SANTA IS HERE!!!

# With Gifts of Image Classification Using CNN

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# Outline

- Introduction
- DNN and CNN Models
- Model Training and Feature Visualization
- Performance Metrics
- Challenges with Labeled Data
- Semi-Supervised Learning with GANs
- Conclusion & References

Santa is lost, Find him !!!!

# Introduction

Santa is lost on Christmas Eve!
We need to find him in a huge pile of images.
Thankfully, we have some labeled data—let's train models to detect Santa!

# A look at dataset

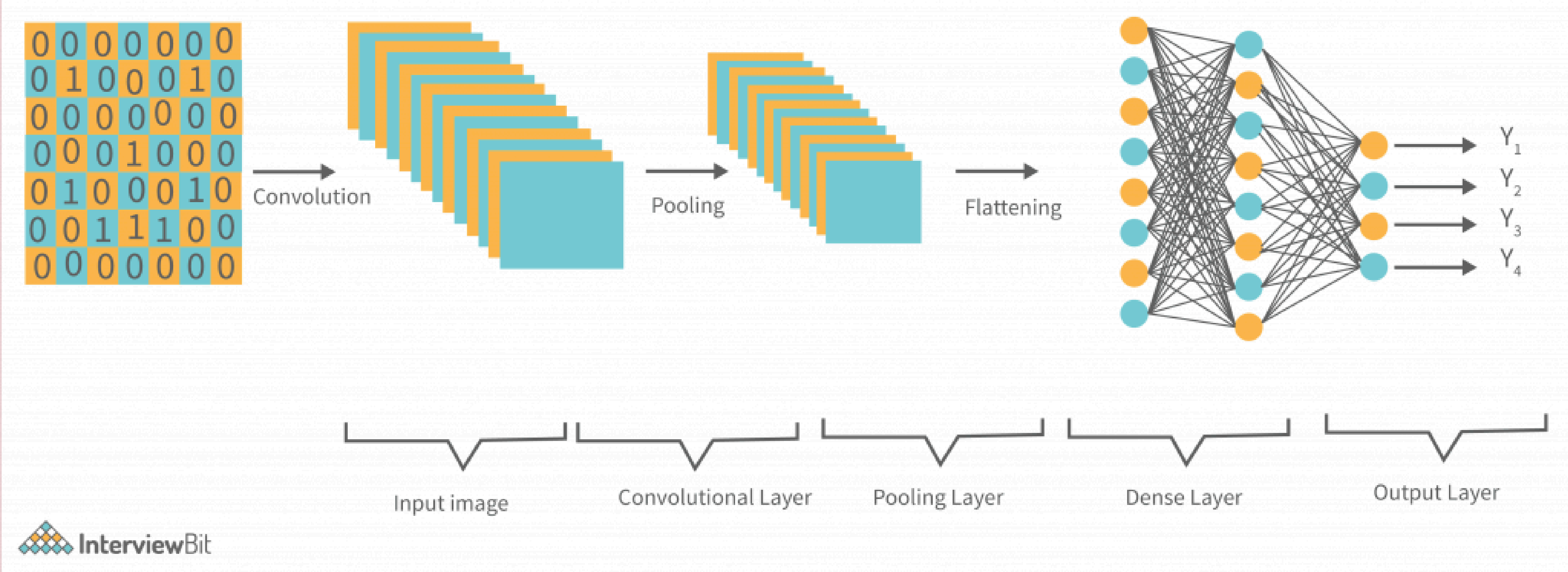

Dataset: Binary image classification (Santa / Not Santa)

Training Set: Labeled images with and without Santa

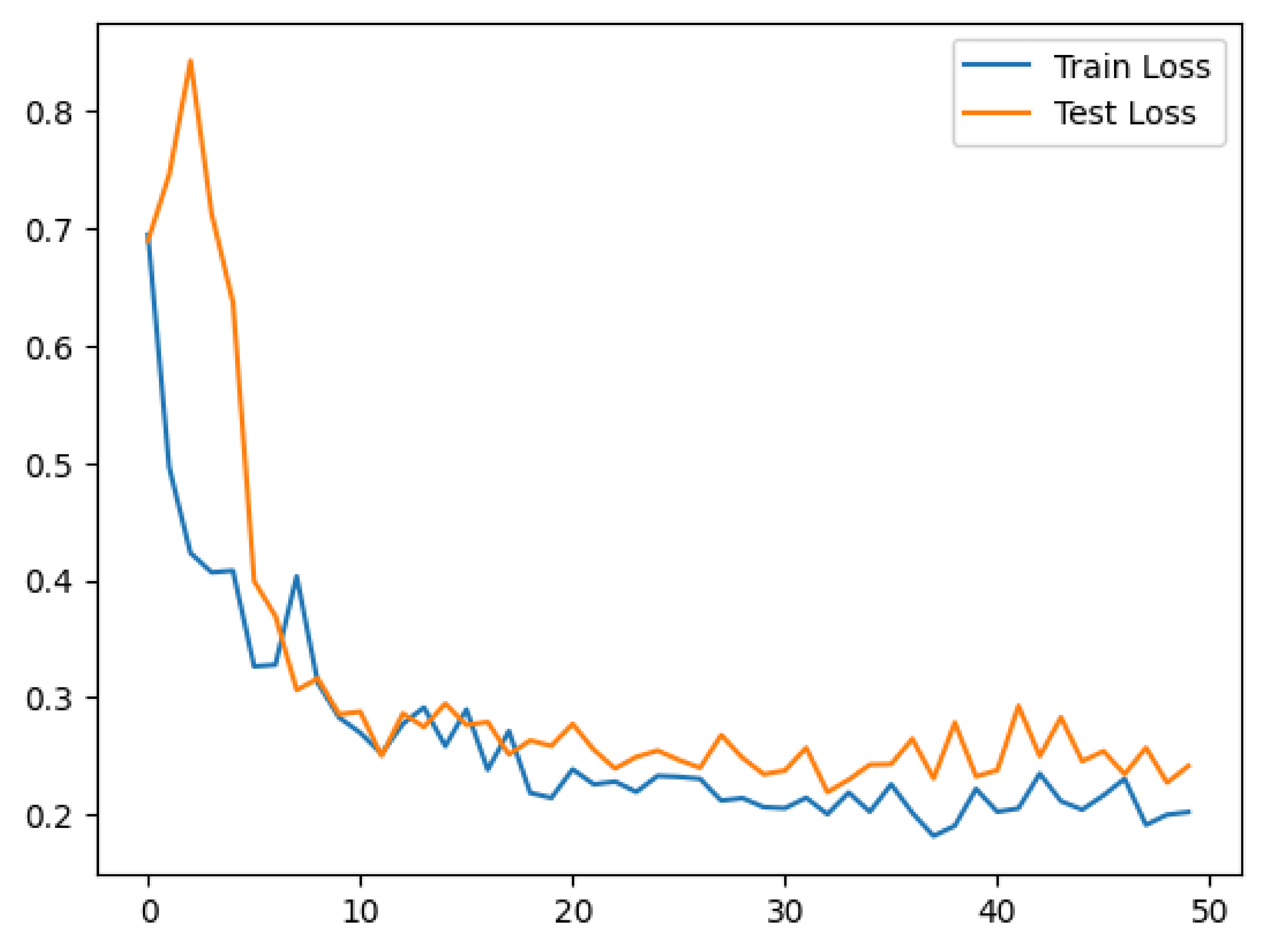
Test Set: Unseen images for evaluation

# CNN Architecture

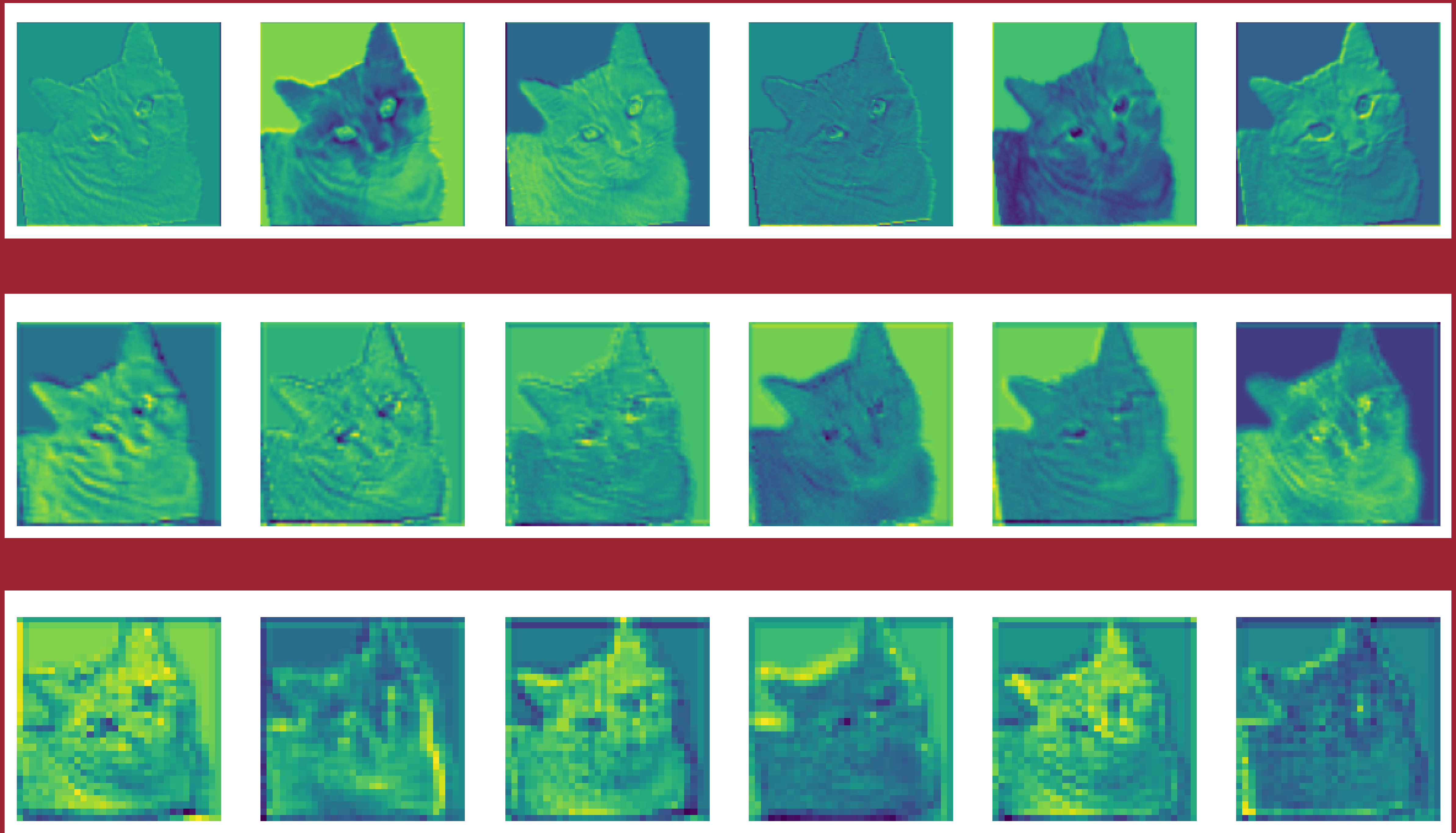
- 3 Conv Layers + BatchNorm + MaxPool.
- Linear layers: [40x16x16] → 100 → 2.
- Dropout for regularization.
- ReLU as activation function



# Training Curve of CNN



# Visualization of CNN layer outputs

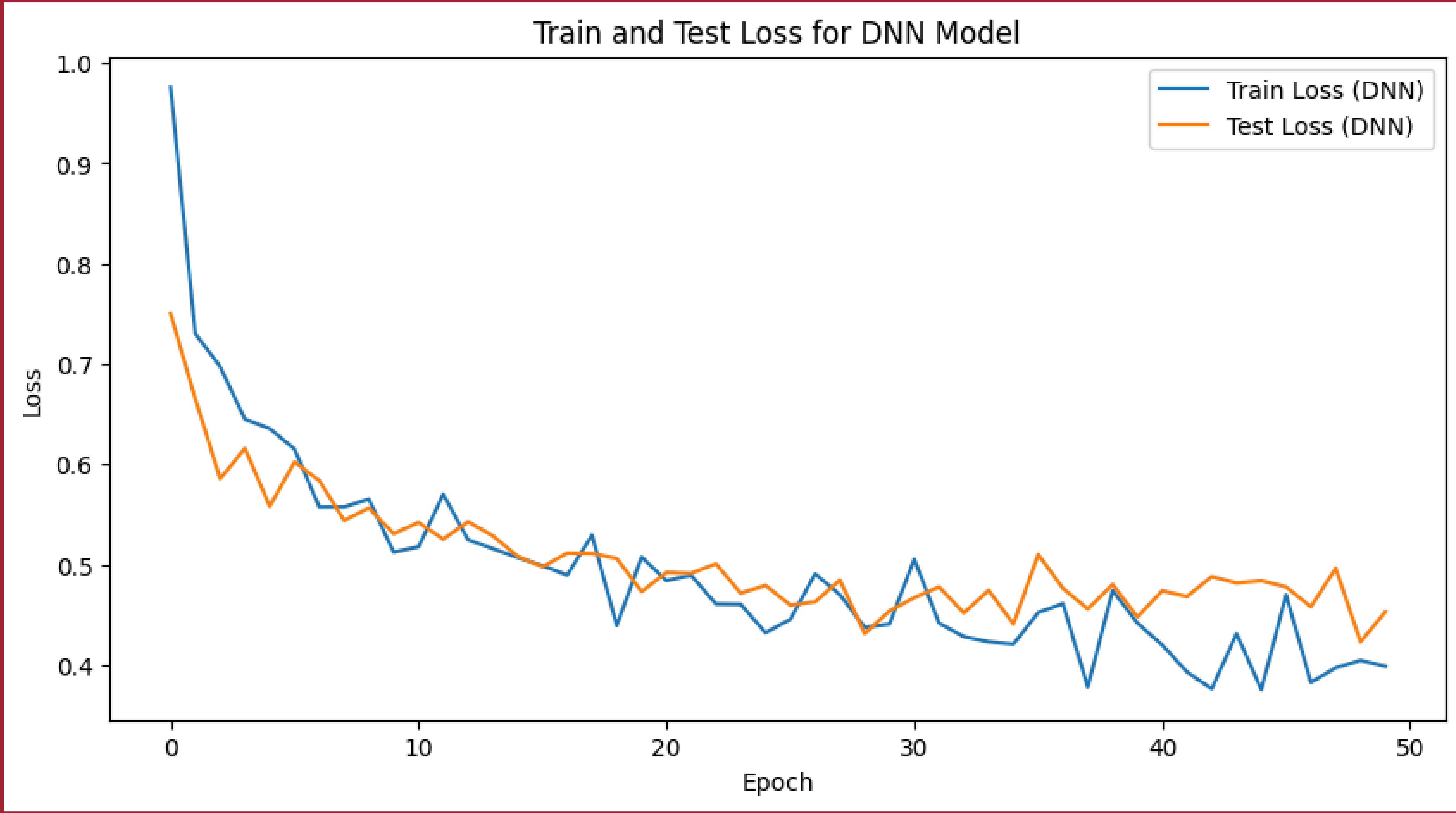


LAYER 1

LAYER 2

LAYER 3

# Training Curve of DNN



# Performances of both Models

| Metric | CNN | DNN |
|---|---|---|
| Accuracy | 0.8961 | 0.7873 |
| Precision | 0.8812 | 0.7902 |
| Recall | 0.9156 | 0.7825 |
| F1-Score | 0.8981 | 0.7863 |
| Runtime (s) | 1533.12 | 1211.24 |
| # Parameters | 1,033,782 | 25,314,242 |

# Challenges in training

1.Overfitting (especially in DNN)

DNNs with many parameters may memorize training data, especially on small datasets.

Regularization (like Dropout) and validation checks are needed.

2. Insufficient Feature Learning (DNN)

DNNs lack spatial inductive bias—don't capture local image patterns effectively.

CNNs are better for visual tasks due to convolutional layers.

3. Vanishing/Exploding Gradients

In deep networks, gradients can vanish or explode during backpropagation.

Batch Normalization and careful initialization help mitigate this.

4. Data Dependency

Both models require a significant amount of labeled data for high performance.

Limited data leads to unstable or poor generalization.

5. Hyperparameter Sensitivity

Learning rate, batch size, number of layers, kernel size, etc., critically affect performance.

Requires extensive tuning and experimentation.

# Problem of labeled data

Labeling Bottleneck

Labeled data is scarce and expensive

Manual labeling is time-consuming

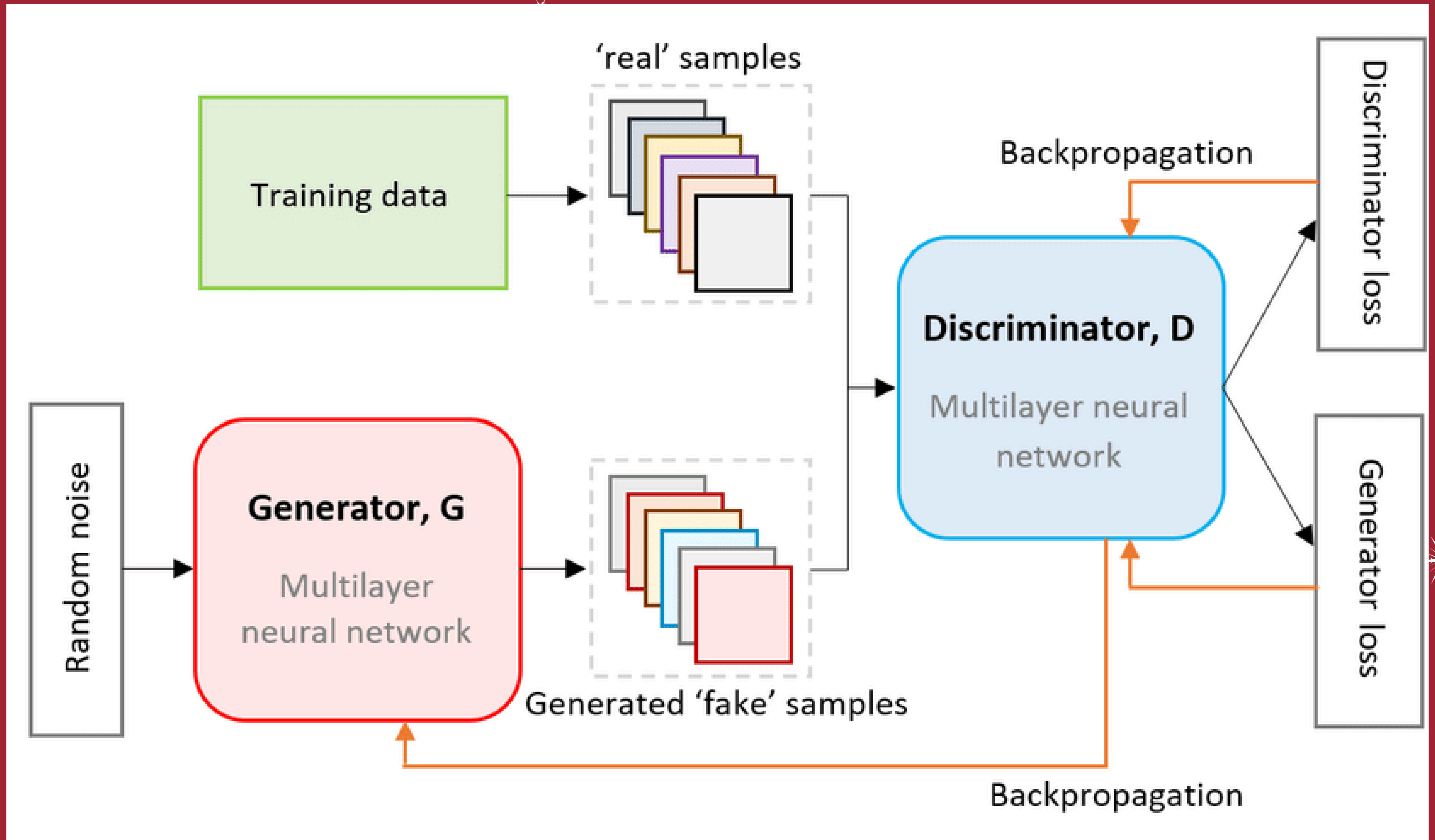
→ Need smarter ways to use unlabeled data

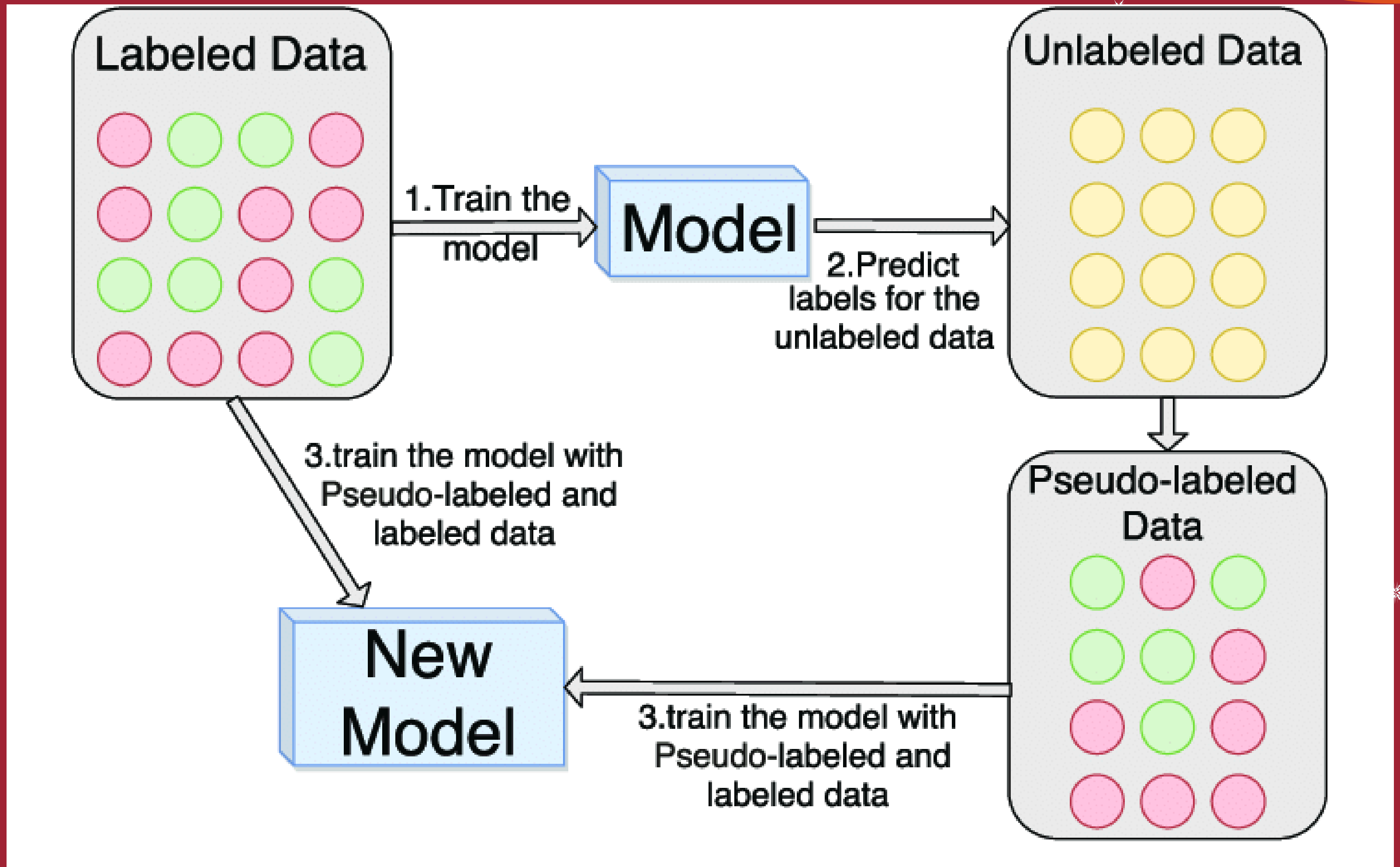
# Santa tells about Semi Supervised learning

Santa suggests a magical idea:

- Train with a small labeled set + a large unlabeled set
- Use pseudo-labeling to guess labels on unlabeled data
- Improve model using confident predictions

# GANs for Semi-Supervised learning



# Results of GAN based pseudo labelling

- Higher accuracy compared to baseline CNN
- Better generalization on unseen test data
- Effective use of unlabeled samples to boost performance

# Challenges in GAN based learning

- GANs are hard to train: mode collapse, instability
- Label noise from incorrect pseudo-labels
- Requires careful balancing of generator and discriminator training

# Conclusion

- 🎁 CNNs outperform DNNs on image data
- 🎁 Semi-supervised learning can bridge the labeling gap
- 🎁 GANs + pseudo-labeling show promise, but need fine-tuning

# References


- Guillaumin et al., “Multimodal Semi-Supervised Learning for Image Classification”
- Kim et al., “Semi-Supervised Image Captioning by Adversarially Propagating Labeled Data”
- Medium blog: “Semi-Supervised Learning with PyTorch and CIFAR-10”

# Thank You