

Supplementary Material of Sparsity- and Hybridity-inspired Visual Parameter-Efficient Fine-Tuning for Medical Diagnosis

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1. Comparison with state-of-the-art PEFT Methods: Table 1 and Table 4 demonstrate that our SH-PEFT outperforms state-of-the-art PEFT when measured by additional indexes including Accuracy and AUC. Overall, our method achieves superior performance across three commonly used classification evaluation metrics, F_1 , ACC, and AUC.

2. Additional Comparison on BUSI and LIUMC datasets: Table 2 and Table 3 present additional comparisons between SH-PEFT and other methods on the BUSI and LIUMC datasets. The results demonstrate that our method achieves superior performance.

References

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Table 1: Comparison with state-of-the-art PEFT methods, in terms of **Accuracy**(%)

Method (Pub'Year)	$\mathcal{D}1$	$\mathcal{D}2$	$\mathcal{D}3$	$\mathcal{D}4$	$\mathcal{D}5$	$\mathcal{D}6$	Avg
Full Finetune	84.9	73.9	84.4	78.4	94.2	75.8	81.9
Adapter-par (NeurIPS'22)	82.0	78.8	86.9	79.7	93.2	76.5	82.8
SSF (NeurIPS'22)	84.3	79.8	90.6	80.3	92.3	79.4	84.5
LoRa (ICLR'22)	86.0	82.8	90.0	80.0	96.3	76.9	85.3
VPT-deep (ECCV'22)	77.1	78.8	79.4	79.4	83.1	73.7	78.6
VPT-shallow (ECCV'22)	80.3	79.3	83.8	81.6	90.4	75.7	81.8
FT-LN (Arxiv'23)	80.1	76.4	82.5	78.4	87.6	76.9	80.3
BitFit (ACL'22)	84.3	80.3	87.5	76.6	93.3	79.4	83.6
FT-Att (ECCV'22)	85.6	81.8	90.6	81.6	95.8	77.9	85.5
SPT-LoRa (ICCV'23)	86.1	80.8	91.9	79.2	96.0	77.3	85.2
SH-PEFT (Ours)	84.8	83.3	91.9	82.9	95.6	79.2	86.3

Table 2: Comparison with latest efforts on BUSI.

Method	F_1	ACC
SwinB(ICCV'21) [2]	71.0	81.8
BVANet(JBHI'20) [5]	-	83.4
HoVer-Trans(TMI'23) [3]	87.2	85.5
SH-PEFT (Ours)	90.5	91.9

Table 3: Comparison with latest efforts on LIUMC.

Method	F_1	ACC
SwinB(ICCV'21) [2]	72.2	77.8
AL+DA(BIBM'23) [1]	67.0	71.0
MoCov3-SB(MICCAI'23w) [4]	71.1	76.7
SH-PEFT (Ours)	72.7	79.2

Table 4: Comparison with state-of-the-art PEFT methods, in terms of **AUC**(%)

Method (Pub'Year)	$\mathcal{D}1$	$\mathcal{D}2$	$\mathcal{D}3$	$\mathcal{D}4$	$\mathcal{D}5$	$\mathcal{D}6$	Avg
Full Finetune	94.3	80.8	92.8	91.2	99.6	90.0	91.4
Adapter-par (NeurIPS'22)	93.9	85.9	95.2	94.8	99.9	94.0	93.9
SSF (NeurIPS'22)	95.2	87.7	96.6	94.2	99.9	94.2	94.6
LoRa (ICLR'22)	95.3	88.7	96.3	91.0	99.9	87.5	93.1
VPT-deep (ECCV'22)	92.0	86.0	91.4	94.3	98.5	91.1	92.2
VPT-shallow (ECCV'22)	93.0	85.3	93.8	95.9	99.5	92.8	93.4
FT-LN (Arxiv'23)	93.4	81.1	94.1	94.8	99.5	93.1	92.7
BitFit (ACL'22)	95.0	86.0	95.5	92.4	99.9	94.4	93.9
FT-Att (ECCV'22)	95.5	88.0	95.0	93.6	99.9	92.7	94.1
SPT-LoRa (ICCV'23)	95.4	88.5	95.7	92.2	100.0	92.5	94.0
SH-PEFT (Ours)	95.5	88.6	95.5	93.4	99.9	94.4	94.6