GRAFIQS: Face Image Quality Assessment Using Gradient Magnitudes Supplementary Material

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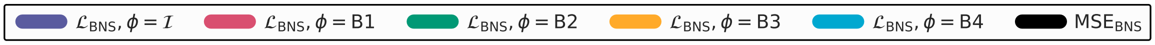
1. Supplementary Material

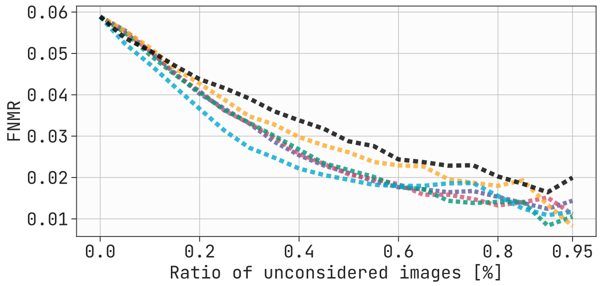
This supplementary material contains the following supporting content:

- An ablation on a different backbone (ResNet50 [4]): To validate the generalizability over different backbones, we present in Table 1 the achieved AUC over the utilized benchmarks and FR models, similar to Table 2 in the main paper, that shows the AUC for the ResNet100 backbone. Similar to Figure 2 in the main paper, Figures 1, 2, 3, 4, 5, 6, 7 show the EDC curves achieved by our $\mathrm{MSE}_{\mathrm{BNS}}$ and $\mathcal{L}_{\mathrm{BNS}}$ approaches on datasets Adience, AgeDB30, CFP-FP, LFW, CALFW, CPLFW, and XQLFW for all utilized FR models, respectively.
- Due to limited space in the main paper, we present here all EDC figures of ResNet100 backbone over all utilized datasets and FR models. Figures 8, 9, 10, 11, 12, 13, 14 show the EDC curves achieved by our $\mathrm{MSE}_{\mathrm{BNS}}$ and $\mathcal{L}_{\mathrm{BNS}}$ approaches on datasets Adience, AgeDB30, CFP-FP, LFW, CALFW, CPLFW, and XQLFW for all utilized FR models, respectively.
- Furthermore we provide all EDC figures that show a comparison between GRAFIQS using ResNet100, reported using the best setting from Table 2 in the main paper, and SOTA methods. Figures 15, 16, 17, 18, 19, 20, 21 show the EDC curves on datasets Adience, AgeDB30, CFP-FP, LFW, CALFW, CPLFW, and XQLFW for all utilized FR models, respectively.

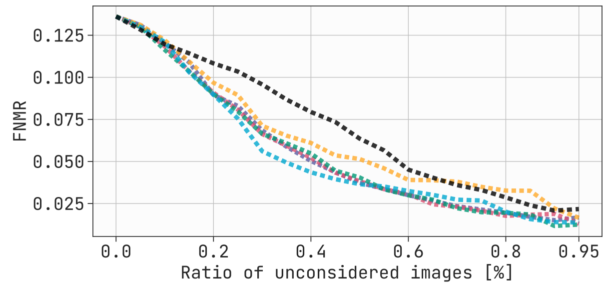
FR	Loss $\mathcal{L}$	FIQ	Gradient	Adience [3]		AgeDB30 [9]		CFP-FP [10]		LFW [5]		CALFW [12]		CPLFW [11]		XQLFW [7]		Mean AUC	
				$1e-3$	$1e-4$	$1e-3$	$1e-4$	$1e-3$	$1e-4$	$1e-3$	$1e-4$	$1e-3$	$1e-4$	$1e-3$	$1e-4$	$1e-3$	$1e-4$	$1e-3$	$1e-4$
ArcFace [2]	-	MSE($\text{BNS}_{\mathcal{M}}, \text{BNS}_{\mathcal{I}}$)	-	0.0311	0.0668	0.0337	0.0470	0.0204	0.0266	0.0034	0.0041	0.0665	0.0700	0.0630	0.0903	0.2436	0.2946	0.0660	0.0856
	$\mathcal{L}_{\text{BNS}}$	$\sum \lvert\partial\mathcal{L}/\partial\phi\rvert$	$\phi = \mathcal{I}$	0.0262	0.0527	0.0312	0.0412	0.0126	0.0199	0.0034	0.0041	0.0637	0.0679	0.0552	0.0867	0.2382	0.2896	0.0615	0.0803
	$\mathcal{L}_{\text{BNS}}$	$\sum \lvert\partial\mathcal{L}/\partial\phi\rvert$	$\phi = \text{B1}$	0.0261	0.0523	0.0288	0.0385	0.0137	0.0236	0.0033	0.0040	0.0673	0.0725	0.0588	0.0898	0.2370	0.2925	0.0621	0.0819
	$\mathcal{L}_{\text{BNS}}$	$\sum \lvert\partial\mathcal{L}/\partial\phi\rvert$	$\phi = \text{B2}$	0.0258	0.0522	0.0286	0.0377	0.0142	0.0235	0.0028	0.0036	0.0732	0.0786	0.0607	0.0927	0.2409	0.2905	0.0637	0.0827
	$\mathcal{L}_{\text{BNS}}$	$\sum \lvert\partial\mathcal{L}/\partial\phi\rvert$	$\phi = \text{B3}$	0.0289	0.0606	0.0308	0.0417	0.0279	0.0377	0.0028	0.0035	0.0771	0.0833	0.1125	0.1420	0.3638	0.4054	0.0920	0.1106
	$\mathcal{L}_{\text{BNS}}$	$\sum \lvert\partial\mathcal{L}/\partial\phi\rvert$	$\phi = \text{B4}$	0.0245	0.0510	0.0248	0.0368	0.0181	0.0285	0.0041	0.0046	0.0582	0.0650	0.0595	0.0893	0.2441	0.2761	0.0619	0.0788
ElasticFace [1]	-	MSE($\text{BNS}_{\mathcal{M}}, \text{BNS}_{\mathcal{I}}$)	-	0.0335	0.0631	0.0314	0.0329	0.0194	0.0243	0.0031	0.0041	0.0628	0.0651	0.0572	0.0754	0.2143	0.2583	0.0602	0.0747
	$\mathcal{L}_{\text{BNS}}$	$\sum \lvert\partial\mathcal{L}/\partial\phi\rvert$	$\phi = \mathcal{I}$	0.0280	0.0505	0.0328	0.0360	0.0118	0.0152	0.0032	0.0041	0.0620	0.0638	0.0549	0.0705	0.2160	0.2445	0.0584	0.0692
	$\mathcal{L}_{\text{BNS}}$	$\sum \lvert\partial\mathcal{L}/\partial\phi\rvert$	$\phi = \text{B1}$	0.0279	0.0503	0.0313	0.0347	0.0127	0.0160	0.0031	0.0040	0.0647	0.0667	0.0556	0.0837	0.2168	0.2468	0.0589	0.0717
	$\mathcal{L}_{\text{BNS}}$	$\sum \lvert\partial\mathcal{L}/\partial\phi\rvert$	$\phi = \text{B2}$	0.0278	0.0500	0.0317	0.0353	0.0132	0.0165	0.0027	0.0036	0.0711	0.0732	0.0577	0.0852	0.2183	0.2555	0.0604	0.0742
	$\mathcal{L}_{\text{BNS}}$	$\sum \lvert\partial\mathcal{L}/\partial\phi\rvert$	$\phi = \text{B3}$	0.0311	0.0571	0.0358	0.0395	0.0244	0.0320	0.0026	0.0035	0.0748	0.0763	0.1044	0.1536	0.3376	0.3845	0.0872	0.1066
	$\mathcal{L}_{\text{BNS}}$	$\sum \lvert\partial\mathcal{L}/\partial\phi\rvert$	$\phi = \text{B4}$	0.0262	0.0488	0.0258	0.0280	0.0139	0.0183	0.0039	0.0046	0.0556	0.0578	0.0546	0.0693	0.2012	0.2416	0.0545	0.0669
MagFace [8]	-	MSE($\text{BNS}_{\mathcal{M}}, \text{BNS}_{\mathcal{I}}$)	-	0.0326	0.0663	0.0329	0.0699	0.0305	0.0486	0.0041	0.0049	0.0664	0.0682	0.0627	0.1414	0.2727	0.3274	0.0717	0.1038
	$\mathcal{L}_{\text{BNS}}$	$\sum \lvert\partial\mathcal{L}/\partial\phi\rvert$	$\phi = \mathcal{I}$	0.0276	0.0546	0.0339	0.0524	0.0188	0.0320	0.0035	0.0046	0.0648	0.0671	0.0601	0.1230	0.2654	0.3009	0.0677	0.0907
	$\mathcal{L}_{\text{BNS}}$	$\sum \lvert\partial\mathcal{L}/\partial\phi\rvert$	$\phi = \text{B1}$	0.0275	0.0550	0.0318	0.0504	0.0197	0.0318	0.0034	0.0045	0.0676	0.0700	0.0624	0.1460	0.2698	0.3119	0.0689	0.0957
	$\mathcal{L}_{\text{BNS}}$	$\sum \lvert\partial\mathcal{L}/\partial\phi\rvert$	$\phi = \text{B2}$	0.0274	0.0552	0.0319	0.0486	0.0206	0.0328	0.0029	0.0041	0.0736	0.0759	0.0673	0.1461	0.2728	0.3099	0.0709	0.0961
	$\mathcal{L}_{\text{BNS}}$	$\sum \lvert\partial\mathcal{L}/\partial\phi\rvert$	$\phi = \text{B3}$	0.0310	0.0631	0.0353	0.0529	0.0393	0.0584	0.0028	0.0040	0.0768	0.0798	0.1239	0.2893	0.4115	0.4721	0.1029	0.1457
	$\mathcal{L}_{\text{BNS}}$	$\sum \lvert\partial\mathcal{L}/\partial\phi\rvert$	$\phi = \text{B4}$	0.0257	0.0525	0.0266	0.0540	0.0214	0.0376	0.0045	0.0060	0.0576	0.0597	0.0625	0.1123	0.2679	0.3092	0.0666	0.0902
Curricular-Face [6]	-	MSE($\text{BNS}_{\mathcal{M}}, \text{BNS}_{\mathcal{I}}$)	-	0.0284	0.0583	0.0313	0.0388	0.0215	0.0280	0.0035	0.0041	0.0659	0.0698	0.0529	0.0798	0.1916	0.2380	0.0564	0.0738
	$\mathcal{L}_{\text{BNS}}$	$\sum \lvert\partial\mathcal{L}/\partial\phi\rvert$	$\phi = \mathcal{I}$	0.0249	0.0459	0.0330	0.0387	0.0140	0.0194	0.0034	0.0041	0.0628	0.0659	0.0499	0.0752	0.1988	0.2275	0.0553	0.0681
	$\mathcal{L}_{\text{BNS}}$	$\sum \lvert\partial\mathcal{L}/\partial\phi\rvert$	$\phi = \text{B1}$	0.0248	0.0457	0.0305	0.0358	0.0149	0.0197	0.0033	0.0040	0.0646	0.0675	0.0509	0.0909	0.2036	0.2288	0.0561	0.0703
	$\mathcal{L}_{\text{BNS}}$	$\sum \lvert\partial\mathcal{L}/\partial\phi\rvert$	$\phi = \text{B2}$	0.0246	0.0455	0.0306	0.0361	0.0153	0.0198	0.0029	0.0036	0.0703	0.0731	0.0516	0.0912	0.2029	0.2320	0.0569	0.0716
	$\mathcal{L}_{\text{BNS}}$	$\sum \lvert\partial\mathcal{L}/\partial\phi\rvert$	$\phi = \text{B3}$	0.0274	0.0512	0.0333	0.0401	0.0294	0.0335	0.0030	0.0037	0.0735	0.0765	0.0981	0.1657	0.3322	0.3716	0.0853	0.1060
	$\mathcal{L}_{\text{BNS}}$	$\sum \lvert\partial\mathcal{L}/\partial\phi\rvert$	$\phi = \text{B4}$	0.0230	0.0438	0.0253	0.0299	0.0170	0.0195	0.0041	0.0046	0.0572	0.0600	0.0495	0.0710	0.2204	0.2639	0.0566	0.0704

Table 1. The achieved AUC of EDC by using two approaches presented in this paper, MSE of BNS (MSE_{BNS}) and gradient magnitudes ($\mathcal{L}_{\text{BNS}}$), and under different settings. The ResNet50 model is used. The gradient magnitudes are extracted during the backpropagation step from different intermediate layers, B1, B2, B3 and B4 ($\phi = \text{B1} - \phi = \text{B4}$) as well as on the pixel level ($\phi = \mathcal{I}$). The results are reported under two operation threshold FMR$= 1e-3$ and FMR$= 1e-4$ and under two protocols, same model (ArcFace) and cross-model (ElasticFace, MagFace and CurricularFace).

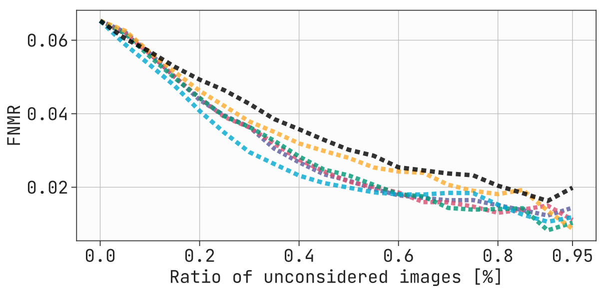




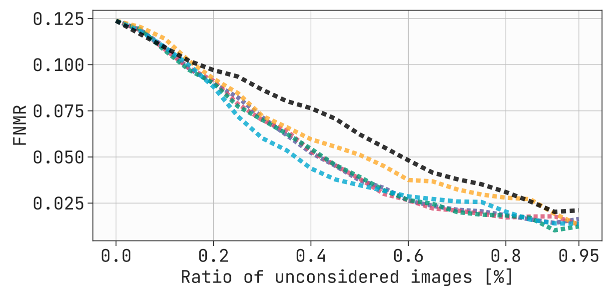
(a) ArcFace [2] Model, Adience [3] Dataset
GRAFIQS with ResNet50, FMR= $1e-3$



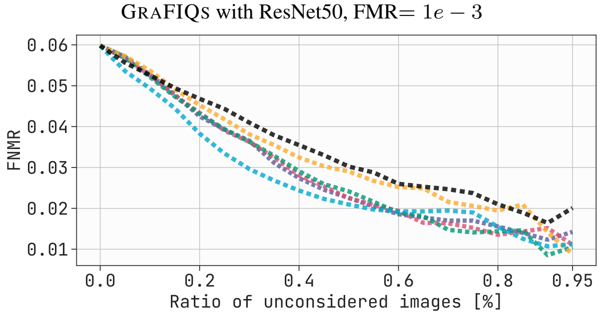
(b) ArcFace [2] Model, Adience [3] Dataset
GRAFIQS with ResNet50, FMR= $1e-4$



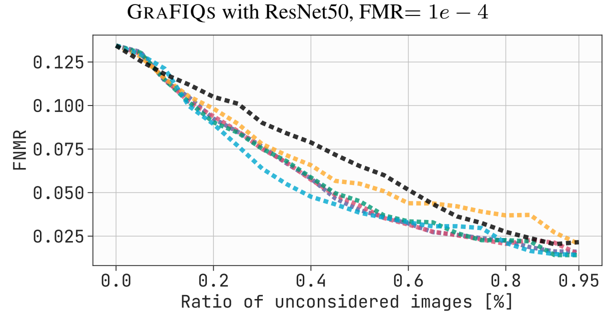
(c) ElasticFace [1] Model, Adience [3] Dataset
GRAFIQS with ResNet50, FMR= $1e-3$



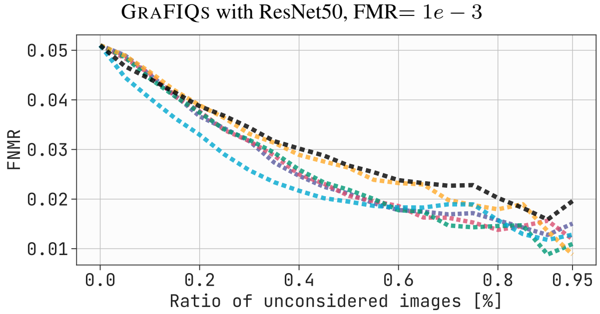
(d) ElasticFace [1] Model, Adience [3] Dataset
GRAFIQS with ResNet50, FMR= $1e-4$



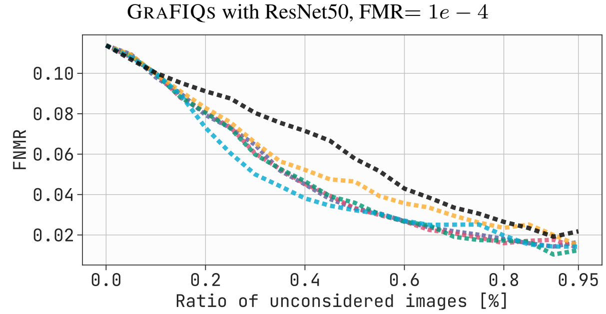
(e) MagFace [8] Model, Adience [3] Dataset
GRAFIQS with ResNet50, FMR= $1e-3$



(f) MagFace [8] Model, Adience [3] Dataset
GRAFIQS with ResNet50, FMR= $1e-4$

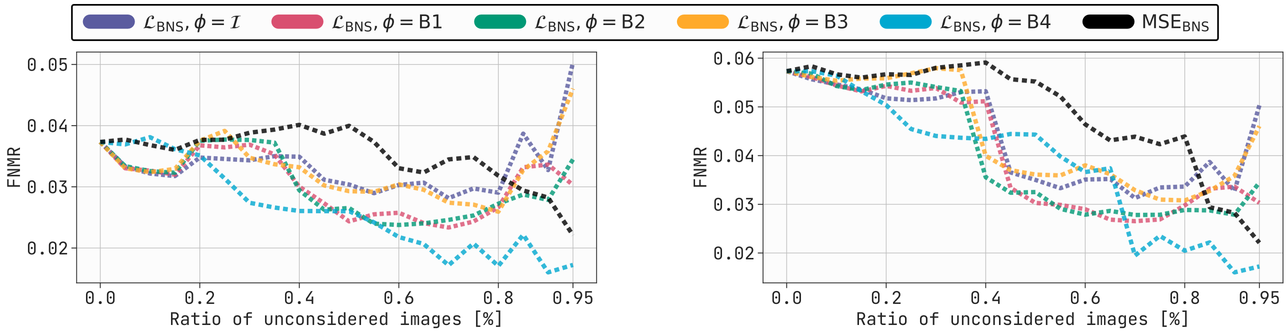


(g) CurricularFace [6] Model, Adience [3] Dataset
GRAFIQS with ResNet50, FMR= $1e-3$



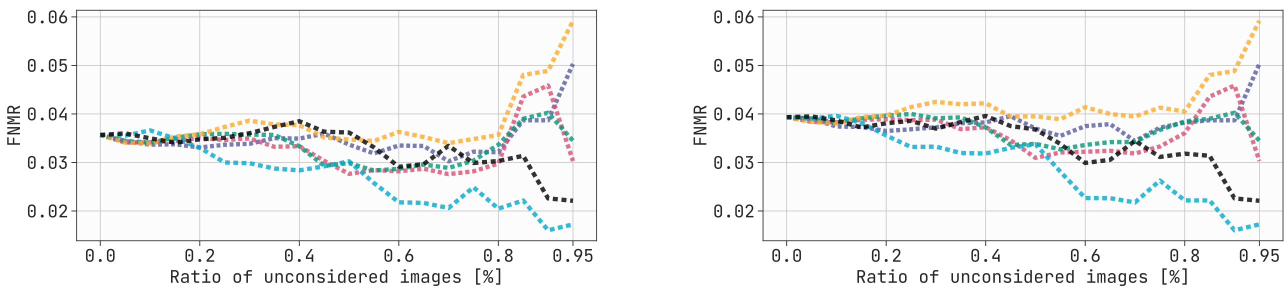
(h) CurricularFace [6] Model, Adience [3] Dataset
GRAFIQS with ResNet50, FMR= $1e-4$

Figure 1. Error-versus-Discard Characteristic (EDC) curves for FNMR@FMR=$1e-3$ and FNMR@FMR=$1e-4$ of our proposed method using $\mathcal{L}_{\text{BNS}}$ as backpropagation loss and absolute sum as FIQ. The gradients at image level ($\phi = \mathcal{I}$), and block levels ($\phi = \text{B1} - \phi = \text{B4}$) are used to calculate FIQ. MSE_{BNS} as FIQ is shown in black. Results shown on benchmark Adience [3] using ArcFace, ElasticFace, MagFace, and, CurricularFace FR models. It is evident that the proposed GRAFIQS method leads to lower verification error when images with lowest utility score estimated from gradient magnitudes are rejected. Furthermore, estimating FIQ by backpropagating $\mathcal{L}_{\text{BNS}}$ yields significantly better results than using MSE_{BNS} directly.



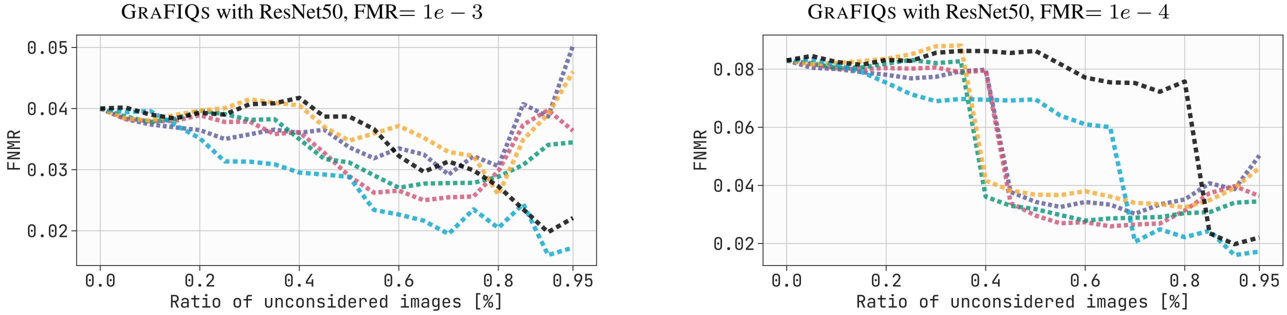
(a) ArcFace [2] Model, AgeDB30 [9] Dataset
GRAFIQS with ResNet50, FMR= $1e-3$

(b) ArcFace [2] Model, AgeDB30 [9] Dataset
GRAFIQS with ResNet50, FMR= $1e-4$



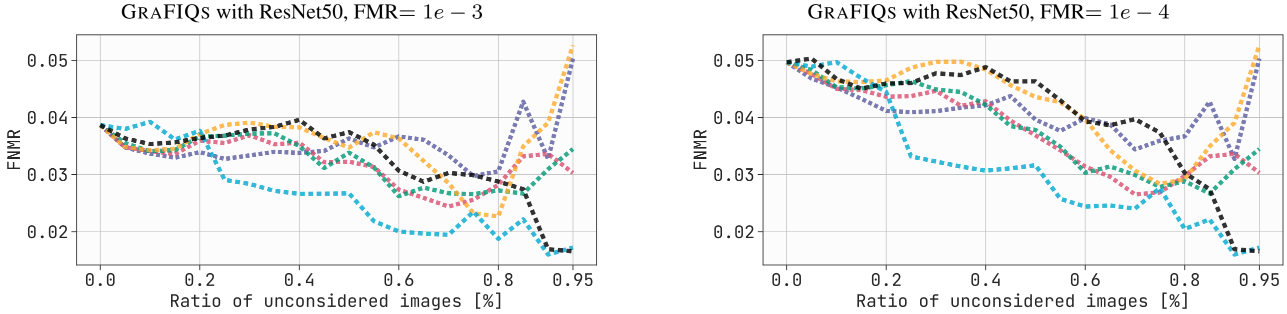
(c) ElasticFace [1] Model, AgeDB30 [9] Dataset
GRAFIQS with ResNet50, FMR= $1e-3$

(d) ElasticFace [1] Model, AgeDB30 [9] Dataset
GRAFIQS with ResNet50, FMR= $1e-4$



(e) MagFace [8] Model, AgeDB30 [9] Dataset
GRAFIQS with ResNet50, FMR= $1e-3$

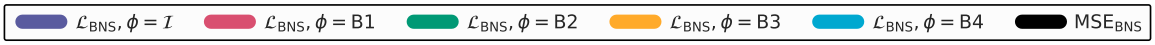
(f) MagFace [8] Model, AgeDB30 [9] Dataset
GRAFIQS with ResNet50, FMR= $1e-4$

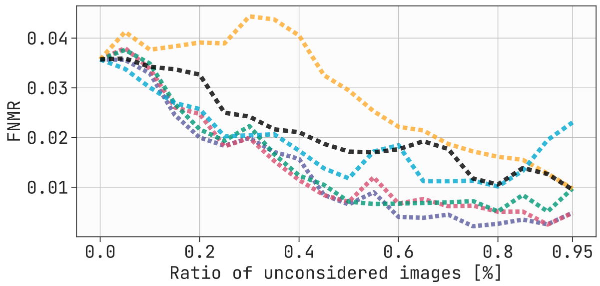


(g) CurricularFace [6] Model, AgeDB30 [9] Dataset
GRAFIQS with ResNet50, FMR= $1e-3$

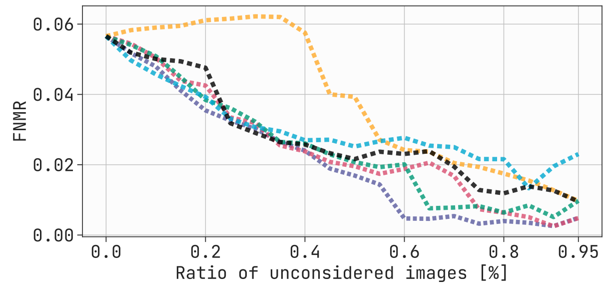
(h) CurricularFace [6] Model, AgeDB30 [9] Dataset
GRAFIQS with ResNet50, FMR= $1e-4$

Figure 2. Error-versus-Discard Characteristic (EDC) curves for FNMR@FMR=$1e-3$ and FNMR@FMR=$1e-4$ of our proposed method using $\mathcal{L}_{\mathrm{BNS}}$ as backpropagation loss and absolute sum as FIQ. The gradients at image level ($\phi = \mathcal{I}$), and block levels ($\phi = \mathrm{B1} - \phi = \mathrm{B4}$) are used to calculate FIQ. $\mathrm{MSE}_{\mathrm{BNS}}$ as FIQ is shown in black. Results shown on benchmark AgeDB30 [9] using ArcFace, ElasticFace, MagFace, and, CurricularFace FR models. It is evident that the proposed GRAFIQS method leads to lower verification error when images with lowest utility score estimated from gradient magnitudes are rejected. Furthermore, estimating FIQ by backpropagating $\mathcal{L}_{\mathrm{BNS}}$ yields significantly better results than using $\mathrm{MSE}_{\mathrm{BNS}}$ directly.

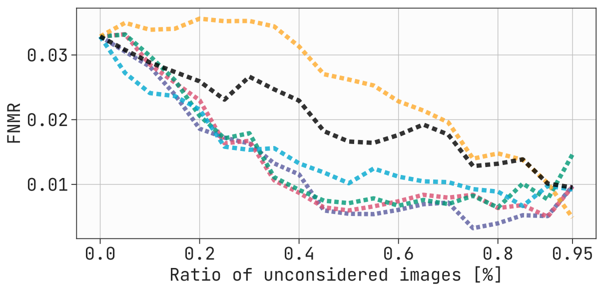




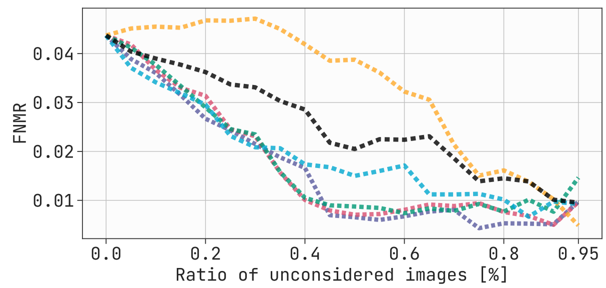
(a) ArcFace [2] Model, CFP-FP [10] Dataset
GRAFIQs with ResNet50, FMR= $1e-3$



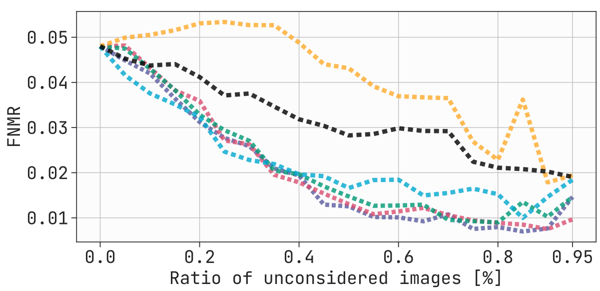
(b) ArcFace [2] Model, CFP-FP [10] Dataset
GRAFIQs with ResNet50, FMR= $1e-4$



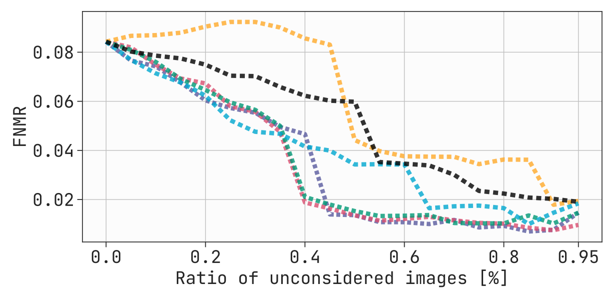
(c) ElasticFace [1] Model, CFP-FP [10] Dataset
GRAFIQs with ResNet50, FMR= $1e-3$



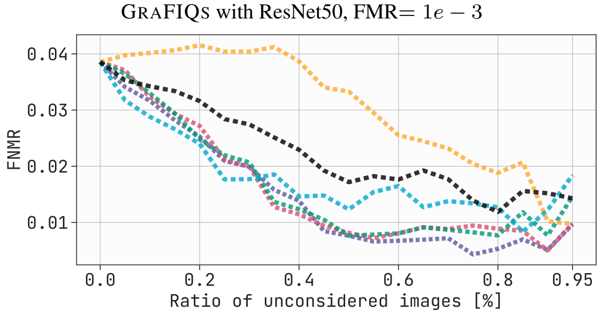
(d) ElasticFace [1] Model, CFP-FP [10] Dataset
GRAFIQs with ResNet50, FMR= $1e-4$



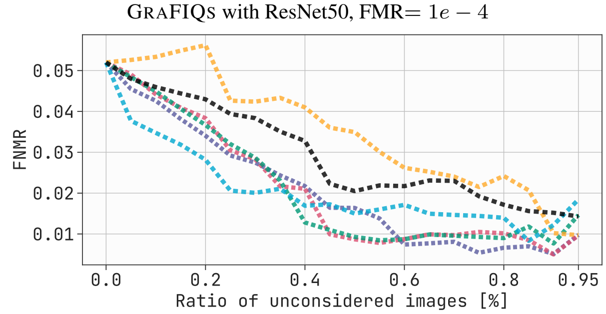
(e) MagFace [8] Model, CFP-FP [10] Dataset
GRAFIQs with ResNet50, FMR= $1e-3$



(f) MagFace [8] Model, CFP-FP [10] Dataset
GRAFIQs with ResNet50, FMR= $1e-4$

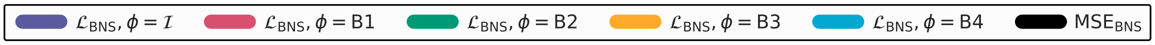


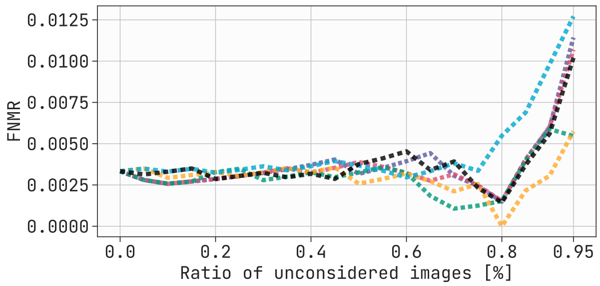
(g) CurricularFace [6] Model, CFP-FP [10] Dataset
GRAFIQs with ResNet50, FMR= $1e-3$



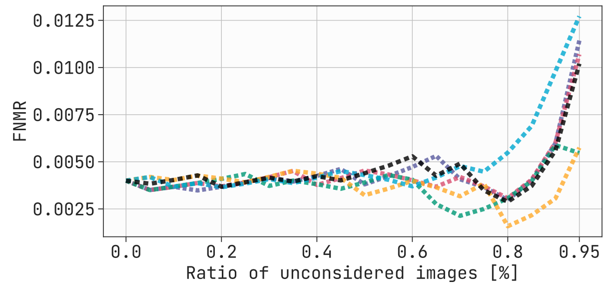
(h) CurricularFace [6] Model, CFP-FP [10] Dataset
GRAFIQs with ResNet50, FMR= $1e-4$

Figure 3. Error-versus-Discard Characteristic (EDC) curves for FNMR@FMR=$1e-3$ and FNMR@FMR=$1e-4$ of our proposed method using $\mathcal{L}_{\text{BNS}}$ as backpropagation loss and absolute sum as FIQ. The gradients at image level ($\phi = \mathcal{I}$), and block levels ($\phi = \text{B1} - \phi = \text{B4}$) are used to calculate FIQ. MSE_{BNS} as FIQ is shown in black. Results shown on benchmark CFP-FP [10] using ArcFace, ElasticFace, MagFace, and, CurricularFace FR models. It is evident that the proposed GRAFIQs method leads to lower verification error when images with lowest utility score estimated from gradient magnitudes are rejected. Furthermore, estimating FIQ by backpropagating $\mathcal{L}_{\text{BNS}}$ yields significantly better results than using MSE_{BNS} directly.

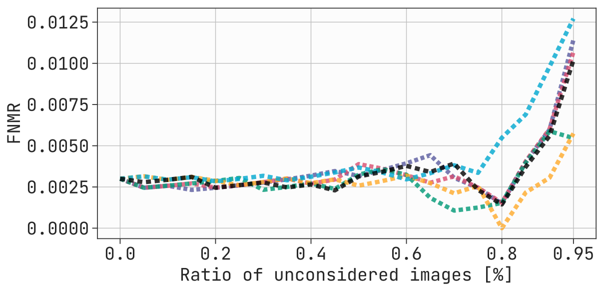




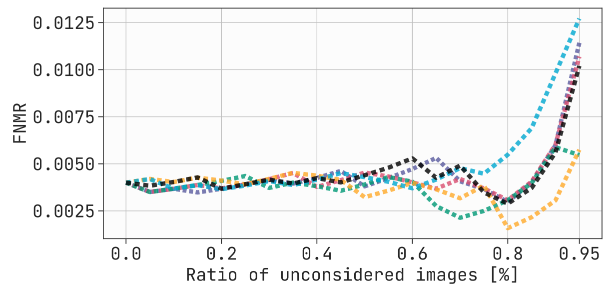
(a) ArcFace [2] Model, LFW [5] Dataset
GRAFIQS with ResNet50, FMR= $1e-3$



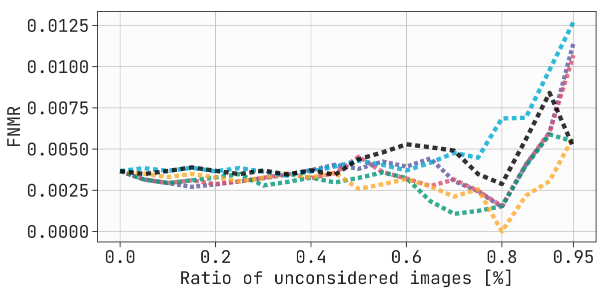
(b) ArcFace [2] Model, LFW [5] Dataset
GRAFIQS with ResNet50, FMR= $1e-4$



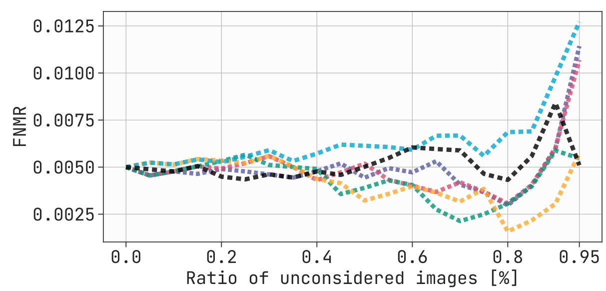
(c) ElasticFace [1] Model, LFW [5] Dataset
GRAFIQS with ResNet50, FMR= $1e-3$



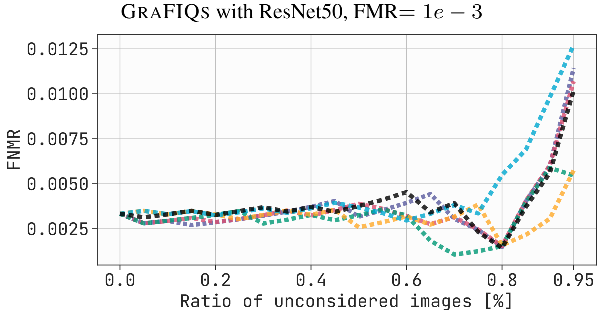
(d) ElasticFace [1] Model, LFW [5] Dataset
GRAFIQS with ResNet50, FMR= $1e-4$



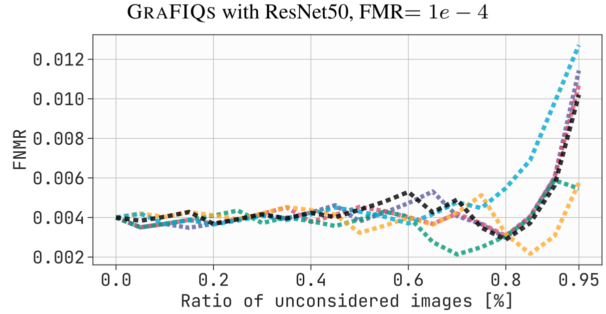
(e) MagFace [8] Model, LFW [5] Dataset
GRAFIQS with ResNet50, FMR= $1e-3$



(f) MagFace [8] Model, LFW [5] Dataset
GRAFIQS with ResNet50, FMR= $1e-4$

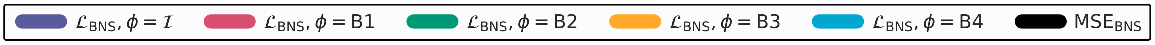


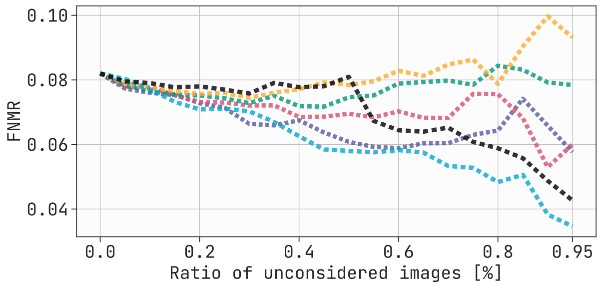
(g) CurricularFace [6] Model, LFW [5] Dataset
GRAFIQS with ResNet50, FMR= $1e-3$



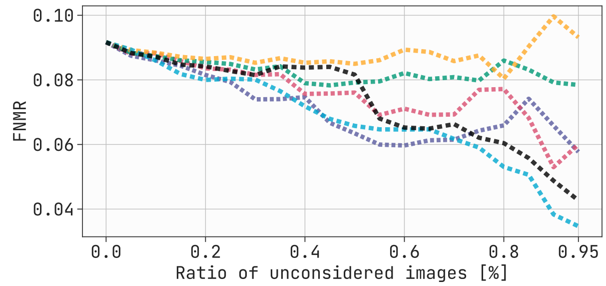
(h) CurricularFace [6] Model, LFW [5] Dataset
GRAFIQS with ResNet50, FMR= $1e-4$

Figure 4. Error-versus-Discard Characteristic (EDC) curves for FNMR@FMR=$1e-3$ and FNMR@FMR=$1e-4$ of our proposed method using $\mathcal{L}_{\text{BNS}}$ as backpropagation loss and absolute sum as FIQ. The gradients at image level ($\phi = \mathcal{I}$), and block levels ($\phi = \text{B1} - \phi = \text{B4}$) are used to calculate FIQ. MSE_{BNS} as FIQ is shown in black. Results shown on benchmark LFW [5] using ArcFace, ElasticFace, MagFace, and, CurricularFace FR models. It is evident that the proposed GRAFIQS method leads to lower verification error when images with lowest utility score estimated from gradient magnitudes are rejected. Furthermore, estimating FIQ by backpropagating $\mathcal{L}_{\text{BNS}}$ yields significantly better results than using MSE_{BNS} directly.

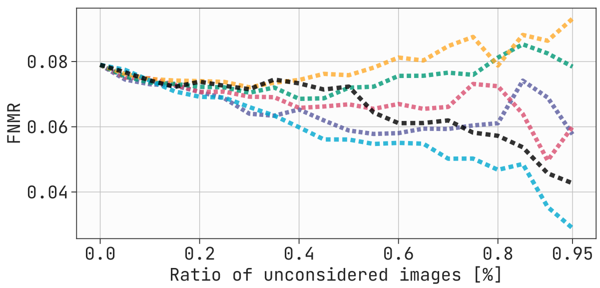




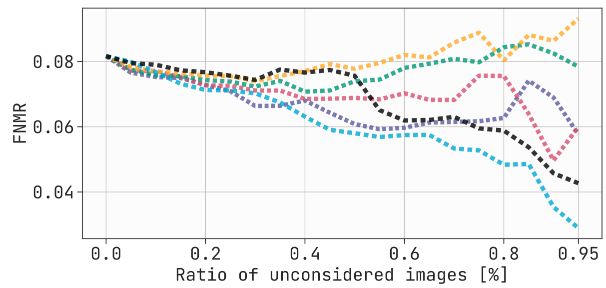
(a) ArcFace [2] Model, CALFW [12] Dataset
GRAFIQS with ResNet50, FMR= $1e-3$



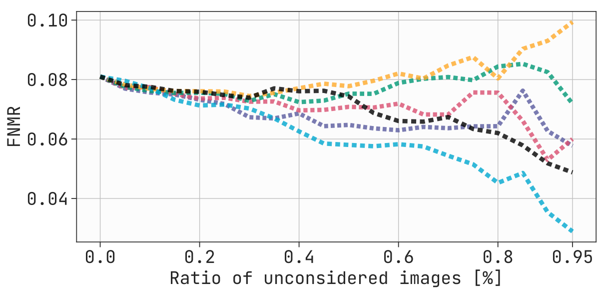
(b) ArcFace [2] Model, CALFW [12] Dataset
GRAFIQS with ResNet50, FMR= $1e-4$



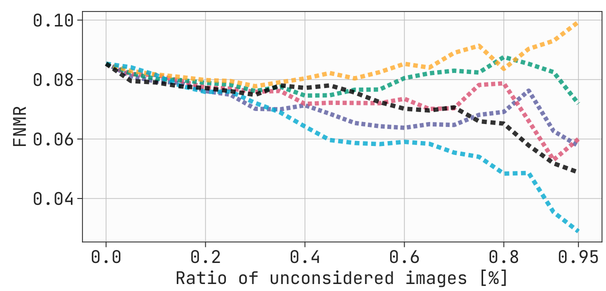
(c) ElasticFace [1] Model, CALFW [12] Dataset
GRAFIQS with ResNet50, FMR= $1e-3$



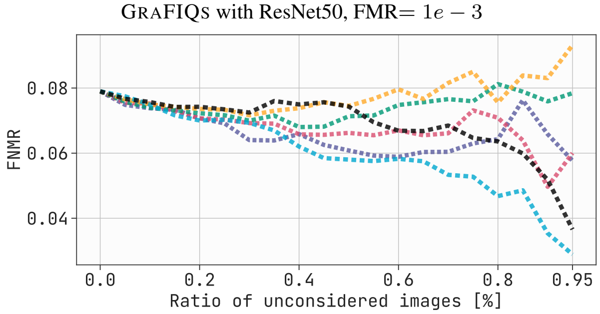
(d) ElasticFace [1] Model, CALFW [12] Dataset
GRAFIQS with ResNet50, FMR= $1e-4$



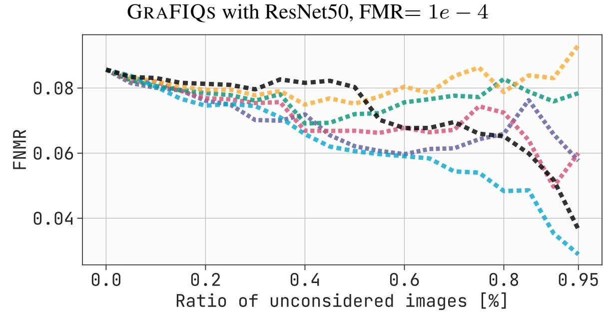
(e) MagFace [8] Model, CALFW [12] Dataset
GRAFIQS with ResNet50, FMR= $1e-3$



(f) MagFace [8] Model, CALFW [12] Dataset
GRAFIQS with ResNet50, FMR= $1e-4$

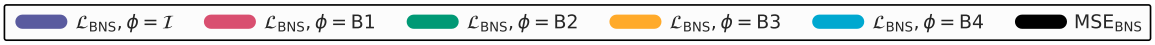


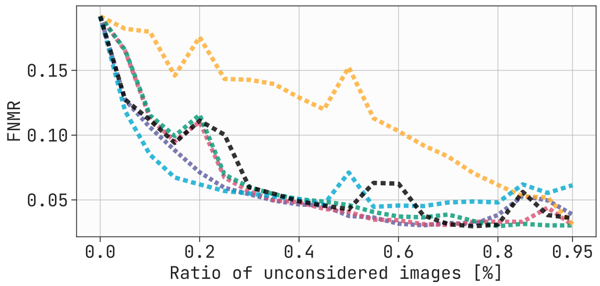
(g) CurricularFace [6] Model, CALFW [12] Dataset
GRAFIQS with ResNet50, FMR= $1e-3$



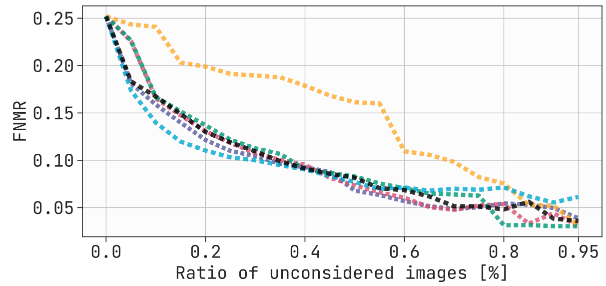
(h) CurricularFace [6] Model, CALFW [12] Dataset
GRAFIQS with ResNet50, FMR= $1e-4$

Figure 5. Error-versus-Discard Characteristic (EDC) curves for FNMR@FMR=$1e-3$ and FNMR@FMR=$1e-4$ of our proposed method using $\mathcal{L}_{\mathrm{BNS}}$ as backpropagation loss and absolute sum as FIQ. The gradients at image level ($\phi = \mathcal{I}$), and block levels ($\phi = \mathrm{B1} - \phi = \mathrm{B4}$) are used to calculate FIQ. $\mathrm{MSE}_{\mathrm{BNS}}$ as FIQ is shown in black. Results shown on benchmark CALFW [12] using ArcFace, ElasticFace, MagFace, and, CurricularFace FR models. It is evident that the proposed GRAFIQS method leads to lower verification error when images with lowest utility score estimated from gradient magnitudes are rejected. Furthermore, estimating FIQ by backpropagating $\mathcal{L}_{\mathrm{BNS}}$ yields significantly better results than using $\mathrm{MSE}_{\mathrm{BNS}}$ directly.

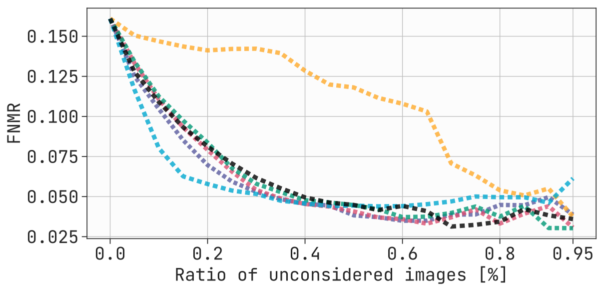




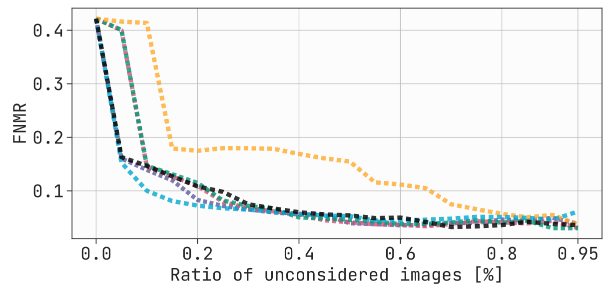
(a) ArcFace [2] Model, CPLFW [11] Dataset
GRAFIQS with ResNet50, FMR= $1e-3$



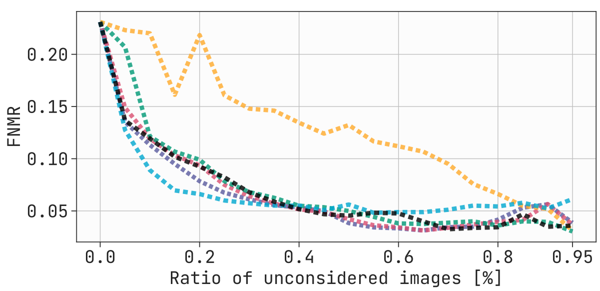
(b) ArcFace [2] Model, CPLFW [11] Dataset
GRAFIQS with ResNet50, FMR= $1e-4$



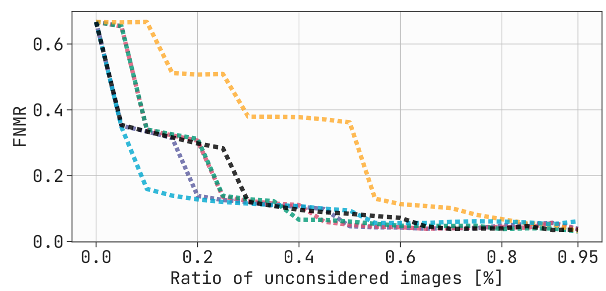
(c) ElasticFace [1] Model, CPLFW [11] Dataset
GRAFIQS with ResNet50, FMR= $1e-3$



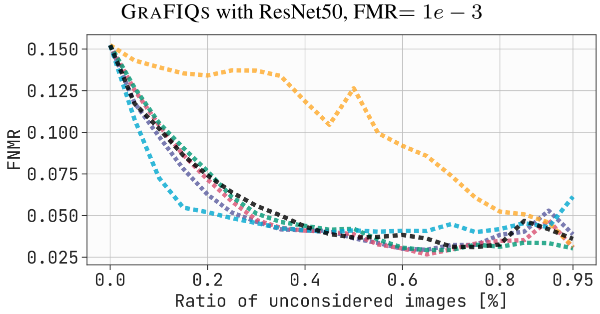
(d) ElasticFace [1] Model, CPLFW [11] Dataset
GRAFIQS with ResNet50, FMR= $1e-4$



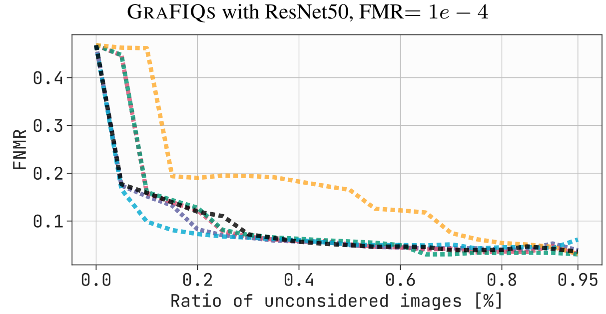
(e) MagFace [8] Model, CPLFW [11] Dataset
GRAFIQS with ResNet50, FMR= $1e-3$



(f) MagFace [8] Model, CPLFW [11] Dataset
GRAFIQS with ResNet50, FMR= $1e-4$

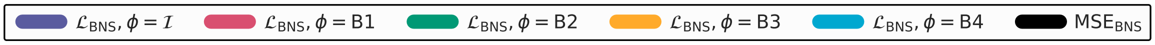


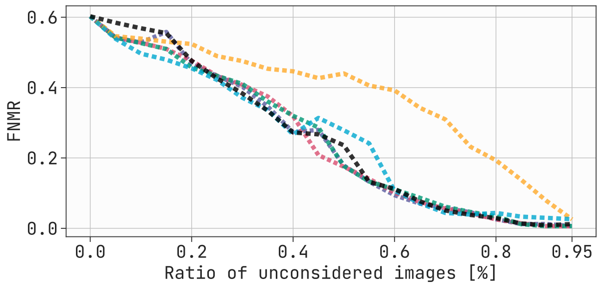
(g) CurricularFace [6] Model, CPLFW [11] Dataset
GRAFIQS with ResNet50, FMR= $1e-3$



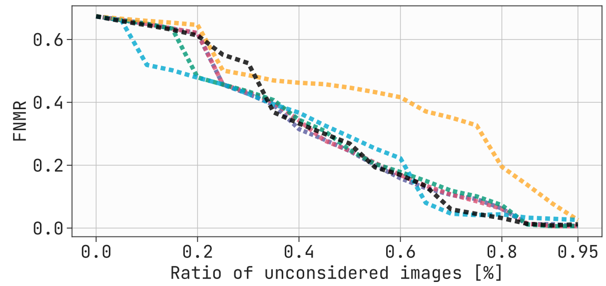
(h) CurricularFace [6] Model, CPLFW [11] Dataset
GRAFIQS with ResNet50, FMR= $1e-4$

Figure 6. Error-versus-Discard Characteristic (EDC) curves for FNMR@FMR=$1e-3$ and FNMR@FMR=$1e-4$ of our proposed method using $\mathcal{L}_{\mathrm{BNS}}$ as backpropagation loss and absolute sum as FIQ. The gradients at image level ($\phi = \mathcal{I}$), and block levels ($\phi = \mathrm{B1} - \phi = \mathrm{B4}$) are used to calculate FIQ. $\mathrm{MSE}_{\mathrm{BNS}}$ as FIQ is shown in black. Results shown on benchmark CPLFW [11] using ArcFace, ElasticFace, MagFace, and, CurricularFace FR models. It is evident that the proposed GRAFIQS method leads to lower verification error when images with lowest utility score estimated from gradient magnitudes are rejected. Furthermore, estimating FIQ by backpropagating $\mathcal{L}_{\mathrm{BNS}}$ yields significantly better results than using $\mathrm{MSE}_{\mathrm{BNS}}$ directly.

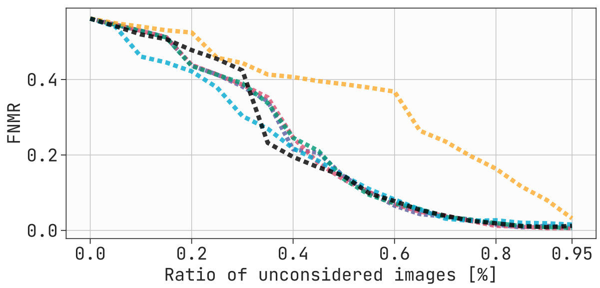




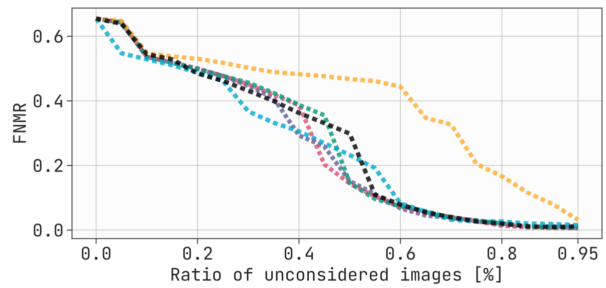
(a) ArcFace [2] Model, XQLFW [7] Dataset
GRAFIQS with ResNet50, FMR= $1e-3$



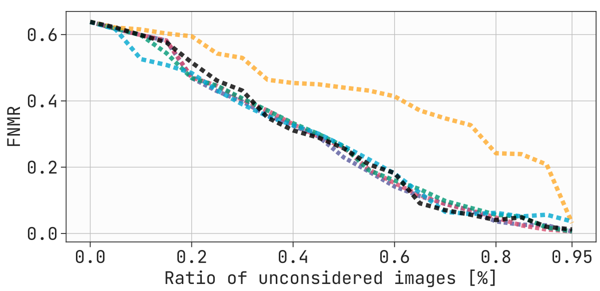
(b) ArcFace [2] Model, XQLFW [7] Dataset
GRAFIQS with ResNet50, FMR= $1e-4$



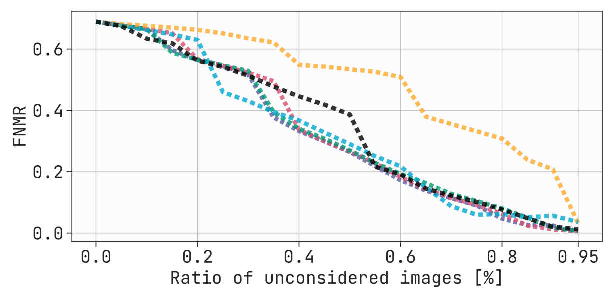
(c) ElasticFace [1] Model, XQLFW [7] Dataset
GRAFIQS with ResNet50, FMR= $1e-3$



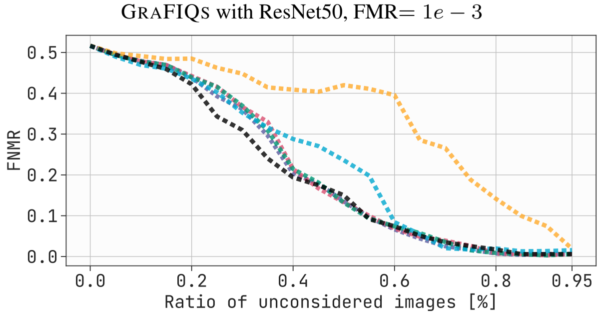
(d) ElasticFace [1] Model, XQLFW [7] Dataset
GRAFIQS with ResNet50, FMR= $1e-4$



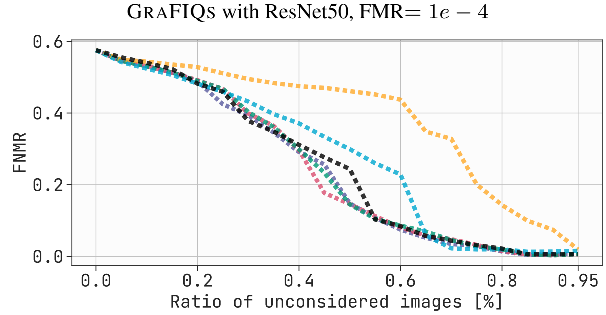
(e) MagFace [8] Model, XQLFW [7] Dataset
GRAFIQS with ResNet50, FMR= $1e-3$



(f) MagFace [8] Model, XQLFW [7] Dataset
GRAFIQS with ResNet50, FMR= $1e-4$

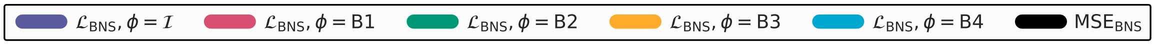


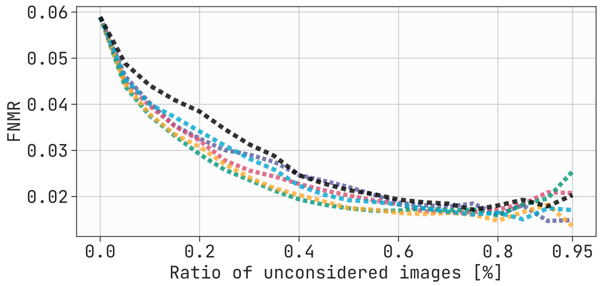
(g) CurricularFace [6] Model, XQLFW [7] Dataset
GRAFIQS with ResNet50, FMR= $1e-3$



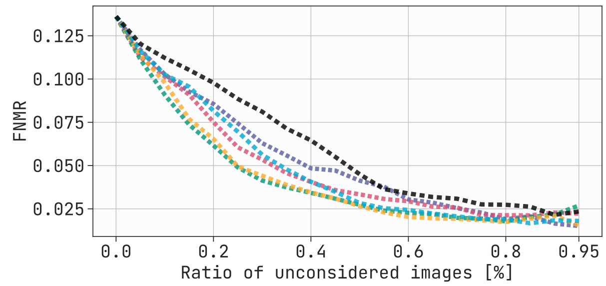
(h) CurricularFace [6] Model, XQLFW [7] Dataset
GRAFIQS with ResNet50, FMR= $1e-4$

Figure 7. Error-versus-Discard Characteristic (EDC) curves for FNMR@FMR=$1e-3$ and FNMR@FMR=$1e-4$ of our proposed method using $\mathcal{L}_{\mathrm{BNS}}$ as backpropagation loss and absolute sum as FIQ. The gradients at image level ($\phi = \mathcal{I}$), and block levels ($\phi = \mathrm{B1} - \phi = \mathrm{B4}$) are used to calculate FIQ. $\mathrm{MSE}_{\mathrm{BNS}}$ as FIQ is shown in black. Results shown on benchmark XQLFW [7] using ArcFace, ElasticFace, MagFace, and, CurricularFace FR models. It is evident that the proposed GRAFIQS method leads to lower verification error in most cases when images with lowest utility score estimated from gradient magnitudes are rejected. Furthermore, estimating FIQ by backpropagating $\mathcal{L}_{\mathrm{BNS}}$ yields on average better results than using $\mathrm{MSE}_{\mathrm{BNS}}$ directly.

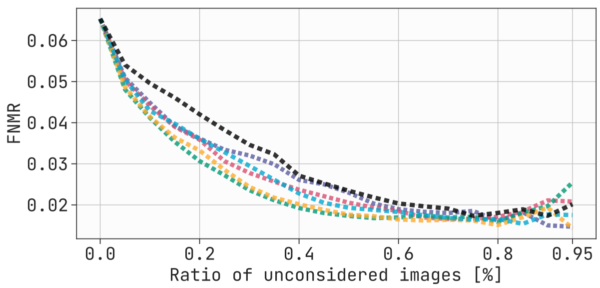




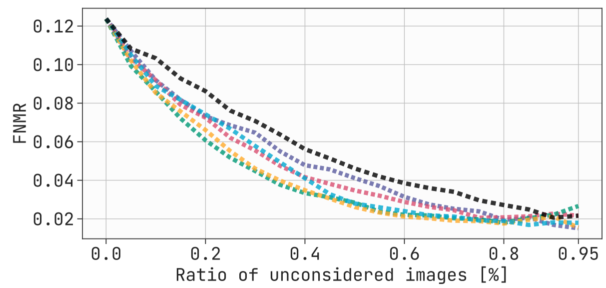
(a) ArcFace [2] Model, Adience [3] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$



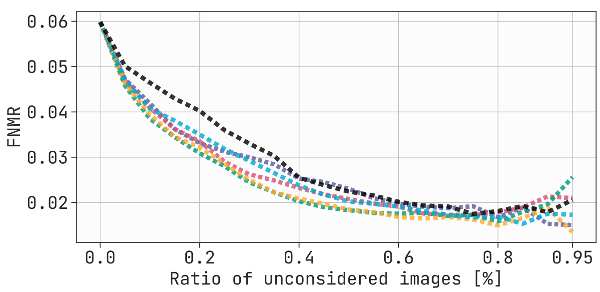
(b) ArcFace [2] Model, Adience [3] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$



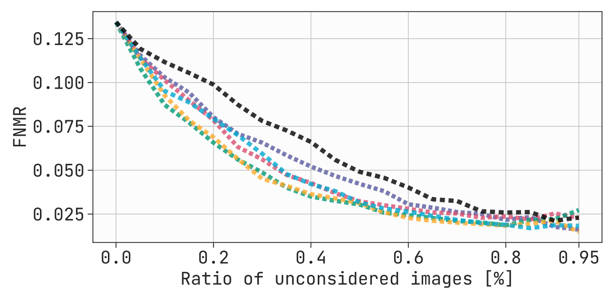
(c) ElasticFace [1] Model, Adience [3] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$



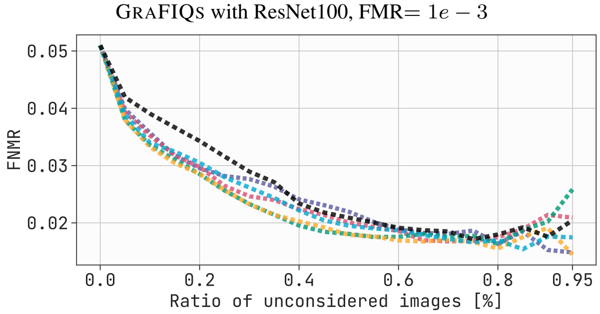
(d) ElasticFace [1] Model, Adience [3] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$



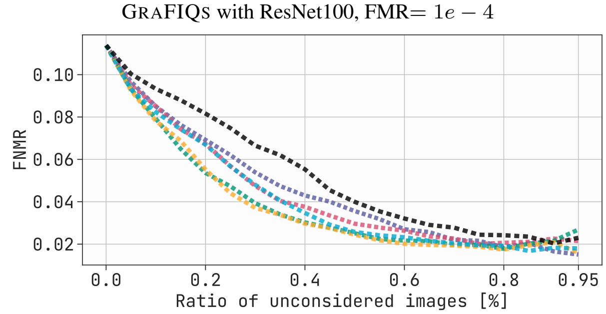
(e) MagFace [8] Model, Adience [3] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$



(f) MagFace [8] Model, Adience [3] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

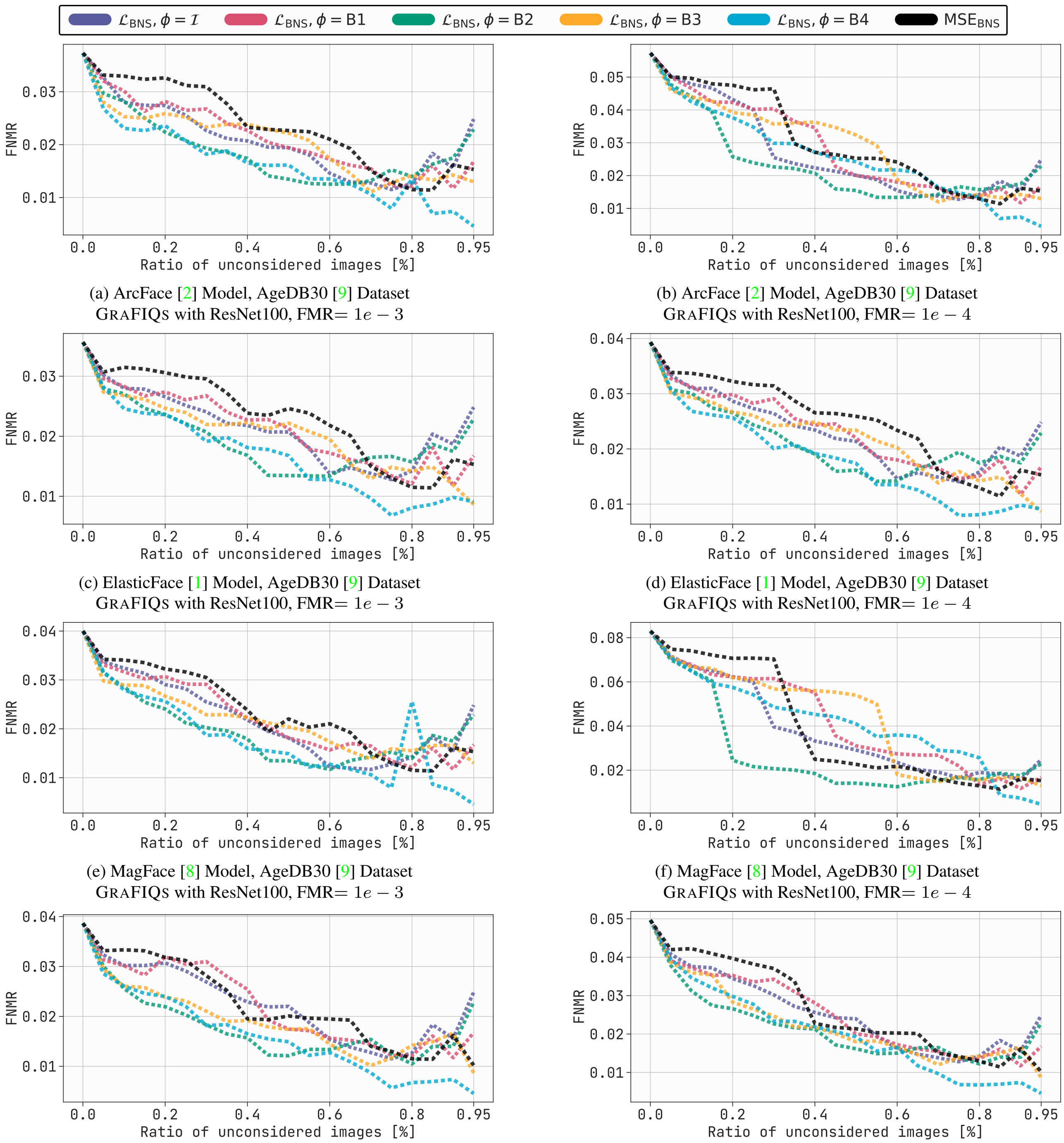


(g) CurricularFace [6] Model, Adience [3] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$



(h) CurricularFace [6] Model, Adience [3] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

Figure 8. Error-versus-Discard Characteristic (EDC) curves for FNMR@FMR=$1e-3$ and FNMR@FMR=$1e-4$ of our proposed method using $\mathcal{L}_{\mathrm{BNS}}$ as backpropagation loss and absolute sum as FIQ. The gradients at image level ($\phi = \mathcal{I}$), and block levels ($\phi = \mathrm{B1} - \phi = \mathrm{B4}$) are used to calculate FIQ. $\mathrm{MSE}_{\mathrm{BNS}}$ as FIQ is shown in black. Results shown on benchmark Adience [3] using ArcFace, ElasticFace, MagFace, and, CurricularFace FR models. It is evident that the proposed GRAFIQS method leads to lower verification error when images with lowest utility score estimated from gradient magnitudes are rejected. Furthermore, estimating FIQ by backpropagating $\mathcal{L}_{\mathrm{BNS}}$ yields significantly better results than using $\mathrm{MSE}_{\mathrm{BNS}}$ directly.



(a) ArcFace [2] Model, AgeDB30 [9] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$

(b) ArcFace [2] Model, AgeDB30 [9] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

(c) ElasticFace [1] Model, AgeDB30 [9] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$

(d) ElasticFace [1] Model, AgeDB30 [9] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

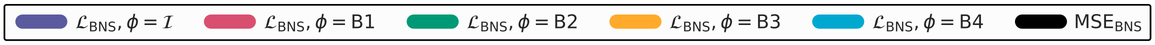
(e) MagFace [8] Model, AgeDB30 [9] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$

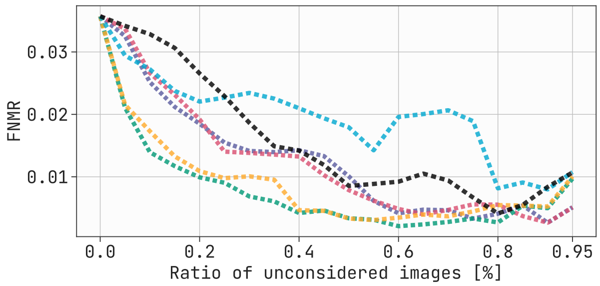
(f) MagFace [8] Model, AgeDB30 [9] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

(g) CurricularFace [6] Model, AgeDB30 [9] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$

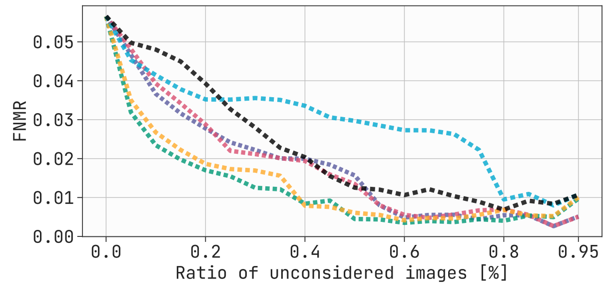
(h) CurricularFace [6] Model, AgeDB30 [9] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

Figure 9. Error-versus-Discard Characteristic (EDC) curves for FNMR@FMR=$1e-3$ and FNMR@FMR=$1e-4$ of our proposed method using $\mathcal{L}_{\mathrm{BNS}}$ as backpropagation loss and absolute sum as FIQ. The gradients at image level ($\phi = \mathcal{I}$), and block levels ($\phi = \mathrm{B1} - \phi = \mathrm{B4}$) are used to calculate FIQ. $\mathrm{MSE}_{\mathrm{BNS}}$ as FIQ is shown in black. Results shown on benchmark AgeDB30 [9] using ArcFace, ElasticFace, MagFace, and, CurricularFace FR models. It is evident that the proposed GRAFIQS method leads to lower verification error when images with lowest utility score estimated from gradient magnitudes are rejected. Furthermore, estimating FIQ by backpropagating $\mathcal{L}_{\mathrm{BNS}}$ yields significantly better results than using $\mathrm{MSE}_{\mathrm{BNS}}$ directly.

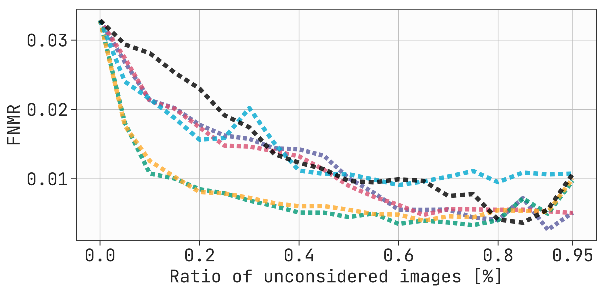




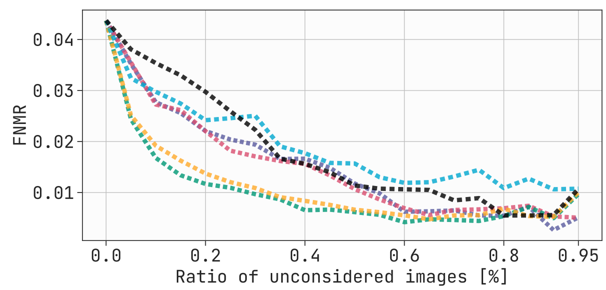
(a) ArcFace [2] Model, CFP-FP [10] Dataset
GRAFIQs with ResNet100, FMR= $1e-3$



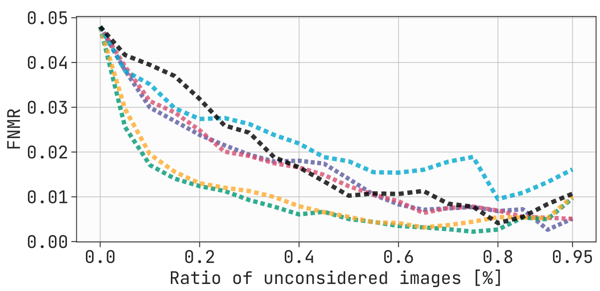
(b) ArcFace [2] Model, CFP-FP [10] Dataset
GRAFIQs with ResNet100, FMR= $1e-4$



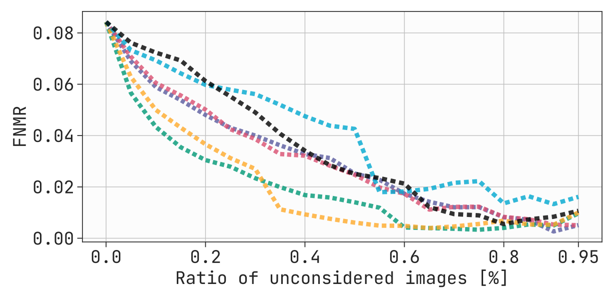
(c) ElasticFace [1] Model, CFP-FP [10] Dataset
GRAFIQs with ResNet100, FMR= $1e-3$



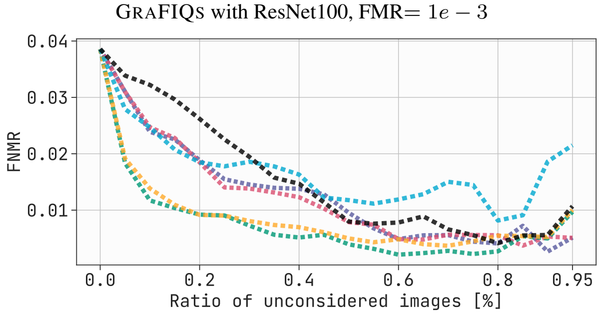
(d) ElasticFace [1] Model, CFP-FP [10] Dataset
GRAFIQs with ResNet100, FMR= $1e-4$



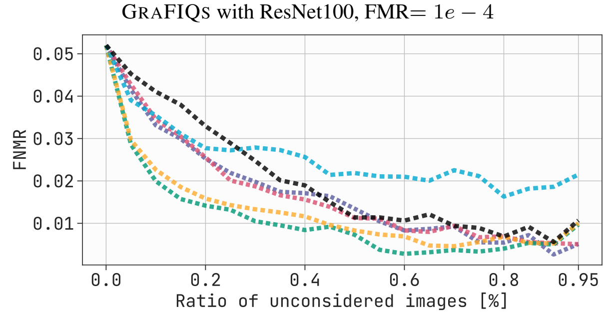
(e) MagFace [8] Model, CFP-FP [10] Dataset
GRAFIQs with ResNet100, FMR= $1e-3$



(f) MagFace [8] Model, CFP-FP [10] Dataset
GRAFIQs with ResNet100, FMR= $1e-4$

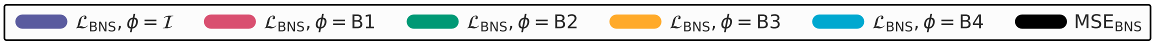


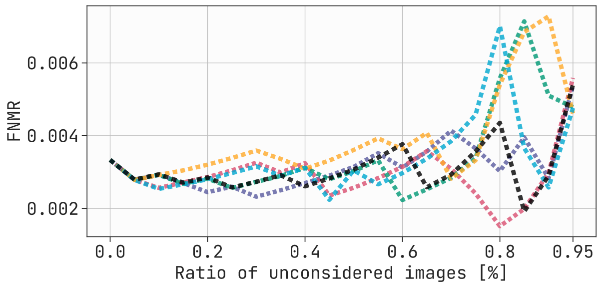
(g) CurricularFace [6] Model, CFP-FP [10] Dataset
GRAFIQs with ResNet100, FMR= $1e-3$



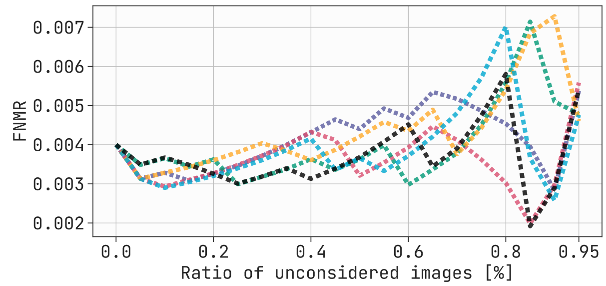
(h) CurricularFace [6] Model, CFP-FP [10] Dataset
GRAFIQs with ResNet100, FMR= $1e-4$

Figure 10. Error-versus-Discard Characteristic (EDC) curves for FNMR@FMR=$1e-3$ and FNMR@FMR=$1e-4$ of our proposed method using $\mathcal{L}_{\mathrm{BNS}}$ as backpropagation loss and absolute sum as FIQ. The gradients at image level ($\phi = \mathcal{I}$), and block levels ($\phi = \mathrm{B1} - \phi = \mathrm{B4}$) are used to calculate FIQ. $\mathrm{MSE}_{\mathrm{BNS}}$ as FIQ is shown in black. Results shown on benchmark CFP-FP [10] using ArcFace, ElasticFace, MagFace, and, CurricularFace FR models. It is evident that the proposed GRAFIQs method leads to lower verification error when images with lowest utility score estimated from gradient magnitudes are rejected. Furthermore, estimating FIQ by backpropagating $\mathcal{L}_{\mathrm{BNS}}$ yields significantly better results than using $\mathrm{MSE}_{\mathrm{BNS}}$ directly.

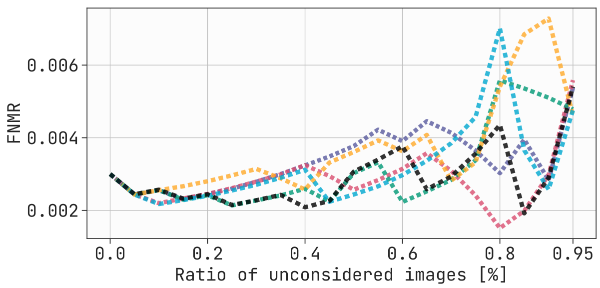




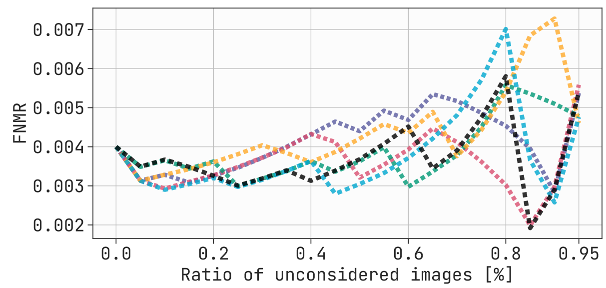
(a) ArcFace [2] Model, LFW [5] Dataset
GRAFIQs with ResNet100, FMR$= 1e-3$



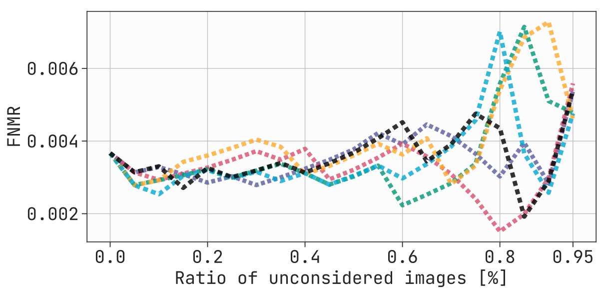
(b) ArcFace [2] Model, LFW [5] Dataset
GRAFIQs with ResNet100, FMR$= 1e-4$



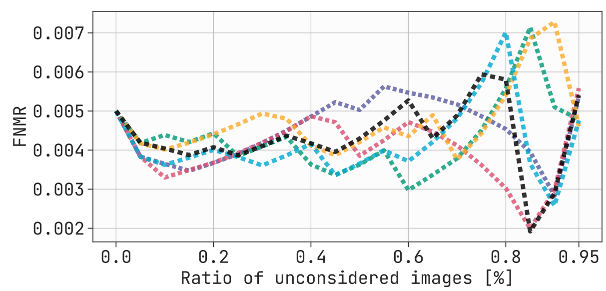
(c) ElasticFace [1] Model, LFW [5] Dataset
GRAFIQs with ResNet100, FMR$= 1e-3$



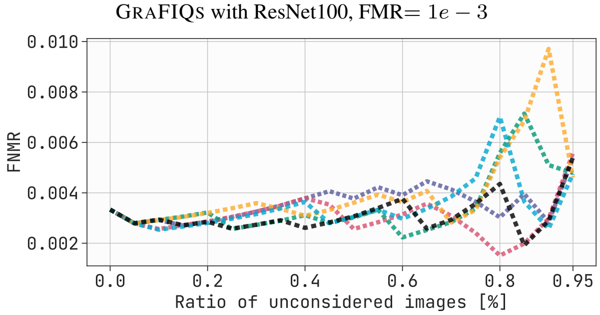
(d) ElasticFace [1] Model, LFW [5] Dataset
GRAFIQs with ResNet100, FMR$= 1e-4$



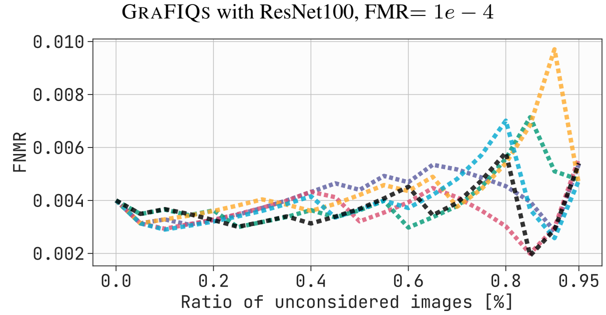
(e) MagFace [8] Model, LFW [5] Dataset
GRAFIQs with ResNet100, FMR$= 1e-3$



(f) MagFace [8] Model, LFW [5] Dataset
GRAFIQs with ResNet100, FMR$= 1e-4$

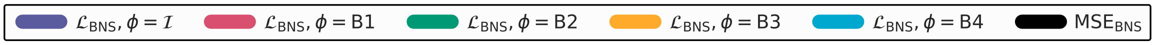


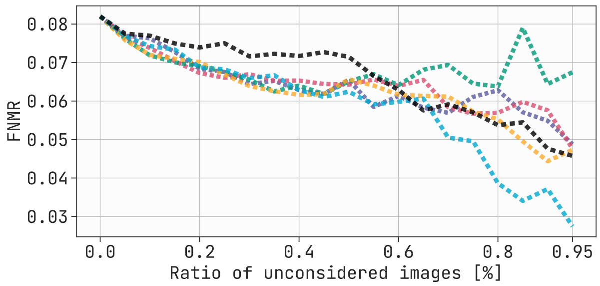
(g) CurricularFace [6] Model, LFW [5] Dataset
GRAFIQs with ResNet100, FMR$= 1e-3$



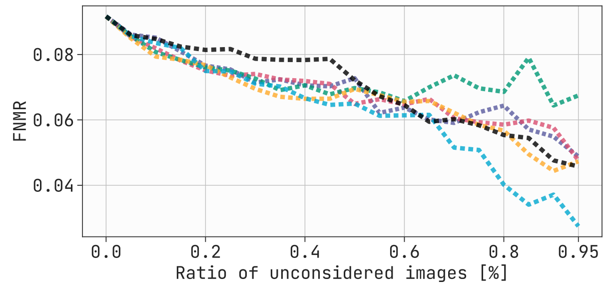
(h) CurricularFace [6] Model, LFW [5] Dataset
GRAFIQs with ResNet100, FMR$= 1e-4$

Figure 11. Error-versus-Discard Characteristic (EDC) curves for FNMR@FMR=$1e-3$ and FNMR@FMR=$1e-4$ of our proposed method using $\mathcal{L}_{\mathrm{BNS}}$ as backpropagation loss and absolute sum as FIQ. The gradients at image level ($\phi = \mathcal{I}$), and block levels ($\phi = \mathrm{B1} - \phi = \mathrm{B4}$) are used to calculate FIQ. $\mathrm{MSE}_{\mathrm{BNS}}$ as FIQ is shown in black. Results shown on benchmark LFW [5] using ArcFace, ElasticFace, MagFace, and, CurricularFace FR models. It is evident that the proposed GRAFIQs method leads to lower verification error when images with lowest utility score estimated from gradient magnitudes are rejected. Furthermore, estimating FIQ by backpropagating $\mathcal{L}_{\mathrm{BNS}}$ yields significantly better results than using $\mathrm{MSE}_{\mathrm{BNS}}$ directly.

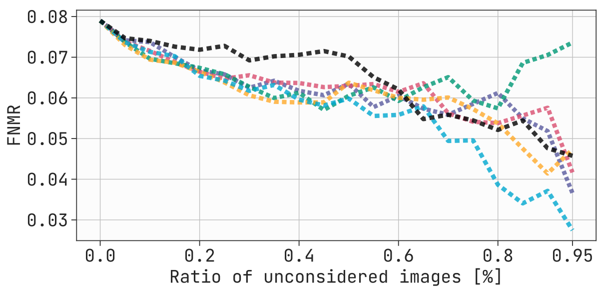




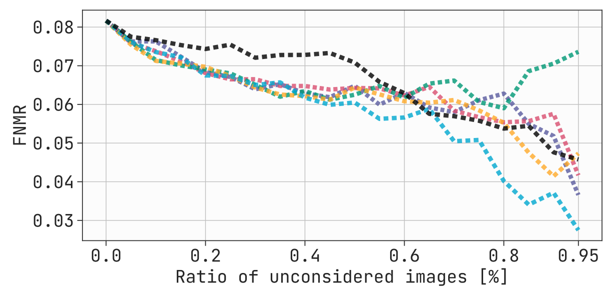
(a) ArcFace [2] Model, CALFW [12] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$



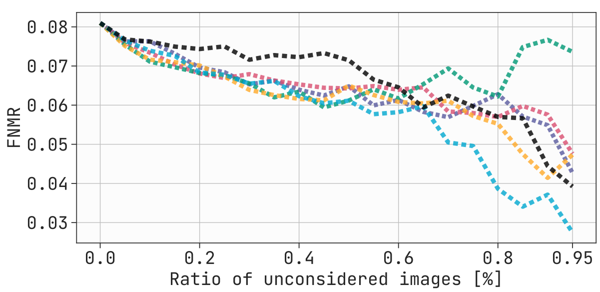
(b) ArcFace [2] Model, CALFW [12] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$



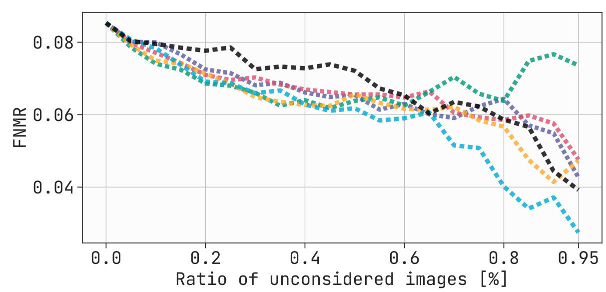
(c) ElasticFace [1] Model, CALFW [12] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$



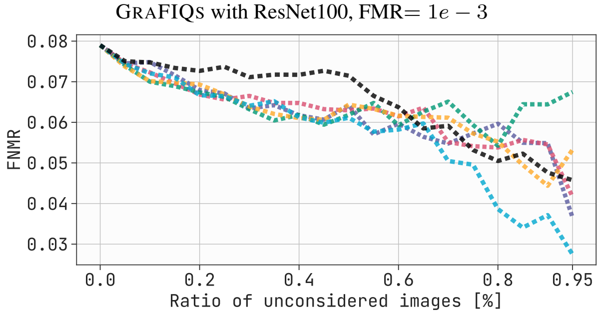
(d) ElasticFace [1] Model, CALFW [12] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$



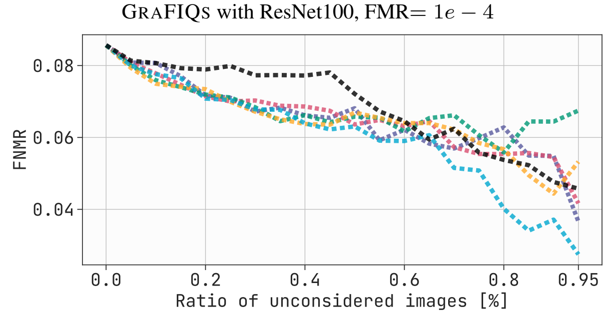
(e) MagFace [8] Model, CALFW [12] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$



(f) MagFace [8] Model, CALFW [12] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

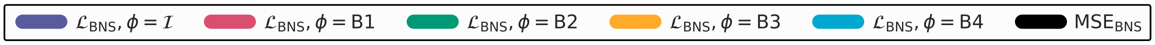


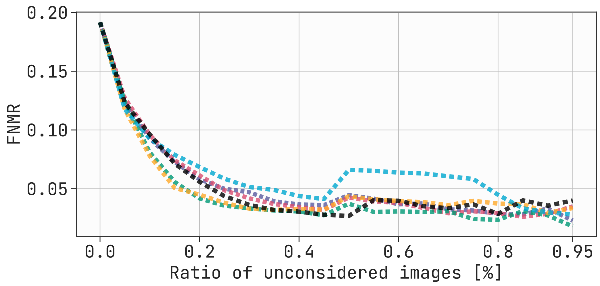
(g) CurricularFace [6] Model, CALFW [12] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$



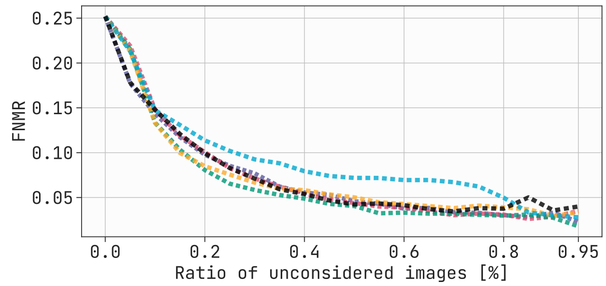
(h) CurricularFace [6] Model, CALFW [12] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

Figure 12. Error-versus-Discard Characteristic (EDC) curves for FNMR@FMR=$1e-3$ and FNMR@FMR=$1e-4$ of our proposed method using $\mathcal{L}_{\text{BNS}}$ as backpropagation loss and absolute sum as FIQ. The gradients at image level ($\phi = \mathcal{I}$), and block levels ($\phi = \text{B1} - \phi = \text{B4}$) are used to calculate FIQ. MSE_{BNS} as FIQ is shown in black. Results shown on benchmark CALFW [12] using ArcFace, ElasticFace, MagFace, and, CurricularFace FR models. It is evident that the proposed GRAFIQS method leads to lower verification error when images with lowest utility score estimated from gradient magnitudes are rejected. Furthermore, estimating FIQ by backpropagating $\mathcal{L}_{\text{BNS}}$ yields significantly better results than using MSE_{BNS} directly.

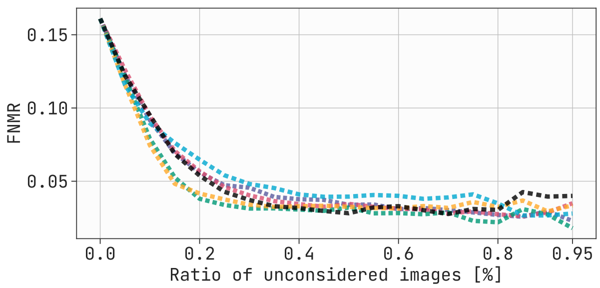




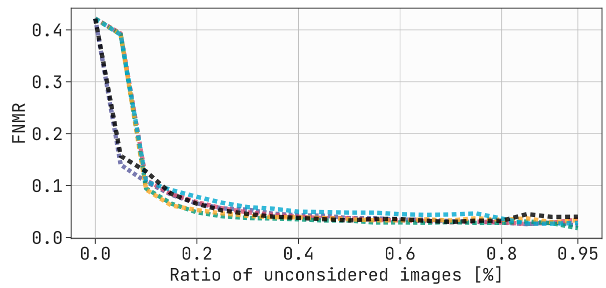
(a) ArcFace [2] Model, CPLFW [11] Dataset
GRAFIQs with ResNet100, FMR= $1e-3$



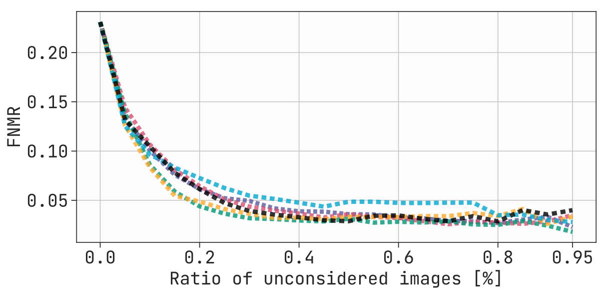
(b) ArcFace [2] Model, CPLFW [11] Dataset
GRAFIQs with ResNet100, FMR= $1e-4$



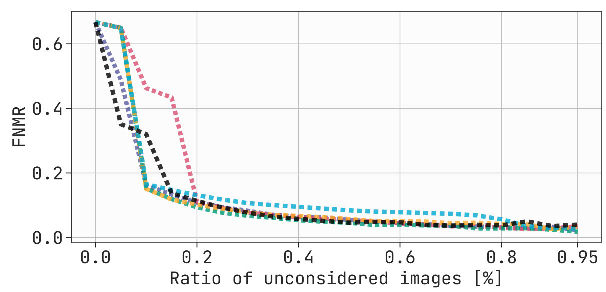
(c) ElasticFace [1] Model, CPLFW [11] Dataset
GRAFIQs with ResNet100, FMR= $1e-3$



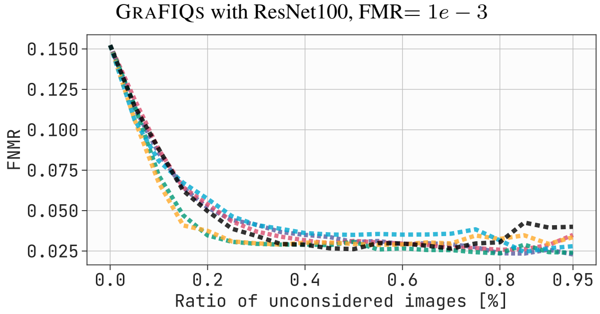
(d) ElasticFace [1] Model, CPLFW [11] Dataset
GRAFIQs with ResNet100, FMR= $1e-4$



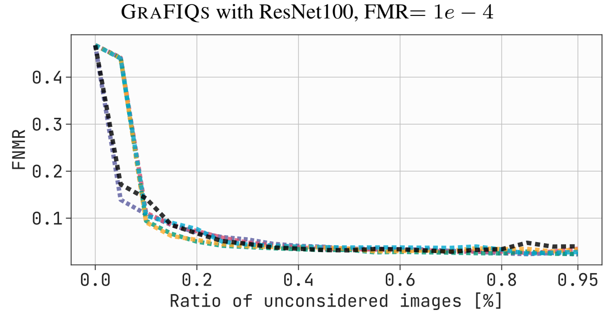
(e) MagFace [8] Model, CPLFW [11] Dataset
GRAFIQs with ResNet100, FMR= $1e-3$



(f) MagFace [8] Model, CPLFW [11] Dataset
GRAFIQs with ResNet100, FMR= $1e-4$

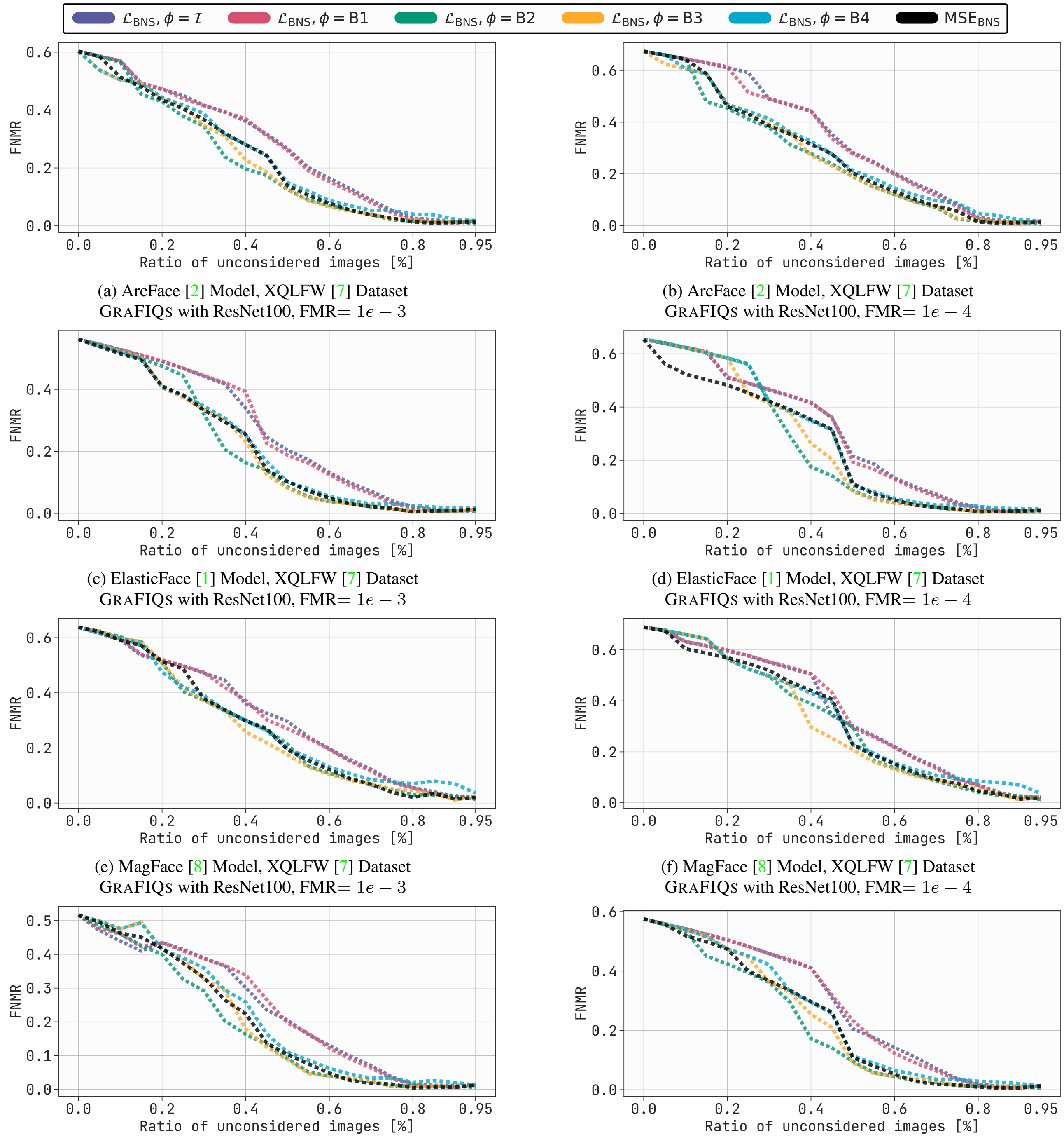


(g) CurricularFace [6] Model, CPLFW [11] Dataset
GRAFIQs with ResNet100, FMR= $1e-3$



(h) CurricularFace [6] Model, CPLFW [11] Dataset
GRAFIQs with ResNet100, FMR= $1e-4$

Figure 13. Error-versus-Discard Characteristic (EDC) curves for FNMR@FMR=$1e-3$ and FNMR@FMR=$1e-4$ of our proposed method using $\mathcal{L}_{\text{BNS}}$ as backpropagation loss and absolute sum as FIQ. The gradients at image level ($\phi = \mathcal{I}$), and block levels ($\phi = \text{B1} - \phi = \text{B4}$) are used to calculate FIQ. MSE_{BNS} as FIQ is shown in black. Results shown on benchmark CPLFW [11] using ArcFace, ElasticFace, MagFace, and, CurricularFace FR models. It is evident that the proposed GRAFIQs method leads to lower verification error when images with lowest utility score estimated from gradient magnitudes are rejected. Furthermore, estimating FIQ by backpropagating $\mathcal{L}_{\text{BNS}}$ yields significantly better results than using MSE_{BNS} directly.



(a) ArcFace [2] Model, XQLFW [7] Dataset
GRAFIQs with ResNet100, FMR= $1e-3$

(b) ArcFace [2] Model, XQLFW [7] Dataset
GRAFIQs with ResNet100, FMR= $1e-4$

(c) ElasticFace [1] Model, XQLFW [7] Dataset
GRAFIQs with ResNet100, FMR= $1e-3$

(d) ElasticFace [1] Model, XQLFW [7] Dataset
GRAFIQs with ResNet100, FMR= $1e-4$

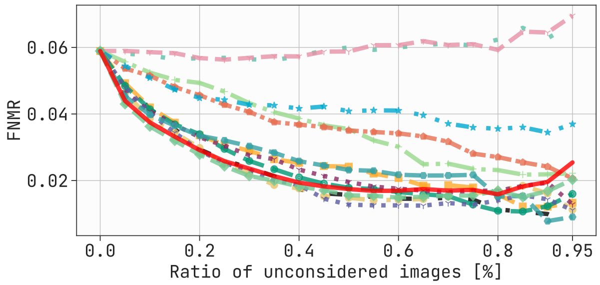
(e) MagFace [8] Model, XQLFW [7] Dataset
GRAFIQs with ResNet100, FMR= $1e-3$

(f) MagFace [8] Model, XQLFW [7] Dataset
GRAFIQs with ResNet100, FMR= $1e-4$

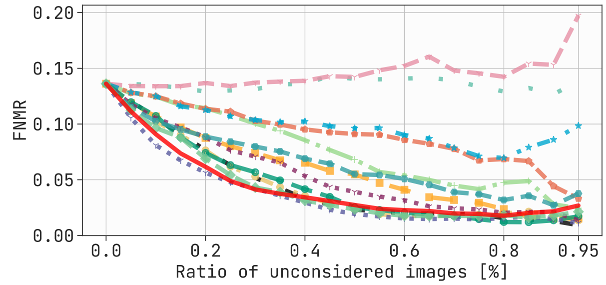
(g) CurricularFace [6] Model, XQLFW [7] Dataset
GRAFIQs with ResNet100, FMR= $1e-3$

(h) CurricularFace [6] Model, XQLFW [7] Dataset
GRAFIQs with ResNet100, FMR= $1e-4$

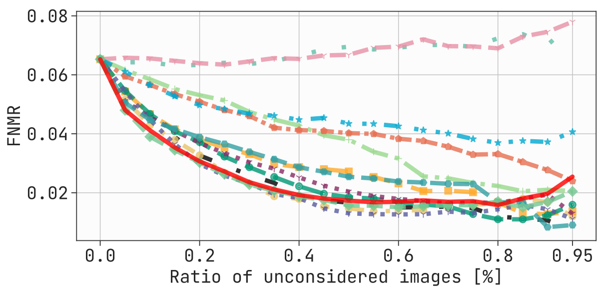
Figure 14. Error-versus-Discard Characteristic (EDC) curves for FNMR@FMR=$1e-3$ and FNMR@FMR=$1e-4$ of our proposed method using $\mathcal{L}_{\text{BNS}}$ as backpropagation loss and absolute sum as FIQ. The gradients at image level ($\phi = \mathcal{I}$), and block levels ($\phi = \text{B1} - \phi = \text{B4}$) are used to calculate FIQ. MSE_{BNS} as FIQ is shown in black. Results shown on benchmark XQLFW [7] using ArcFace, ElasticFace, MagFace, and, CurricularFace FR models. It is evident that the proposed GRAFIQs method leads to lower verification error when images with lowest utility score estimated from gradient magnitudes are rejected. Furthermore, estimating FIQ by backpropagating $\mathcal{L}_{\text{BNS}}$ yields significantly better results than using MSE_{BNS} directly.



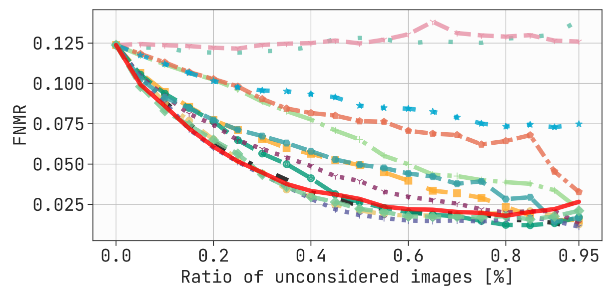
(a) ArcFace [2] Model, Adience [3] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$



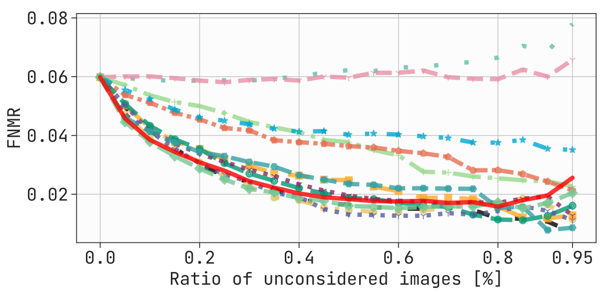
(b) ArcFace [2] Model, Adience [3] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$



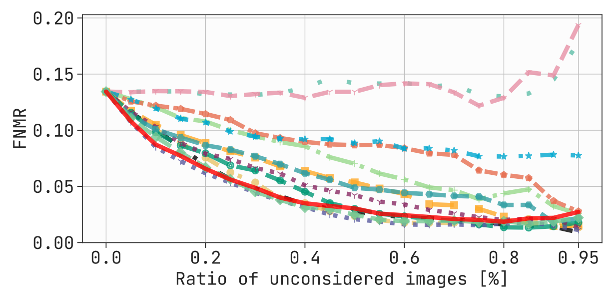
(c) ElasticFace [1] Model, Adience [3] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$



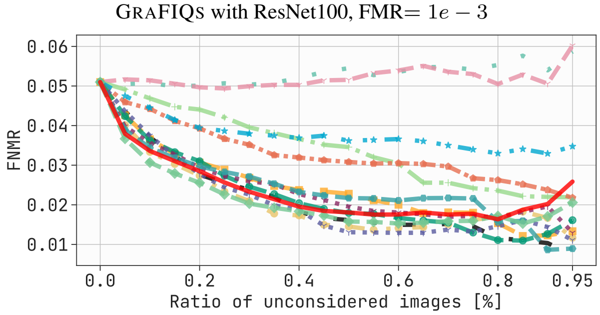
(d) ElasticFace [1] Model, Adience [3] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$



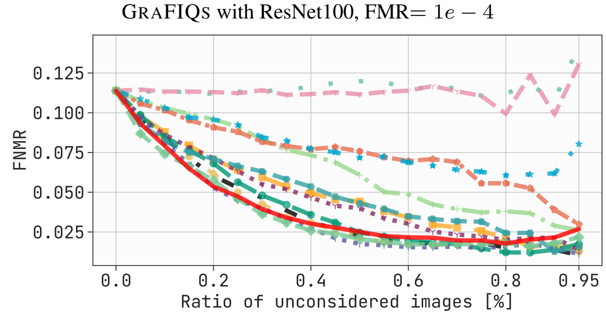
(e) MagFace [8] Model, Adience [3] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$



(f) MagFace [8] Model, Adience [3] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

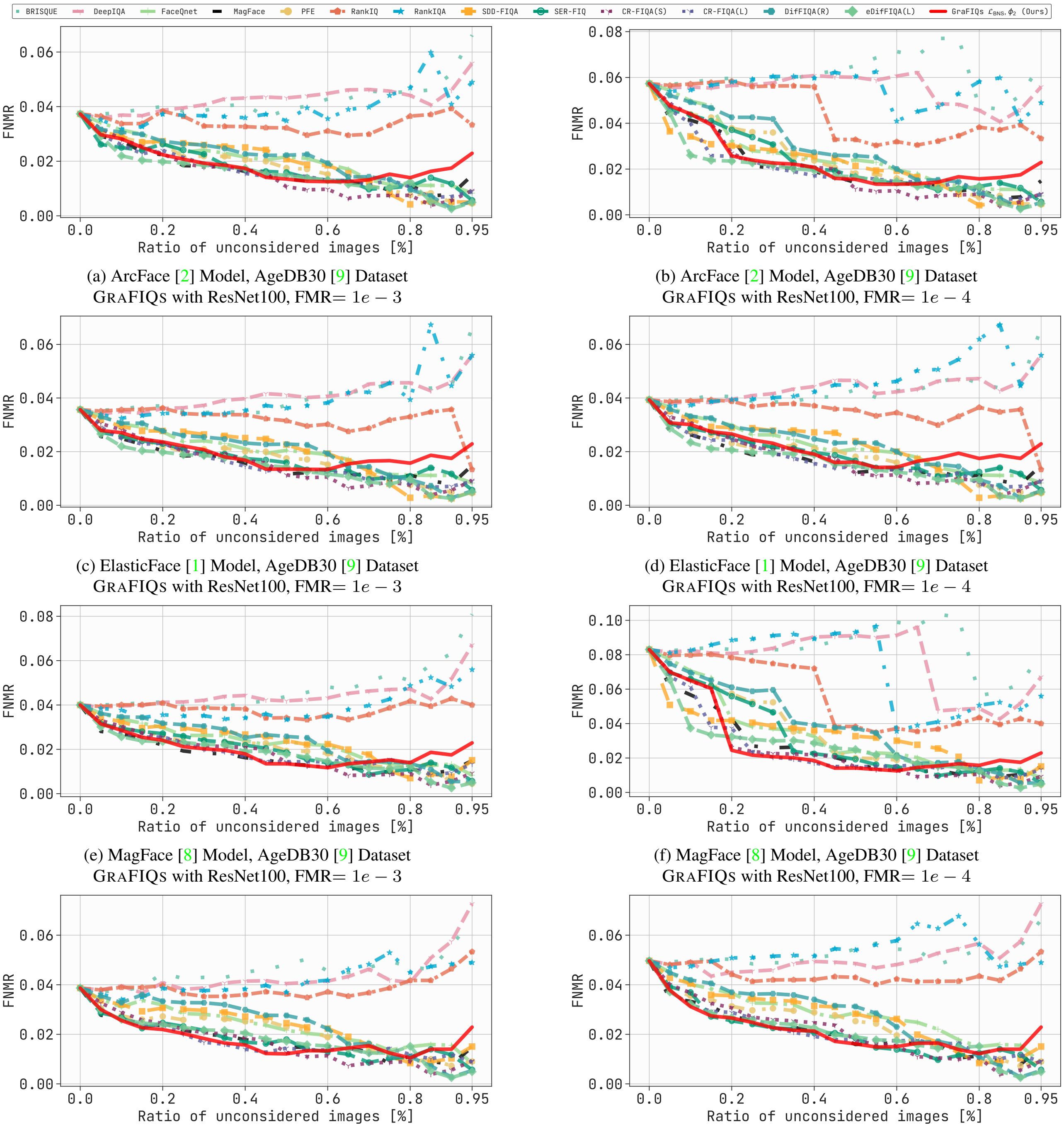


(g) CurricularFace [6] Model, Adience [3] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$



(h) CurricularFace [6] Model, Adience [3] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

Figure 15. EDC curves for FNMR@FMR=$1e-3$ and FNMR@FMR=$1e-4$ on dataset Adience [3] using ArcFace, ElasticFace, MagFace, and CurricularFace FR models. The proposed GRAFIQS method, shown in solid red, utilizes gradient magnitudes and it is reported using the best setting from Table 2 in the main paper.



(a) ArcFace [2] Model, AgeDB30 [9] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$

(b) ArcFace [2] Model, AgeDB30 [9] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

(c) ElasticFace [1] Model, AgeDB30 [9] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$

(d) ElasticFace [1] Model, AgeDB30 [9] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

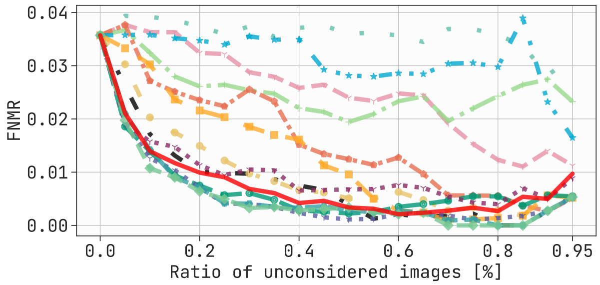
(e) MagFace [8] Model, AgeDB30 [9] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$

(f) MagFace [8] Model, AgeDB30 [9] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

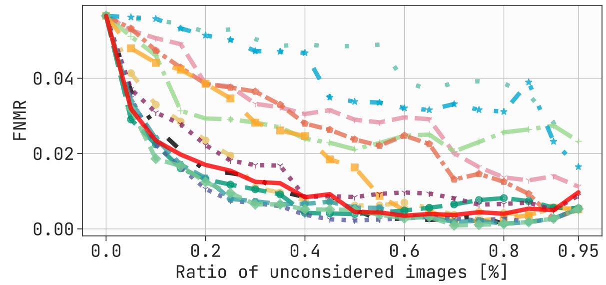
(g) CurricularFace [6] Model, AgeDB30 [9] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$

(h) CurricularFace [6] Model, AgeDB30 [9] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

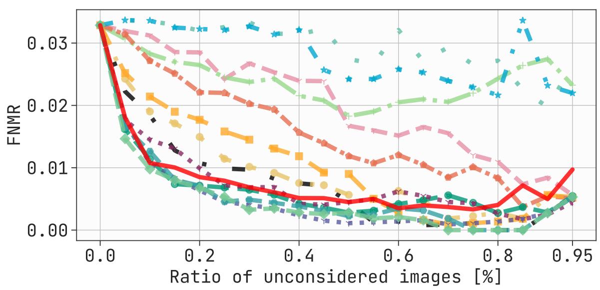
Figure 16. EDC curves for FNMR@FMR=$1e-3$ and FNMR@FMR=$1e-4$ on dataset AgeDB30 [9] using ArcFace, ElasticFace, MagFace, and CurricularFace FR models. The proposed GRAFIQS method, shown in solid red, utilizes gradient magnitudes and it is reported using the best setting from Table 2 in the main paper.



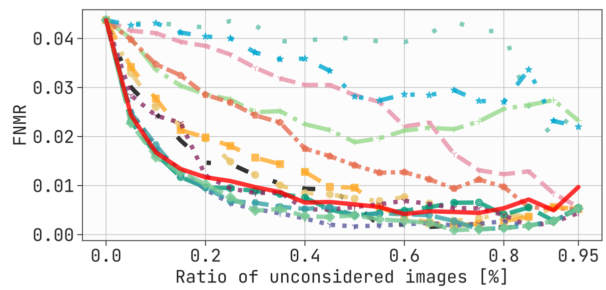
(a) ArcFace [2] Model, CFP-FP [10] Dataset
GRAFIQs with ResNet100, FMR= $1e-3$



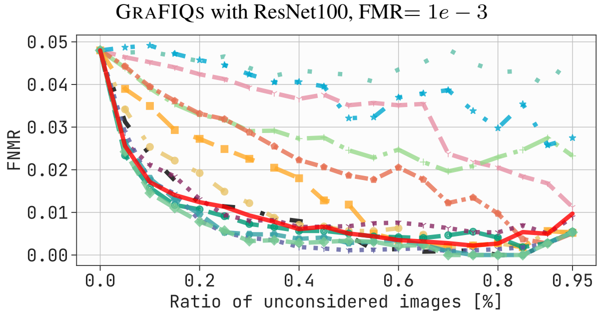
(b) ArcFace [2] Model, CFP-FP [10] Dataset
GRAFIQs with ResNet100, FMR= $1e-4$



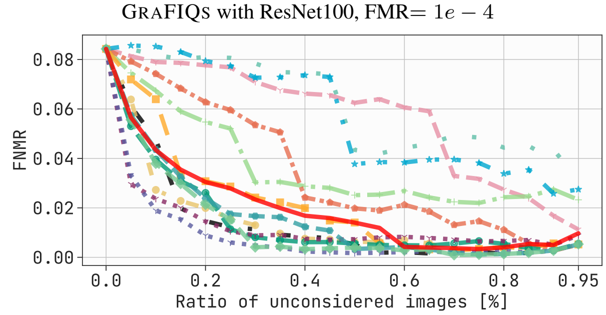
(c) ElasticFace [1] Model, CFP-FP [10] Dataset
GRAFIQs with ResNet100, FMR= $1e-3$



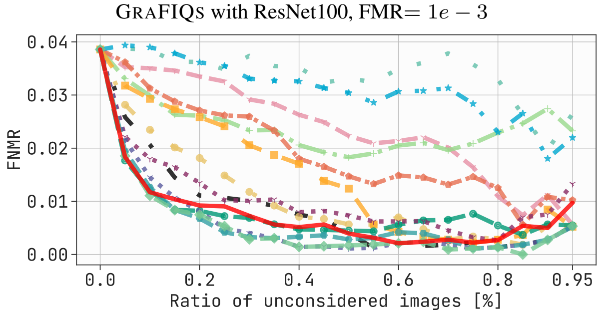
(d) ElasticFace [1] Model, CFP-FP [10] Dataset
GRAFIQs with ResNet100, FMR= $1e-4$



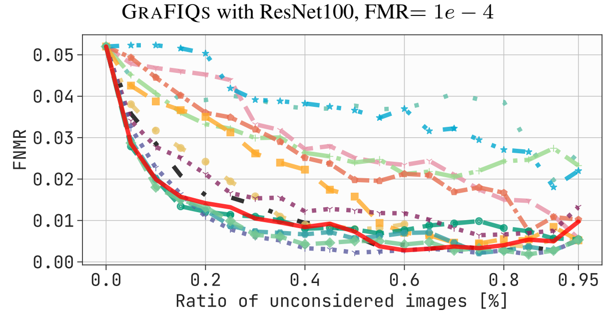
(e) MagFace [8] Model, CFP-FP [10] Dataset
GRAFIQs with ResNet100, FMR= $1e-3$



(f) MagFace [8] Model, CFP-FP [10] Dataset
GRAFIQs with ResNet100, FMR= $1e-4$

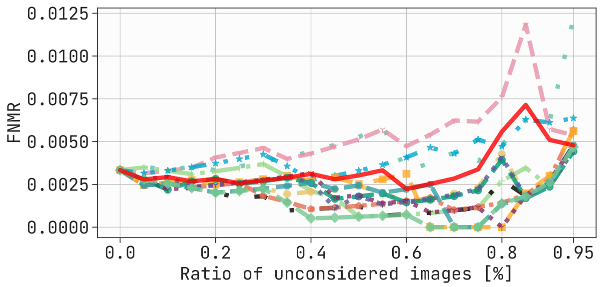


(g) CurricularFace [6] Model, CFP-FP [10] Dataset
GRAFIQs with ResNet100, FMR= $1e-3$

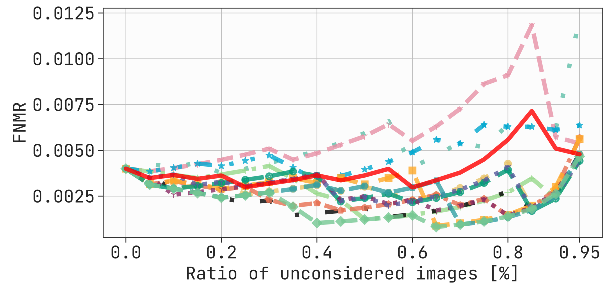


(h) CurricularFace [6] Model, CFP-FP [10] Dataset
GRAFIQs with ResNet100, FMR= $1e-4$

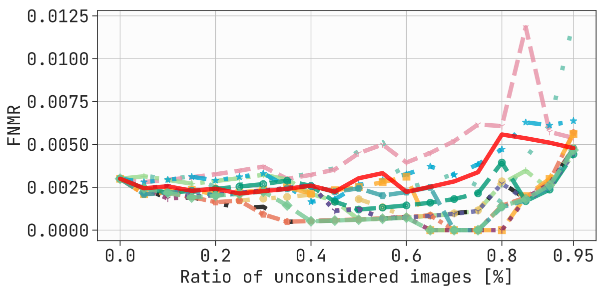
Figure 17. EDC curves for FNMR@FMR=$1e-3$ and FNMR@FMR=$1e-4$ on dataset CFP-FP [10] using ArcFace, ElasticFace, MagFace, and CurricularFace FR models. The proposed GRAFIQs method, shown in solid red, utilizes gradient magnitudes and it is reported using the best setting from Table 2 in the main paper.



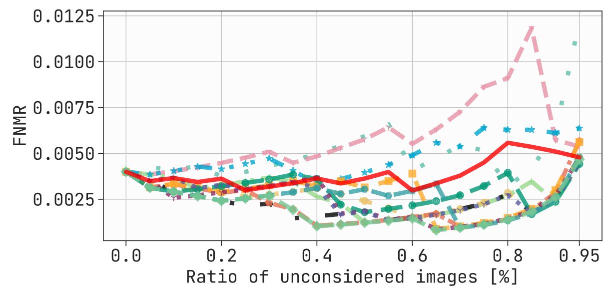
(a) ArcFace [2] Model, LFW [5] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$



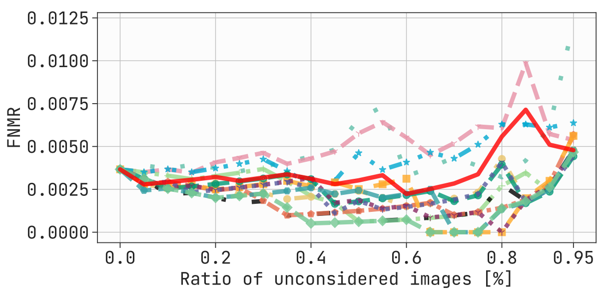
(b) ArcFace [2] Model, LFW [5] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$



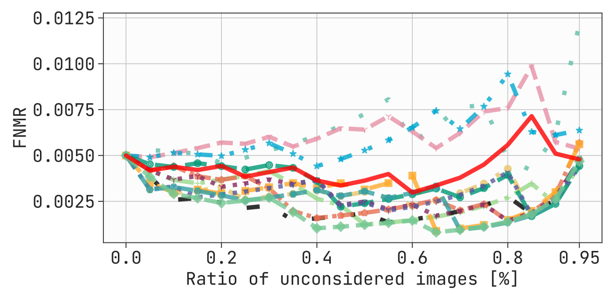
(c) ElasticFace [1] Model, LFW [5] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$



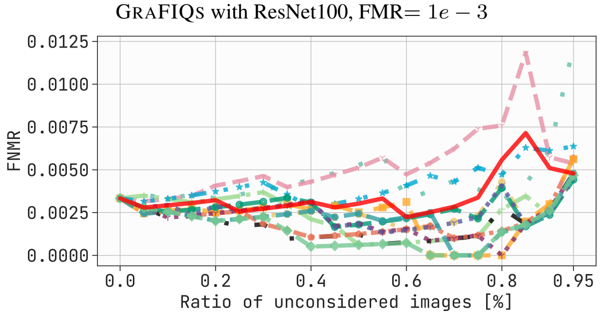
(d) ElasticFace [1] Model, LFW [5] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$



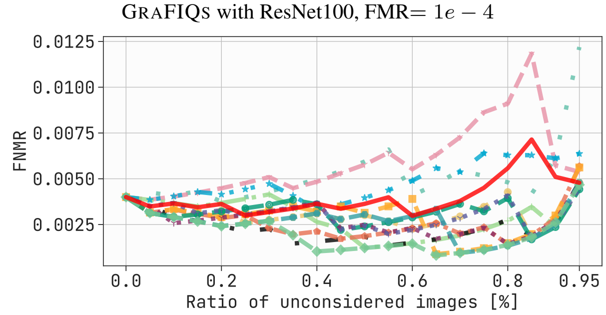
(e) MagFace [8] Model, LFW [5] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$



(f) MagFace [8] Model, LFW [5] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

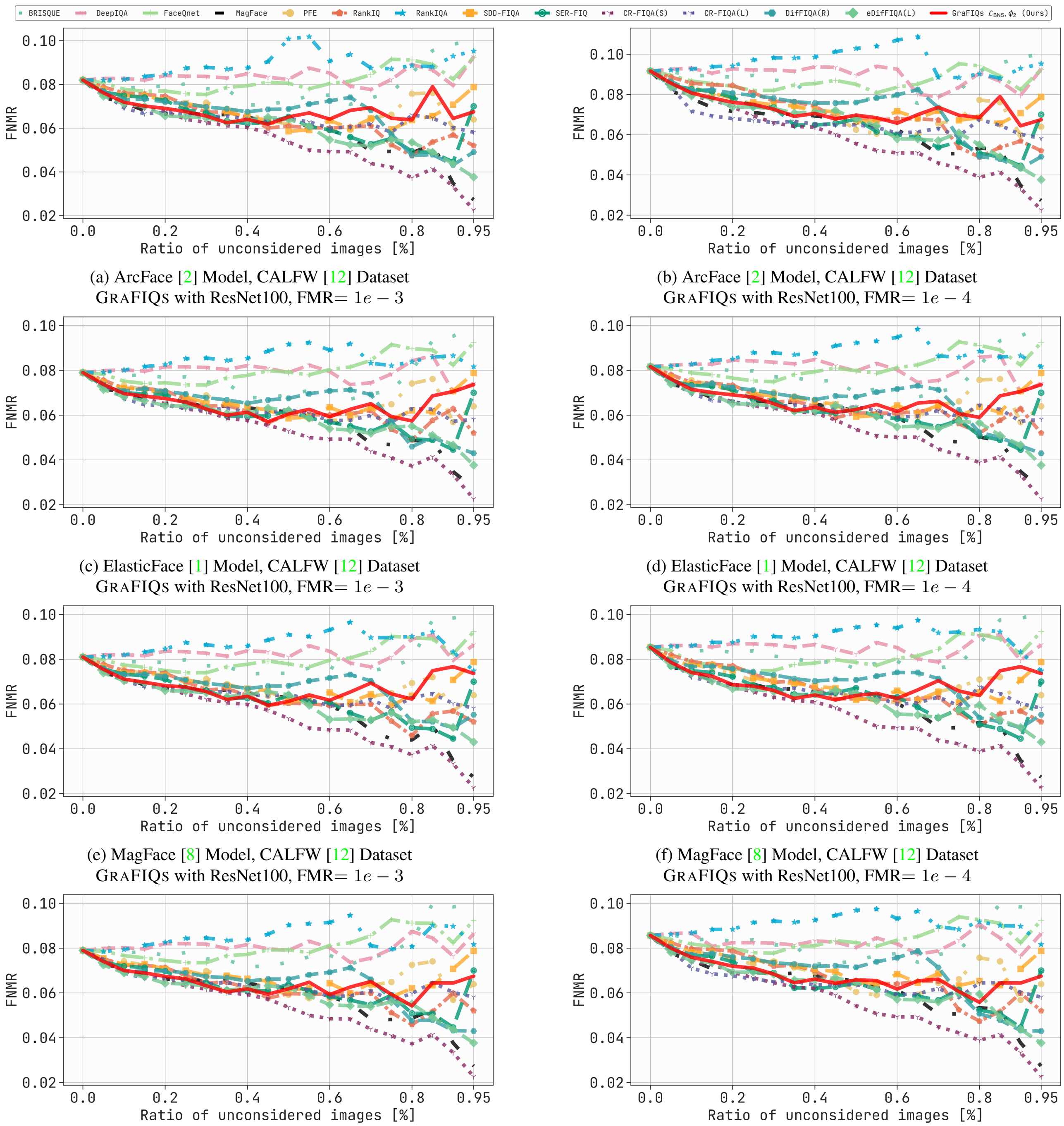


(g) CurricularFace [6] Model, LFW [5] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$



(h) CurricularFace [6] Model, LFW [5] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

Figure 18. EDC curves for FNMR@FMR=$1e-3$ and FNMR@FMR=$1e-4$ on dataset LFW [5] using ArcFace, ElasticFace, MagFace, and CurricularFace FR models. The proposed GRAFIQS method, shown in solid red, utilizes gradient magnitudes and it is reported using the best setting from Table 2 in the main paper.



(a) ArcFace [2] Model, CALFW [12] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$

(b) ArcFace [2] Model, CALFW [12] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

(c) ElasticFace [1] Model, CALFW [12] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$

(d) ElasticFace [1] Model, CALFW [12] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

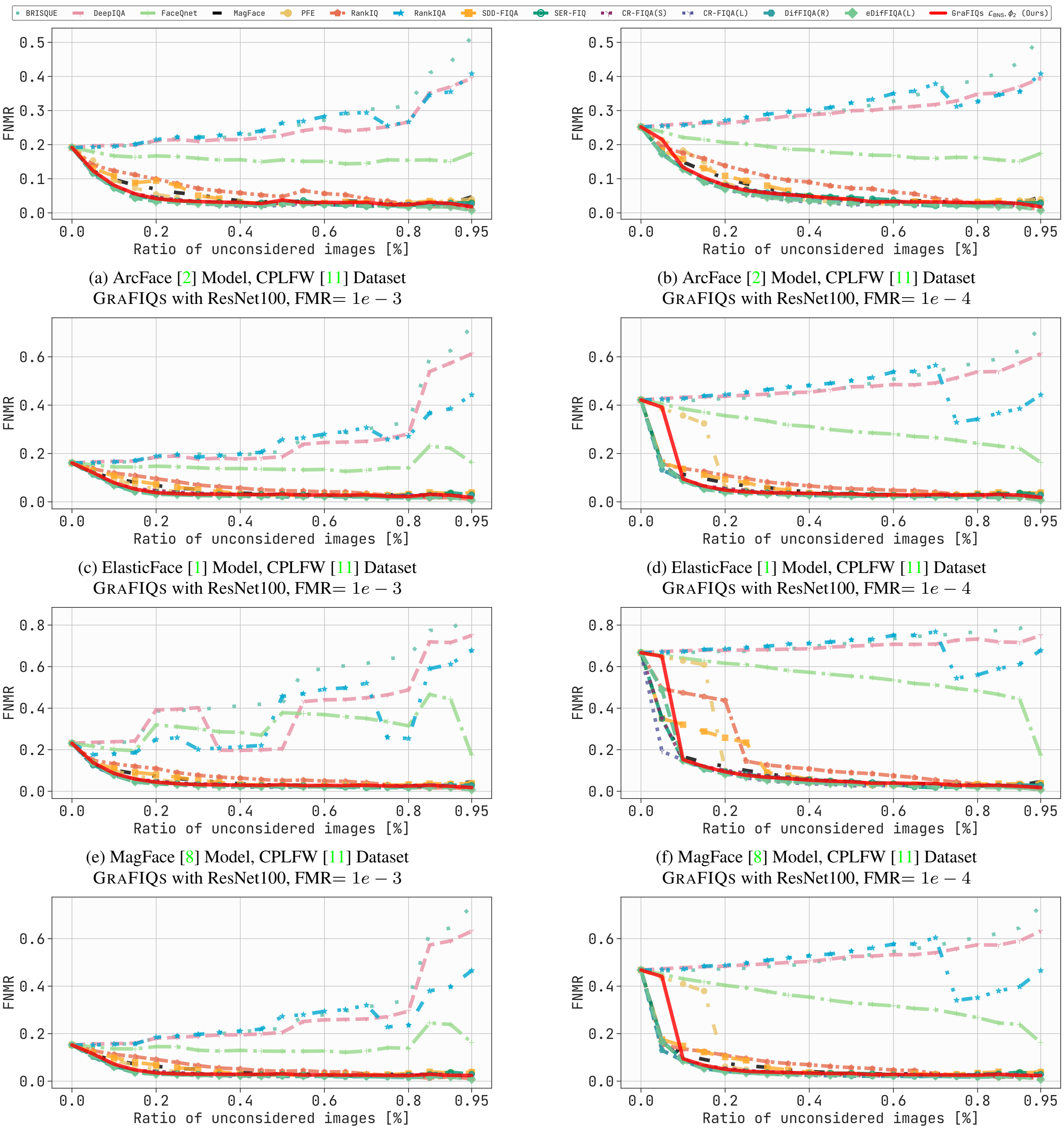
(e) MagFace [8] Model, CALFW [12] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$

(f) MagFace [8] Model, CALFW [12] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

(g) CurricularFace [6] Model, CALFW [12] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$

(h) CurricularFace [6] Model, CALFW [12] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

Figure 19. EDC curves for FNMR@FMR=$1e-3$ and FNMR@FMR=$1e-4$ on dataset CALFW [12] using ArcFace, ElasticFace, MagFace, and CurricularFace FR models. The proposed GRAFIQS method, shown in solid red, utilizes gradient magnitudes and it is reported using the best setting from Table 2 in the main paper.



(a) ArcFace [2] Model, CPLFW [11] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$

(b) ArcFace [2] Model, CPLFW [11] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

(c) ElasticFace [1] Model, CPLFW [11] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$

(d) ElasticFace [1] Model, CPLFW [11] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

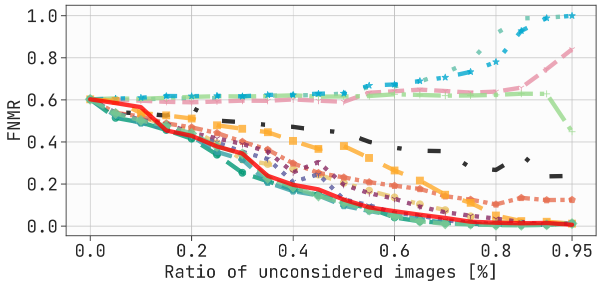
(e) MagFace [8] Model, CPLFW [11] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$

(f) MagFace [8] Model, CPLFW [11] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

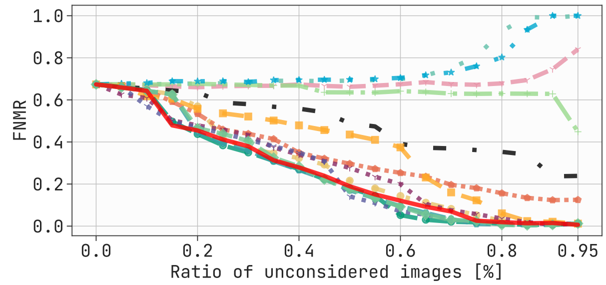
(g) CurricularFace [6] Model, CPLFW [11] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$

(h) CurricularFace [6] Model, CPLFW [11] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

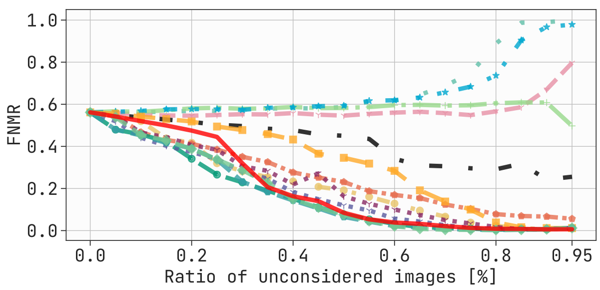
Figure 20. EDC curves for FNMR@FMR=$1e-3$ and FNMR@FMR=$1e-4$ on dataset CPLFW [11] using ArcFace, ElasticFace, MagFace, and CurricularFace FR models. The proposed GRAFIQS method, shown in solid red, utilizes gradient magnitudes and it is reported using the best setting from Table 2 in the main paper.



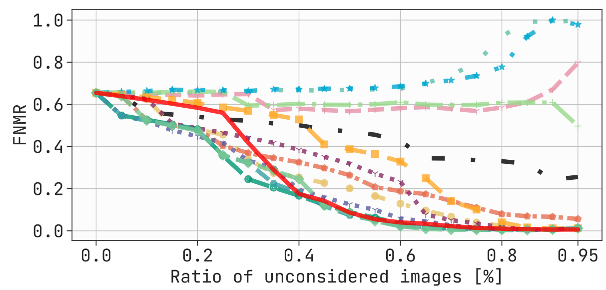
(a) ArcFace [2] Model, XQLFW [7] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$



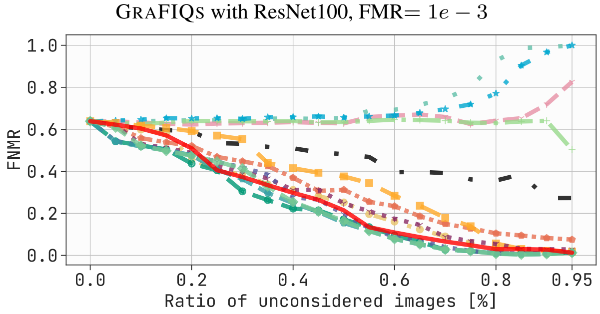
(b) ArcFace [2] Model, XQLFW [7] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$



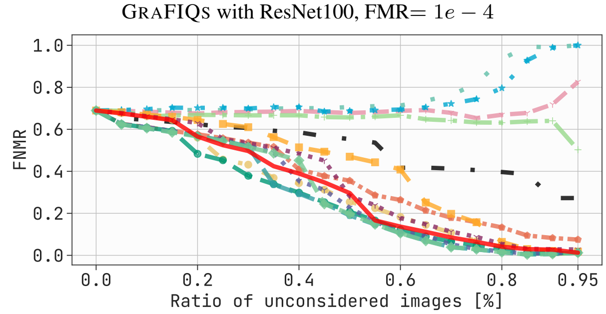
(c) ElasticFace [1] Model, XQLFW [7] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$



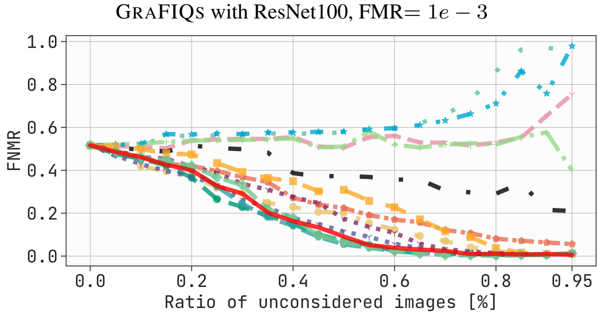
(d) ElasticFace [1] Model, XQLFW [7] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$



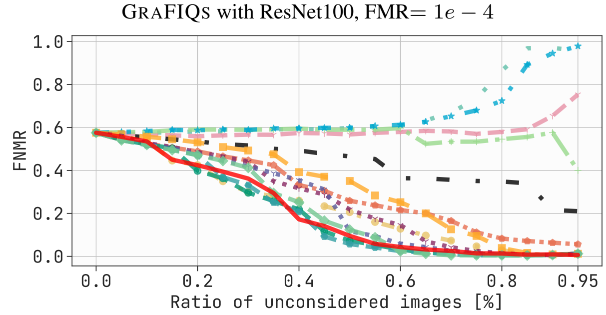
(e) MagFace [8] Model, XQLFW [7] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$



(f) MagFace [8] Model, XQLFW [7] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$



(g) CurricularFace [6] Model, XQLFW [7] Dataset
GRAFIQS with ResNet100, FMR= $1e-3$



(h) CurricularFace [6] Model, XQLFW [7] Dataset
GRAFIQS with ResNet100, FMR= $1e-4$

Figure 21. EDC curves for FNMR@FMR=$1e-3$ and FNMR@FMR=$1e-4$ on dataset XQLFW [7] using ArcFace, ElasticFace, MagFace, and CurricularFace FR models. The proposed GRAFIQS method, shown in solid red, utilizes gradient magnitudes and it is reported using the best setting from Table 2 in the main paper.

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