



**ICLR 2024**

# **PAC-FNO: Parallel-Structured All-Component Fourier Neural Operators for Recognizing Low-Quality Images**

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# Outlines

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- **Motivation**
- **Related Works**
- **PAC-FNO**
- **Experiments**
- **Results**

# Motivation

- When deep **learning models** are deployed to the real world, they are likely to **face low-quality inputs at inference** (e.g., low-resolution or natural input variations)
- The use of such **low-quality inputs significantly degrades the performance** of visual recognition models.

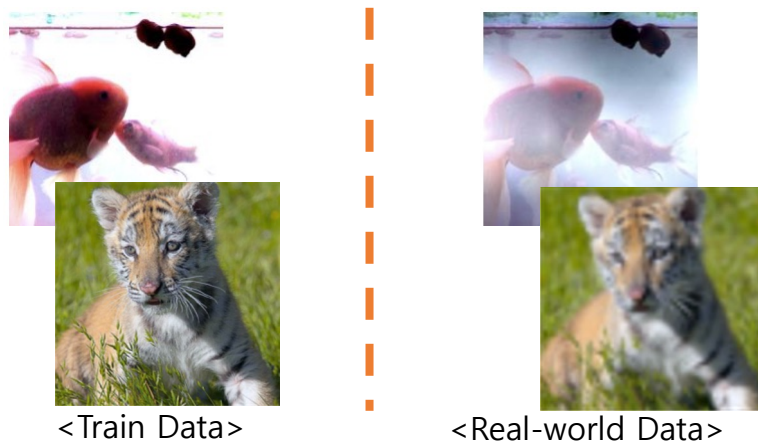


Figure 1: Comparing train data and real-world data.

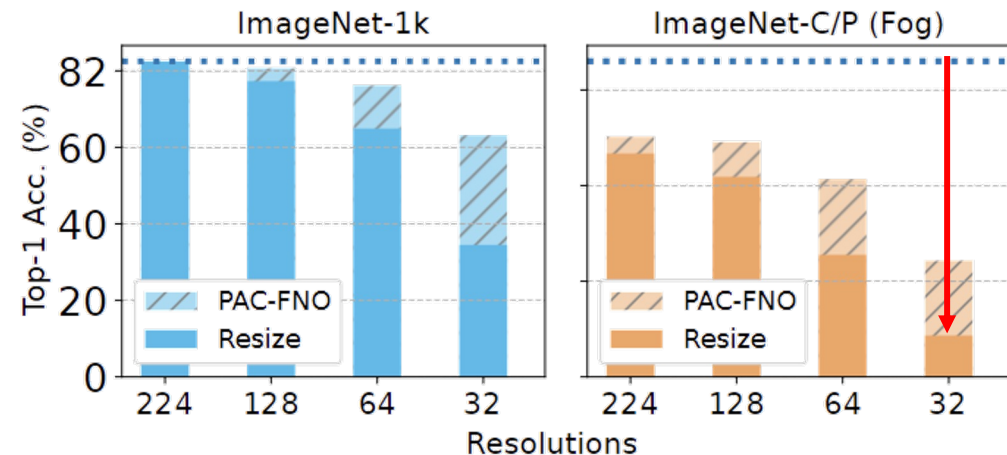


Figure 2: Performance degradation in ImageNet-1k and ImageNet-C/P (Fog).

# Related Works

- **Fourier Neural Operators (FNOs)** which achieve remarkable performance in solving PDEs, are mathematically defined under the infinite-dimensional continuous space regime and for this reason, **they can process various resolutions of the continuous space without model change.**
- For efficiency, FNOs restrict the size of the learnable parameter  $R_\theta$  by using an ideal low-pass filter  $\xi$ .

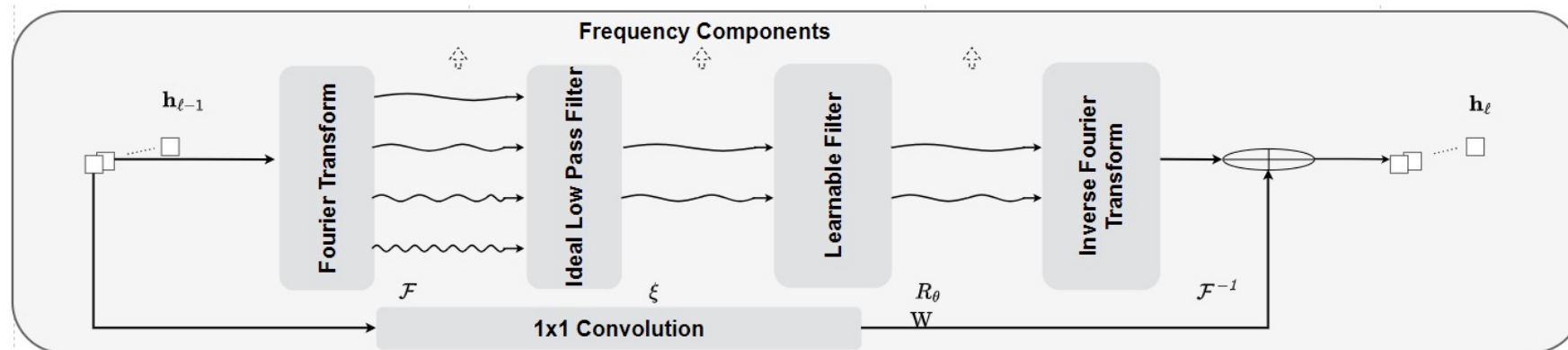
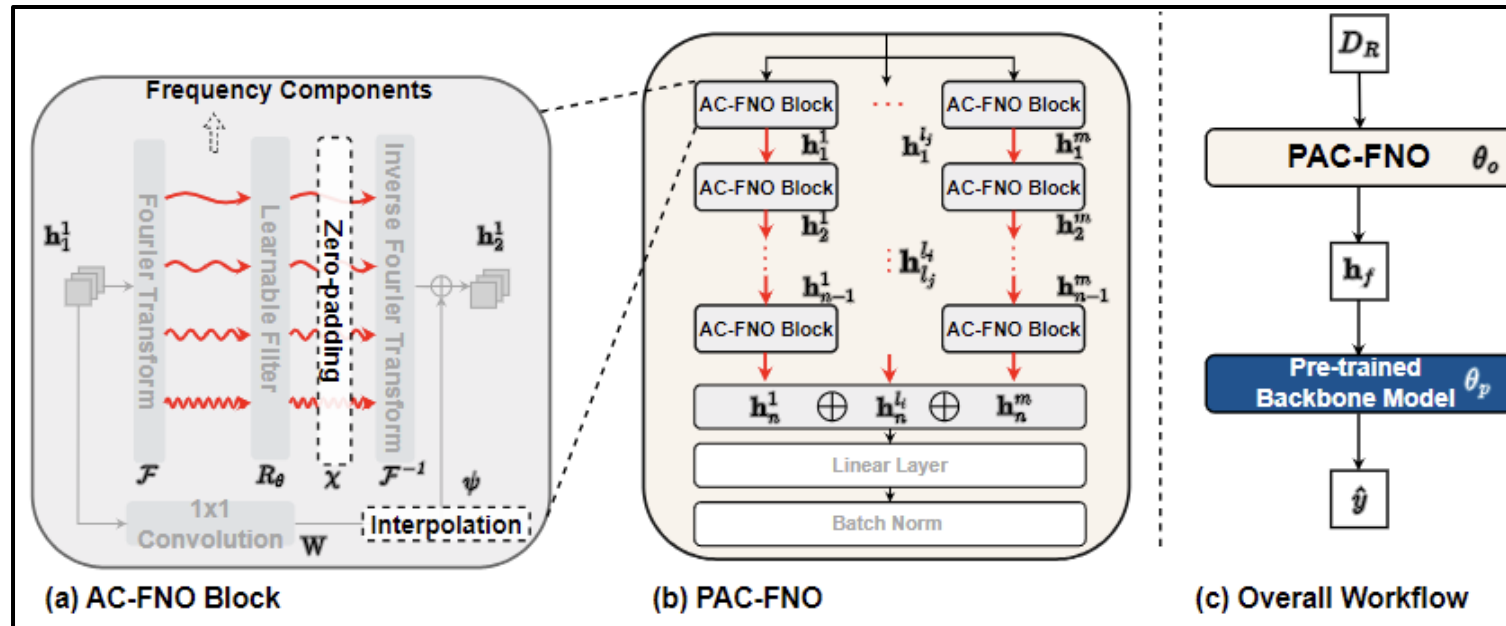


Figure 3: Fourier Neural Operators.

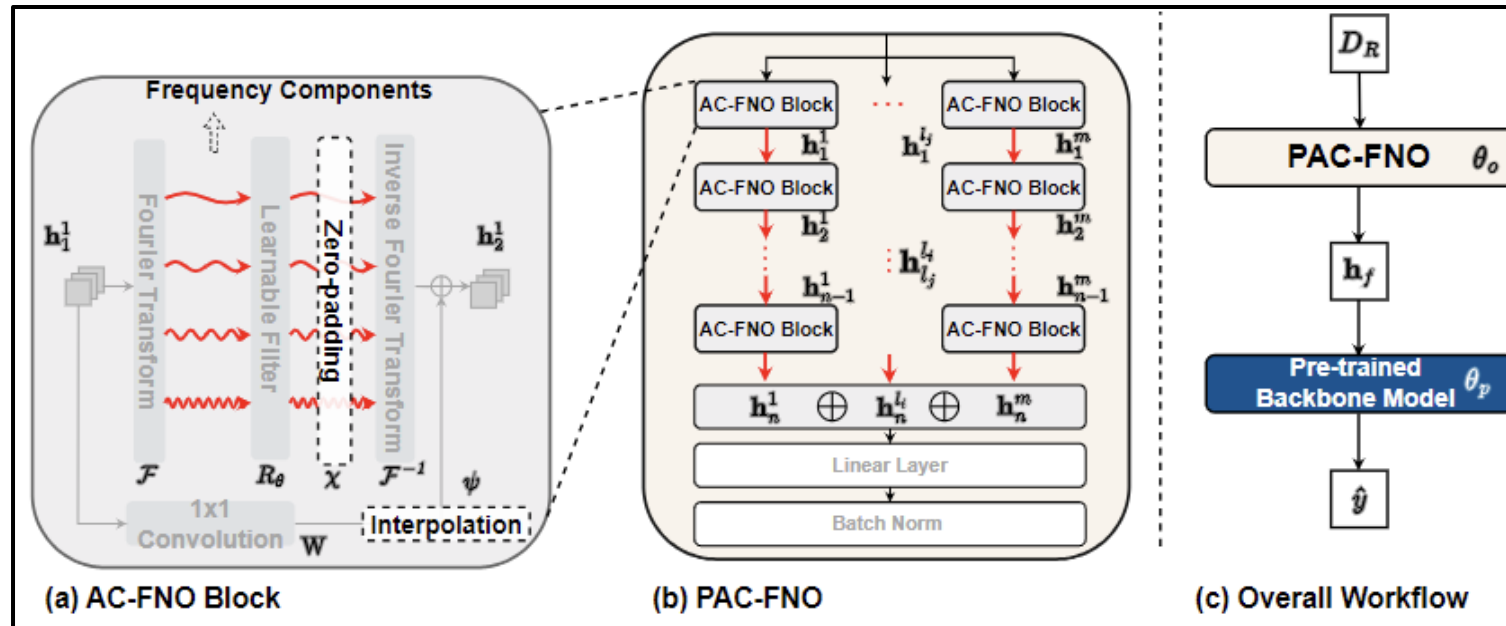
# PAC-FNO: Parallel-Structured All-Component Fourier Neural Operators for Recognizing Low-Quality Images



## (a) All-Component-FNO (AC-FNO) Block

- In the case of images, high-frequency information sometimes plays an important role in image classification, especially when detailed information is required (type of bird, type of car, etc). To this end, we propose an AC-FNO block without any band pass filters.
- AC-FNO blocks use all frequency components and rely on Zero-padding and Interpolation to construct the images for the target resolution.
- $\mathcal{F}$  is a Fourier transform that transforms the hidden vector into the frequency domain,  $\chi$  a zero-padding,  $R_\theta$  is a learnable filter,  $\psi$  is an interpolation and  $W$  is a 1x1 convolutional operation.

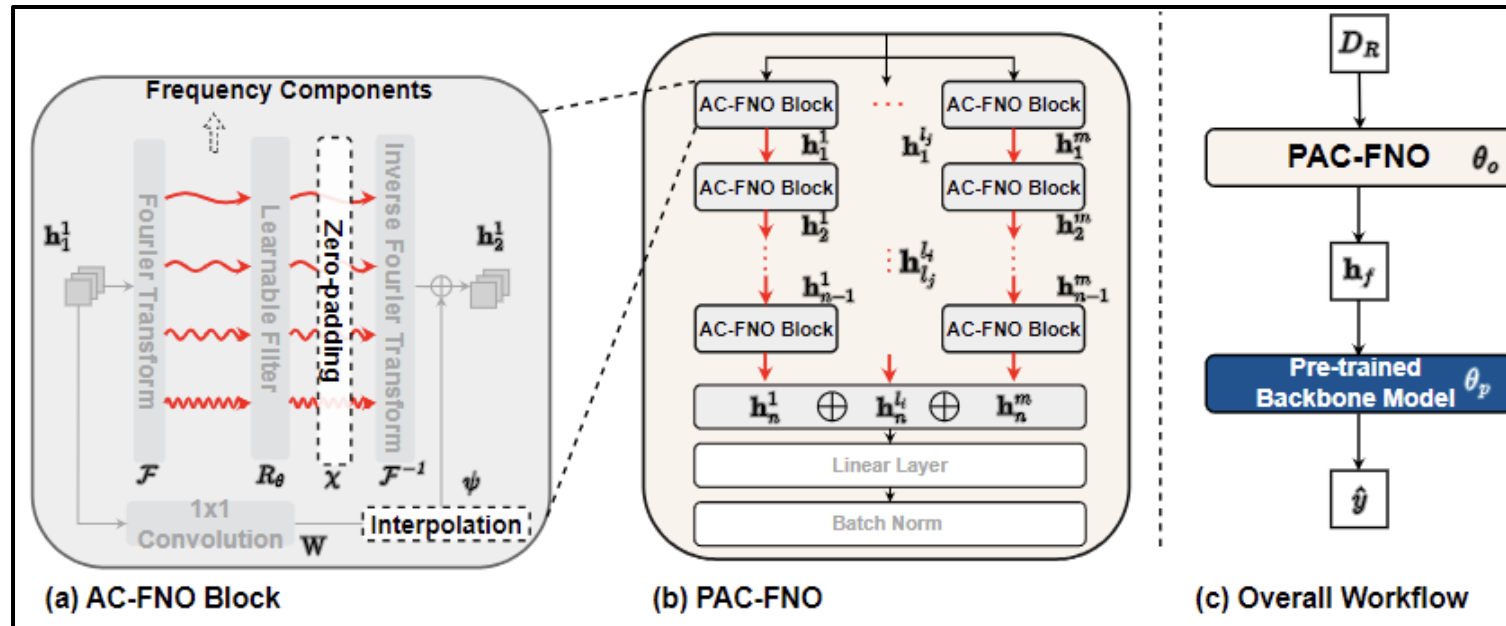
# PAC-FNO: Parallel-Structured All-Component Fourier Neural Operators for Recognizing Low-Quality Images



## (b) Parallel Configuration of AC-FNO Blocks

- To increase the capacity to learn various types of input variations, we propose to configure AC-FNO blocks in a parallel structure.
- There are  $n \times m$  AC-FNO blocks, where  $n$  is the number of stages and  $m$  is the number of parallel AC-FNO blocks in a stage.

# PAC-FNO: Parallel-Structured All-Component Fourier Neural Operators for Recognizing Low-Quality Images



## Two-stage Learning Algorithm

- First stage: We jointly train the PAC-FNO and the pre-trained backbone model together using only the target resolution for which the backbone model was trained.
- Second stage: We fine-tune the well-harmonized model with images in low resolution to generate a unified hidden space for all resolutions. In this stage, the backbone model is frozen.

# Experiments

Table 1: Performance of PAC-FNO on the low-resolution tasks using ImageNet-1k

Model	Method	Resolution							
		28	32	56	64	112	128	224	299
ResNet-18	Resize	16.7	22.1	45.7	50.5	63.7	65.5	69.8	-
	Fine-tune	1.01	2.15	10.2	16.3	34.5	50.6	65.0	-
	DRLN	0.22	-	17.1	-	62.8	-	69.8	-
	DRPN	31.6	-	55.6	-	67.5	-	69.8	-
	FNO	40.2	45.2	59.1	61.5	67.6	68.5	70.1	-
	UNO	39.9	45.3	58.9	61.3	67.1	68.1	69.4	-
	A-FNO	<b>43.3</b>	<b>49.5</b>	60.2	62.5	66.9	67.5	68.5	-
	PAC-FNO	42.7	47.7	<b>60.5</b>	<b>62.8</b>	<b>68.3</b>	<b>69.1</b>	<b>70.2</b>	-
	Inception-V3	Resize	16.7	22.0	48.6	53.9	69.5	71.8	-
Fine-tune	39.6	47.2	63.7	69.8	72.9	73.3	-	77.5	
FNO	48.9	54.0	68.5	70.2	74.9	76.5	-	<b>78.4</b>	
UNO	42.2	48.1	65.4	68.0	74.7	75.5	-	77.3	
A-FNO	33.4	39.6	59.6	62.7	71.0	72.1	-	74.9	
PAC-FNO	<b>49.3</b>	<b>54.9</b>	<b>68.8</b>	<b>70.7</b>	<b>76.1</b>	<b>76.9</b>	-	<b>78.4</b>	

Table 2: Performance of PAC-FNO on low-resolution tasks using fine-grained datasets and input variation tasks

Dataset	Method	Resolution							
		28	32	56	64	112	128	224	
Oxford-IIIT Pets	Resize	29.4	36.4	70.1	77.0	89.9	91.2	93.7	
	Fine-tune	32.6	41.1	73.2	79.3	91.0	<b>91.5</b>	<b>93.8</b>	
	DRLN	3.37	-	36.8	-	88.1	-	93.7	
	DRPN	41.5	-	84.2	-	<b>92.6</b>	-	93.7	
	FNO	19.1	54.0	60.6	70.2	86.7	90.4	91.4	
	UNO	11.1	15.7	43.2	50.5	80.1	83.8	90.3	
	A-FNO	27.0	33.3	63.5	70.2	85.2	86.9	89.1	
	PAC-FNO	<b>73.4</b>	<b>77.3</b>	<b>86.0</b>	<b>87.6</b>	<b>90.5</b>	<b>91.1</b>	<b>91.7</b>	
	Flowers	Resize	39.5	47.6	75.3	80.3	92.1	93.7	95.9
Fine-tune	44.3	51.1	78.8	81.9	92.5	94.0	95.9		
DRLN	9.92	-	53.4	-	91.3	-	95.9		
DRPN	64.5	-	89.0	-	<b>95.0</b>	-	95.9		
FNO	25.3	32.8	65.9	73.0	91.7	93.7	<b>96.6</b>		
UNO	23.2	30.2	64.5	71.7	90.8	92.6	96.1		
A-FNO	26.8	33.6	63.7	70.0	86.2	88.8	91.9		
PAC-FNO	<b>74.1</b>	<b>78.0</b>	<b>87.6</b>	<b>89.3</b>	<b>93.6</b>	<b>94.2</b>	<b>94.4</b>		
Fog	Resize	8.21	10.8	27.2	31.9	48.5	52.3	58.4	
	Fine-tune	23.2	28.2	47.5	51.4	<b>61.0</b>	<b>62.2</b>	<b>63.0</b>	
	DRLN	0.16	-	6.54	-	33.5	-	58.4	
	DRPN	0.67	-	0.99	-	1.32	-	58.4	
	FNO	14.4	18.6	38.9	43.5	56.6	58.4	60.3	
UNO	24.6	29.7	46.8	49.5	59.2	60.4	59.0		
A-FNO	11.0	14.9	33.4	38.3	51.9	53.6	53.3		
PAC-FNO	<b>25.4</b>	<b>30.4</b>	<b>48.2</b>	<b>51.7</b>	<b>60.1</b>	<b>61.4</b>	<b>62.8</b>		
Brightness	Resize	22.0	28.2	52.7	56.8	67.8	69.9	73.5	
	Fine-tune	42.8	48.9	65.8	68.1	<b>73.5</b>	<b>74.4</b>	<b>75.7</b>	
	DRLN	6.64	-	35.71	-	56.1	-	58.4	
	DRPN	3.09	-	1.08	-	8.01	-	58.4	
	FNO	34.9	40.7	59.4	62.6	70.0	71.3	73.1	
UNO	50.8	55.6	66.7	67.9	71.4	72.1	72.8		
A-FNO	37.6	43.2	59.4	62.5	68.8	69.8	70.0		
PAC-FNO	<b>51.9</b>	<b>56.5</b>	<b>68.2</b>	<b>69.8</b>	<b>73.4</b>	<b>74.1</b>	<b>74.7</b>		

**Resize:** Resize is a method that directly feeds the resized images to a pre-trained classification model using interpolation

**Fine-tune:** Fine-tune is a method of fine-tuning the pre-trained classification model with the resized images.

**DRLN and DRPN:** These two models are representative models capable of up to 8 times super-resolution (SR). With SR models, low-resolution images are upsampled to the target resolution and fed into a pre-trained model.

**FNO, UNO, A-FNO:** These three models are Fourier neural operator models. These models are most similar to our PAC-FNO and are trained by our proposed training method for fair comparison.



# Experiments

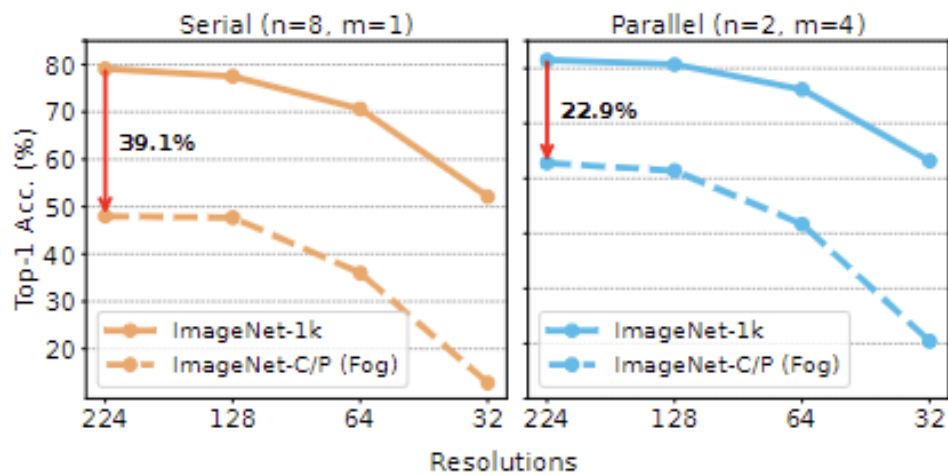


Figure 3: Benefit of parallel structure.

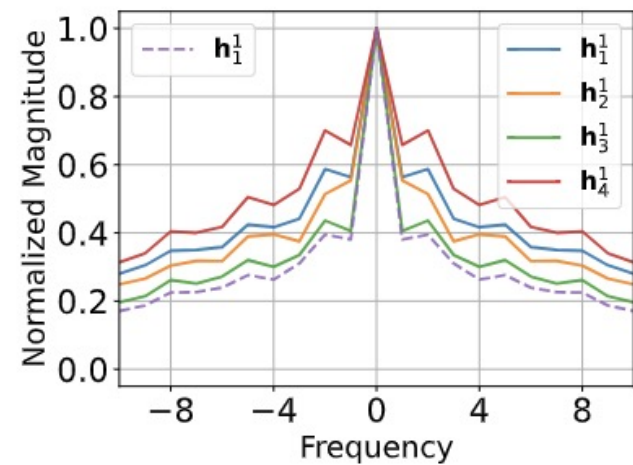


Figure 4: Comparison of spectral responses according to the configuration of the AC-FNO block

# Results

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- We proposed **parallel-structured and all-component Fourier neural operators** (PAC-FNOs) for visual recognition under low-quality images.
- To this end, we design i) an **AC-FNO** and ii) a **parallel** configuration of AC-FNO blocks and also propose a **two-stage training algorithm**.
- As a result, PAC-FNO provides **two advantages** over existing methods: (i) **It can handle both low-resolution and input variations** typically observed in low-quality images with a single model; (ii) **One can attach PAC-FNO to any visual recognition model** and fine-tune it.
- In the evaluation with four visual recognition models and seven datasets, we show that PAC-FNO achieves high accuracy for various resolutions and input variations.



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