



TEAM 9 : FINAL

버찌 OR NOT

버찌 202000000

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Problem Identification

Many tourists visit Korea University hoping to see the famous campus cat, Beoiji.

But two main problems often happen:

1. “Is this Beoiji?” 
2. “Is Beoiji likely to be at home now?” 

Techniques: Supervised Learning

1. Binary Image Classification

CNN to extract visual
features of Beoiji



K-Nearest Neighbors (KNN)
classifier for prediction.

2. Tabular Classification

Random Forest to predict
Beoiji's behaviour pattern

DATASET PREPARATION

Dataset 1: Beoiji or not

Tabby: 80 images

similar features with Beoiji – such as body shape, stripe pattern, and overall fatness.



Not_Tabby: 80 images

any image that is not Tabby cat



Dataset 2: Beoiji is home or not

manually constructed 72 rows in csv format

	A	B	C	D	E
1	season	time_of_day	is_raining	noise_level	home_or_not
2	winter	morning		0 low	1
3	winter	morning		0 medium	1
4	winter	morning		0 high	1
5	winter	morning		1 low	1
6	winter	morning		1 medium	1
7	winter	morning		1 high	1
8	winter	evening		0 low	1
9	winter	evening		0 medium	1

winter

summer

spring

autumn

morning

evening

night

Yes -1

No -0

low

medium

high

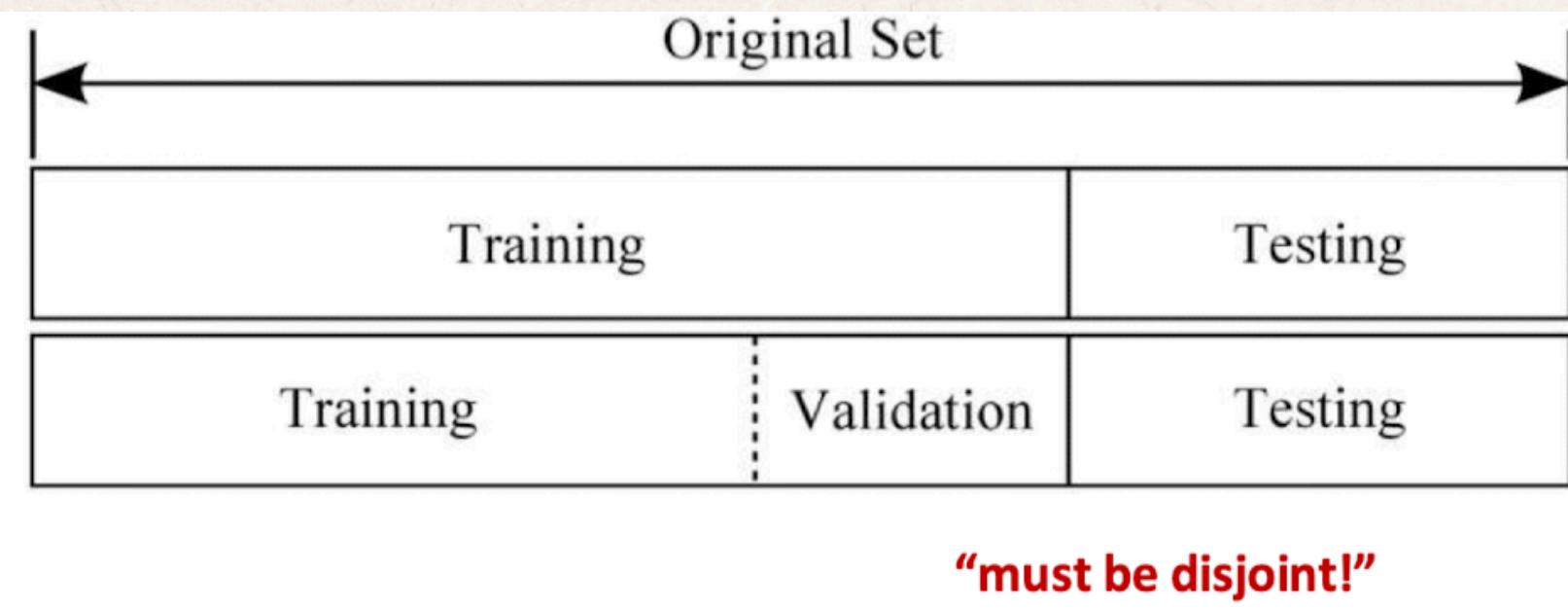
Yes -1

No -0

- **Data Preprocessing:**

- Resize to 224×224
- Normalize using ***ToTensor()***

- **Split:** 80% train, 10% validation, 10% test



Our custom CNN with a pre-trained ResNet18 backbone

- **Purpose:** To utilize a pretrained Convolutional Neural Network (CNN), specifically ResNet18, as a feature extractor for input cat images.
- **Approach:**
 - Load ResNet18 with pretrained weights from ImageNet.
 - The final fully connected (classification) layer is removed.
 - The model is used only for feature extraction, with **`torch.no_grad()`** and **`eval()`** to prevent training.

Our custom CNN with a pre-trained ResNet18 backbone

1 - Training Configuration

- Loss Function: ***nn.CrossEntropyLoss***
=> measure the error between the model's prediction and the actual label.
- Optimizer: ***optim.Adam***
(Learning Rate = 0.001) => efficiently updates model weights to minimize the loss.
- LR Scheduler: ***StepLR***
=> reduce learning rate by 90% (gamma=0.1) every 5 epochs to help the model fine-tune more precisely over time.

```
#training CNN
model=CNN(num_classes=2).to(device)

criterion=nn.CrossEntropyLoss()
optimizer=optim.Adam(model.parameters(), lr=0.001)
scheduler=StepLR(optimizer, step_size=5, gamma=0.1)
```

Our custom CNN with a pre-trained ResNet18 backbone

2 - Training Process (10 Epochs)

- Training Phase (*model.train()*)
 - The model learns patterns from the ***train_loader***.
 - Weights are updated via backpropagation after calculating loss.
- Validation Phase (*model.eval()*)
 - The model's performance is tested on the ***valid_loader*** (data it has not seen before).
 - We calculate Validation Accuracy (***val_acc***) to check for generalization.

```
for images,labels in train_loader:  
    #train_loader = DataLoader(train_dataset, batch_size=8, shuffle=True)  
    images,labels =images.to(device), labels.to(device)  
  
    # backprop compute output-> compute loss-> backprop-> update weight  
    optimizer.zero_grad()  
    outputs =model(images)  
    loss = criterion(outputs, labels)  
    loss.backward()  
    optimizer.step()  
  
    total_loss += loss.item() #accumulate loss  
  
    #to get predicted class index for each sample in batch  
    # find mac value and index  
    _, predicted = torch.max(outputs, 1)  
    total+=labels.size(0)  
  
    correct+=(predicted==labels).nonzero().size(0)  
    # calculate avg loss and training acc  
    avg_loss = total_loss/len(train_loader)  
  
    train_acc = correct/total  
    train_losses.append(avg_loss)  
    scheduler.step()  
  
    #track how lr reduced  
    for param_group in optimizer.param_groups:  
        current_lr = param_group['lr']  
    print(f"Learning Rate: {current_lr}")  
  
model.eval() #use eval  
correct=0  
total= 0  
total_valloss=0.0
```

Our custom CNN with a pre-trained ResNet18 backbone

```
# save the best model based on validation accuracy
if val_acc>best_val_acc:
    best_val_acc=val_acc
    torch.save(model.state_dict(), "best_model.pth")
    print(f"Saved new best model with Val Acc: {val_acc:.2f}")

print(f"Epoch {epoch+1}/{num_epochs} | Loss: {avg_loss:.4f} | Train Acc: {train_acc:.2f} | Val Acc: {val_acc:.2f}")
```

3. Saving the Best Model

- Goal: To prevent overfitting and select the model that performs best on new, unseen data.
- Method:
 - We monitor **val_acc** after every epoch.
 - If the current **val_acc** is higher than any previous one, we save the model's weights to **best_model.pth**.
 - This ensures our final model is the one that generalizes the best.

LOSS FUNCTION

Cross Entropy Loss()

- for classification (binary or multi class)
- combine: LogSoftmax and Negative Log Likelihood Loss (NLLLoss)
- to predict right class with high confidence

$$\text{Loss} = - \sum_{i=1}^C y_i \cdot \log(\hat{y}_i)$$

loss near 0-> confident and right
loss is high-> confident and wrong

1. `self.classifier=nn.Linear(512, num_classes)`

- Model Structure: final fully connected layer
- converts the 512-dim CNN feature vector into raw class scores (**logits**)

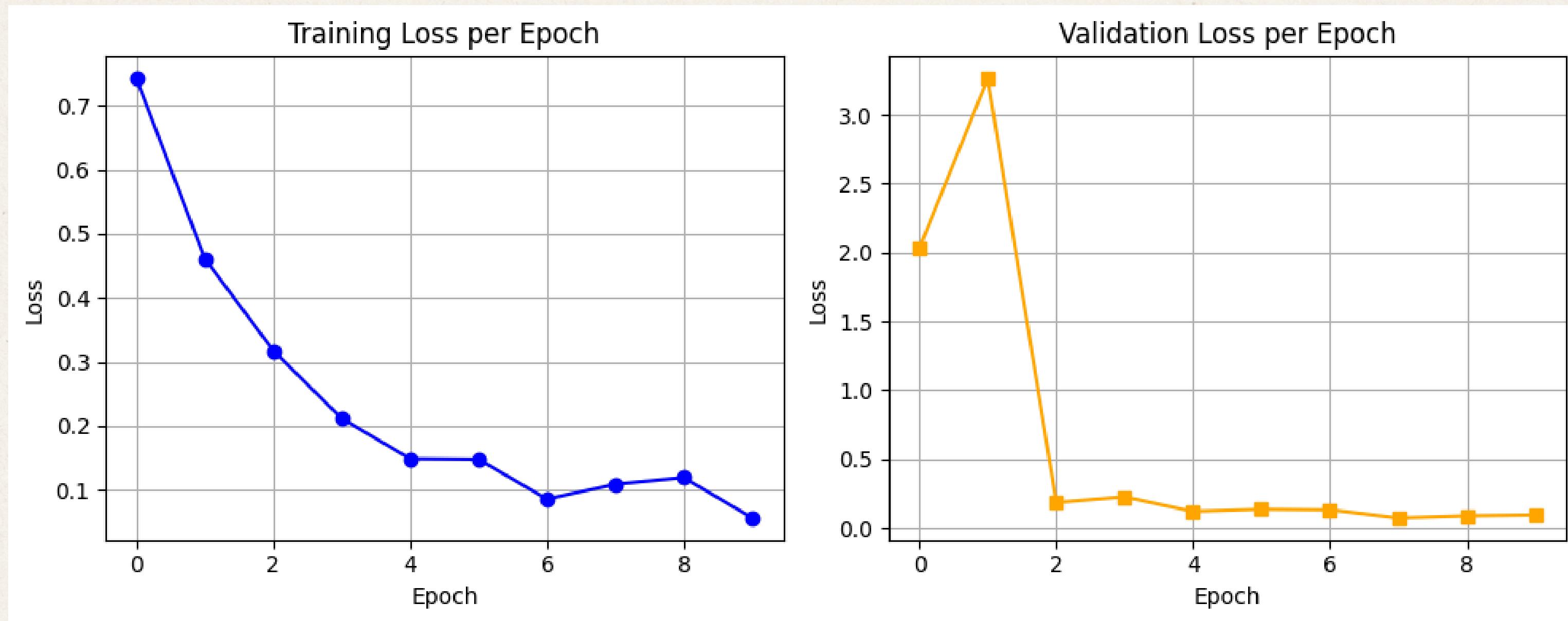
2. `criterion=nn.CrossEntropyLoss()`
`loss = criterion(outputs, labels)`
`loss.backward()`

- takes raw scores from `self.classifier()`
- applies softmax: **convert logits to probabilities**
- **compares** with true labels
- **backpropagates** error: adjust model weights to increase confidence in the correct class

Saved new best model with Val Acc: 1.00
Epoch 5/10 | Loss: 0.1488 | Train Acc: 0.95 | Val Acc: 1.00

Saved new best model with Train Loss: 0.0564
Learning Rate: 1e-05
Epoch 10/10 | Loss: 0.0564 | Train Acc: 0.99 | Val Acc: 1.00

Training vs Validation Loss



model is learning well and
fitting the training data

model generalize well on
(new,unseen) validation data

KNN: IMAGE CLASSIFICATION

- **Purpose:** To train a K-Nearest Neighbors (KNN) classifier to distinguish between Tabby and other cats based on the extracted features.
- **Implementation:**
 - Train KNN models with k values of 3, 5, and 7.
 - Accuracy is measured on the validation set to determine the best k.
 - The best-performing KNN model is retrained on the full training set.

Importance of a Reliable Dataset

1. Initial dataset2 (csv)

- randomly constructed dataset with no clear logic
- Result: Model struggled to learn patterns
- Accuracy: **low → ~0.60**

2. Improved dataset2(csv)

- constructed with clear conditions:
 - Winter → at home
 - Morning → at home
 - Spring/Autumn Evening → not at home
 - Summer + Rain + Medium/High → not at home
- Accuracy: **higher → up to 0.92 !**

why?

- Random Forest now can **better** detect **decision thresholds** when data is structured
- Even simple models perform well with reliable dataset

EVALUATION METRICS

Confusion Matrix

Class 0 (e.g., Not Tabby):

- True Negatives (TN): 7
- False Positives (FP): 0

Class 1 (e.g., Tabby):

- True Positives (TP) : 11
- False Negatives (FN): 0

 Perfect Classification:

- No misclassifications.
- Accuracy = 100%.
- Precision, recall, and F1-score = 1.00 for both classes.

Accuracy: 1.0

Confusion Matrix:

```
[[ 5  0]
 [ 0 11]]
```

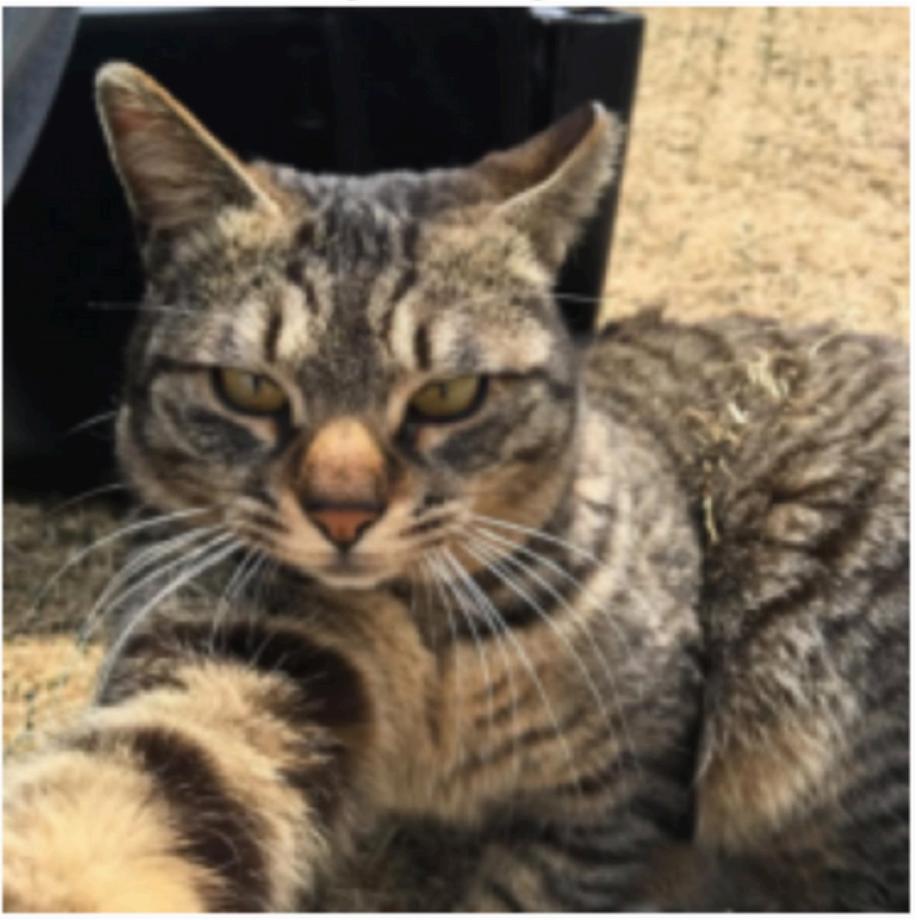
Classification Report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	5
1	1.00	1.00	1.00	11
accuracy			1.00	16
macro avg	1.00	1.00	1.00	16
weighted avg	1.00	1.00	1.00	16

RESULT ANALYSIS

```
predict_image("IMG_1.jpg", feature_extractor, knn, device, dataset.classes, tabby_mean)
```

Prediction: Tabby
Similarity to Tabby: 96.99%



TABBY



('Tabby', np.float32(96.9885))

```
predict_image("IMG_2.jpg", feature_extractor, knn, device, dataset.classes, tabby_mean)
```

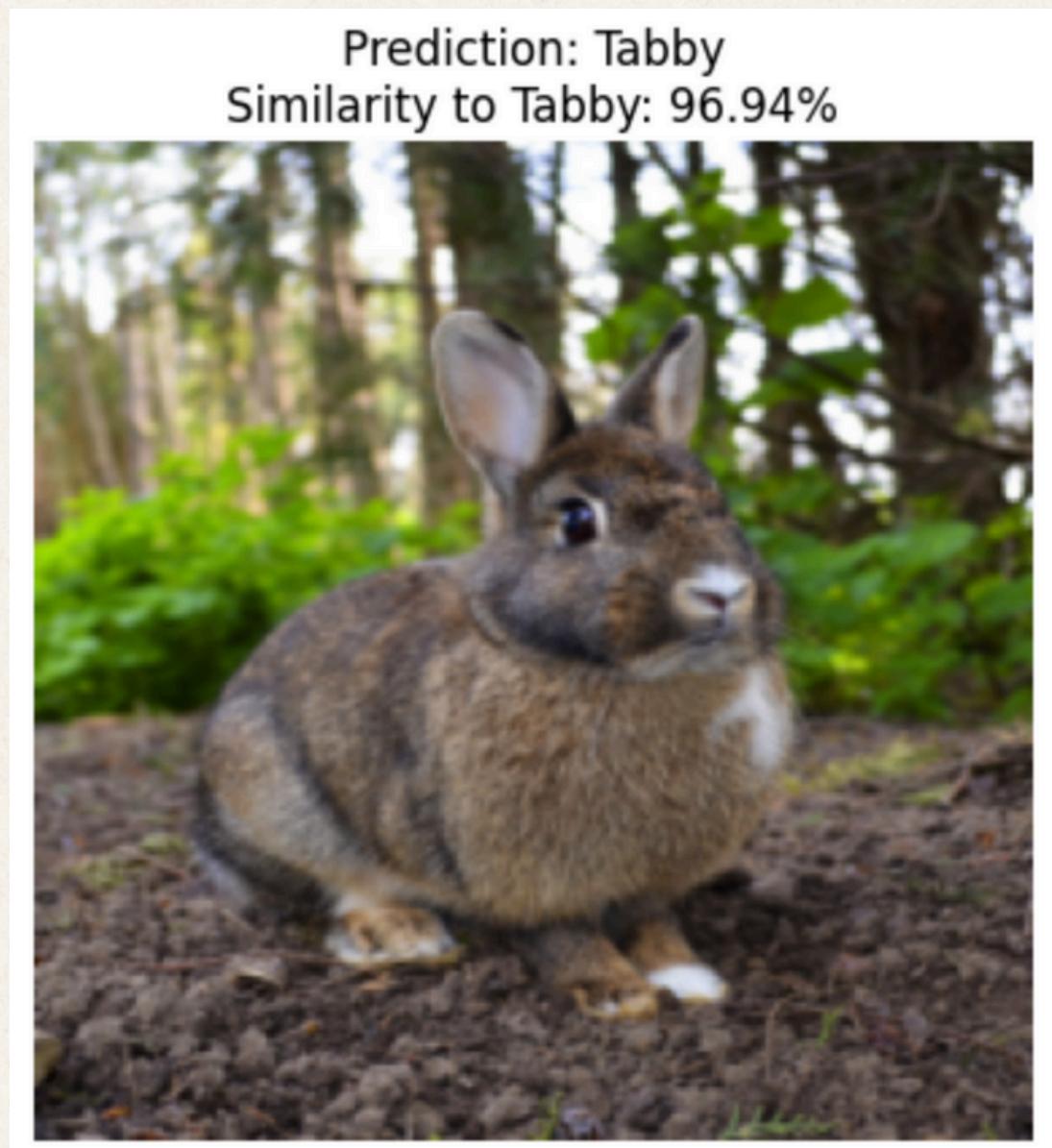
Prediction: Not_Tabby
Similarity to Tabby: 29.61%



('Not_Tabby', np.float32(29.6101))

NOPE

- **Model Limitation:** Analysis of a Misclassification
- **Input:** An image of a rabbit
- **Prediction:** Tabby (Similarity: 96.94%)



Why did this happen?

- The model learns **visual patterns**, not concepts. Our CNN does not understand "cat" or "rabbit." It learns to associate specific textures, colors, and patterns with a label.
- **Dominant Feature:** The model identified the rabbit's brownish, mottled fur as the most critical feature. This pattern is visually very similar to the striped pattern of our Tabby cat.

Random Forest

- Our goal is to predict whether Tabby is likely to be at home or not based on season, time of day, raining condition and noise level
- Transformed using one-hot encoding and passed to the model
- Each tree gives a vote: home(1) or not home(0)
- Forest picks the majority vote as final prediction
- Accuracy : ~93%
- General behavioral trends : winter/morning → at home, spring/autumn night → not at home

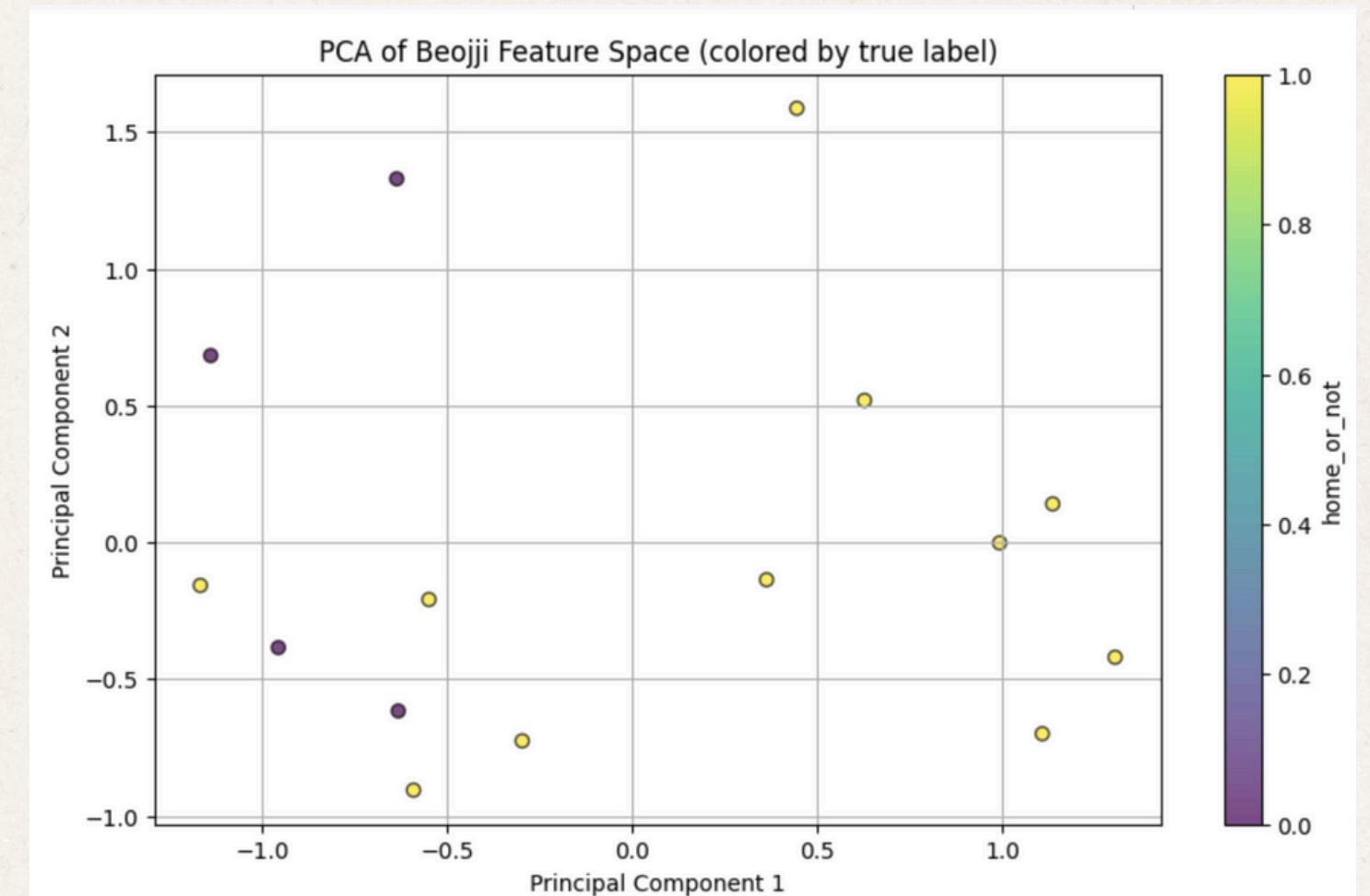
Season (spring/summer/autumn/winter): summer
Time of day (morning/evening/night): night
Is it raining? (yes=1, no=0): 1
Noise level (low/medium/high)): high
Tabby is probably out and about.

Visualization: PCA

- Each point represents a single test sample (day/time/weather condition)
- Color:-
 - Yellow : $\text{home_or_not} = 1$ (Tabby was at home)
 - Dark purple : $\text{home_or_not} = 0$ (Tabby was outside)

Observation:

- There is some overlap between the two labels, especially in the center.
- Despite that, the model achieved 93% accuracy, meaning it can still separate the classes well.
- This suggests the original features have useful patterns that the model can learn, even if they're not obvious in 2D.



**THANK
YOU**



CHECKPOINT PRESENTATION

Problem statement

Detecting 베찌 or not using Image classification

베찌 = Tabby (due to limited dataset of real 베찌)

Learning Algorithm

CNN as feature extractor

- Use models like MobileNetV2, ResNet50
- Image input → output feature vector

KNN as image classification using the feature extracted by CNN

- A set of features from labeled images: “Tabby” or “not Tabby”
- For a new input image: extract features → compare with the known feature set → use KNN (or cosine similarity) for classification

Next Step

- **Training Loss:** Using Gradient Descent technique e.g. ADAM optimizer + Categorical Crossentropy loss function
- **Evaluation Metrics:** Confusion Matrix → Accuracy + Similarity Threshold Analysis
- **Visualization:** PCA of feature space to show clusters (泚 vs. non-泚)