# A Supplementary Section

Here, we include the following which could not be included in the main paper due to space limitation:

- Preliminary information which would help better understanding of the context.
- Complete result, which contains the accuracies of each method on all domains.

## A.1 Preliminaries

### A.1.1 Domain Generalization

In domain generalization we are given training data from different domains and the objective is to generalize over a novel domain. Let the training dataset be $D_i = \{X_{ij}, Y_{ij}\}_{1 \leq j \leq n_i}$ and the test dataset be $D_t = \{X_j^t, Y_j^t\}_{1 \leq j \leq n_t}$ where $n_i$ refers to the number of examples in $i^{th}$ domain. In domain generalization framework the label space of all $D_i$ and $D_t$ is same.

We define a domain as the joint distribution of feature and label space such that $(X_{ij}, Y_{ij}) \sim P_{XY}^i$ and $P_{XY}^i \sim \mu$. The test data set is $(X_j^T, Y_j^T) \sim P^T$ and $P^T \sim \mu$. We assume all $(X, Y)$ pairs are drawn iid from their respective distributions, and that $P_1, \ldots, P_N, P^T$ are iid from $\mu$. The main objective of domain generalization is to train a model on all the training domains $D = \{D_1, D_2, \ldots D_N\}$ which performs well on $D^T$.

### A.1.2 Zero Shot Learning

In zero-shot learning the classes seen during training is disjoint from the classes present in the test phase. Let $Y^{tr}$ and $Y^{ts}$ represent the set of classes in the training and testing phase. Let the training dataset be $D^{tr} = \{x_i, y_i\}_{1 \leq i \leq n_{tr}}$, $y_i \in Y^{tr}$. The test dataset be $D^{ts} = \{x_i, y_i\}_{1 \leq i \leq n_{ts}}$, $y_i \in Y^{ts}$. In zero-shot learning framework the objective is to learn a model on $D^{tr}$ which can generalize well on novel classes from $D^{ts}$.

# B Complete Results

Section 4.3 in the main paper reports the average accuracy across different domains for each of the method. In this section, we show the complete breakdown of the accuracies across domains. Table 1, 2, 3, 4 showcases the domain generalization (DG) results and zero-shot domain generalization (ZSDG) results on Fashion-MNIST [3], CIFAR-10 [1], CIFAR-100 [1] and PACS [2] datasets. All the experiments are run with five different seeds and the reported accuracies are in the form of mean ± standard-deviation. Experiments with MTAE on CIFAR-100 was run using single seed because rotations of CIFAR-100 contains 250,000 images, which made it computationally expensive. Experiments with large scale datasets like CIFAR 100 provide further insights into the problem.

We observe that semantic loss not only helps with zero-shot domain generalization, but also helps in effectively solving the domain generalization problem as well. This is evident in Table 1 where S-MTAE dominates all the other algorithms in DG setting. Overall, we note that semantic counterparts of the domain generalization methods are able to perform better over the vanilla DG methods while solving zero shot domain generalization problem.

| | TARGET | Setting 1 | | Setting 2 | | Setting 3 | | Setting 4 | |
|---|---|---|---|---|---|---|---|---|---|
| | | DG | ZSDG | DG | ZSDG | DG | ZSDG | DG | ZSDG |
| AGG | | 55.33±1.60 | 65.60±16.03 | 53.96±1.40 | 49.08±2.83 | 55.74±0.31 | 60.80±24.64 | **48.63±1.41** | 49.11±12.21 |
| S-AGG | | 55.11±2.30 | 57.32±4.17 | 56.95±3.67 | 53.86±3.20 | **55.93±2.69** | 62.81±11.30 | 47.97±2.48 | 54.15±4.90 |
| FC | $D_0$ | 53.18±4.42 | 53.40±6.48 | 54.35±3.99 | 54.18±9.23 | 54.55±1.33 | 54.81±11.35 | 46.68±1.21 | 50.04±1.23 |
| S-FC | | 54.52±2.17 | 54.52±2.17 | 56.41±1.23 | 50.23±3.93 | 55.52±2.71 | 59.71±5.23 | 46.38±2.84 | 51.20±2.38 |
| MTAE | | 16.85±5.75 | 71.18±10.87 | 21.22±5.28 | **79.10±11.76** | 19.46±4.93 | **81.61±18.32** | 18.48±6.44 | 60.88±12.21 |
| S-MTAE | | **55.82±4.40** | **78.95±2.65** | **57.97±5.02** | 70.61±3.10 | 52.20±2.75 | 64.63±8.29 | 44.41±3.90 | **63.56±8.53** |
| AGG | | 75.87±0.94 | 58.70±11.95 | 81.58±1.65 | 52.25±8.01 | 75.98±1.06 | 57.85±18.11 | 69.95±1.96 | 55.23±8.34 |
| S-AGG | | 76.57±0.88 | 67.87±3.94 | 82.37±0.76 | 57.41±2.01 | 76.64±0.40 | 35.78±6.05 | 70.70±1.88 | **57.70±8.04** |
| FC | $D_1$ | 75.26±1.22 | 47.96±15.50 | 79.87±1.58 | 36.65±14.88 | 74.75±1.10 | 49.15±1.86 | 68.12±2.42 | 52.46±1.76 |
| S-FC | | 74.41±1.39 | 30.46±8.63 | 79.14±2.36 | 53.47±7.97 | 73.4±1.43 | 41.44±9.10 | 66.66±2.99 | 51.01±1.62 |
| MTAE | | 19.11±6.2 | 73.92±13.76 | 20.36±3.85 | 71.35±3.46 | 14.69±5.44 | 83.62±15.65 | 17.84±3.41 | 57.50±14.93 |
| S-MTAE | | **79.43±1.31** | **91.51±2.38** | **84.67±2.44** | **87.32±1.12** | **79.09±0.86** | **90.64±8.78** | **73.73±2.09** | 55±4.27 |
| AGG | | 74.06±1.42 | 62.23±18.68 | 79.23±1.78 | 52.03±15.65 | 73.97±1.07 | 52.69±21.74 | 68.35±1.29 | 50.67±6.02 |
| S-AGG | | 75.46±1.00 | 51.89±2.44 | 80.54±1.27 | 14.03±2.14 | 75.34±2.60 | 10.58±2.60 | 68.65±0.63 | 55.78±8.18 |
| FC | $D_2$ | 73.42±1.36 | 69.62±17.44 | 77.67±2.50 | 58.69±9.41 | 73.50±1.87 | 61.98±13.79 | 67.36±1.57 | 52.45±3.40 |
| S-FC | | 73.33±1.09 | 40.94±5.97 | 77.02±1.58 | 54.37±3.00 | 73.68±0.85 | 55.13±4.77 | 65.4±0.97 | **53.99±3.98** |
| MTAE | | 20.73±3.52 | 65.57±18.23 | 16.97±3.41 | 66.21±17.80 | 15.12±7.77 | 75.52±19.55 | 15.13±3.54 | 69.38±10.73 |
| S-MTAE | | **78.08±0.69** | **94.26±1.03** | **83.39±1.28** | **92.03±1.52** | **77.75±1.07** | **92.54±4.72** | **70.74±0.61** | 50.10±3.81 |
| AGG | | 72.70±1.37 | 62.52±26.81 | 77.13±1.81 | 47.46±27.99 | 72.75±0.80 | 57.99±21.65 | 67.08±0.80 | 52.72±5.35 |
| S-AGG | | 74.84±1.57 | 53.65±2.30 | 80.04±1.58 | 70.91±3.61 | 75.11±0.66 | 49.18±0.49 | 68.16±1.55 | 52.22±4.05 |
| FC | $D_3$ | 72.29±1.17 | 59.45±23.74 | 76.52±2.10 | 53.58±10.01 | 71.84±1.32 | 51.45±24.36 | 65.44±0.41 | 49.43±4.49 |
| S-FC | | 72.87±1.21 | 67.54±8.12 | 76.68±2.56 | 83.23±9.01 | 71.95±1.02 | 82.22±13.5 | 64.90±1.34 | 51.87±2.37 |
| MTAE | | 20.92±14.23 | 77.11±8.28 | 15.56±4.61 | 69.80±17.75 | 16.77±4.25 | 73.05±17.10 | 21.18±2.46 | **61.04±6.14** |
| S-MTAE | | **77.60±1.50** | **96.4±0.63** | **83.54±1.48** | **94.83±2.75** | **77.42±0.43** | **91.03±4.94** | **72.76±2.51** | 49.17±0.53 |
| AGG | | 75.35±1.19 | 52.45±25.22 | 80.36±1.41 | 50.65±9.08 | 75.57±1.02 | 48.77±33.40 | 70.25±1.11 | 53.58±4.31 |
| S-AGG | | 76.54±1.20 | 51.62±1.68 | 82.67±1.07 | 72.04±3.86 | 77.18±0.72 | 49.68±0.39 | 70.50±1.86 | 51.91±5.99 |
| FC | $D_4$ | 75.23±0.81 | 54.57±18.00 | 80.06±1.92 | 52.30±10.47 | 75.07±0.83 | 53.87±17.51 | 68.73±1.06 | 54.87±6.90 |
| S-FC | | 73.77±0.79 | 50.01±0.02 | 79.36±1.99 | 32.83±9.54 | 73.83±1.67 | 46.10±3.23 | 67.44±0.79 | 65.57±6.44 |
| MTAE | | 16.37±1.81 | 67.55±12.57 | 19.67±3.21 | 74.76±14.21 | 19.43±2.11 | 75.15±15.29 | 15.27±4.99 | **68.26±7.61** |
| S-MTAE | | **80.99±1.13** | **97.97±0.53** | **86.22±1.14** | **97.84±0.53** | **80.10±0.98** | **97.24±2.35** | **75.62±1.21** | 49.85±0.53 |
| AGG | | 49.65±2.56 | 67.60±14.64 | 49.18±2.57 | 58.12±14.59 | 49.27±2.24 | 64.71±18.83 | 40.97±2.75 | 58.90±10.51 |
| S-AGG | | 56.14±1.56 | 63.69±2.54 | 56.57±2.36 | 72.98±0.74 | 48.28±2.80 | 43.25±6.41 | 48.28±2.80 | 43.25±6.41 |
| FC | $D_5$ | 47.69±4.35 | 54.68±10.87 | 45.74±1.85 | 58.63±12.93 | 47.18±2.83 | 47.84±10.82 | 38.78±2.55 | 49.25±2.96 |
| S-FC | | 50.33±3.03 | 50.74±0.58 | 50.98±2.79 | 51.36±0.67 | 49.61±3.72 | 81.64±13.09 | 42.22±2.60 | 50.02±0.04 |
| MTAE | | 14.78±2.28 | 83.31±5.91 | 16.76±2.16 | 63.55±10.74 | 19.56±9.67 | 87.73±4.96 | 17.84±3.10 | **68.53±13.33** |
| S-MTAE | | **65.93±2.13** | **95.62±2.47** | **68.00±3.62** | **94.64±2.72** | **66.47±3.03** | **97.94±1.24** | **56.13±3.67** | 48.63±1.30 |

Table 1: Domain Generalization (DG) and Zero-Shot Domain Generalization (ZSDG) performance of different domains on **Fashion-MNIST** dataset.

| | TARGET | Setting 1 | | Setting 2 | | Setting 3 | | Setting 4 | | Setting 5 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | DG | ZSDG | DG | ZSDG | DG | ZSDG | DG | ZSDG | DG | ZSDG |
| AGG | | **43.98±1.88** | 49.67±9.49 | **43.92±1.05** | 49.45±1.94 | 41.38±1.26 | 45.20±10.70 | 42.13±0.83 | 51.93±16.18 | 40.82±1.09 | 51.68±6.70 |
| S-AGG | | 39.26±1.28 | 73.28±2.94 | 40.28±0.33 | 52.98±0.87 | 38.38±0.25 | **76.77±1.65** | 37.58±1.67 | **77.26±1.97** | 36.92±1.66 | 60.10±2.18 |
| FC | $D_0$ | 43.81±0.83 | 52.20±11.78 | 43.86±0.87 | 50.42±0.95 | **41.74±0.84** | 50.66±3.58 | **43.32±0.94** | 45.03±6.97 | **41.52±0.72** | 52.70±2.72 |
| S-FC | | 43.09±1.20 | **74.62±2.70** | 43.20±1.28 | **54.89±0.97** | 40.41±1.05 | 67.99±4.36 | 42.38±0.84 | 74.95±2.46 | 40.91±1.38 | **68.01±5.99** |
| MTAE | | 11.52±1.38 | 52.46±5.01 | 9.83±5.31 | 52.77±2.18 | 14.05±1.75 | 59.63±11.88 | 12.12±1.67 | 54.09±6.50 | 12.35±1.70 | 53.60±4.32 |
| S-MTAE | | 38.08±4.31 | 73.23±5.22 | 39.74±2.91 | 53.51±1.47 | 36.28±1.93 | 72.75±3.32 | 37.05±1.59 | 75.67±2.62 | 36.76±1.27 | 65.94±1.87 |
| AGG | | 54.83±0.79 | 49.01±12.77 | 53.79±0.60 | 49.78±3.13 | 52.08±1.03 | 43.26±14.61 | 52.58±1.09 | 53.77±18.67 | 50.63±1.22 | 50.85±8.82 |
| S-AGG | | 51.36±1.41 | 82.26±0.37 | 51.18±1.67 | 54.13±1.11 | 48.78±1.78 | **84.21±1.40** | 48.80±1.24 | 84.84±0.57 | 47.66±1.39 | 67.33±1.31 |
| FC | $D_1$ | **55.85±0.46** | 54.05±15.35 | 55.31±0.60 | 50.16±0.77 | **52.80±0.80** | 52.56±2.91 | **53.30±0.48** | 43.99±13.70 | **51.42±0.90** | 51.53±3.78 |
| S-FC | | 54.29±0.89 | **83.17±1.64** | 53.70±0.35 | 55.48±1.03 | 50.76±0.84 | 80.18±3.00 | 52.40±1.05 | **84.86±0.82** | 50.25±1.34 | 72.64±4.03 |
| MTAE | | 11.85±2.78 | 53.10±6.58 | 9.82±5.14 | 50.67±0.74 | 13.31±1.31 | 60.15±10.68 | 13.01±2.43 | 54.84±4.60 | 14.29±2.48 | 51.84±1.48 |
| S-MTAE | | 55.34±1.61 | 81.38±0.91 | **55.38±1.04** | **56.27±0.62** | 51.76±1.78 | 81.08±1.88 | 52.33±0.73 | 84.28±1.86 | 50.87±2.53 | **73.54±2.37** |
| AGG | | 55.98±0.97 | 48.12±11.63 | 55.31±1.10 | 49.94±3.64 | 53.02±0.51 | 41.50±11.43 | 53.54±0.75 | 52.51±18.52 | 52.40±0.58 | 50.33±4.17 |
| S-AGG | | 53.52±1.25 | 82.99±0.87 | 52.97±1.15 | 54.04±1.39 | 50.44±0.55 | **84.60±2.07** | 51.44±1.37 | 85.50±0.78 | 49.58±1.09 | 68.48±1.97 |
| FC | $D_2$ | 56.70±1.04 | 55.88±16.21 | 56.03±0.87 | 50.30±1.11 | 53.60±0.88 | 52.32±5.38 | 53.82±0.96 | 43.37±9.78 | **52.57±0.24** | 52.23±2.65 |
| S-FC | | 55.86±0.79 | **84.77±1.48** | 55.37±0.49 | 55.83±0.68 | 53.14±0.67 | 81.77±2.96 | 53.02±1.47 | 84.52±2.35 | 51.91±1.16 | 72.45±3.36 |
| MTAE | | 10.63±4.72 | 56.44±6.23 | 13.72±1.39 | 50.93±1.07 | 13.16±1.66 | 59.11±11.37 | 12.40±1.19 | 51.99±3.54 | 12.33±4.03 | 55.71±3.76 |
| S-MTAE | | **56.92±1.41** | 82.82±1.05 | **57.00±0.79** | **56.34±0.74** | **54.01±1.98** | 84.54±1.71 | **54.96±1.49** | **87.09±1.16** | 52.25±1.26 | **72.84±1.86** |
| AGG | | 54.92±0.80 | 49.98±10.45 | 53.99±0.80 | 49.98±3.07 | 51.81±1.16 | 40.87±12.03 | 52.27±0.79 | 51.96±17.96 | 50.59±1.17 | 51.41±5.32 |
| S-AGG | | 51.92±1.00 | 82.42±1.25 | 52.40±1.29 | 53.67±1.36 | 49.24±0.53 | **84.20±1.62** | 49.47±1.07 | 84.75±0.84 | 47.78±1.14 | 67.67±1.48 |
| FC | $D_3$ | 55.55±0.94 | 56.65±11.81 | 55.41±0.83 | 49.88±0.99 | 52.61±1.03 | 53.16±5.25 | 52.41±1.65 | 43.34±8.43 | **50.88±1.82** | 51.29±3.34 |
| S-FC | | 54.27±1.82 | **82.92±1.69** | 54.27±1.34 | 55.63±2.65 | 51.80±1.38 | 81.57±4.28 | 51.59±0.43 | 83.86±1.37 | 50.08±1.35 | 71.83±2.94 |
| MTAE | | 11.66±4.37 | 58.13±4.41 | 12.96±1.42 | 51.29±1.64 | 12.64±0.46 | 49.16±5.73 | 13.04±1.00 | 51.20±5.94 | 13.58±1.43 | 57.38±5.85 |
| S-MTAE | | **57.22±0.33** | 82.03±1.77 | **56.36±1.19** | **56.34±0.64** | **52.70±1.06** | 81.26±2.40 | **53.17±1.18** | **84.85±1.76** | 50.77±1.39 | **71.98±2.48** |
| AGG | | 54.32±0.56 | 49.99±9.20 | 52.9±0.67 | 50.04±3.09 | 50.80±0.34 | 40.14±11.88 | 51.57±0.57 | 51.97±18.27 | 50.01±1.00 | 51.71±6.28 |
| S-AGG | | 51.64±1.99 | 82.30±1.0 | 51.5±1.27 | 53.45±0.77 | 48.91±1.55 | 83.47±2.20 | 48.80±1.45 | 83.96±1.14 | 47.63±1.46 | 67.57±1.49 |
| FC | $D_4$ | 54.82±0.76 | 56.22±14.31 | 54.34±0.52 | 49.79±0.63 | 51.86±0.92 | 51.36±4.38 | 52.13±0.77 | 47.56±9.94 | 50.47±0.60 | 52.64±2.94 |
| S-FC | | 54.17±1.21 | 83.13±1.47 | 53.41±0.87 | **55.38±0.62** | 50.52±1.36 | 80.63±3.26 | 51.75±1.02 | 84.05±1.98 | 49.88±0.79 | 71.55±3.37 |
| MTAE | | 13.78±3.39 | 53.79±4.63 | 12.23±4.09 | 51.14±1.47 | 11.41±4.78 | 56.12±7.81 | 11.1±2.03 | 53.03±4.48 | 12.16±1.35 | 53.85±3.68 |
| S-MTAE | | **56.61±1.30** | **83.36±1.60** | **56.03±1.58** | 55.36±0.68 | **53.69±0.75** | **84.38±1.44** | **53.96±0.42** | **87.09±1.49** | **52.73±1.06** | **73.73±1.30** |
| AGG | | 45.50±0.77 | 49.60±7.48 | 45.21±1.19 | 50.03±2.76 | 43.65±0.73 | 44.83±8.22 | 44.45±0.55 | 52.28±16.93 | 43.17±0.98 | 51.32±8.59 |
| S-AGG | | 43.65±0.81 | 75.41±2.98 | 43.75±1.29 | 53.21±0.47 | 40.73±1.50 | **77.26±1.29** | 41.50±1.21 | 79.25±1.76 | 40.11±0.72 | 64.04±1.73 |
| FC | $D_5$ | 46.40±0.90 | 53.92±13.88 | 46.28±0.99 | 50.61±1.09 | 44.79±0.21 | 50.13±8.69 | 44.76±0.88 | 46.76±7.40 | 43.41±0.89 | 54.06±5.11 |
| S-FC | | 46.45±2.06 | **78.04±2.25** | 45.97±0.76 | **54.60±0.52** | 44.60±0.97 | 72.09±4.84 | 44.61±1.05 | 77.34±2.49 | 43.74±0.83 | 70.42±4.30 |
| MTAE | | 13.40±2.15 | 53.41±4.68 | 11.93±5.00 | 50.39±1.20 | 11.49±2.17 | 55.13±6.83 | 12.82±3.41 | 52.35±2.13 | 11.29±4.51 | 55.34±2.07 |
| S-MTAE | | **47.40±0.62** | 77.9±1.99 | **47.16±1.15** | 54.31±0.84 | **46.39±1.26** | 75.63±1.92 | **45.08±0.53** | **80.22±3.06** | **44.36±1.80** | **71.76±1.25** |

Table 2: Domain Generalization (DG) and Zero-Shot Domain Generalization (ZSDG) performance of different domains on **CIFAR-10** dataset.

| | TARGET | Setting 1 | | Setting 2 | |
|---|---|---|---|---|---|
| | | DG | ZSDG | DG | ZSDG |
| AGG | | 49.73±0.26 | 6.07±0.61 | 49.40±0.97 | 5.94±0.91 |
| S-AGG | | 37.91±0.70 | 16.03±0.20 | 39.14±0.74 | 18.00±0.17 |
| FC | $D_0$ | **53.42±0.57** | 5.68±1.24 | **53.76±0.48** | 5.62±1.37 |
| S-FC | | 52.47±2.67 | **17.13±0.95** | 52.46±2.73 | **18.64±0.81** |
| MTAE | | 1.275 | 5 | 1.25 | 4.9 |
| S-MTAE | | 26.68 | 15.5 | 27.66 | 15.05 |
| | | | | | |
| AGG | | 90.23±0.13 | 5.97±0.59 | 90.41±0.59 | 6.33±0.54 |
| S-AGG | | 77.56±0.94 | 19.77±0.45 | 77.96±0.64 | 20.30±0.08 |
| FC | $D_1$ | 95.25±0.27 | 5.65±0.81 | 95.02±0.31 | 5.32±1.34 |
| S-FC | | **95.53±1.43** | **21.62±2.31** | **95.53±1.43** | **21.6±2.31** |
| MTAE | | 1.815 | 5.03 | 1.25 | 5.25 |
| S-MTAE | | 88.85 | 18.44 | 90.37 | 18.25 |
| | | | | | |
| AGG | | 92.77±0.37 | 6.07±1.13 | 93.05±0.80 | 6.27±0.60 |
| S-AGG | | 85.00±0.72 | 20.66±0.80 | 85.61±0.72 | 20.58±0.58 |
| FC | $D_2$ | 96.37±0.34 | 5.32±0.53 | 96.40±0.36 | 5.27±1.04 |
| S-FC | | 95.97±0.63 | **21.32±1.83** | **96.95±0.69** | **21.63±1.10** |
| MTAE | | 1.395 | 5 | 1.47 | 5.37 |
| S-MTAE | | **98.48** | 19.45 | 96.59 | 20.43 |
| | | | | | |
| AGG | | 93.21±0.79 | 5.79±0.51 | 93.40±0.76 | 6.12±0.66 |
| S-AGG | | 88.61±1.04 | **21.07±0.42** | 88.87±1.29 | 20.41±0.62 |
| FC | $D_3$ | 95.74±0.35 | 5.56±0.78 | 95.75±0.47 | 5.27±1.59 |
| S-FC | | 96.14±0.73 | 20.92±0.72 | 95.94±1.14 | **21.73±1.01** |
| MTAE | | 1.432 | 5 | 1.25 | 6.47 |
| S-MTAE | | **99.72** | 19.78 | **99.67** | 20.53 |
| | | | | | |
| AGG | | 94.55±0.45 | 5.97±1.08 | 94.89±0.64 | 6.11±0.44 |
| S-AGG | | 93.90±0.49 | 22.38±0.50 | 94.09±0.33 | 21.62±0.37 |
| FC | $D_4$ | 96.25±0.21 | 5.36±0.73 | 96.30±0.30 | 5.88±1.31 |
| S-FC | | 96.87±0.66 | 21.60±1.01 | 96.39±0.71 | 21.35±1.14 |
| MTAE | | 1.23 | 5 | 1.3275 | 5.18 |
| S-MTAE | | **99.95** | **23.21** | **99.88** | **22.00** |
| | | | | | |
| AGG | | 61.37±0.56 | 5.36±0.53 | 61.70±0.44 | 5.73±0.64 |
| S-AGG | | 66.90±0.81 | **20.06±0.24** | 67.37±0.83 | **19.75±0.51** |
| FC | $D_5$ | 64.74±1.72 | 5.48±0.80 | 64.53±0.86 | 5.81±1.55 |
| S-FC | | 63.88±2.82 | 18.48±1.34 | 64.46±2.39 | 19.26±0.60 |
| MTAE | | 1.567 | 5 | 1.25 | 5.48 |
| S-MTAE | | **78.52** | 19.21 | **78.81** | 19.23 |

Table 3: Domain Generalization (DG) and Zero-Shot Domain Generalization (ZSDG) performance of different domains on **CIFAR-100** dataset.

| | TARGET | Setting 1 | | Setting 2 | | Setting 3 | | Setting 4 | |
|---|---|---|---|---|---|---|---|---|---|
| | | DG | ZSDG | DG | ZSDG | DG | ZSDG | DG | ZSDG |
| AGG | P | 91.23±0.27 | 43.23±13.95 | 88.30±0.85 | 60.17±3.20 | 87.79±0.45 | 56.20±24.44 | 87.06±0.33 | 50.37±14.73 |
| S-AGG | | 88.61±0.93 | **87.81±2.82** | 83.11±0.84 | **88.92±1.50** | 82.35±0.73 | **67.51±1.40** | 82.79±0.77 | **71.46±1.53** |
| FC | | **91.60±0.57** | 31.04±6.31 | **89.10±0.52** | 52.35±10.79 | **88.51±0.66** | 59.12±24.60 | **87.48±0.19** | 46.32±12.79 |
| S-FC | | 87.48±1.14 | 81.95±1.59 | 82.25±0.87 | 82.35±3.54 | 81.95±1.46 | 58.07±11.15 | 82.37±1.08 | 67.30±1.67 |
| AGG | A | **65.03±1.10** | 57.81±12.33 | 65.85±0.69 | 48.06±3.65 | 73.53±0.63 | 54.07±7.33 | 64.14±0.39 | 53.73±7.86 |
| S-AGG | | 58.82±1.15 | **58.40±4.87** | 60.67±0.88 | **61.90±0.76** | 69.91±1.47 | 36.94±2.01 | 59.73±1.08 | 49.29±0.96 |
| FC | | 64.73±0.84 | 48.84±17.75 | **66.42±0.63** | 46.93±5.99 | **75.21±0.89** | **57.79±10.56** | **65.21±1.29** | **53.96±6.93** |
| S-FC | | 52.18±1.07 | 55.68±2.93 | 55.97±1.21 | 61.78±2.05 | 63.25±2.31 | 52.55±2.39 | 54.38±0.88 | 47.20±1.31 |
| AGG | C | **70.89±0.94** | 50.39±9.42 | **79.13±1.10** | 57.86±13.64 | **72.40±1.15** | **60.05±6.54** | 69.13±1.07 | 44.80±15.57 |
| S-AGG | | 68.48±1.36 | **82.30±1.70** | 75.55±1.05 | **70.48±3.16** | 71.62±1.71 | 50.93±1.76 | 68.61±0.76 | **60.11±4.13** |
| FC | | 67.50±1.25 | 48.62±11.79 | 78.79±0.74 | 53.95±7.99 | 71.66±0.89 | 57.91±5.27 | **69.16±0.22** | 41.07±16.56 |
| S-FC | | 64.77±1.26 | 74.35±4.52 | 69.93±2.19 | 65.67±3.03 | 66.61±1.51 | 54.02±2.81 | 63.47±1.57 | 53.35±5.87 |
| AGG | S | **70.17±1.22** | 40.72±42.45 | 76.31±1.21 | 37.52±25.91 | **68.21±1.41** | 51.57±28.41 | **66.24±2.00** | 27.36±24.88 |
| S-AGG | | 63.93±1.27 | 92.02±0.66 | 69.17±1.44 | **90.47±1.55** | 61.10±2.67 | 45.47±9.09 | 61.69±0.91 | **86.52±2.86** |
| FC | | 67.89±2.91 | 53.63±33.71 | **76.76±2.04** | 32.36±34.76 | 67.37±1.24 | 54.66±28.20 | 65.04±0.87 | 33.04±31.48 |
| S-FC | | 60.02±1.79 | **92.92±1.69** | 62.06±2.16 | 90.11±4.09 | 58.62±1.99 | **69.17±9.07** | 55.90±2.69 | 84.49±6.75 |

Table 4: Domain Generalization (DG) and Zero-Shot Domain Generalization (ZSDG) performance on **PACS** Dataset.

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