Generating Machine Learning Models Using Machine Learning Models

A Project Report

Presented to Prof. Mark Stamp

Department of Computer Science

San Jose State University

In Partial Fulfilment

Of the Requirements for the Class

Fall-2024: CS 271

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December 2024

ABSTRACT

Through this project, we investigate the use of a CycleGAN to merge the feature representations of two Convolutional Neural Networks (CNNs) trained on distinct domains to create a new CNN capable of performing a novel task distinct from original models. This project introduces a novel perspective on leveraging generative models like CycleGANs for ML model fusion, opening pathways for automating the creation of task-specific classifiers. By exploring the fusion of knowledge across domains, it also provides insights into the interpretability and reusability of neural network features. The project demonstrates that new models can be generated by combining the features of other similar machine learning models. By combining the extracted features with clustering algorithms and dimensionality reduction techniques like UMAP we showed that CNN can learn in an unsupervised manner. Future works can be directed towards end to end pipeline development for generating machine learning models based on semantics.

Keywords **– Machine Learning, convolutional neural networks, generative adversarial networks, cyclegan**

Table of Contents

I. Introduction 1
II. Methodology 2
A. Hypothesis 2
B. Datasets 2
C. Experimental Setup 3
D. Models and Algorithms 4
E. Implementation 7
F. Evaluation Metrics 8
III. Results 10
A. Kernels 10
B. Cosine Similarity 12
C. UMAP visualization 12
D. K-means Clustering and DBSCAN 13
E. Observations 14
IV. Discussion 17
V. Conclusion and Future Work 17
6. References 18

I. Introduction

The potential for combining the learned features of different specialized Machine Learning (ML) models to create a third novel, task-specific model poses new challenges.

Through this project, we investigate the use of a CycleGAN to merge the feature representations of two Convolutional Neural Networks (CNNs) trained on distinct domains - one on images of cats and the other on images of black objects -to create a new CNN capable of classifying black cats. The core idea hinges on the observation that the filters learned by CNNs capture domain-specific features, such as shape, texture, and color. By employing a CycleGAN - a generative adversarial network architecture designed for domain translation, effectively transferring knowledge from different domains to generate a third model. Through our results, we see that the new CNN inherits the feature-extraction capabilities necessary for identifying black cats.

This project introduces a novel perspective on leveraging generative models like CycleGANs for ML model fusion, opening pathways for automating the creation of task-specific classifiers. By exploring the fusion of knowledge across domains, it also provides insights into the interpretability and reusability of neural network features. The methodology has implications beyond meagre black cat classification, offering a framework for scarcity of labelled data as well as immense processing power. Through this work, we aim to contribute to the growing field of meta-learning, model-generative strategies and ML architecture design.

II. Methodology

A. Hypothesis

It is possible to use existing models and train a machine learning model on the learnable parameters of said models to generate a new model capable of performing a novel task that is different from the original models. In this case, merging a CNN model that detects cats and a CNN model that detects the color black will generate a CNN capable of detecting black cats.

B. Datasets

1. Dataset for CNN Model A

A collection of 1,826 images classified into two classes – 'black' and 'random'. The dataset consists of 1,745 black images and 81 random images sourced from Unsplash[1] and Kaggle[2], respectively.

2. Dataset for CNN Model B

A collection of 30,405 images classified into two classes – 'cat' and 'random'. The dataset consists of 29,843 cat images and 562 random images sourced from Kaggle[2][3].

3. Dataset for CycleGAN 1

4498 sets of 6 kernels each, obtained in the first convolutional layers after training CNN Model A and CNN Model B.

4. Dataset for CycleGAN 2

4498 sets of 16 kernels each, obtained in the second convolutional layers after training CNN Model A and CNN Model B.

C. Experimental Setup

This project conducted experiments on a Lenovo Legion Y540-15IRH laptop with the following specifications:

- **Processor:** Intel Core i5-9300H (4 cores, 8 threads, up to 4.1 GHz)
- **GPU:** NVIDIA GeForce GTX 1660 Ti with 6GB GDDR6 VRAM
- **RAM:** 16GB DDR4

The software environment was configured as follows:

- **Operating System:** Windows 11
- **Programming Language:** Python 3.11
- **Development Environment:** JupyterLab 4.3.0
- **Libraries and Frameworks:** Pytorch 2.5, torchvision, numpy, scikit-learn, seaborn, matplotlib, tqdm

JupyterLab was used as the primary development environment, providing an interactive interface for model training and evaluation. It allowed seamless execution of code cells, visualization of results, and easy experimentation with model architectures.

The Lenovo Legion Y540-15IRH laptop provided adequate computational resources, with the GPU accelerating the training and inference times.

D. Models and Algorithms

This project utilized a combination of CNNs, CycleGANs, and clustering algorithms like t-SNE, KMeans, and DBSCAN. The following subsections describe the architecture and hyperparameters used for each model.

1. CNN Models

Convolutional neural network trained on different datasets were used to learn complimentary feature representations.

a. Architecture

- **Input Layer:** 32x32 pixel images with 3 channels
- **Convolutional Layers:** 2 convolutional layers with kernel size 5x5, Activation function ReLU, and max-pooling layers after each convolutional layer with pool size 2x2
- **Fully Connected Layer:** 1 dense layer with 400 neurons
- **Output Layer:** 2 neurons for binary classification

b. Hyperparameters

- **Optimizer:** Adam, with learning rate = 0.01
- **Batch Size:** 128
- **Epochs:** 20
- **Loss Function:** Cross-entropy loss

2. CycleGAN

A variant of GAN known as CycleGAN[4] architecture was used to learn feature representations of two models using two generator models and two discriminator models. It is a framework designed to learn unpaired image-to-image translations.

a. Architecture

Generator (G_A2B and G_B2A)

The generator models, G_A2B and G_B2A, are designed to perform transformation between the domains A and B.

- **Input Channels:** 6
- **Convolutional Layers:** 2 3D convolutional layers with kernel size 3x3, Activation function ReLU after first conv3D layer and Activation function Tanh after second convo3D layer
- **Output:** Input transformed from domain A to domain B (or vice versa)

Discriminator (D_A and D_B)

The discriminator models, D_A and D_B are designed to distinguish real images and fake images in domains A and B respectively. Both use a PatchGAN architecture, which uses patches of images instead of whole image to determine whether sample is real or fake.

- **Input Channels:** 6
- **Convolutional Layers:** 2 3D convolutional layers with kernel size 3x3, Activation function LeakyReLU with negative slope of 0.2 after first conv3D layer and Sigmoid function after second convo3D layer to output a probability of real or fake.

b. Hyperparameters

- **Optimizers:** Adam, with learning rate = 0.0002, and betas = (0.5, 0.999)
- **Batch Size:** 64
- **Epochs:** 200
- **Loss Functions:** MSE Loss for Adversarial loss L1 loss for both cycle consistency loss and identity loss. Cycle consistency loss ensure generated images can be transformed back to original images.

3. Generated CNN

A custom convolutional neural network for which the convolutional layer filters (kernels) are made up of filters generated by CycleGANs.

a. **Architecture**

- **Input Layer:** 32x32 pixel images with 3 channels
- **Convolutional Layers:** 2 convolutional layers with kernel size 5x5, Activation function ReLU, and max-pooling layers after each convolutional layer with pool size 2x2
- **Output:** A feature vector of length = 400

4. t-SNE (t-Distributed Stochastic Neighbor Embedding)

t-SNE was applied to visualize and reduce the dimensionality of the feature vectors created by the Generated CNN for test images. It reduces the dimensionality of high-dimensional data while preserving local structure.

a. **Hyperparameters:**

- **Perplexity:** Varies depending on data.

5. K-means Clustering

K-means clustering was used to analyze the feature vectors, and to group the vectors into clusters.

a. **Hyperparameters:**

- **Number of clusters (k):** 2 or 3

6. DBSCAN

DBSCAN was used to group feature vectors generated by the CNN for test images into clusters.

a. **Hyperparameters:**

- **Epsilon:** 3
- **Min Samples:** 3

7. UMAP

UMAP was used to construct a weighted graph representing the high-dimensional feature vectors and (thereby reduce dimensionality), where each point was connected to its nearest neighbors based on a chosen distance metric.(different for each model tested).

8. One Class SVM :

One-Class SVM was used to learn a decision boundary around the feature vectors and identify whether new points belong to this class or are outliers.

a.Hyperparameters:

- **kernel='rbf'**
- **nu=0.1**
- **gamma='scale'**

E. Implementation

The implementation steps involved were as follows:

a. Train 1749 CNNs on the ‘cat’ dataset and 2749 CNNs on the ‘black’ dataset.
b. Train two CycleGANs to learn and merge feature representations from the original models, one for each convolutional layer.
c. Create the third model by using the generated kernels from each CycleGAN.

d. Perform clustering on the feature vectors obtained by passing test images to the generated model.
e. Evaluate and study the clusters.

F. Evaluation Metrics

1. Cluster Entropy

Cluster entropy is a measure of randomness or uncertainty in the cluster. Lower entropy values mean that cluster contains datapoints from the same class.

$$H(C_k) = -\sum_{j=1}^{M} p_{j,k} \log_2(p_{j,k})$$

Where M is number of classes, $p_{j,k}$ is the probability that points in cluster C_k belong to class j. The overall cluster entropy is the weighted average of individual entropies of all clusters.

$$H = \frac{1}{N} \sum_{k=1}^{K} n_k H(C_k)$$

2. Cluster Purity

Cluster purity is used to measure the quality of clusters produced. It is a simple measure of cluster homogeneity. High purity indicates more data points in a cluster belong to the same class.

$$U(C_k) = \frac{\max_j n_{j,k}}{n_{j,k}}$$

3. Accuracy

Accuracy measures the number of correct predictions out of total predictions. It can be calculated as follows:

$$\text{Accuracy} = \text{True Positive (TP)} + \text{True Negative (TN)}\text{Total Samples Accuracy} = \frac{True\ Positive\ (TP) + True\ Negatives\ (TN)}{Total\ Samples}$$

4. Precision

Precision is the ratio of True positives and total number of points classified as positive. It can be calculated as follows:

$$\text{Precision} = \frac{True\ Positive\ (TP)}{True\ Positivc\ (TP) + False\ Positives\ (FP)}$$

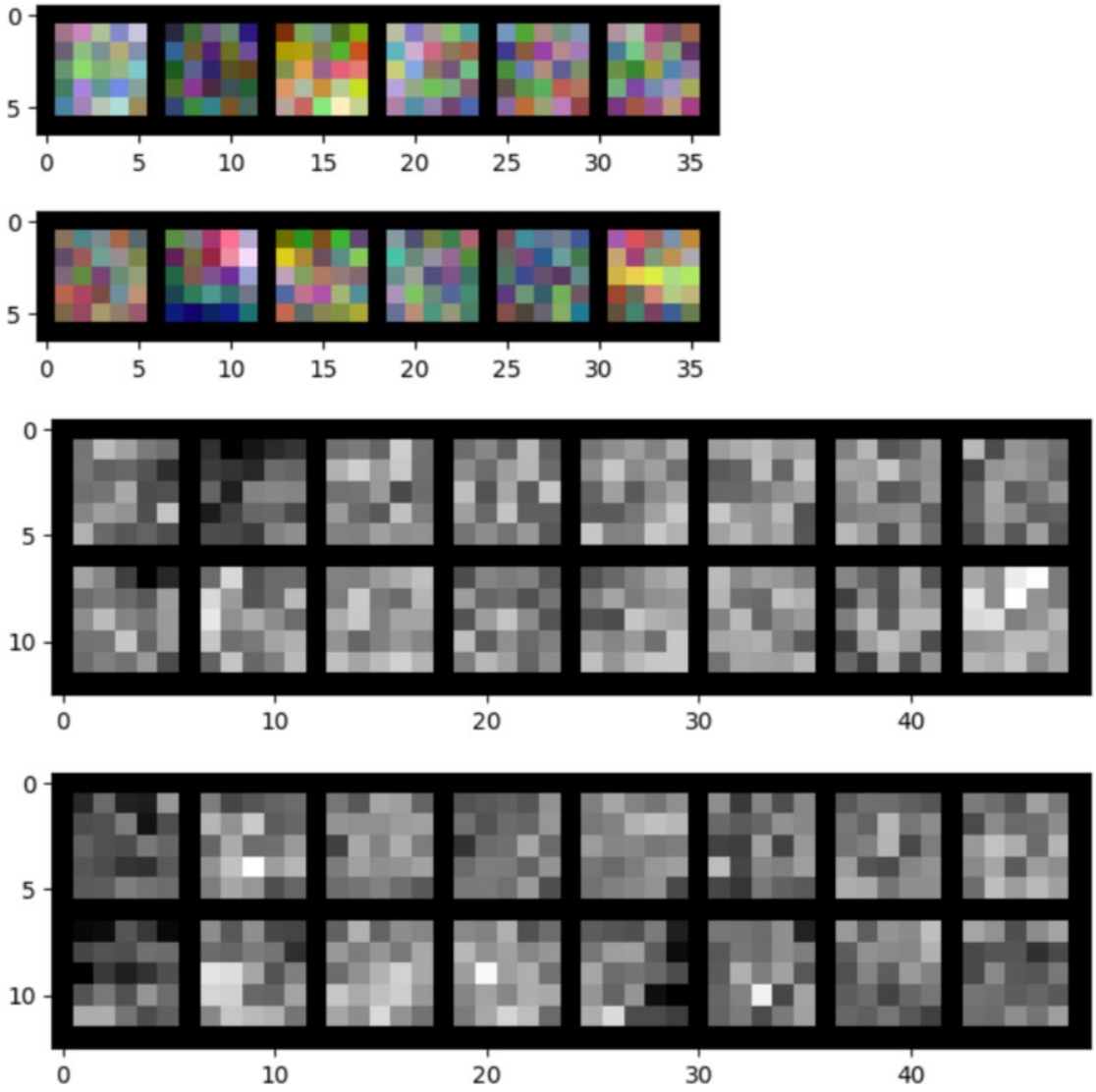
5. Recall

Recall is the ratio of corrected predicted positive instances out of all actual positive instances. It can be calculated as follows:

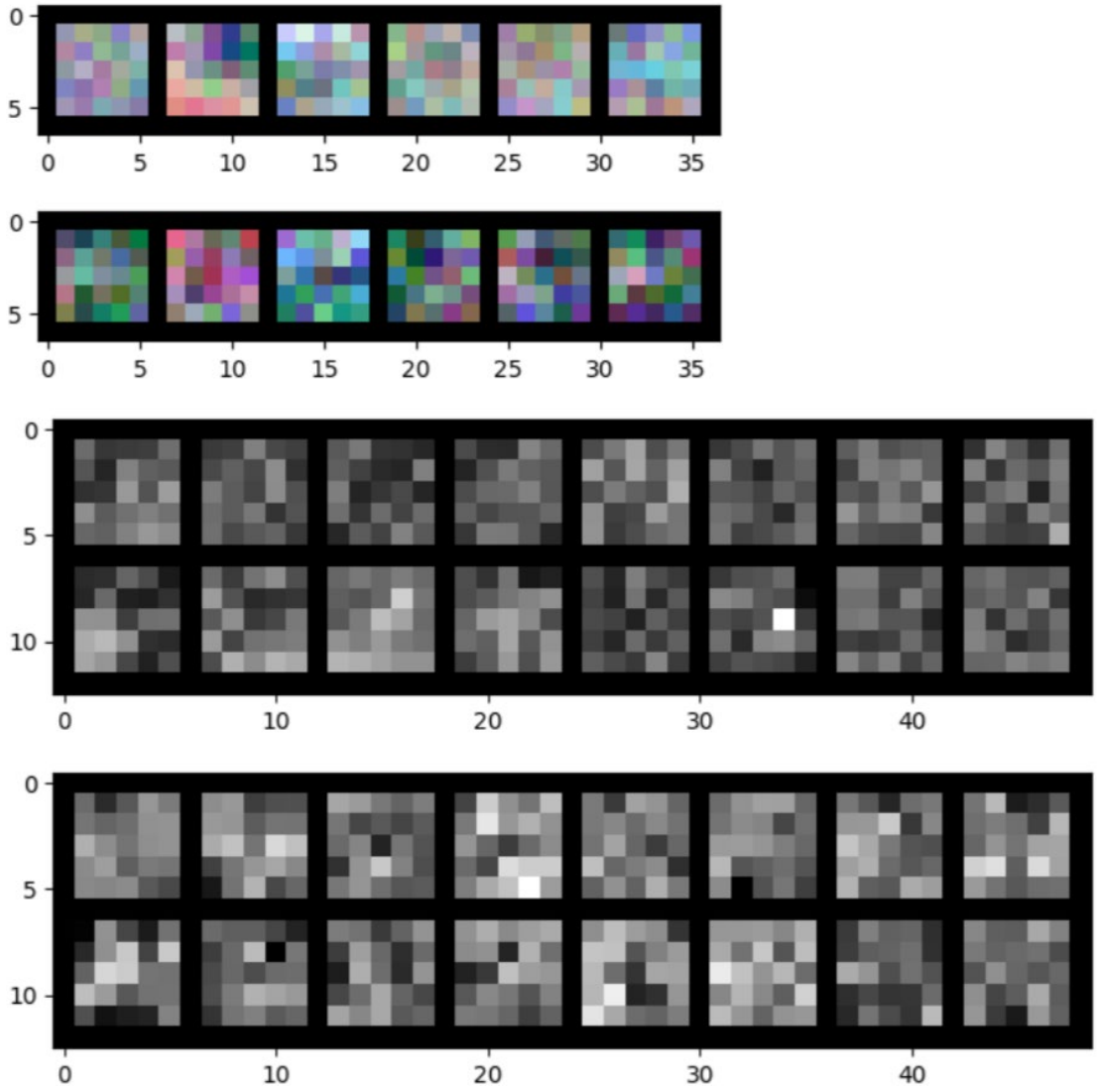
$$\text{Recall} = \frac{True\ Positive\ (TP)}{True\ Positivc\ (TP) + False\ Negatives\ (FN)}$$

III. Results

A. Kernels

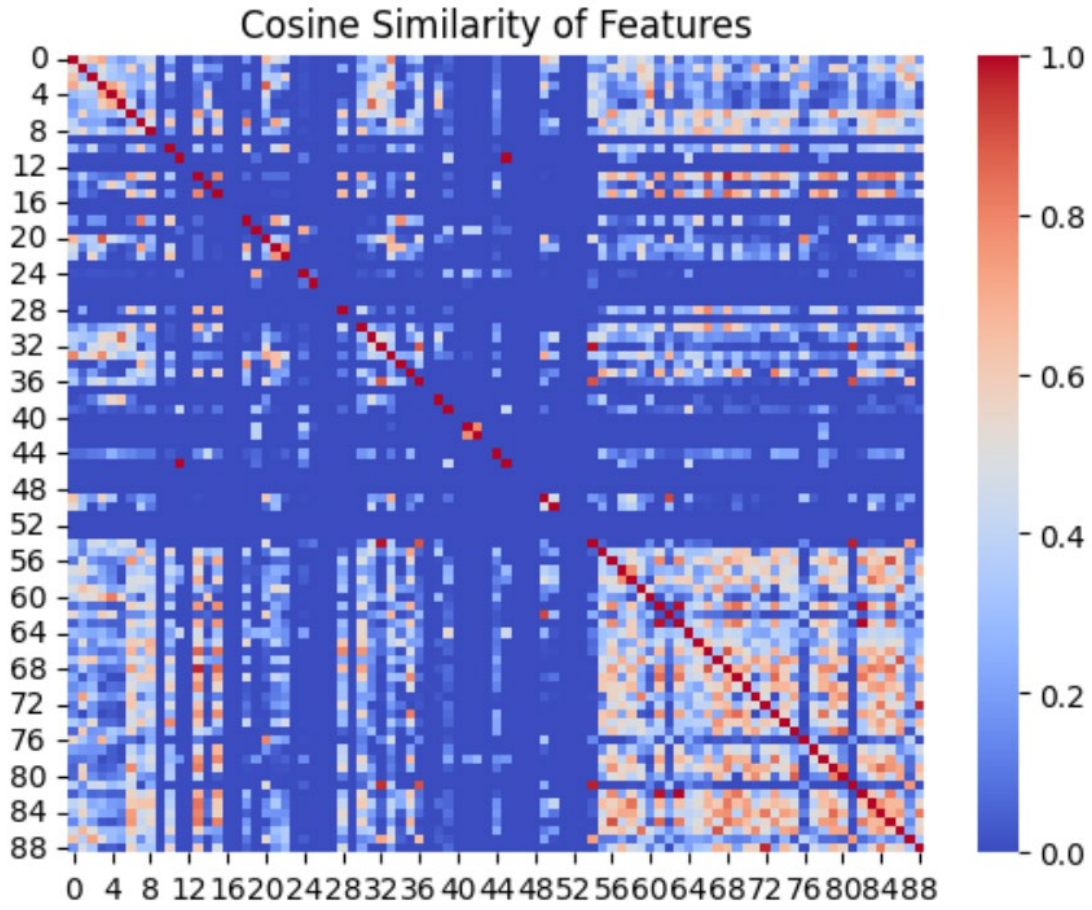


Kernels of CNN Model A and the kernels generated from them using CycleGAN



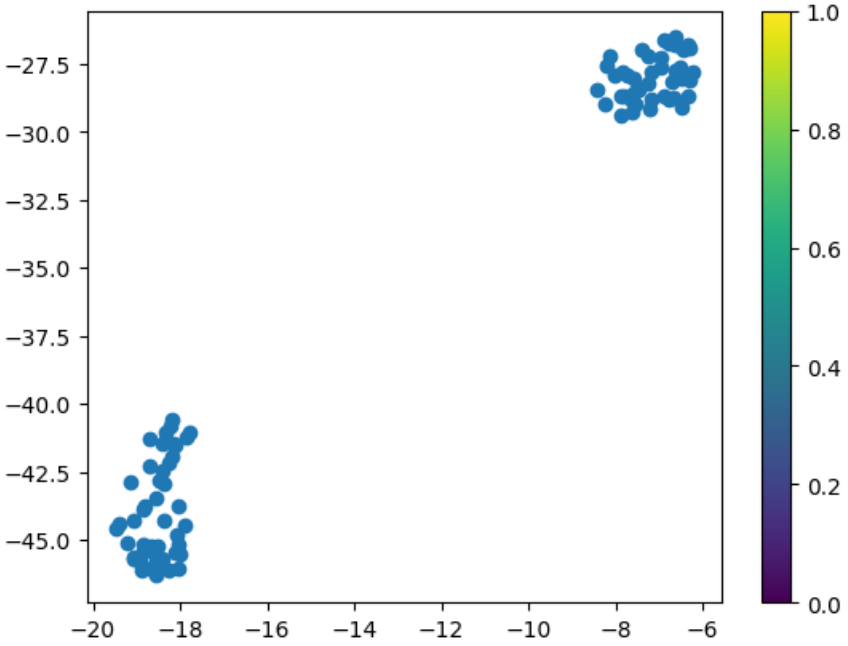
Kernels of CNN Model B and the kernels generated from them using CycleGAN

B. Cosine Similarity



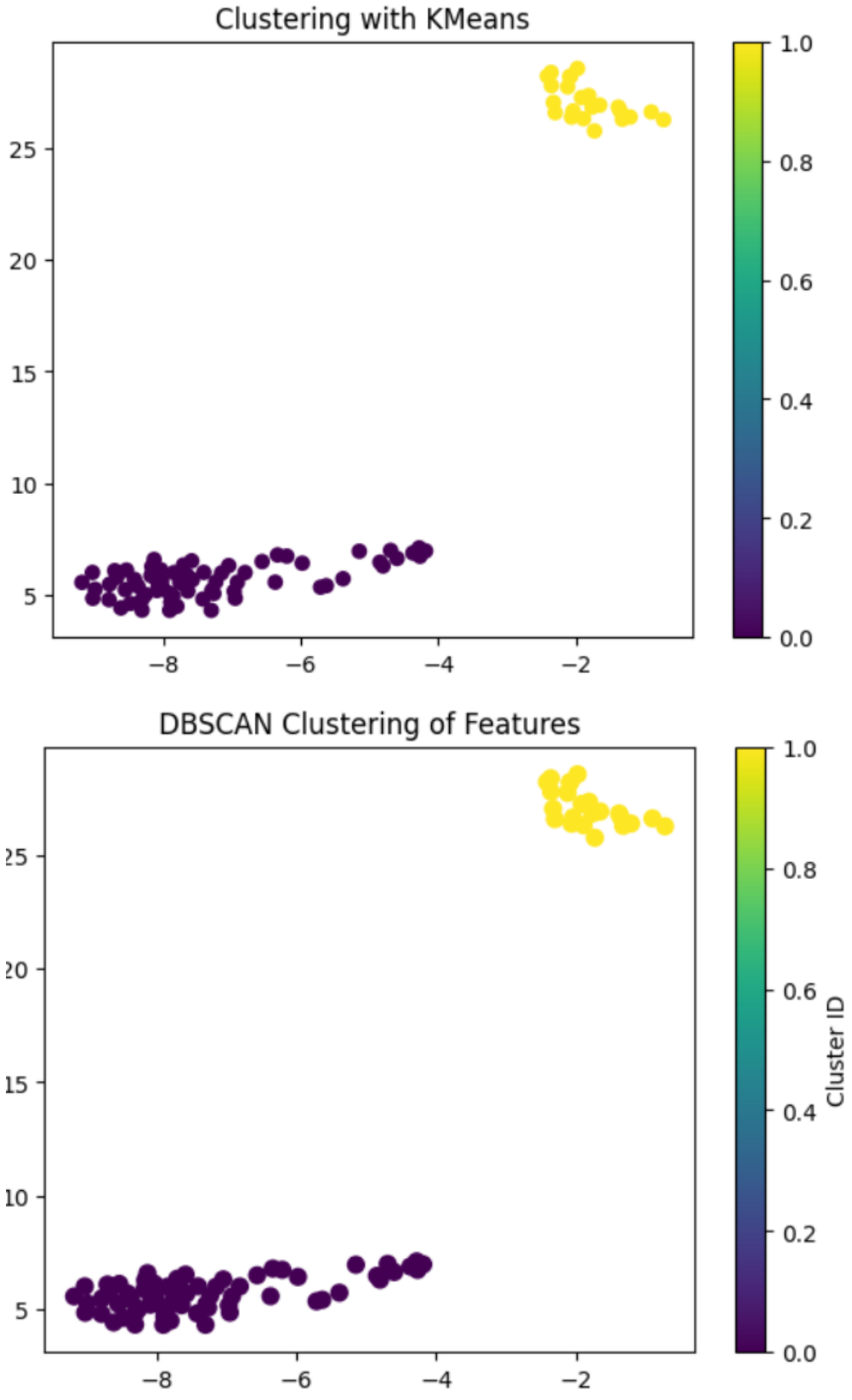
Cosine similarity heat map of feature vectors obtained from Generated Model 229

C. UMAP visualization



UMAP visualization of feature vectors obtained from Generated Model 229

D. K-means Clustering and DBSCAN



E. Observations

		Kmeans				
Model	Generated Filter Domain	Accuracy	Precision	Recall	Entropy	Purity
229	A	0.876	0.852	0.828	0.537	0.876
1486	A	0.876	0.823	0.848	0.528	0.876
1234	A	0.842	0.911	0.738	0.61	0.842
1330	A	0.842	0.735	0.833	0.59	0.842
1304	A	0.82	0.852	0.725	0.672	0.82
1314	A	0.82	0.9411	0.695	0.629	0.82
226	A	0.808	0.588	0.869	0.562	0.809
307	A	0.797	0.558	0.863	0.566	0.797
229	B	0.797	0.823	0.7	0.724	0.797
478	B	0.797	0.588	0.833	0.605	0.797
805	B	0.797	0.764	0.722	0.723	0.797
1291	B	0.797	0.676	0.766	0.686	0.797
1205	A	0.786	0.617	0.777	0.673	0.786
1567	A	0.786	0.617	0.777	0.673	0.786
311	B	0.786	0.647	0.758	0.697	0.786
253	A	0.775	0.705	0.705	0.756	0.775
1215	B	0.764	0.882	0.638	0.75	0.764
1278	A	0.752	0.911	0.62	0.739	0.752
1703	A	0.752	0.705	0.666	0.801	0.752
214	A	0.741	0.676	0.657	0.814	0.741
959	A	0.741	0.529	0.72	0.72	0.741
282	B	0.741	0.794	0.627	0.817	0.741
1470	A	0.73	0.735	0.625	0.84	0.73
1507	A	0.73	0.794	0.613	0.831	0.73
1311	A	0.696	0.823	0.571	0.849	0.696
1337	A	0.696	0.911	0.563	0.775	0.696
1540	B	0.606	0.735	0.49	0.935	0.606

Clustering feature vectors using k-means.

		One -class SVM				
Model	Generated Filter Domain	Accuracy	Precision	Recall	Entropy	Purity
1304	A	0.82	0.882	0.714	0.667	0.82
1314	A	0.764	0.852	0.644	0.767	0.764
229	A	0.752	0.911	0.62	0.739	0.752
1337	A	0.741	0.941	0.603	0.716	0.741
1486	A	0.741	0.941	0.603	0.716	0.741
1234	A	0.73	0.911	0.596	0.757	0.73
1278	A	0.73	0.911	0.596	0.757	0.73
1507	A	0.719	0.9411	0.581	0.729	0.719
1205	A	0.707	0.911	0.574	0.7704	0.707
282	B	0.685	0.911	0.553	0.778	0.685
1291	B	0.685	0.911	0.553	0.778	0.685
1311	A	0.64	0.911	0.516	0.781	0.674
253	A	0.629	0.911	0.508	0.778	0.685
805	B	0.5955	0.9411	0.484	0.716	0.741
1215	B	0.55	0.911	0.455	0.728	0.764
1703	A	0.505	0.941	0.432	0.61	0.831
307	A	0.494	0.9411	0.426	0.591	0.842
214	A	0.449	0.911	0.402	0.561	0.865
959	A	0.426	0.882	0.389	0.569	0.865
1540	B	0.426	0.882	0.389	0.569	0.865
311	B	0.415	0.911	0.387	0.471	0.898
229	B	0.404	0.941	0.385	0.355	0.932
1470	A	0.382	0.941	0.376	0.262	0.955
226	A	0.359	0.882	0.361	0.338	0.932
1330	A	0.359	0.911	0.364	0.245	0.955
1567	A	0.359	0.911	0.364	0.245	0.955
478	B	0.359	0.911	0.364	0.245	0.955

Classifying feature vectors using One-class SVM.

		DBSCAN				
Model	Generated Filter Domain	Accuracy	Precision	Recall	Entropy	Purity
229	A	0.887	0.852	0.852	0.501	0.887
1486	A	0.887	0.823	0.875	0.568	0.876
282	B	0.865	0.764	0.866	1.926	0.573
229	B	0.853	0.705	0.888	1.281	0.707
1234	A	0.842	0.911	0.738	0.61	0.842
1330	A	0.842	0.705	0.857	0.698	0.831
1470	A	0.842	0.647	0.916	1.5	0.606
1540	B	0.842	0.647	0.916	1.793	0.483
1314	A	0.831	0.882	0.731	1.396	0.662
1304	A	0.82	0.852	0.725	0.794	0.808
226	A	0.808	0.588	0.869	0.562	0.809
478	B	0.797	0.588	0.833	1.178	0.617
805	B	0.797	0.764	0.722	0.723	0.797
307	A	0.786	0.529	0.857	0.569	0.786
1567	A	0.786	0.617	0.777	0.673	0.786
1703	A	0.786	0.676	0.741	1.268	0.707
311	B	0.786	0.647	0.758	1.292	0.528
1291	B	0.786	0.588	0.8	1.62	0.573
253	A	0.775	0.705	0.705	0.756	0.775
1507	A	0.775	0.529	0.818	1.737	0.5584
214	A	0.764	0.676	0.696	0.769	0.764
1205	A	0.752	0.5	0.772	0.653	0.752
959	A	0.741	0.529	0.72	0.781	0.741
1311	A	0.719	0.617	0.636	1.777	0.539
1337	A	0.696	0.911	0.563	0.877	0.685
1278	A	0.674	0.676	0.56	1.818	0.46
1215	B	0.606	0.294	0.476	2.017	0.449

Clustering feature vectors using DBSCAN

IV. Discussion

With this project, we used generated CNNs as feature extractors to recognize and differentiate images. After extracting features, we applied dimensionality reduction(UMAP) and clustered similar results together with K-means and DBSCAN . We find that the black cat images were clustered together effectively demonstrating unsupervised learning, i.e. the generated CNN was able to differentiate black cat images from others without being trained on any data.

Similarity metrics such as cosine similarity further validated the ability of CNN to produce meaningful features. This highlights the potential of such a technique to perform well even with scarce data and computation power.

A few challenges observed during the project were that of hyperparameter selection and dimensionality of the feature vectors, which impacted the clustering results significantly. Additionally, the translation of filters from one domain to another was abrupt due to diverse dataset, thereby further affecting the performance of the CNN as a feature extractor.

V. Conclusion and Future Work

The project demonstrates that new models can be generated by combining the features of other similar machine learning models. It is possible to use existing models and train a machine learning model on the learnable parameters of said models to generate a new model capable of performing a novel task that is different from the original models. In this case, merging a CNN model that detects cats and a CNN model that detects the color black will generate a CNN capable of detecting black cats.

By combining the extracted features with clustering algorithms and dimensionality reduction techniques like UMAP we showed that CNN can learn in an unsupervised manner.

Several directions for future work can be highlighted

- Hyper-parameter Optimization for Clustering
- Feature space exploration with alternative metrics and feature weighting
- Semi Supervised Learning with small dataset
- Improving Domain translation
- End to End pipeline development based on semantics

6. References

[1] https://unsplash.com/s/photos/black

[2] https://www.kaggle.com/datasets/ezzzio/random-images

[3] https://www.kaggle.com/datasets/borhanitrash/cat-dataset/data

[4] J. Y. Zhu, T. Park, P. Isola and A. A. Efros, "Unpaired image-to-image translation using cycle-consistent adversarial networks," 2017 IEEE International Conference on Computer Vision (ICCV), Venice, Italy, 2017, pp. 2242-2251, doi: 10.1109/ICCV.2017.244.