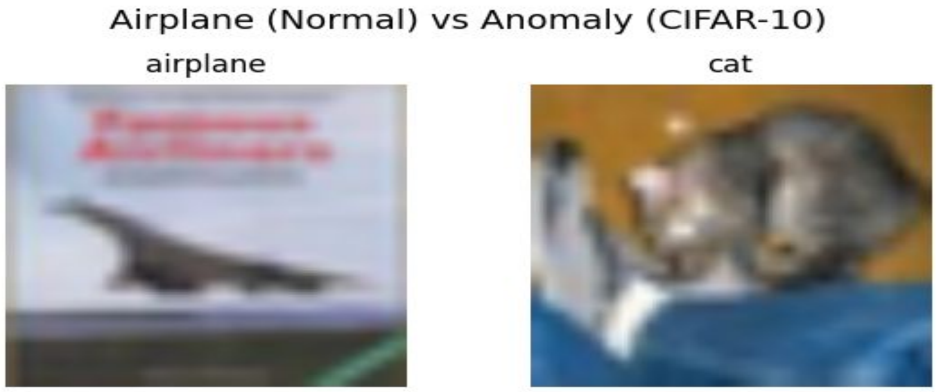
One-Class Classification for Anomaly Detection on CIFAR-10

Learning from Data-BLG454E

Ahsen Beyza Ozkul, Tesnime Jemmazi

Why Anomaly Detection?



Only *normal class* used for training

Detects rare or unknown anomalies

Use-case: airplanes = normal, all others = anomaly

Hypothesis

We expected Deep SVDD + ResNet18 to outperform classical models

- ➔ Deep SVDD learns to compress normal data near a center
- ➔ It should be better than One-Class SVM and Isolation Forest

Methodology

- Pretrained ResNet18 → 128-dim latent space
- Deep SVDD minimizes distance to center
- Compared to: One-Class SVM and Isolation Forest (classical)

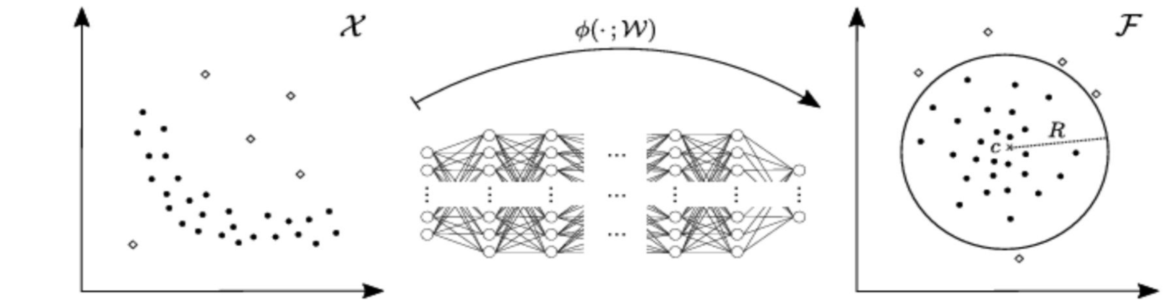
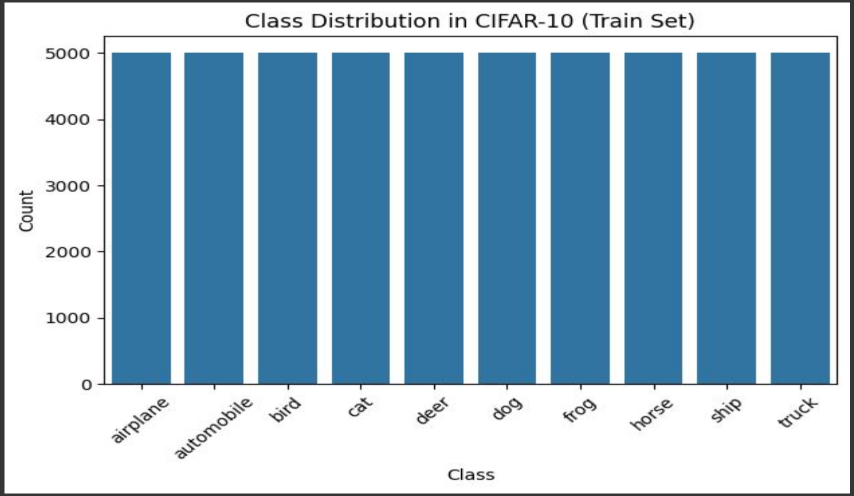


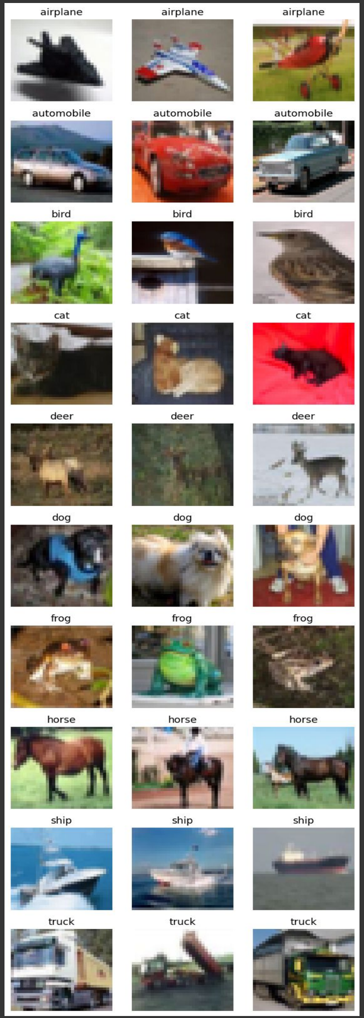
Figure 1. Deep SVDD learns a neural network transformation $\phi(\cdot\,;\mathcal{W})$ with weights $\mathcal{W}$ from input space $\mathcal{X} \subseteq \mathbb{R}^d$ to output space $\mathcal{F} \subseteq \mathbb{R}^p$ that attempts to map most of the data network representations into a hypersphere characterized by center c and radius R of minimum volume. Mappings of normal examples fall within, whereas mappings of anomalies fall outside the hypersphere.

Dataset & Preprocessing

CIFAR-10 stats:

- **60,000 images, 10 classes**
- **5K airplane for training, 1K for testing**
- **9 other classes = 9,000 anomalies**

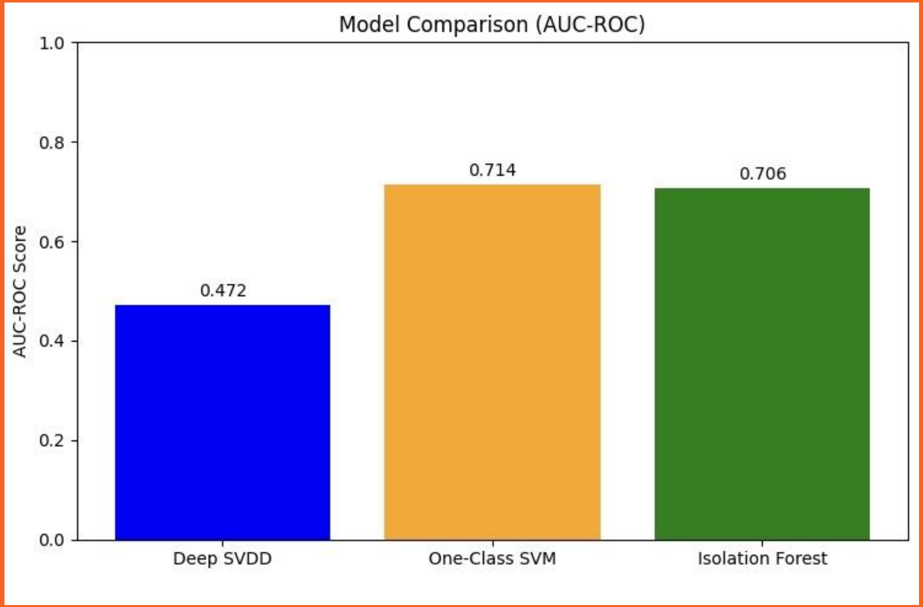




Results

Model	AUC	Prec.	Rec.
Deep SVDD	0.4715	0.61	0.10
One-Class SVM	0.7145	0.93	0.81
Isolation Forest	0.7057	0.93	0.73

- → Deep SVDD AUC = 0.47
- → One-Class SVM AUC = 0.71
- → Isolation Forest AUC = 0.70



Discussion :

- Deep SVDD underperformed, especially in recall (0.10)
- One-Class SVM did better with pre-extracted features
- Deep SVDD may have overfit / needed better tuning

Future Work

Tune Deep SVDD hyperparameters (learning rate, v)

Fine-tune or train ResNet from scratch

Try multi-center SVDD or semi-supervised labels