NEURAL INFORMATION PROCESSING SYSTEMS

Evolutionary Multi-View Classification via Eliminating Individual Fitness Bias

Xinyan Liang, Shuai Li, Qian Guo, Yuhua Qian, Bingbing Jiang, Tingjin Luo , Liang Du

(1) GitHub: https://github.com/LiShuailzn/Neurips-2025-EFB-EMVC

(2) If you have any detailed questions or suggestions, you can email us: lishuai_liuzhaona@163.com

Background

Evolutionary multi-view classification (EMVC) dynamically fuses different views through the adaptive mechanism of evolutionary algorithms, thereby automatically constructing high-quality multi-view fusion models.

Fitness evaluation (FE), which aims to calculate the classification performance of each individual in the population and provide reliable performance ranking for subsequent operations, is a core step in such methods. Its accuracy directly determines the correctness of the evolutionary direction.

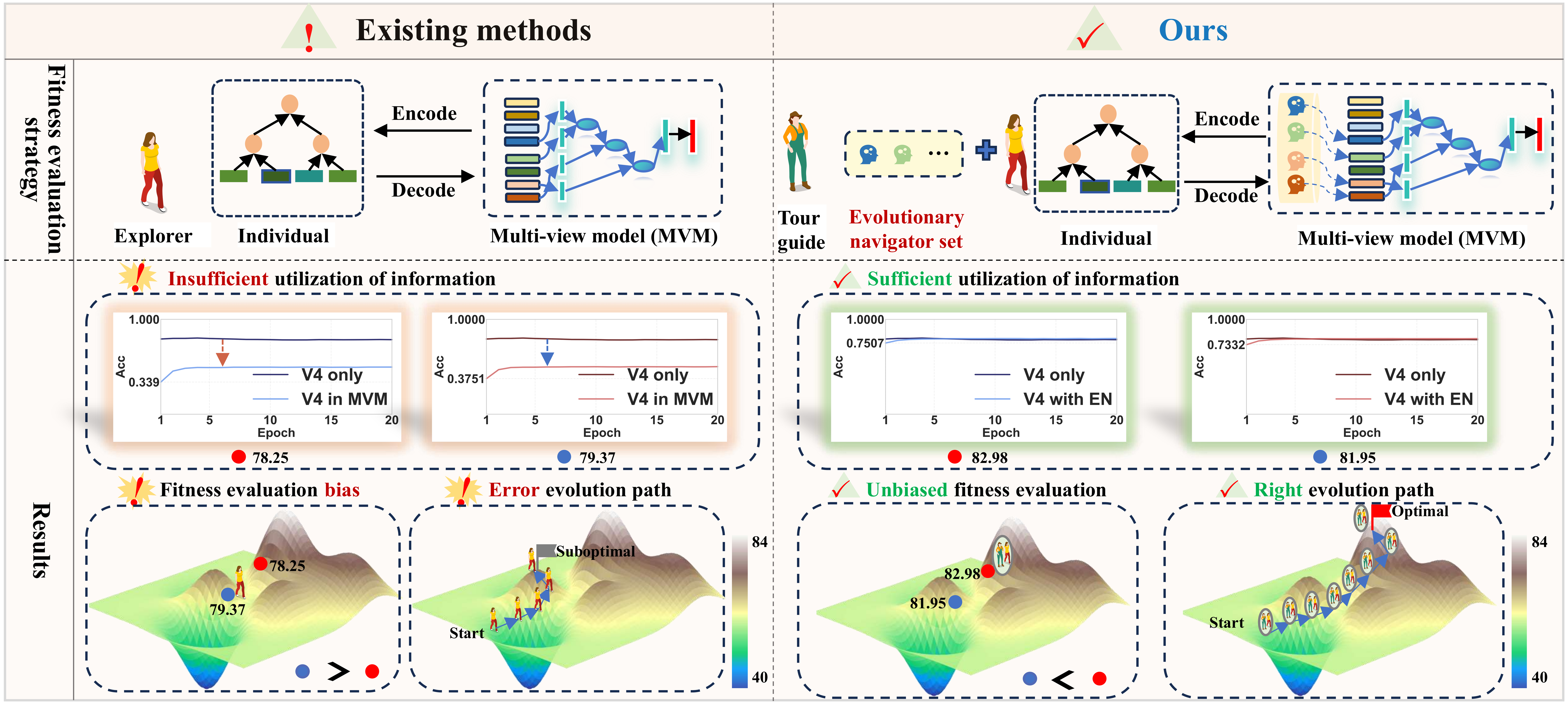
However, when FE fails to correctly reflect the ***superiority-inferiority relationship*** among individuals, it will lead to confusion in individual performance ranking, which in turn misleads the evolutionary direction and results in trapping into local optima.

This paper is the ***first*** to identify the aforementioned issue in the field of EMVC and call it as ***fitness evaluation bias (FEB)***.

Contributions

- In the field of EMVC, we are the ***first*** to identify and formally define the problem of ***FEB***, and systematically analyze its impact on the entire evolutionary process.
- To alleviate FEB, we equip multi-view model with evolutionary navigators (ENs) to fully explore the rich corresponding category and cross-category information therein, thereby achieving efficient utilization of multi-view data.

Motivation



!Evaluation method: ***Joint training strategy***.

!Problem: ***Insufficient*** mining of key information in low-information views.

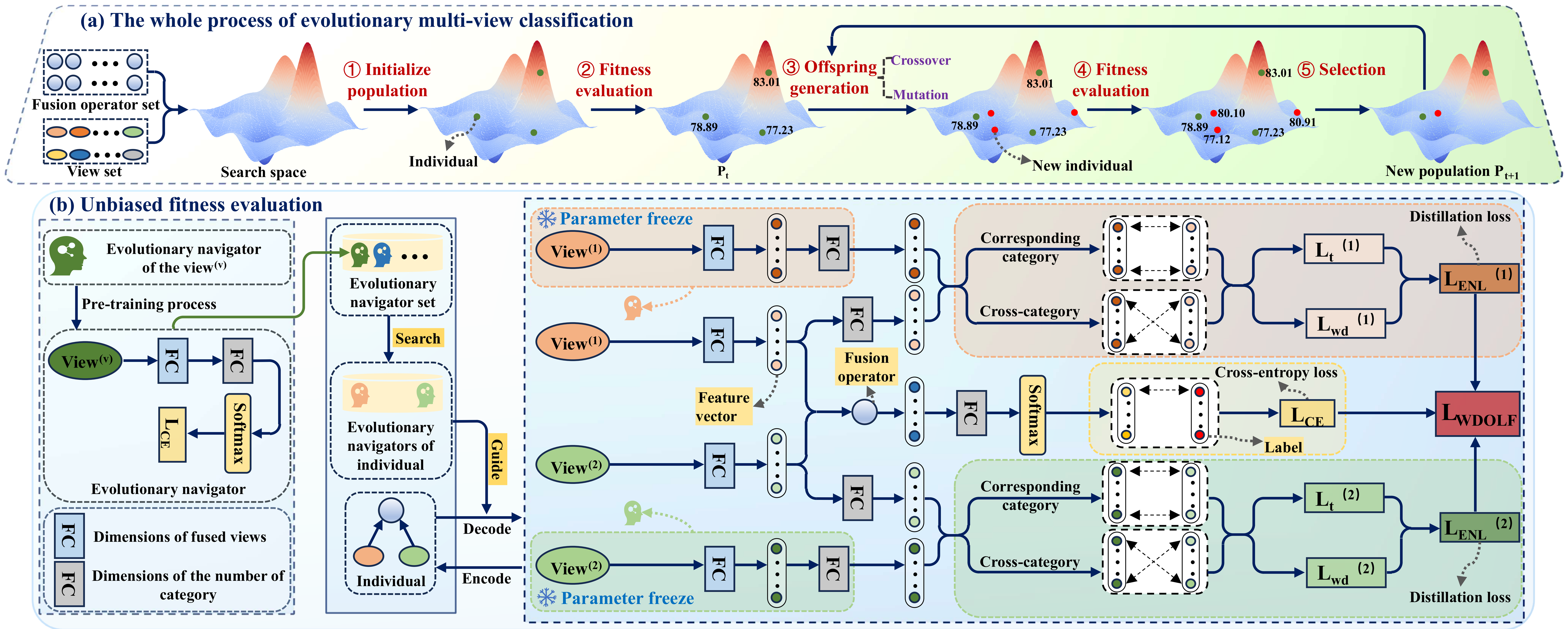
!Result: ***Disorder*** in individual ranking, ***misleads the evolutionary direction***.

✓ Evaluation method: Introduce an ***EN***.

✓ Solution: Through EN, it can ***fully mine*** the rich information in each view.

✓ Result: ***More accurate*** individual ranking and real-time ***correction of the evolutionary direction***.

Method



This paper proposes an ***unbiased FE method***, which consists of two steps:

(1) EN Pre-training: EN is encoded as a teacher model and achieves superior performance through pre-training, thereby providing reliable knowledge for the view branches;

(2) View Distillation: Leveraging the rich corresponding category and cross-category information in EN to improve the accuracy of FE, it achieves more reasonable individual performance ranking and effectively alleviates the FEB issue.

Experiment

➢ ***(1) Existence***

EN	Sort the fitness values of 15 individuals	PC	SRC	KT
✗	[4, 15, 5, 7, 1, 8, 13, 10, 11, 2, 14, 6, 12, 3, 9]	0.2143	0.2143	0.1429
✓	[4, 15, 5, 7, 8, 13, 2, 11, 1, 10, 12, 6, 14, 9, 3]			

Individual Pair	EN (✗)	EN (✓)
[4,0,2,3,-0,-1, -0] vs [0,2,3,4,-2,-3,-0]	82.00 vs 78.70	83.09 vs 83.92
[4,0,2,3,-0,-1, -0] vs [1,0,4,2,-4,-2,-2]	82.00 vs 81.81	83.09 vs 84.12
[4,0,2,3,-0,-1, -0] vs [3,2,4,-3,-4]	82.00 vs 79.09	83.09 vs 83.11
[4,0,2,3,-0,-1, -0] vs [1,4,2,-4,-2]	82.00 vs 81.71	83.09 vs 84.02
[0,2,3,4,-2,-3,-0] vs [0,4,3,-4,-0]	78.70 vs 79.75	83.92 vs 82.93
[0,2,3,4,-2,-3,-0] vs [3,2,4,-3,-4]	78.70 vs 79.09	83.92 vs 83.11
[2,4,-4] vs [0,3,-4]	70.17 vs 58.39	72.33 vs 79.11
[3,4,-3] vs [3,4,0,2,-0,-2,-3]	77.73 vs 76.69	82.41 vs 82.66
[3,4,-3] vs [3,2,-1]	77.73 vs 78.45	82.41 vs 79.12
[0,4,3,-4,-0] vs [3,2,4,-3,-4]	79.75 vs 79.09	82.93 vs 83.11
[3,4,0,2,-0,-2,-3] vs [3,2,-1]	76.69 vs 78.45	82.66 vs 79.12

Compared with existing methods, the order relationship of individual performance shows ***extremely low correlation***, which verifies the ***existence of FEB***. Meanwhile, among the 15 individuals, the order relationships between ***11 pairs*** of individuals have been ***reconstructed***, which confirms that FEB has a significant impact on the **order relationship** of existing methods.

Experiment

➢ *(2) Effectiveness*

Methods	MVoxCeleb	YoutubeFace	NUS	Reuters5	Reuters3	CB
Add	87.53±0.41	82.40±0.23	72.81±0.70	79.70±0.25	83.46±0.28	87.16±0.17
Mul	72.31±0.90	83.18±0.14	64.58±0.63	77.02±0.38	81.89±0.70	80.87±1.16
Cat	87.98±0.20	83.05±0.56	72.32±0.50	79.91±0.28	83.66±0.17	86.58±0.11
Max	81.57±0.41	81.49±0.29	71.36±0.47	80.02±0.20	84.01±0.28	84.21±0.11
Avg	87.27±0.33	82.23±0.17	73.00±0.51	79.69±0.30	83.58±0.28	87.05±0.20
MLB (ICLR17)	87.11±0.67	85.20±0.28	70.60±0.29	80.16±0.15	83.80±0.28	82.38±0.32
MFB (TNNLS18)	85.23±0.20	82.85±0.17	71.34±0.40	79.28±0.21	83.25±0.18	87.94±0.32
TFN (EMNLP17)	57.53±0.92	81.33±0.19	63.66±1.22	79.95±0.30	83.73±0.31	73.45±0.30
LMF (ACL18)	89.92±0.25	85.58±0.22	71.74±0.70	80.03±0.15	83.75±0.28	82.81±0.18
PTP (NeurIPS19)	88.61±0.36	85.18±0.30	71.83±0.50	80.10±0.10	84.06±0.20	85.08±0.11
TMC (ICLR22)	73.13±0.15	71.18±2.27	72.73±0.30	79.60±0.56	84.23±0.35	77.87±0.22
TMOA (AAAI22)	84.72±0.21	84.35±0.25	72.60±0.48	79.11±0.43	84.19±0.27	86.80±0.10
ETMC (TPAMI23)	88.70±0.15	79.63±1.89	73.05±0.67	79.80±0.41	84.25±0.42	- -
RCML (AAAI24)	80.51±0.41	81.95±0.20	72.53±0.55	81.39±0.18	85.88±0.29	- -
BV (TEVC2021)	63.25±0.14	82.01±0.18	68.69±0.59	80.61±0.25	83.98±0.14	77.08±0.15
SSV (TEVC2021)	85.10±0.23	84.43±0.31	63.70±0.64	79.51±0.41	84.71±0.22	87.02±0.13
MR (TEVC2021)	79.92±0.29	84.78±0.21	64.39±0.85	78.24±0.45	84.17±0.19	83.36±0.21
EmbraceNet (IF19)	81.74±0.34	80.90±1.04	72.43±0.38	80.07±0.21	83.58±0.25	85.85±0.09
AWDR(PR19)	91.08±0.09	85.11±0.15	72.44±0.66	79.69±0.27	83.32±0.32	86.66±0.16
RMAR(INS22)	91.54±0.11	85.21±0.17	72.51±0.67	79.84±0.25	83.48±0.25	85.36±0.46
EDF (TEVC2021)	93.09±0.20	85.83±0.08	74.73±0.45	81.12±0.25	85.49±0.21	88.55±0.20
CoMO-NAS (ACMMM24)	- -	- -	74.24±0.29	- -	- -	88.69±0.38
CSG-NAS (IJCAI24)	- -	- -	74.52±0.40	- -	- -	89.20±0.06
DC-NAS (AAAI24)	92.19±0.07	85.28±0.14	74.35±0.58	81.35±0.28	85.86±0.14	88.52±0.13
TEF (ICLR25)	92.41±0.12	86.02±0.41	75.12±0.57	82.26±0.23	86.49±0.10	- -
EFB-EMVC (ours)	**94.82±0.12**	**87.67±0.17**	**75.79±0.76**	**82.66±0.24**	**86.51±0.12**	**89.67±0.18**

Method	MM-IMDB		NTU RGB-D		EgoGesture	
	Modality	F1-W (%)	Modality	Acc (%)	Modality	Acc (%)
Uni-view methods						
Modality 1	Text (T)	57.54	Video (V)	83.91	RGB (R)	93.75
Modality 2	Image (I)	49.21	Pose (P)	85.24	Depth (D)	94.03
Multi-view methods						
Two-stream (NeurIPS14)	I+T	60.81	V+P	88.60	- -	- -
GMU (ICLR17)	I+T	61.70	V+P	85.80	- -	- -
CentralNet (ECCV18)	I+T	62.23	V+P	89.36	- -	- -
MFAS (CVPR19)	I+T	62.50	V+P	89.50±0.60	- -	- -
MMTM (ICCV20)	- -	- -	V+P	88.92	R+D	93.51
MTUT (3DV19)	- -	- -	- -	- -	R+D	93.87
3D-CDC-NAS2 (TIP21)	- -	- -	- -	- -	R+D	94.38
BM-NAS (AAAI22)	I+T	62.92±0.03	V+P	90.48±0.24	R+D	94.96±0.07
DC-NAS (AAAI24)	I+T	63.70±0.11	V+P	90.85±0.05	R+D	95.22±0.05
CoMO-NAS (ACMMM24)	I+T	63.84±0.16	V+P	90.94±0.02	R+D	95.25±0.03
CSG-NAS (IJCAI24)	I+T	64.12±0.12	V+P	91.12±0.03	R+D	95.25±0.04
MCTS-CSG (IJMLC25)	- -	- -	V+P	91.21±0.10	R+D	95.27±0.01
HF-MNAS (TIP25)	I+T	64.17	V+P	91.15	R+D	**95.31**
EFB-EMVC (ours)	I+T	**64.53±0.05**	V+P	**91.30±0.03**	R+D	95.30±0.03

Experimental results on a large number of multi-view datasets verify the ***effectiveness*** of the proposed method.

Experiment

➢ ***(3) Compatibility***

Methods	MVoxCeleb	YoutubeFace	NUS	Reuters5	Reuters3
EDF	93.09±0.20	85.83±0.08	74.73±0.45	81.12±0.25	85.49±0.21
EDF+EN	**94.70±0.23**	**87.29±0.43**	**75.81±0.71**	**82.72±0.16**	**86.48±0.15**
DC-NAS	92.19±0.07	85.28±0.14	74.35±0.58	81.35±0.28	85.86±0.14
DC-NAS+EN	**94.82±0.12**	**87.67±0.17**	**75.79±0.76**	**82.66±0.24**	**86.51±0.12**

Integrating the EN into various methods all leads to significant performance improvements, which verifies the ***generality*** of the EN.