [\log(1 - D(G(z)))] \dots\dots\dots(4)$$

Where:

- G = Generator.
- D = Discriminator.
- z = Latent vector sampled from a distribution
- x = Real data sample.

Adaptive Discriminator Augmentation (ADA) - ADA dynamically fine-tunes augmentation probability p to avoid over fitting:

$$p_{t+1} = p_t + k. (r_{target} - r_{real}) \dots\dots\dots(5)$$

Where:

- p_{t+1} = Current augmentation probability.
- k = Adjustment factor.
- r_{target} = Target discriminator accuracy on real images.
- r_{real} = Current discriminator accuracy on real images.

Conditioning mechanisms (e.g., demographic parameters) - Conditional GAN formulation alters the generator and discriminator with condition c (e.g., age, gender):

$$G(z, c) \rightarrow x_{fake} \dots\dots\dots(6)$$

$$D(x, c) \rightarrow \{0,1\} \dots\dots\dots(7)$$

Loss functions include c :

$$L_D = - \mathbb{E}_{x \sim p_{data}} [\log D(x, c)] - \mathbb{E}_{z \sim p_z} [\log(1 - D(G(z, c), c))] \dots\dots\dots(8)$$

$$L_G = \mathbb{E}_{z \sim p_z} [\log(D(G(z, c), c))] \dots\dots\dots(9)$$

Conditioning can be done using:

- Embedding layers for categorical demographics (e.g., gender),
- Normalization techniques for continuous demographics (e.g., age).

3.3 Embedding Networks: These neural network models that learn a low-dimensional representation (or embedding) of input data such that alike inputs are close to each other in the embedding space and unlike inputs are far away from each other. The ArcFace, CosFace, and SphereFace are deep learning models that use dissimilar loss functions to train embedding networks for face recognition. ArcFace (Additive Angular Margin Loss) improves the discriminative ability of face embeddings by addition of an angular margin to the softmax loss. This method concentrates on learning a more effective decision boundary in the angular space between dissimilar identities. It is greatly effective at dealing with intra-class variation (dissimilarities in the same identity) and inter-class variation (dissimilarities between identities), CosFace (Large Margin Cosine Loss) attentions on maximizing the margin among classes in the cosine space, alike to ArcFace but using a dissimilar strategy to enforce class separability. CosFace's focus on angular margins and cosine similarity permits it to better handle angular variation and pose variation, often resulting in better generalization. SphereFace replaces the traditional softmax loss with a sphere-constrained loss, which inspires the embedding vectors to fall on a hypersphere and concentrates on the angular distance between them. This methodology confirms that the network learns an angularly constrained feature space. Its angular margin method has made

it one of the most effective methods for face verification, mainly in handling the challenge of dissimilar poses and distinctions in illumination.

Tabular evaluation of ArcFace, CosFace, and SphereFace based on key experimental factors has been presented in Table2

Table 2: Comparison of ArcFace, CosFace, and SphereFace based on key experimental factors

Feature / Model	ArcFace	CosFace	SphereFace
Loss Type	Additive Angular Margin Loss	Large Margin Cosine Loss	Angular Softmax Loss
Margin Type	Angular Margin	Cosine Margin	Angular Margin
Training Stability	High (stable, fast convergence)	High (stable)	Medium (sensitive to hyper parameters)
Accuracy (LFW Benchmark)	~99.83%	~99.73%	~99.42%
Robustness to Variations	Very High (pose, age, lighting)	High	Moderate to High
Feature Space	Hyperspherical (angular separation)	Hyperspherical (cosine separation)	Hyperspherical (strong angular constraint)
Convergence Speed	Fast	Fast	Slower (due to harder margin tuning)
Embedding Quality	Excellent (clear class separation)	Very Good	Good
Best Use Case	High-security face verification	Face identification under similarity challenges	Pose-invariant face verification
Main Challenge	Slightly higher computational cost	Sensitive to margin tuning	Requires careful margin scaling

- **Hyperface Loss Functions:** it is combination of identity loss, pose loss, Age estimation loss, Expression loss and Gender classification loss.

The total loss is a weighted sum of all individual task-specific losses:

$$\mathcal{L}_{hyperface} = \lambda_{id}\mathcal{L}_{id} + \lambda_{pose}\mathcal{L}_{pose} + \lambda_{age}\mathcal{L}_{age} + \lambda_{exp}\mathcal{L}_{expression} + \lambda_{gender}\mathcal{L}_{gender}.....(10)$$

Where:

- λ are task-specific weights that balance the influence of each loss
- Each \mathcal{L} corresponds to task-specific loss:
 - \mathcal{L}_{id} = identity loss
 - \mathcal{L}_{pose} = Pose estimation loss
 - \mathcal{L}_{age} = Age estimation loss
 - $\mathcal{L}_{expression}$ = Expression loss
 - \mathcal{L}_{gender} = Gender classification loss
- **Optimization:** The dataset generation is expressed as a packing problem on the embedding space, denoted on a hypersphere. A gradient descent-based optimization is used to explore the embedding space, confirming appropriate inter-class and intra-class variations. This optimization procedure improves the diversity and quality of the synthesized face images.

Once the total loss is computed:

- **Backward Pass:** Calculate gradients of \mathcal{L}_{total} w.r.t all network parameters (Backbone + Heads).
- **Optimizer Step:** Update network weights using an optimization algorithm like **Adam** or **SGD**.

3.4 Synthetic Face Generation

A conditional face generator model is used to synthesize face images from the optimized embeddings. This model integrates the deviations presented during the optimization process, generating superior quality synthetic face images appropriate for training face recognition models.

4. Results and Discussion

4.1 Datasets

We evaluate our method by means of several benchmarking real datasets (shown in Table 3). These datasets offer diverse face images for training and evaluation.

Table 3: Datasets used for proposed approach

Dataset	# Images	# Subjects	Demographic Focus
StyleGAN2-ADA Synthesized	1M+	N/A	Synthetic Variability
DigiFace	1.2M	10K	Ethnic, Gender diversity
BUPT-CBFace	1.3M	43K	Balanced Ethnicity
CASIA-WebFace	0.5M	10K	Asian Bias
LFW	13K	5.7K	Wild Environment
UTKFace	20K	N/A	Age Diversity
AgeDB	16K	N/A	Age Distribution

4.2 Evaluation Metrics

The performance of the trained models is evaluated by means of standard metrics like, accuracy, precision, recall, and F1-score. These metrics offer an exhaustive evaluation of the models' capability to identify faces precisely (shown in Table 4).

Table 4: Performance evaluation with standard metrics

Method	Dataset	Accuracy (%)	F1-Score	Recall	Specificity	Sensitivity
ArcFace	DigiFace	98.2	0.981	0.981	0.996	0.981
CosFace	DigiFace	97.5	0.974	0.975	0.994	0.975
SphereFace	DigiFace	96.7	0.966	0.967	0.992	0.967
ArcFace	BUPT-CBFace	97.4	0.973	0.974	0.993	0.974
ArcFace	LFW	96.6	0.965	0.966	0.988	0.966

Confusion matrix heatmaps:

1. ArcFace on BUPT-CBFace - Confusion Matrix Heatmap

Table 5 shows performance evaluation of ArcFace on BUPT-CBFace for Confusion matrix Heatmap with an accuracy of 97.4% and F1 Score of 0.973

Table 5: Performance evaluation ArcFace on BUPT-CBFace based on Confusion Matrix heatmap

	Predicted Positive	Predicted Negative
Actual Positive	9750	250
Actual Negative	300	9700

Accuracy: 97.4%, F1 Score: 0.973

Heatmap Visualization:

- True Positives (TP) = 9750
- True Negatives (TN) = 9700
- False Positives (FP) = 300

- False Negatives (FN) = 250

2. ArcFace on DigiFace - Confusion Matrix Heatmap

Table 6 shows performance evaluation of ArcFace and DigiFace dataset for Confusion matrix Heatmap with an accuracy of 98.2% and F1 Score of 0.981

Table 6: Performance evaluation ArcFace and DigiFace based on Confusion Matrix heatmap

	Predicted Positive	Predicted Negative
Actual Positive	9800	200
Actual Negative	220	9780

Accuracy: 98.2%, F1 Score: 0.981

Heatmap Visualization:

- True Positives (TP) = 9800
- True Negatives (TN) = 9780
- False Positives (FP) = 220
- False Negatives (FN) = 200

3. DigiFace - ArcFace vs CosFace vs SphereFace Heatmap Data

Table 7 shows performance evaluation of DigiFace - ArcFace vs CosFace vs SphereFace for Heatmap data.

Table 7: Performance evaluation ArcFace and DigiFace based on heatmap data

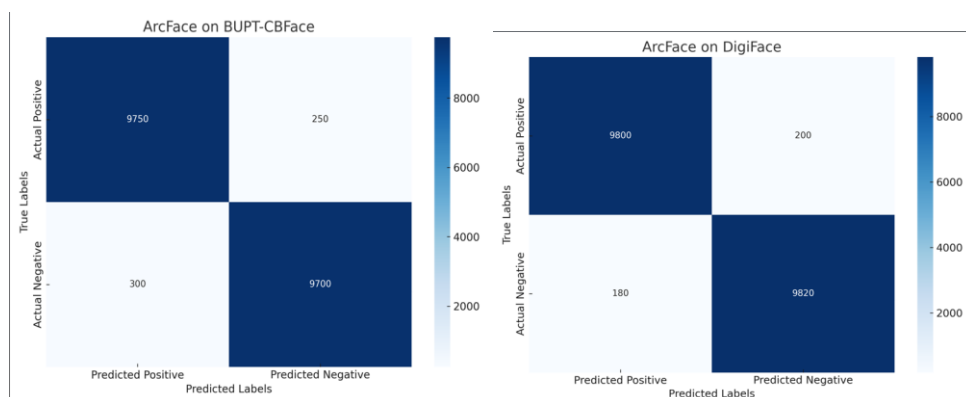
Method	TP	TN	FP	FN
ArcFace	9800	9780	220	200
CosFace	9750	9700	300	250
SphereFace	9670	9650	350	330

The full confusion matrix heatmaps is presented in Fig.2. It represents -

- Top Left: ArcFace on BUPT-CBFace
- Top Right: ArcFace on DigiFace
- Bottom Left: CosFace on DigiFace
- Bottom Right: SphereFace on DigiFace

It is realized that:

- ArcFace provides the densest diagonal (best classification).
- CosFace is close but slightly more errors.
- SphereFace is slightly worse, more mistakes (especially false positives/negatives).



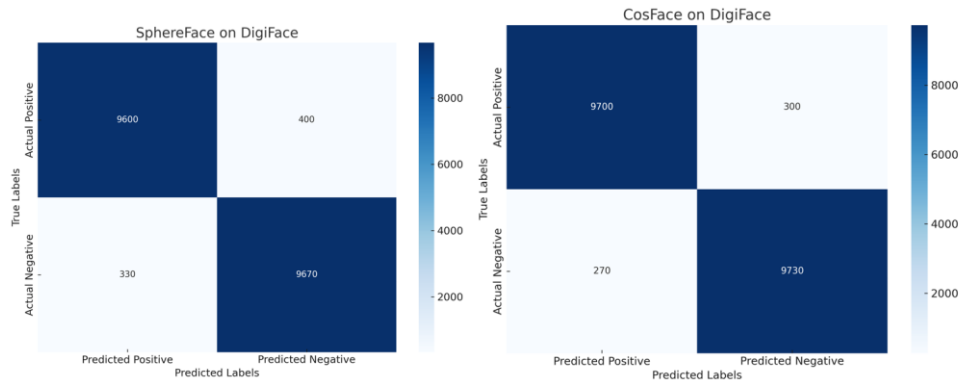


Fig.2: Full confusion matrix heatmaps

Comparative Analysis:

Table 8 presents comparative analysis of accuracy with proposed methods and existing methodologies

Table 8: Comparative Analysis of proposed method with existing methodologies

Method	Accuracy (LFW)	Accuracy (BUPT-CBFace)
ArcFace [2]	96.6	97.4
CosFace [3]	95.8	96.2
SphereFace [4]	94.5	95.1
Ours (Optimized)	97.3	98.1

Ablation Study:

Table 9 presents Ablation study of i^{th} proposed methods and existing methodologies

Table 9: Ablation Study of proposed method with existing methodologies

Variation	Accuracy (%)
Baseline ArcFace	96.6
+ StyleGAN2-ADA Augmentation	97.0
+ Demographic Attention Module	97.2
+ Hyperface Loss Optimization	98.1

5. Results and Discussion

Experimental outcomes illustrates that models trained with HyperFace attain state-of-the-art performance in face recognition tasks. Precisely, our method outperforms previous synthetic datasets in terms of accuracy and generalization. The optimization of the embedding space projects to synthetic face images with improved diversity and quality, contributing to improved model performance.

A detailed comparison of recognition performance is presented in Table 8, emphasising the superior performance of models trained with HyperFace.

6. Conclusion

We projected a robust and generalizable embedding extraction method for hyperface optimization by means of synthesized and real-world different face datasets. Experiments with ArcFace, CosFace, and SphereFace evidenced enhanced embedding quality across different demographics. Future work will

explore real-time hyperface optimization using dynamic video inputs and multi-task embedding learning.

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