CLAIMS:

1. A computer system configured to fine-tune a trained neural network to generate an improved predicted output, the computer system comprising:
   a computer processor; and
   a non-transitory media readable by the processing unit, the media storing instructions that when executed by the processing unit, causes the processing unit to:
      predict, using the trained neural network, latent features from a first plurality of unlabeled non-target data, whereby the neural network was trained based on a second plurality of unlabeled non-target data, and whereby the neural network comprises an unsupervised neural network;
      predict, using the trained neural network, latent features of a plurality of labeled target data;
      compute similarity values between the predicted latent features of the first plurality of unlabeled non-target data and the predicted latent features of the plurality of labeled target data;
      select unlabeled non-target data that have similarity values below a defined contrastive distance from the first set of unlabeled non-target data;
      fine-tune the trained neural network by re-training the trained neural network using the selected unlabeled non-target data;
      generate, using the fine-tuned trained neural network, the improved predicted output when a dataset is provided to the fine-tuned trained neural network.

2. The computer system according to claim 1, whereby the unsupervised neural network comprises a convolutional neural network-variational autoencoder (CNN-VAE).

3. The computer system according to claim 1, whereby the instructions to predict latent features from a first plurality of unlabeled non-target data comprises instructions for directing the processing unit to:
      perform the prediction of the latent features using a few-shot contrastive learning technique.

4. The computer system according to claim 1, whereby the neural network was trained by maximizing a log-likelihood $\log_{\rho_\Theta}(N|z_n)$ and by regularizing the training using a Kullback-Leibler (KL) divergence, where ρ_Θ is defined as a predicted bias of the neural network, N is defined as the second plurality of unlabeled non-target data and z_n is defined as latent features of the second plurality of unlabeled non-target data.

5. The computer system according to any one of claims 1 to 4, whereby the instructions to compute the similarity values between the predicted latent features of the first plurality of unlabeled non-target data and latent features of a plurality of labeled target data comprises instructions for directing the processing unit to:

compute contrastive distances between a computed Gaussian distribution of the first plurality of unlabeled non-target data and a computed Gaussian distribution of the plurality of labeled target data, wherein the similarity values are defined as the computed contrastive distances.

6. The computer system according to claim 5, wherein the contrastive distances between the computed Gaussian distribution of the first plurality of unlabeled non-target data and the computed Gaussian distribution of the plurality of labeled target data is defined as:

$$Constrative\ distance = -EQ_\Theta(z_x|\mathrm{N})\left[\log_\rho(X|z_x)\right] + KL(q_\Theta(z_x|N)||q(z_x))$$

where $-EQ_\Theta(z_x|\mathrm{N})\left[\log_\rho(X|z_x)\right]$ is defined as a reconstruction loss function and $KL(q_\Theta(z_x|N)||q(z_x))$ is defined as a Kullback-Leibler (KL) divergence function.

7. A method to fine-tune a trained neural network using a computer system to generate an improved predicted output, the method comprising:

predicting, using the trained neural network, latent features from a first plurality of unlabeled non-target data, whereby the neural network was trained based on a second plurality of unlabeled non-target data, and whereby the neural network comprises an unsupervised neural network;

predicting, using the trained neural network, latent features of a plurality of labeled target data;

computing, using the computer system, similarity values between the predicted latent features of the first plurality of unlabeled non-target data and the predicted latent features of the plurality of labeled target data;

selecting, using the computer system, unlabeled non-target data that have similarity values below a defined contrastive distance from the first set of unlabeled non-target data;

fine-tuning, using the computer system, the trained neural network by re-training the trained neural network using the selected unlabeled non-target data

generating, using the fine-tuned trained neural network, the improved predicted output when a dataset is provided to the fine-tuned trained neural network.

8. The method according to claim 7, whereby the unsupervised neural network comprises a convolutional neural network-variational autoencoder (CNN-VAE).

9. The method according to claim 7, whereby the predicting of the latent features from a first plurality of unlabeled non-target data comprises the steps of:

performing the prediction of the latent features using a few-shot contrastive learning technique.

10. The method according to claim 7, whereby the neural network was trained by maximizing a log-likelihood $\log_{\rho_\Theta}(N|z_n)$ and by regularizing the training using a Kullback-Leibler (KL) divergence, where ρ_Θ is defined as a predicted bias of the neural network, N is defined as the second plurality of unlabeled non-target data and z_n is defined as latent features of the second plurality of unlabeled non-target data.

11. The method according to any one of claims 7 to 9, whereby the computing the similarity values between the predicted latent features of the first plurality of unlabeled non-target data and latent features of a plurality of labeled target data comprises the steps of:

computing contrastive distances between a computed Gaussian distribution of the first plurality of unlabeled non-target data and a computed Gaussian distribution of the plurality of labeled target data, wherein the similarity values are defined as the computed contrastive distances.

12. The method according to claim 10, wherein the contrastive distances between the computed Gaussian distribution of the first plurality of unlabeled non-target data and the computed Gaussian distribution of the plurality of labeled target data is defined as:

$$Constrative\ distance = -EQ_{\Theta}(z_x|\mathrm{N})\left[\log_{\rho}(X|z_x)\right] + KL(q_{\Theta}(z_x|N)||q(z_x))$$

where $-EQ_{\Theta}(z_x|\mathrm{N})\left[\log_{\rho}(X|z_x)\right]$ is defined as a reconstruction loss function and $KL(q_{\Theta}(z_x|N)||q(z_x))$ is defined as a Kullback-Leibler (KL) divergence function.

13. A computer system configured to fine-tune a trained neural network to generate an improved predicted output, the computer system comprising:

a neural network module comprising the trained neural network, and whereby the neural network comprises an unsupervised neural network, and whereby the neural network was trained based on a second plurality of unlabeled non-target data, the neural network module being configured to:

predict latent features from a first plurality of unlabeled non-target data;

predict latent features of a plurality of labeled target data;

compute similarity values between the predicted latent features of the first plurality of unlabeled non-target data and the predicted latent features of the plurality of labeled target data;

select unlabeled non-target data that have similarity values below a defined contrastive distance from the first set of unlabeled non-target data;

fine-tune the trained neural network by re-training the trained neural network using the selected unlabeled non-target data;

generate, using the fine-tuned trained neural network, the improved predicted output when a dataset is provided to the fine-tuned trained neural network.

14. The computer system according to claim 13, whereby the neural network comprises a convolutional neural network-variational autoencoder (CNN-VAE).

15. The computer system according to claim 13, whereby the predicting of the latent features from a first plurality of unlabeled non-target data comprises the neural network module being configured to:

perform the prediction of the latent features using a few-shot contrastive learning technique.

16. The computer system according to claim 13, whereby the neural network was trained by maximizing a log-likelihood $\log_{\rho_\Theta}(N|z_n)$ and by regularizing the training using a Kullback-Leibler (KL) divergence, where ρ_Θ is defined as a predicted bias of the neural network, N is defined as the second plurality of unlabeled non-target data and z_n is defined as latent features of the second plurality of unlabeled non-target data.

17. The computer system according to any one of claims 13 to 16, whereby the computing the similarity values between the predicted latent features of the first plurality of unlabeled non-target data and latent features of a plurality of labeled target data comprises the neural network module being configured to:

compute contrastive distances between a computed Gaussian distribution of the first plurality of unlabeled non-target data and a computed Gaussian distribution of the plurality of labeled target data, wherein the similarity values are defined as the computed contrastive distances.

18. The computer system according to claim 17, wherein the contrastive distances between the computed Gaussian distribution of the first plurality of unlabeled non-target data and the computed Gaussian distribution of the plurality of labeled target data is defined as:

$$Constrative\ distance = -EQ_\Theta(z_x|\mathrm{N})\left[\log_\rho(X|z_x)\right] + KL(q_\Theta(z_x|N)||q(z_x))$$

where $-EQ_\Theta(z_x|\mathrm{N})\left[\log_\rho(X|z_x)\right]$ is defined as a reconstruction loss function and $KL(q_\Theta(z_x|N)||q(z_x))$ is defined as a Kullback-Leibler (KL) divergence function.