In [1]:
```
"""
Active Learning CIFAR-10 - Google Colab Version
Copy this entire file into a Colab notebook cell
"""

# ============================================================
# CELL 1: Setup and Mount Google Drive + reproducibility
# ============================================================

!pip install scikit-learn -q

from google.colab import drive
drive.mount('/content/drive')

import os, sys, time
SAVE_DIR = '/content/drive/MyDrive/AL_Results'
os.makedirs(SAVE_DIR, exist_ok=True)
print(f"Results will be saved to: {SAVE_DIR}")

# Verify GPU
import torch
print(f"GPU available: {torch.cuda.is_available()}")
if torch.cuda.is_available():
    try:
        print(f"GPU: {torch.cuda.get_device_name(0)}")
    except Exception:
        pass

# ---------- reproducibility helpers ----------
import random, copy
import numpy as np

def set_all_seeds(seed):
    """Seed python, numpy, torch (CPU & CUDA) for reproducibility.
       Note: setting deterministic flags may slow training slightly."""
    random.seed(seed)
    np.random.seed(seed)
    torch.manual_seed(seed)
    try:
        torch.cuda.manual_seed_all(seed)
    except Exception:
        pass
    # Make cuDNN deterministic (may slow). Keep explicit.
    torch.backends.cudnn.deterministic = True
    torch.backends.cudnn.benchmark = False

def make_initial_model_state(device):
    """Return a state_dict for SimpleCNN to use as the common initial weights
    m = SimpleCNN().to(device)
    state = copy.deepcopy(m.state_dict())
    del m
```

```
    return state

def load_state_into_model(model, state_dict, device):
    model.load_state_dict(state_dict)
    model.to(device)
    return model

# DataLoader worker initialization for determinism
def worker_init_fn(worker_id):
    worker_seed = (torch.initial_seed() + worker_id) % (2**32)
    np.random.seed(worker_seed)
    random.seed(worker_seed)
```

```
Mounted at /content/drive
Results will be saved to: /content/drive/MyDrive/AL_Results
GPU available: True
GPU: Tesla T4
```

In [ ]:

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# ============================================================
# CELL 2: Main code (AL simulation)
# ============================================================
import argparse, os, copy, math, random, time
import numpy as np
import torch
import torch.nn as nn
import torch.optim as optim
import torch.nn.functional as F
from torch.utils.data import Dataset, DataLoader, Subset
from torchvision import datasets, transforms
from sklearn.cluster import KMeans, MiniBatchKMeans
from sklearn.metrics import accuracy_score

class SimpleCNN(nn.Module):
    def __init__(self, embedding_dim=128, num_classes=10):
        super().__init__()
        # Layer 1: Conv -> BN -> ReLU -> Pool
        self.conv1 = nn.Conv2d(3, 32, 3, padding=1)
        self.bn1 = nn.BatchNorm2d(32)
        self.pool = nn.MaxPool2d(2, 2)

        # Layer 2: Conv -> BN -> ReLU -> Pool
        self.conv2 = nn.Conv2d(32, 64, 3, padding=1)
        self.bn2 = nn.BatchNorm2d(64)

        # Layer 3: Conv -> BN -> ReLU -> Pool
        self.conv3 = nn.Conv2d(64, 64, 3, padding=1) # Kept at 64 to save par
        self.bn3 = nn.BatchNorm2d(64)

        # Classifier
        self.fc1 = nn.Linear(64 * 4 * 4, embedding_dim) # 64 channels * 4x4 i
        self.fc2 = nn.Linear(embedding_dim, num_classes)

    def forward(self, x, return_embedding=False):
```

```
        # Block 1, 2 and 3
        x = self.pool(F.relu(self.bn1(self.conv1(x))))
        x = self.pool(F.relu(self.bn2(self.conv2(x))))
        x = self.pool(F.relu(self.bn3(self.conv3(x))))

        # Flatten
        x = x.view(x.size(0), -1)

        # Embedding & Logits
        embedding = F.relu(self.fc1(x))
        logits = self.fc2(embedding)

        return (logits, embedding) if return_embedding else logits

# ------------------------
# Training & Eval
# ------------------------
def train_epoch(model, dataloader, device, optimizer, criterion=nn.CrossEntro
    model.train()
    total_loss = 0.0
    n = 0
    for x,y in dataloader:
        x,y = x.to(device), y.to(device)
        optimizer.zero_grad()
        out = model(x)
        loss = criterion(out, y)
        loss.backward()
        optimizer.step()
        total_loss += loss.item() * x.size(0)
        n += x.size(0)
    return total_loss / max(1, n)

def evaluate(model, dataloader, device):
    model.eval()
    preds, trues = [], []
    with torch.no_grad():
        for x,y in dataloader:
            x = x.to(device)
            p = model(x).argmax(1).cpu().numpy()
            preds.append(p)
            trues.append(y.numpy())
    return accuracy_score(np.concatenate(trues), np.concatenate(preds))

# ------------------------
# Noisy annotator (use rng for determinism)
# ------------------------
def noisy_label(true_label, num_classes, epsilon, rng=None):
    if rng is None:
        rng = np.random
    if rng.rand() < epsilon:
        choices = list(range(num_classes))
        choices.remove(int(true_label))
        return int(rng.choice(choices))
```

```
    return int(true_label)

# -------------------------
# Query strategies (accept rng where needed)
# -------------------------
def query_random(unlabeled_indices, k, rng):
    return list(rng.choice(unlabeled_indices, size=k, replace=False))

def query_uncertainty(model, dataset, unlabeled_indices, k, device, batch_siz
    model.eval()
    # Subset temporarily; unlabeled_indices are absolute indices into dataset
    loader = DataLoader(Subset(dataset, unlabeled_indices), batch_size=batch_
    scores, idx_list = [], []
    base = 0
    with torch.no_grad():
        for xb, _ in loader:
            xb = xb.to(device)
            probs = F.softmax(model(xb), dim=1)
            unc = (1.0 - probs.max(1)[0]).cpu().numpy()
            scores.append(unc)
            # Compute indices corresponding to this batch
            batch_inds = unlabeled_indices[base: base + xb.size(0)]
            idx_list.extend(batch_inds)
            base += xb.size(0)
    scores = np.concatenate(scores)
    order = np.argsort(-scores)  # Descending uncertainty
    chosen = np.array(idx_list)[order[:k]].tolist()
    return chosen

def extract_embeddings(model, dataset, indices, device, batch_size=128):
    model.eval()
    loader = DataLoader(Subset(dataset, indices), batch_size=batch_size, shuf
    emb_list = []
    with torch.no_grad():
        for xb, _ in loader:
            xb = xb.to(device)
            _, emb = model(xb, return_embedding=True)
            emb_list.append(emb.cpu().numpy())
    if len(emb_list) == 0:
        return np.zeros((0, 128))
    return np.vstack(emb_list)

def query_diversity_kmeans(model, dataset, unlabeled_indices, k, device, rng=
    if rng is None:
        rng = np.random.RandomState()
    if n_clusters is None:
        n_clusters = k
    if len(unlabeled_indices) == 0:
        return []
    embeddings = extract_embeddings(model, dataset, unlabeled_indices, device
    if embeddings.shape[0] == 0:
        return []
    # use MiniBatchKMeans as faster alternative when pool large
```

```
    try:
        if use_minibatch:
            km = MiniBatchKMeans(n_clusters=min(n_clusters, embeddings.shape[
        else:
            km = KMeans(n_clusters=min(n_clusters, embeddings.shape[0]), rand
    except Exception:
        km = KMeans(n_clusters=min(n_clusters, embeddings.shape[0]), random_s
    centers = km.cluster_centers_
    chosen = []
    for ci in range(km.n_clusters):
        cluster_idx = np.where(km.labels_==ci)[0]
        if len(cluster_idx)==0:
            continue
        pts = embeddings[cluster_idx]
        dists = np.linalg.norm(pts - centers[ci], axis=1)
        chosen.append(int(unlabeled_indices[cluster_idx[dists.argmin()]]))
        if len(chosen) >= k:
            break
    if len(chosen) < k:
        remaining = list(set(unlabeled_indices) - set(chosen))
        if remaining:
            pad = list(rng.choice(remaining, size=min(len(remaining), k-len(c
            chosen.extend(list(map(int, pad)))
    return chosen[:k]

# ------------------------
# Dataset wrapper (NoisyLabelDataset)
# ------------------------
class NoisyLabelDataset(Dataset):
    """Wraps an underlying torchvision-style dataset. The base dataset should
       expose `.targets` and index with absolute indices.
       Use .noisy_label_map to set noisy labels (mapping absolute_index -> no
    def __init__(self, base_dataset):
        self.base = base_dataset
    def __len__(self):
        return len(self.base)
    def __getitem__(self, idx):
        x, y_true = self.base[idx]
        y = getattr(self.base, 'noisy_label_map', {}).get(idx, y_true)
        return x, y

# ------------------------
# Single AL simulation
# ------------------------
def run_single_simulation(dataset_train, dataset_test, initial_labeled_indice
                          strategy, labeling_budget, batch_size_query, device
                          epsilon, seed, max_epochs=10, early_stopping=True,
                          patience=3, verbose=True, init_state=None, rng=None
    """
    init_state: state_dict for model initial weights (for CRN)
    rng: numpy RandomState for this run (for deterministic noisy labels & sel
    """
    if rng is None:
```

```
        rng = np.random.RandomState(seed)
    set_all_seeds(seed)
    labeled_set = list(initial_labeled_indices)[:] # Absolute indices into da
    all_indices = list(range(len(dataset_train)))
    unlabeled_set = list(sorted(set(all_indices) - set(labeled_set)))
    results = []

    # Build model with init state for CRN
    model = SimpleCNN().to(device)
    if init_state is not None:
        model.load_state_dict(init_state)

    def make_labeled_loader():
        # Use worker_init_fn to keep deterministic worker seeds if num_worker
        return DataLoader(Subset(dataset_train, labeled_set), batch_size=64, 
    test_loader = DataLoader(dataset_test, batch_size=256, shuffle=False)

    round_num = 0
    while True:
        optimizer = optim.Adam(model.parameters(), lr=1e-3)
        scheduler = optim.lr_scheduler.ReduceLROnPlateau(optimizer, mode='max

        best_acc = 0.0
        patience_counter = 0

        for epoch in range(max_epochs):
            train_loss = train_epoch(model, make_labeled_loader(), device, op
            if early_stopping and epoch > 0:
                current_acc = evaluate(model, make_labeled_loader(), device)
                scheduler.step(current_acc)

                if current_acc > best_acc:
                    best_acc = current_acc
                    patience_counter = 0
                else:
                    patience_counter += 1

                if patience_counter >= patience and epoch >= 5:
                    if verbose:
                        print(f"  Early stopping at epoch {epoch+1}")
                    break

        acc = evaluate(model, test_loader, device)
        results.append((len(labeled_set), acc))

        if verbose:
            print(f"Round {round_num}: {len(labeled_set)} labels, accuracy={a

        if len(labeled_set) >= labeling_budget or len(unlabeled_set) == 0:
            break

        k = min(batch_size_query, labeling_budget - len(labeled_set))
        if strategy == 'random':
```

```
            chosen = query_random(np.array(unlabeled_set), k, rng)
        elif strategy == 'uncertainty':
            chosen = query_uncertainty(model, dataset_train, np.array(unlabele
        elif strategy == 'diversity':
            chosen = query_diversity_kmeans(model, dataset_train, np.array(un
        else:
            raise ValueError("Unknown strategy")

        annotated = []
        base = dataset_train.base
        for idx in chosen:
            true_label = base.targets[int(idx)]
            noisy = noisy_label(true_label, 10, epsilon, rng=rng)
            annotated.append((int(idx), noisy))

        if not hasattr(dataset_train.base, 'noisy_label_map'):
            dataset_train.base.noisy_label_map = {}
        for idx, lab in annotated:
            dataset_train.base.noisy_label_map[int(idx)] = int(lab)

        # Update sets
        labeled_set.extend(list(map(int, chosen)))
        unlabeled_set = [i for i in unlabeled_set if i not in set(map(int, ch

        del model, optimizer, scheduler
        torch.cuda.empty_cache()
        model = SimpleCNN().to(device)
        if init_state is not None:
            model.load_state_dict(init_state)
        round_num += 1

    del model
    torch.cuda.empty_cache()

    return results

# -------------------------
# Main experiment runner
# -------------------------
def run_experiment(config):
    device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
    print(f"Using device: {device}")

    # Add RandomHorizontalFlip and RandomCrop
    transform_train = transforms.Compose([
        transforms.RandomCrop(32, padding=4),
        transforms.RandomHorizontalFlip(),
        transforms.ToTensor(),
        transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
    ])

    transform_test = transforms.Compose([
        transforms.ToTensor(),
```

```
        transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
    ])

    cifar_train_full = datasets.CIFAR10(root='./data', train=True, download=T
    cifar_test_full = datasets.CIFAR10(root='./data', train=False, download=T

    # Optionally use a subset (preserve absolute indices by creating a mappin
    if config.get('subset') is not None:
        subset_n = config['subset']
        assert subset_n <= len(cifar_train_full)
        subset_indices = list(range(subset_n))
        cifar_train = Subset(cifar_train_full, subset_indices)
        # make a small wrapper that preserves `.targets` for absolute indexin
        class SubsetWithTargets(Dataset):
            def __init__(self, subset, abs_indices):
                self.subset = subset
                self.abs_indices = abs_indices
                # expose targets aligned with absolute indexing
                self.targets = [cifar_train_full.targets[i] for i in abs_indi
            def __len__(self): return len(self.subset)
            def __getitem__(self, idx):
                return self.subset[idx]
        cifar_train = SubsetWithTargets(cifar_train, subset_indices)
    else:
        cifar_train = cifar_train_full

    dataset_train = NoisyLabelDataset(cifar_train)
    dataset_test = NoisyLabelDataset(cifar_test_full)

    strategies = config['strategies']
    save_dir = config['save_dir']
    os.makedirs(save_dir, exist_ok=True)

    print(f"Experiment configuration:")
    print(f"  Dataset size: {len(dataset_train)}")
    print(f"  Initial labels: {config['initial_labels']}")
    print(f"  Labeling budget: {config['labeling_budget']}")
    print(f"  Max epochs: {config['max_epochs']}")
    print(f"  Strategies: {strategies}")
    print(f"  Epsilon values: {config['epsilons']} (if sampling enabled, valu
    print(f"  Replications: {config['replications']}")
    print(f"  Save directory: {save_dir}")

    total_experiments = len(config['epsilons']) * len(strategies) * config['r
    print(f"Total experiments (approx): {total_experiments}")

    start_time = time.time()
    completed = 0

    # For each epsilon in the grid (or if sampling, we'll ignore the grid and
    for epsilon in config['epsilons']:
        print(f"{'='*60}")
        print(f"Running epsilon = {epsilon}")
```

```
    print(f"{'='*60}")

    all_results = {s:[] for s in strategies}

    for rep in range(config['replications']):
        seed = config['seed'] + rep
        rng = np.random.RandomState(seed)
        # sample epsilon per replication if requested
        eps_this_rep = epsilon
        if config.get('sample_epsilon_per_rep', False):
            # example: uniform prior between 0 and given epsilon (or use
            eps_this_rep = float(rng.uniform(0.0, epsilon))

        initial_labeled = rng.choice(list(range(len(dataset_train))), siz

        # prepare CRN initial model state for this replication (same for
        set_all_seeds(seed)
        init_state = make_initial_model_state(device)

        for s in strategies:
            # clear noisy labels
            if hasattr(dataset_train.base, 'noisy_label_map'):
                dataset_train.base.noisy_label_map = {}

            print(f"  Rep {rep+1}/{config['replications']}, Strategy: {s}
            rep_start = time.time()

            res = run_single_simulation(
                dataset_train, dataset_test, initial_labeled,
                strategy=s, labeling_budget=config['labeling_budget'],
                batch_size_query=config['query_batch'], device=device,
                epsilon=eps_this_rep, seed=seed, max_epochs=config['max_e
                early_stopping=config['early_stopping'], patience=config[
                verbose=config['verbose'], init_state=init_state, rng=rng
            )
            all_results[s].append(res)

            completed += 1
            elapsed = time.time() - rep_start
            total_elapsed = time.time() - start_time
            avg_time = total_elapsed / max(1, completed)
            remaining = (total_experiments - completed) * avg_time

            print(f"    Completed in {elapsed:.1f}s")
            print(f"    Progress: {completed}/{total_experiments} ({100*c
            print(f"    Rough ETA (minutes): {remaining/60:.1f}")

    # Save results for this epsilon value
    fname = os.path.join(save_dir, f"al_results_e{int(epsilon*100)}.pkl")
    import pickle
    with open(fname,"wb") as f:
        pickle.dump(all_results,f)
    print(f"✓ Saved: {fname}")
```

```
    total_time = time.time() - start_time
    print(f"{'='*60}")
    print(f"All experiments completed! Total time: {total_time/3600:.2f} hour
    print(f"Results saved to: {save_dir}")
    print(f"{'='*60}")

    return save_dir

print("✓ Code loaded successfully!")
```

```
✓ Code loaded successfully!
```

In [ ]:

```
# ============================================================
# CELL 3: Run Quick Validation (small subset, quick)
# ============================================================

config = {
    'save_dir': SAVE_DIR,
    'subset': None,
    'initial_labels': 100,
    'labeling_budget': 2000,
    'query_batch': 100,
    'max_epochs': 12,
    'strategies': ['random', 'uncertainty', 'diversity'],
    'epsilons': [0.0], # grid values; if sample_epsilon_per_rep=True, epsilon
    'replications': 1, # Keep at 1 for this test
    'seed': 123,
    'early_stopping': True,
    'patience': 3,
    'verbose': True,
    'sample_epsilon_per_rep': False # set True to draw epsilon ~ Uniform(0, e
}

results_dir = run_experiment(config)
print(f"✓ Results saved to: {results_dir}")
print(f"Download these files from Google Drive to analyze locally:")
print(f"  {results_dir}/al_results_e0.pkl")
```

```
Using device: cuda
100%|██████████| 170M/170M [00:16<00:00, 10.5MB/s]
Experiment configuration:
  Dataset size: 50000
  Initial labels: 100
  Labeling budget: 2000
  Max epochs: 12
  Strategies: ['random', 'uncertainty', 'diversity']
  Epsilon values: [0.0] (if sampling enabled, values may be drawn per-replicat
ion)
  Replications: 1
  Save directory: /content/drive/MyDrive/AL_Results
Total experiments (approx): 3
============================================================
```

```
Running epsilon = 0.0
============================================================
  Rep 1/1, Strategy: random, eps=0.0000
  Early stopping at epoch 7
Round 0: 100 labels, accuracy=0.1477
Round 1: 200 labels, accuracy=0.3089
Round 2: 300 labels, accuracy=0.3198
Round 3: 400 labels, accuracy=0.3302
Round 4: 500 labels, accuracy=0.3786
Round 5: 600 labels, accuracy=0.3640
Round 6: 700 labels, accuracy=0.4071
Round 7: 800 labels, accuracy=0.4603
  Early stopping at epoch 10
Round 8: 900 labels, accuracy=0.4109
Round 9: 1000 labels, accuracy=0.4691
Round 10: 1100 labels, accuracy=0.4744
Round 11: 1200 labels, accuracy=0.4804
Round 12: 1300 labels, accuracy=0.5021
Round 13: 1400 labels, accuracy=0.5180
  Early stopping at epoch 11
Round 14: 1500 labels, accuracy=0.4771
Round 15: 1600 labels, accuracy=0.5272
Round 16: 1700 labels, accuracy=0.5212
Round 17: 1800 labels, accuracy=0.5004
Round 18: 1900 labels, accuracy=0.5206
Round 19: 2000 labels, accuracy=0.5440
    Completed in 257.7s
    Progress: 1/3 (33.3%)
    Rough ETA (minutes): 8.6
  Rep 1/1, Strategy: uncertainty, eps=0.0000
  Early stopping at epoch 7
Round 0: 100 labels, accuracy=0.1477
  Early stopping at epoch 7
Round 1: 200 labels, accuracy=0.1533
  Early stopping at epoch 6
Round 2: 300 labels, accuracy=0.1582
  Early stopping at epoch 12
Round 3: 400 labels, accuracy=0.2903
Round 4: 500 labels, accuracy=0.3327
Round 5: 600 labels, accuracy=0.3696
Round 6: 700 labels, accuracy=0.3919
Round 7: 800 labels, accuracy=0.4043
Round 8: 900 labels, accuracy=0.3933
Round 9: 1000 labels, accuracy=0.4497
Round 10: 1100 labels, accuracy=0.4233
Round 11: 1200 labels, accuracy=0.4598
Round 12: 1300 labels, accuracy=0.4271
Round 13: 1400 labels, accuracy=0.5029
Round 14: 1500 labels, accuracy=0.4714
Round 15: 1600 labels, accuracy=0.4468
Round 16: 1700 labels, accuracy=0.4757
  Early stopping at epoch 10
Round 17: 1800 labels, accuracy=0.4209
Round 18: 1900 labels, accuracy=0.4972
Round 19: 2000 labels, accuracy=0.5260
    Completed in 613.4s
    Progress: 2/3 (66.7%)
```

```
    Rough ETA (minutes): 7.3
  Rep 1/1, Strategy: diversity, eps=0.0000
  Early stopping at epoch 7
Round 0: 100 labels, accuracy=0.1477
Round 1: 200 labels, accuracy=0.2930
Round 2: 300 labels, accuracy=0.3537
Round 3: 400 labels, accuracy=0.3384
Round 4: 500 labels, accuracy=0.3766
Round 5: 600 labels, accuracy=0.4103
Round 6: 700 labels, accuracy=0.4165
Round 7: 800 labels, accuracy=0.4153
Round 8: 900 labels, accuracy=0.4077
Round 9: 1000 labels, accuracy=0.4263
Round 10: 1100 labels, accuracy=0.4657
Round 11: 1200 labels, accuracy=0.4921
Round 12: 1300 labels, accuracy=0.4756
Round 13: 1400 labels, accuracy=0.4927
  Early stopping at epoch 11
Round 14: 1500 labels, accuracy=0.4470
Round 15: 1600 labels, accuracy=0.5221
Round 16: 1700 labels, accuracy=0.5086
Round 17: 1800 labels, accuracy=0.4852
Round 18: 1900 labels, accuracy=0.5052
Round 19: 2000 labels, accuracy=0.5358
    Completed in 623.3s
    Progress: 3/3 (100.0%)
    Rough ETA (minutes): 0.0
✓ Saved: /content/drive/MyDrive/AL_Results/al_results_e0.pkl
============================================================
All experiments completed! Total time: 0.42 hours
Results saved to: /content/drive/MyDrive/AL_Results
============================================================
✓ Results saved to: /content/drive/MyDrive/AL_Results
Download these files from Google Drive to analyze locally:
  /content/drive/MyDrive/AL_Results/al_results_e0.pkl
```

In [ ]:

```
# ============================================================
# CELL 4: Run Full Experiment (long)
# ============================================================

config_full = {
    'save_dir': SAVE_DIR,
    'subset': None,
    'initial_labels': 100,
    'labeling_budget': 2000,
    'query_batch': 100,
    'max_epochs': 10,
    'strategies': ['random', 'uncertainty', 'diversity'],
    'epsilons': [0.0, 0.05, 0.10, 0.15],  # grid
    'replications': 5,
    'seed': 123,
    'early_stopping': True,
    'patience': 3,
    'verbose': True,
    'sample_epsilon_per_rep': False  # set True to sample eps ~ Uniform(0, ep
}

# Run full experiment (this can be long)
results_dir = run_experiment(config_full)
print(f"✓ Results saved to: {results_dir}")
```

```
Using device: cuda
Experiment configuration:
  Dataset size: 50000
  Initial labels: 100
  Labeling budget: 2000
  Max epochs: 10
  Strategies: ['random', 'uncertainty', 'diversity']
  Epsilon values: [0.0, 0.05, 0.1, 0.15] (if sampling enabled, values may be d
rawn per-replication)
  Replications: 5
  Save directory: /content/drive/MyDrive/AL_Results
Total experiments (approx): 60
============================================================
Running epsilon = 0.0
============================================================
  Rep 1/5, Strategy: random, eps=0.0000
  Early stopping at epoch 7
Round 0: 100 labels, accuracy=0.1477
Round 1: 200 labels, accuracy=0.2115
Round 2: 300 labels, accuracy=0.2934
Round 3: 400 labels, accuracy=0.3467
Round 4: 500 labels, accuracy=0.3758
Round 5: 600 labels, accuracy=0.3972
Round 6: 700 labels, accuracy=0.4337
Round 7: 800 labels, accuracy=0.4309
Round 8: 900 labels, accuracy=0.4073
Round 9: 1000 labels, accuracy=0.4551
Round 10: 1100 labels, accuracy=0.4594
Round 11: 1200 labels, accuracy=0.4397
```

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  Early stopping at epoch 10
Round 12: 1300 labels, accuracy=0.4255
Round 13: 1400 labels, accuracy=0.4747
Round 14: 1500 labels, accuracy=0.4738
Round 15: 1600 labels, accuracy=0.5010
Round 16: 1700 labels, accuracy=0.4862
Round 17: 1800 labels, accuracy=0.5107
Round 18: 1900 labels, accuracy=0.5239
Round 19: 2000 labels, accuracy=0.5109
    Completed in 225.2s
    Progress: 1/60 (1.7%)
    Rough ETA (minutes): 221.5
  Rep 1/5, Strategy: uncertainty, eps=0.0000
  Early stopping at epoch 7
Round 0: 100 labels, accuracy=0.1477
  Early stopping at epoch 7
Round 1: 200 labels, accuracy=0.1533
  Early stopping at epoch 6
Round 2: 300 labels, accuracy=0.1582
Round 3: 400 labels, accuracy=0.3150
Round 4: 500 labels, accuracy=0.3294
Round 5: 600 labels, accuracy=0.3786
Round 6: 700 labels, accuracy=0.3693
Round 7: 800 labels, accuracy=0.4232
Round 8: 900 labels, accuracy=0.3457
  Early stopping at epoch 9
Round 9: 1000 labels, accuracy=0.3311
Round 10: 1100 labels, accuracy=0.4281
Round 11: 1200 labels, accuracy=0.4287
Round 12: 1300 labels, accuracy=0.3903
Round 13: 1400 labels, accuracy=0.4507
Round 14: 1500 labels, accuracy=0.4494
Round 15: 1600 labels, accuracy=0.4018
Round 16: 1700 labels, accuracy=0.4540
Round 17: 1800 labels, accuracy=0.4759
Round 18: 1900 labels, accuracy=0.5012
Round 19: 2000 labels, accuracy=0.5189
    Completed in 580.8s
    Progress: 2/60 (3.3%)
    Rough ETA (minutes): 389.6
  Rep 1/5, Strategy: diversity, eps=0.0000
  Early stopping at epoch 7
Round 0: 100 labels, accuracy=0.1477
Round 1: 200 labels, accuracy=0.2126
Round 2: 300 labels, accuracy=0.2997
Round 3: 400 labels, accuracy=0.3331
Round 4: 500 labels, accuracy=0.3410
Round 5: 600 labels, accuracy=0.3965
Round 6: 700 labels, accuracy=0.3763
Round 7: 800 labels, accuracy=0.4321
Round 8: 900 labels, accuracy=0.4013
Round 9: 1000 labels, accuracy=0.4041
Round 10: 1100 labels, accuracy=0.4240
Round 11: 1200 labels, accuracy=0.4115
Round 12: 1300 labels, accuracy=0.4521
Round 13: 1400 labels, accuracy=0.4491
Round 14: 1500 labels, accuracy=0.4714
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Round 15: 1600 labels, accuracy=0.4967
Round 16: 1700 labels, accuracy=0.4881
Round 17: 1800 labels, accuracy=0.4874
Round 18: 1900 labels, accuracy=0.4953
Round 19: 2000 labels, accuracy=0.4911
    Completed in 581.8s
    Progress: 3/60 (5.0%)
    Rough ETA (minutes): 439.5
  Rep 2/5, Strategy: random, eps=0.0000
  Early stopping at epoch 10
Round 0: 100 labels, accuracy=0.1878
Round 1: 200 labels, accuracy=0.2421
  Early stopping at epoch 6
Round 2: 300 labels, accuracy=0.1520
Round 3: 400 labels, accuracy=0.3554
Round 4: 500 labels, accuracy=0.3745
Round 5: 600 labels, accuracy=0.4096
Round 6: 700 labels, accuracy=0.3972
Round 7: 800 labels, accuracy=0.4017
  Early stopping at epoch 8
Round 8: 900 labels, accuracy=0.4221
Round 9: 1000 labels, accuracy=0.4095
Round 10: 1100 labels, accuracy=0.4219
Round 11: 1200 labels, accuracy=0.4034
Round 12: 1300 labels, accuracy=0.4365
Round 13: 1400 labels, accuracy=0.4664
Round 14: 1500 labels, accuracy=0.5066
  Early stopping at epoch 10
Round 15: 1600 labels, accuracy=0.4555
Round 16: 1700 labels, accuracy=0.4932
Round 17: 1800 labels, accuracy=0.4698
Round 18: 1900 labels, accuracy=0.5001
Round 19: 2000 labels, accuracy=0.5077
    Completed in 219.9s
    Progress: 4/60 (6.7%)
    Rough ETA (minutes): 375.2
  Rep 2/5, Strategy: uncertainty, eps=0.0000
  Early stopping at epoch 10
Round 0: 100 labels, accuracy=0.1878
  Early stopping at epoch 7
Round 1: 200 labels, accuracy=0.2575
Round 2: 300 labels, accuracy=0.3147
Round 3: 400 labels, accuracy=0.3147
Round 4: 500 labels, accuracy=0.3822
Round 5: 600 labels, accuracy=0.3818
Round 6: 700 labels, accuracy=0.3877
Round 7: 800 labels, accuracy=0.3698
  Early stopping at epoch 9
Round 8: 900 labels, accuracy=0.3678
Round 9: 1000 labels, accuracy=0.4548
Round 10: 1100 labels, accuracy=0.3872
Round 11: 1200 labels, accuracy=0.4236
Round 12: 1300 labels, accuracy=0.4384
Round 13: 1400 labels, accuracy=0.4088
Round 14: 1500 labels, accuracy=0.4509
Round 15: 1600 labels, accuracy=0.4731
Round 16: 1700 labels, accuracy=0.4587
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Round 17: 1800 labels, accuracy=0.4611
Round 18: 1900 labels, accuracy=0.4919
Round 19: 2000 labels, accuracy=0.4437
    Completed in 577.6s
    Progress: 5/60 (8.3%)
    Rough ETA (minutes): 400.7
  Rep 2/5, Strategy: diversity, eps=0.0000
  Early stopping at epoch 10
Round 0: 100 labels, accuracy=0.1878
Round 1: 200 labels, accuracy=0.2544
Round 2: 300 labels, accuracy=0.3297
Round 3: 400 labels, accuracy=0.3342
Round 4: 500 labels, accuracy=0.3363
Round 5: 600 labels, accuracy=0.3799
Round 6: 700 labels, accuracy=0.3909
Round 7: 800 labels, accuracy=0.4127
  Early stopping at epoch 9
Round 8: 900 labels, accuracy=0.3368
Round 9: 1000 labels, accuracy=0.4272
Round 10: 1100 labels, accuracy=0.4294
Round 11: 1200 labels, accuracy=0.4376
  Early stopping at epoch 10
Round 12: 1300 labels, accuracy=0.4201
Round 13: 1400 labels, accuracy=0.4472
Round 14: 1500 labels, accuracy=0.4171
Round 15: 1600 labels, accuracy=0.4869
Round 16: 1700 labels, accuracy=0.4665
Round 17: 1800 labels, accuracy=0.4511
Round 18: 1900 labels, accuracy=0.4674
Round 19: 2000 labels, accuracy=0.5297
    Completed in 587.1s
    Progress: 6/60 (10.0%)
    Rough ETA (minutes): 415.9
  Rep 3/5, Strategy: random, eps=0.0000
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1108
Round 1: 200 labels, accuracy=0.2847
Round 2: 300 labels, accuracy=0.3578
Round 3: 400 labels, accuracy=0.3717
Round 4: 500 labels, accuracy=0.3937
Round 5: 600 labels, accuracy=0.4273
Round 6: 700 labels, accuracy=0.4316
Round 7: 800 labels, accuracy=0.4404
Round 8: 900 labels, accuracy=0.4157
Round 9: 1000 labels, accuracy=0.4638
  Early stopping at epoch 8
Round 10: 1100 labels, accuracy=0.4081
Round 11: 1200 labels, accuracy=0.4883
Round 12: 1300 labels, accuracy=0.4838
Round 13: 1400 labels, accuracy=0.4873
  Early stopping at epoch 10
Round 14: 1500 labels, accuracy=0.4733
Round 15: 1600 labels, accuracy=0.4632
Round 16: 1700 labels, accuracy=0.5079
  Early stopping at epoch 8
Round 17: 1800 labels, accuracy=0.4454
Round 18: 1900 labels, accuracy=0.5158
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Round 19: 2000 labels, accuracy=0.4931
    Completed in 217.5s
    Progress: 7/60 (11.7%)
    Rough ETA (minutes): 377.3
  Rep 3/5, Strategy: uncertainty, eps=0.0000
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1108
  Early stopping at epoch 6
Round 1: 200 labels, accuracy=0.1658
  Early stopping at epoch 6
Round 2: 300 labels, accuracy=0.1346
Round 3: 400 labels, accuracy=0.3142
Round 4: 500 labels, accuracy=0.3772
Round 5: 600 labels, accuracy=0.3569
Round 6: 700 labels, accuracy=0.3725
Round 7: 800 labels, accuracy=0.4396
Round 8: 900 labels, accuracy=0.3816
Round 9: 1000 labels, accuracy=0.4292
Round 10: 1100 labels, accuracy=0.4152
Round 11: 1200 labels, accuracy=0.4310
Round 12: 1300 labels, accuracy=0.4410
Round 13: 1400 labels, accuracy=0.4374
Round 14: 1500 labels, accuracy=0.4488
Round 15: 1600 labels, accuracy=0.4750
Round 16: 1700 labels, accuracy=0.4415
Round 17: 1800 labels, accuracy=0.4076
Round 18: 1900 labels, accuracy=0.5000
Round 19: 2000 labels, accuracy=0.5136
    Completed in 577.1s
    Progress: 8/60 (13.3%)
    Rough ETA (minutes): 386.4
  Rep 3/5, Strategy: diversity, eps=0.0000
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1108
Round 1: 200 labels, accuracy=0.3002
Round 2: 300 labels, accuracy=0.3471
Round 3: 400 labels, accuracy=0.3929
Round 4: 500 labels, accuracy=0.3800
Round 5: 600 labels, accuracy=0.3717
Round 6: 700 labels, accuracy=0.3956
Round 7: 800 labels, accuracy=0.4599
Round 8: 900 labels, accuracy=0.4142
Round 9: 1000 labels, accuracy=0.4396
Round 10: 1100 labels, accuracy=0.4382
Round 11: 1200 labels, accuracy=0.4685
Round 12: 1300 labels, accuracy=0.4873
Round 13: 1400 labels, accuracy=0.4897
Round 14: 1500 labels, accuracy=0.4787
Round 15: 1600 labels, accuracy=0.4610
Round 16: 1700 labels, accuracy=0.5163
Round 17: 1800 labels, accuracy=0.5213
Round 18: 1900 labels, accuracy=0.5356
Round 19: 2000 labels, accuracy=0.5141
    Completed in 585.0s
    Progress: 9/60 (15.0%)
    Rough ETA (minutes): 392.1
  Rep 4/5, Strategy: random, eps=0.0000
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  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1299
Round 1: 200 labels, accuracy=0.2421
Round 2: 300 labels, accuracy=0.3406
Round 3: 400 labels, accuracy=0.3387
Round 4: 500 labels, accuracy=0.3879
Round 5: 600 labels, accuracy=0.4052
Round 6: 700 labels, accuracy=0.4166
Round 7: 800 labels, accuracy=0.4136
Round 8: 900 labels, accuracy=0.3824
Round 9: 1000 labels, accuracy=0.4106
  Early stopping at epoch 9
Round 10: 1100 labels, accuracy=0.3950
Round 11: 1200 labels, accuracy=0.4516
  Early stopping at epoch 9
Round 12: 1300 labels, accuracy=0.4359
Round 13: 1400 labels, accuracy=0.4994
Round 14: 1500 labels, accuracy=0.5006
Round 15: 1600 labels, accuracy=0.5126
  Early stopping at epoch 9
Round 16: 1700 labels, accuracy=0.4688
Round 17: 1800 labels, accuracy=0.5011
Round 18: 1900 labels, accuracy=0.5166
Round 19: 2000 labels, accuracy=0.5259
    Completed in 222.1s
    Progress: 10/60 (16.7%)
    Rough ETA (minutes): 364.5
  Rep 4/5, Strategy: uncertainty, eps=0.0000
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1299
Round 1: 200 labels, accuracy=0.2698
Round 2: 300 labels, accuracy=0.3084
Round 3: 400 labels, accuracy=0.3298
Round 4: 500 labels, accuracy=0.3429
Round 5: 600 labels, accuracy=0.3892
Round 6: 700 labels, accuracy=0.3908
Round 7: 800 labels, accuracy=0.4031
Round 8: 900 labels, accuracy=0.3838
Round 9: 1000 labels, accuracy=0.3960
Round 10: 1100 labels, accuracy=0.4211
Round 11: 1200 labels, accuracy=0.4444
Round 12: 1300 labels, accuracy=0.4363
Round 13: 1400 labels, accuracy=0.4618
Round 14: 1500 labels, accuracy=0.4370
Round 15: 1600 labels, accuracy=0.4604
Round 16: 1700 labels, accuracy=0.4493
Round 17: 1800 labels, accuracy=0.3974
Round 18: 1900 labels, accuracy=0.5100
Round 19: 2000 labels, accuracy=0.4425
    Completed in 585.7s
    Progress: 11/60 (18.3%)
    Rough ETA (minutes): 368.2
  Rep 4/5, Strategy: diversity, eps=0.0000
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1299
Round 1: 200 labels, accuracy=0.2573
Round 2: 300 labels, accuracy=0.3219
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Round 3: 400 labels, accuracy=0.3744
Round 4: 500 labels, accuracy=0.3826
Round 5: 600 labels, accuracy=0.3999
Round 6: 700 labels, accuracy=0.4209
Round 7: 800 labels, accuracy=0.4061
Round 8: 900 labels, accuracy=0.3705
Round 9: 1000 labels, accuracy=0.4480
Round 10: 1100 labels, accuracy=0.3945
Round 11: 1200 labels, accuracy=0.4541
Round 12: 1300 labels, accuracy=0.4619
Round 13: 1400 labels, accuracy=0.4687
Round 14: 1500 labels, accuracy=0.4656
  Early stopping at epoch 8
Round 15: 1600 labels, accuracy=0.4115
Round 16: 1700 labels, accuracy=0.4738
Round 17: 1800 labels, accuracy=0.4650
Round 18: 1900 labels, accuracy=0.4838
Round 19: 2000 labels, accuracy=0.5008
    Completed in 581.6s
    Progress: 12/60 (20.0%)
    Rough ETA (minutes): 369.4
  Rep 5/5, Strategy: random, eps=0.0000
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1615
Round 1: 200 labels, accuracy=0.2444
Round 2: 300 labels, accuracy=0.3129
Round 3: 400 labels, accuracy=0.3485
Round 4: 500 labels, accuracy=0.3482
Round 5: 600 labels, accuracy=0.3958
Round 6: 700 labels, accuracy=0.4188
Round 7: 800 labels, accuracy=0.4147
Round 8: 900 labels, accuracy=0.4182
Round 9: 1000 labels, accuracy=0.4214
Round 10: 1100 labels, accuracy=0.4458
Round 11: 1200 labels, accuracy=0.4631
Round 12: 1300 labels, accuracy=0.4686
Round 13: 1400 labels, accuracy=0.4519
Round 14: 1500 labels, accuracy=0.4417
Round 15: 1600 labels, accuracy=0.4850
Round 16: 1700 labels, accuracy=0.5083
Round 17: 1800 labels, accuracy=0.4741
Round 18: 1900 labels, accuracy=0.5208
Round 19: 2000 labels, accuracy=0.5184
    Completed in 225.2s
    Progress: 13/60 (21.7%)
    Rough ETA (minutes): 347.5
  Rep 5/5, Strategy: uncertainty, eps=0.0000
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1615
  Early stopping at epoch 6
Round 1: 200 labels, accuracy=0.1633
Round 2: 300 labels, accuracy=0.3030
Round 3: 400 labels, accuracy=0.3271
Round 4: 500 labels, accuracy=0.3473
Round 5: 600 labels, accuracy=0.3696
Round 6: 700 labels, accuracy=0.4141
Round 7: 800 labels, accuracy=0.3999
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Round 8: 900 labels, accuracy=0.3799
Round 9: 1000 labels, accuracy=0.4221
Round 10: 1100 labels, accuracy=0.3962
Round 11: 1200 labels, accuracy=0.4382
Round 12: 1300 labels, accuracy=0.4114
Round 13: 1400 labels, accuracy=0.4290
Round 14: 1500 labels, accuracy=0.4799
Round 15: 1600 labels, accuracy=0.4602
Round 16: 1700 labels, accuracy=0.5042
Round 17: 1800 labels, accuracy=0.4635
Round 18: 1900 labels, accuracy=0.4310
Round 19: 2000 labels, accuracy=0.4924
    Completed in 581.8s
    Progress: 14/60 (23.3%)
    Rough ETA (minutes): 347.7
  Rep 5/5, Strategy: diversity, eps=0.0000
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1615
Round 1: 200 labels, accuracy=0.2644
Round 2: 300 labels, accuracy=0.3162
Round 3: 400 labels, accuracy=0.3601
  Early stopping at epoch 10
Round 4: 500 labels, accuracy=0.3785
Round 5: 600 labels, accuracy=0.3848
Round 6: 700 labels, accuracy=0.4392
Round 7: 800 labels, accuracy=0.4066
Round 8: 900 labels, accuracy=0.4048
Round 9: 1000 labels, accuracy=0.4430
Round 10: 1100 labels, accuracy=0.4629
Round 11: 1200 labels, accuracy=0.4761
Round 12: 1300 labels, accuracy=0.4578
Round 13: 1400 labels, accuracy=0.4698
Round 14: 1500 labels, accuracy=0.4870
Round 15: 1600 labels, accuracy=0.5164
Round 16: 1700 labels, accuracy=0.5162
Round 17: 1800 labels, accuracy=0.5059
Round 18: 1900 labels, accuracy=0.5077
Round 19: 2000 labels, accuracy=0.5011
    Completed in 582.3s
    Progress: 15/60 (25.0%)
    Rough ETA (minutes): 346.5
✓ Saved: /content/drive/MyDrive/AL_Results/al_results_e0.pkl
============================================================
Running epsilon = 0.05
============================================================
  Rep 1/5, Strategy: random, eps=0.0500
  Early stopping at epoch 7
Round 0: 100 labels, accuracy=0.1477
Round 1: 200 labels, accuracy=0.1930
Round 2: 300 labels, accuracy=0.2734
Round 3: 400 labels, accuracy=0.3213
Round 4: 500 labels, accuracy=0.3683
Round 5: 600 labels, accuracy=0.3754
Round 6: 700 labels, accuracy=0.3858
Round 7: 800 labels, accuracy=0.4278
Round 8: 900 labels, accuracy=0.3734
Round 9: 1000 labels, accuracy=0.4562
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Round 10: 1100 labels, accuracy=0.4070
Round 11: 1200 labels, accuracy=0.4131
Round 12: 1300 labels, accuracy=0.4691
Round 13: 1400 labels, accuracy=0.4641
Round 14: 1500 labels, accuracy=0.4474
Round 15: 1600 labels, accuracy=0.5008
Round 16: 1700 labels, accuracy=0.4859
Round 17: 1800 labels, accuracy=0.4771
Round 18: 1900 labels, accuracy=0.5041
Round 19: 2000 labels, accuracy=0.4597
    Completed in 227.9s
    Progress: 16/60 (26.7%)
    Rough ETA (minutes): 328.1
  Rep 1/5, Strategy: uncertainty, eps=0.0500
  Early stopping at epoch 7
Round 0: 100 labels, accuracy=0.1477
  Early stopping at epoch 7
Round 1: 200 labels, accuracy=0.1396
Round 2: 300 labels, accuracy=0.2532
Round 3: 400 labels, accuracy=0.2607
Round 4: 500 labels, accuracy=0.2751
Round 5: 600 labels, accuracy=0.3043
Round 6: 700 labels, accuracy=0.3544
Round 7: 800 labels, accuracy=0.3921
Round 8: 900 labels, accuracy=0.3938
Round 9: 1000 labels, accuracy=0.4391
Round 10: 1100 labels, accuracy=0.4505
Round 11: 1200 labels, accuracy=0.4174
Round 12: 1300 labels, accuracy=0.4031
Round 13: 1400 labels, accuracy=0.3458
Round 14: 1500 labels, accuracy=0.4270
Round 15: 1600 labels, accuracy=0.4198
Round 16: 1700 labels, accuracy=0.4758
Round 17: 1800 labels, accuracy=0.4620
Round 18: 1900 labels, accuracy=0.4768
Round 19: 2000 labels, accuracy=0.4454
    Completed in 583.4s
    Progress: 17/60 (28.3%)
    Rough ETA (minutes): 326.4
  Rep 1/5, Strategy: diversity, eps=0.0500
  Early stopping at epoch 7
Round 0: 100 labels, accuracy=0.1477
  Early stopping at epoch 6
Round 1: 200 labels, accuracy=0.1856
Round 2: 300 labels, accuracy=0.2455
Round 3: 400 labels, accuracy=0.3141
Round 4: 500 labels, accuracy=0.3909
Round 5: 600 labels, accuracy=0.3909
Round 6: 700 labels, accuracy=0.4100
  Early stopping at epoch 8
Round 7: 800 labels, accuracy=0.3304
Round 8: 900 labels, accuracy=0.3914
Round 9: 1000 labels, accuracy=0.4439
Round 10: 1100 labels, accuracy=0.4582
Round 11: 1200 labels, accuracy=0.4143
Round 12: 1300 labels, accuracy=0.4417
Round 13: 1400 labels, accuracy=0.4392
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Round 14: 1500 labels, accuracy=0.4667
Round 15: 1600 labels, accuracy=0.4558
Round 16: 1700 labels, accuracy=0.4771
  Early stopping at epoch 10
Round 17: 1800 labels, accuracy=0.4635
Round 18: 1900 labels, accuracy=0.4698
Round 19: 2000 labels, accuracy=0.4935
    Completed in 578.7s
    Progress: 18/60 (30.0%)
    Rough ETA (minutes): 323.6
  Rep 2/5, Strategy: random, eps=0.0500
  Early stopping at epoch 10
Round 0: 100 labels, accuracy=0.1878
Round 1: 200 labels, accuracy=0.2326
Round 2: 300 labels, accuracy=0.2736
Round 3: 400 labels, accuracy=0.3620
Round 4: 500 labels, accuracy=0.3475
Round 5: 600 labels, accuracy=0.3978
Round 6: 700 labels, accuracy=0.4122
Round 7: 800 labels, accuracy=0.3920
Round 8: 900 labels, accuracy=0.3909
Round 9: 1000 labels, accuracy=0.4264
Round 10: 1100 labels, accuracy=0.4387
Round 11: 1200 labels, accuracy=0.4338
Round 12: 1300 labels, accuracy=0.4159
Round 13: 1400 labels, accuracy=0.4323
Round 14: 1500 labels, accuracy=0.4541
Round 15: 1600 labels, accuracy=0.4722
Round 16: 1700 labels, accuracy=0.4484
  Early stopping at epoch 9
Round 17: 1800 labels, accuracy=0.4462
Round 18: 1900 labels, accuracy=0.4932
Round 19: 2000 labels, accuracy=0.4995
    Completed in 220.4s
    Progress: 19/60 (31.7%)
    Rough ETA (minutes): 307.2
  Rep 2/5, Strategy: uncertainty, eps=0.0500
  Early stopping at epoch 10
Round 0: 100 labels, accuracy=0.1878
  Early stopping at epoch 7
Round 1: 200 labels, accuracy=0.2147
Round 2: 300 labels, accuracy=0.2766
Round 3: 400 labels, accuracy=0.3525
Round 4: 500 labels, accuracy=0.3771
Round 5: 600 labels, accuracy=0.3601
Round 6: 700 labels, accuracy=0.3610
Round 7: 800 labels, accuracy=0.3960
Round 8: 900 labels, accuracy=0.3751
Round 9: 1000 labels, accuracy=0.4037
Round 10: 1100 labels, accuracy=0.3909
Round 11: 1200 labels, accuracy=0.4064
Round 12: 1300 labels, accuracy=0.4402
Round 13: 1400 labels, accuracy=0.4556
Round 14: 1500 labels, accuracy=0.4572
Round 15: 1600 labels, accuracy=0.4310
Round 16: 1700 labels, accuracy=0.4239
Round 17: 1800 labels, accuracy=0.4220
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Round 18: 1900 labels, accuracy=0.4813
Round 19: 2000 labels, accuracy=0.4789
    Completed in 577.9s
    Progress: 20/60 (33.3%)
    Rough ETA (minutes): 304.0
  Rep 2/5, Strategy: diversity, eps=0.0500
  Early stopping at epoch 10
Round 0: 100 labels, accuracy=0.1878
Round 1: 200 labels, accuracy=0.2994
Round 2: 300 labels, accuracy=0.2848
Round 3: 400 labels, accuracy=0.3550
Round 4: 500 labels, accuracy=0.3823
Round 5: 600 labels, accuracy=0.3980
Round 6: 700 labels, accuracy=0.3818
  Early stopping at epoch 10
Round 7: 800 labels, accuracy=0.4082
Round 8: 900 labels, accuracy=0.3777
Round 9: 1000 labels, accuracy=0.4434
Round 10: 1100 labels, accuracy=0.4447
Round 11: 1200 labels, accuracy=0.4264
Round 12: 1300 labels, accuracy=0.4535
Round 13: 1400 labels, accuracy=0.4516
Round 14: 1500 labels, accuracy=0.4444
Round 15: 1600 labels, accuracy=0.4702
Round 16: 1700 labels, accuracy=0.4454
Round 17: 1800 labels, accuracy=0.4660
Round 18: 1900 labels, accuracy=0.4698
Round 19: 2000 labels, accuracy=0.4950
    Completed in 591.1s
    Progress: 21/60 (35.0%)
    Rough ETA (minutes): 300.6
  Rep 3/5, Strategy: random, eps=0.0500
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1108
Round 1: 200 labels, accuracy=0.2765
Round 2: 300 labels, accuracy=0.3702
Round 3: 400 labels, accuracy=0.3800
Round 4: 500 labels, accuracy=0.3756
Round 5: 600 labels, accuracy=0.4086
Round 6: 700 labels, accuracy=0.4351
Round 7: 800 labels, accuracy=0.3969
  Early stopping at epoch 7
Round 8: 900 labels, accuracy=0.3648
Round 9: 1000 labels, accuracy=0.3963
Round 10: 1100 labels, accuracy=0.4054
Round 11: 1200 labels, accuracy=0.4798
Round 12: 1300 labels, accuracy=0.4691
Round 13: 1400 labels, accuracy=0.4992
Round 14: 1500 labels, accuracy=0.5024
Round 15: 1600 labels, accuracy=0.5016
Round 16: 1700 labels, accuracy=0.4804
Round 17: 1800 labels, accuracy=0.4871
Round 18: 1900 labels, accuracy=0.5193
Round 19: 2000 labels, accuracy=0.5039
    Completed in 220.7s
    Progress: 22/60 (36.7%)
    Rough ETA (minutes): 285.9
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  Rep 3/5, Strategy: uncertainty, eps=0.0500
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1108
Round 1: 200 labels, accuracy=0.2126
Round 2: 300 labels, accuracy=0.2626
Round 3: 400 labels, accuracy=0.3043
Round 4: 500 labels, accuracy=0.3430
Round 5: 600 labels, accuracy=0.3468
Round 6: 700 labels, accuracy=0.3937
Round 7: 800 labels, accuracy=0.3877
Round 8: 900 labels, accuracy=0.3984
Round 9: 1000 labels, accuracy=0.4420
Round 10: 1100 labels, accuracy=0.4126
Round 11: 1200 labels, accuracy=0.4174
Round 12: 1300 labels, accuracy=0.4401
  Early stopping at epoch 10
Round 13: 1400 labels, accuracy=0.4167
Round 14: 1500 labels, accuracy=0.4617
Round 15: 1600 labels, accuracy=0.4638
Round 16: 1700 labels, accuracy=0.4667
Round 17: 1800 labels, accuracy=0.4417
Round 18: 1900 labels, accuracy=0.4985
Round 19: 2000 labels, accuracy=0.5115
    Completed in 581.9s
    Progress: 23/60 (38.3%)
    Rough ETA (minutes): 281.9
  Rep 3/5, Strategy: diversity, eps=0.0500
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1108
Round 1: 200 labels, accuracy=0.2433
Round 2: 300 labels, accuracy=0.2955
Round 3: 400 labels, accuracy=0.3148
Round 4: 500 labels, accuracy=0.3965
Round 5: 600 labels, accuracy=0.4048
Round 6: 700 labels, accuracy=0.4106
Round 7: 800 labels, accuracy=0.4121
Round 8: 900 labels, accuracy=0.4139
Round 9: 1000 labels, accuracy=0.4207
  Early stopping at epoch 9
Round 10: 1100 labels, accuracy=0.4191
  Early stopping at epoch 9
Round 11: 1200 labels, accuracy=0.4119
Round 12: 1300 labels, accuracy=0.4450
Round 13: 1400 labels, accuracy=0.4473
Round 14: 1500 labels, accuracy=0.4877
  Early stopping at epoch 10
Round 15: 1600 labels, accuracy=0.4576
Round 16: 1700 labels, accuracy=0.4846
Round 17: 1800 labels, accuracy=0.4847
Round 18: 1900 labels, accuracy=0.4753
Round 19: 2000 labels, accuracy=0.4393
    Completed in 585.1s
    Progress: 24/60 (40.0%)
    Rough ETA (minutes): 277.4
  Rep 4/5, Strategy: random, eps=0.0500
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1299
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Round 1: 200 labels, accuracy=0.2297
Round 2: 300 labels, accuracy=0.2722
Round 3: 400 labels, accuracy=0.3361
Round 4: 500 labels, accuracy=0.3861
Round 5: 600 labels, accuracy=0.3792
Round 6: 700 labels, accuracy=0.4066
Round 7: 800 labels, accuracy=0.4187
Round 8: 900 labels, accuracy=0.3636
Round 9: 1000 labels, accuracy=0.4190
Round 10: 1100 labels, accuracy=0.4406
Round 11: 1200 labels, accuracy=0.4655
Round 12: 1300 labels, accuracy=0.4500
Round 13: 1400 labels, accuracy=0.4648
Round 14: 1500 labels, accuracy=0.4577
Round 15: 1600 labels, accuracy=0.4787
Round 16: 1700 labels, accuracy=0.4910
Round 17: 1800 labels, accuracy=0.4869
Round 18: 1900 labels, accuracy=0.4883
Round 19: 2000 labels, accuracy=0.4854
    Completed in 225.7s
    Progress: 25/60 (41.7%)
    Rough ETA (minutes): 264.2
  Rep 4/5, Strategy: uncertainty, eps=0.0500
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1299
Round 1: 200 labels, accuracy=0.2464
  Early stopping at epoch 10
Round 2: 300 labels, accuracy=0.3076
Round 3: 400 labels, accuracy=0.3262
Round 4: 500 labels, accuracy=0.3674
Round 5: 600 labels, accuracy=0.3450
Round 6: 700 labels, accuracy=0.3956
Round 7: 800 labels, accuracy=0.3436
Round 8: 900 labels, accuracy=0.3668
Round 9: 1000 labels, accuracy=0.3954
Round 10: 1100 labels, accuracy=0.3578
Round 11: 1200 labels, accuracy=0.4326
Round 12: 1300 labels, accuracy=0.3849
Round 13: 1400 labels, accuracy=0.4500
Round 14: 1500 labels, accuracy=0.4476
Round 15: 1600 labels, accuracy=0.4983
Round 16: 1700 labels, accuracy=0.4626
Round 17: 1800 labels, accuracy=0.4849
Round 18: 1900 labels, accuracy=0.4914
Round 19: 2000 labels, accuracy=0.4405
    Completed in 582.8s
    Progress: 26/60 (43.3%)
    Rough ETA (minutes): 259.5
  Rep 4/5, Strategy: diversity, eps=0.0500
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1299
Round 1: 200 labels, accuracy=0.2400
  Early stopping at epoch 8
Round 2: 300 labels, accuracy=0.2327
Round 3: 400 labels, accuracy=0.3051
Round 4: 500 labels, accuracy=0.3826
Round 5: 600 labels, accuracy=0.4146
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Round 6: 700 labels, accuracy=0.4171
Round 7: 800 labels, accuracy=0.4025
Round 8: 900 labels, accuracy=0.3868
Round 9: 1000 labels, accuracy=0.4259
Round 10: 1100 labels, accuracy=0.4269
Round 11: 1200 labels, accuracy=0.4478
Round 12: 1300 labels, accuracy=0.4017
Round 13: 1400 labels, accuracy=0.4720
Round 14: 1500 labels, accuracy=0.4687
Round 15: 1600 labels, accuracy=0.4774
  Early stopping at epoch 8
Round 16: 1700 labels, accuracy=0.4393
Round 17: 1800 labels, accuracy=0.4755
Round 18: 1900 labels, accuracy=0.4846
Round 19: 2000 labels, accuracy=0.4859
    Completed in 582.5s
    Progress: 27/60 (45.0%)
    Rough ETA (minutes): 254.4
  Rep 5/5, Strategy: random, eps=0.0500
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1615
Round 1: 200 labels, accuracy=0.2329
Round 2: 300 labels, accuracy=0.3507
Round 3: 400 labels, accuracy=0.3465
Round 4: 500 labels, accuracy=0.3259
Round 5: 600 labels, accuracy=0.3688
Round 6: 700 labels, accuracy=0.4272
Round 7: 800 labels, accuracy=0.4257
Round 8: 900 labels, accuracy=0.3969
Round 9: 1000 labels, accuracy=0.4577
Round 10: 1100 labels, accuracy=0.4511
Round 11: 1200 labels, accuracy=0.4281
Round 12: 1300 labels, accuracy=0.4632
Round 13: 1400 labels, accuracy=0.4772
Round 14: 1500 labels, accuracy=0.5030
Round 15: 1600 labels, accuracy=0.4974
Round 16: 1700 labels, accuracy=0.4977
Round 17: 1800 labels, accuracy=0.5022
Round 18: 1900 labels, accuracy=0.5232
Round 19: 2000 labels, accuracy=0.4892
    Completed in 225.9s
    Progress: 28/60 (46.7%)
    Rough ETA (minutes): 242.2
  Rep 5/5, Strategy: uncertainty, eps=0.0500
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1615
Round 1: 200 labels, accuracy=0.2414
Round 2: 300 labels, accuracy=0.2933
Round 3: 400 labels, accuracy=0.3336
Round 4: 500 labels, accuracy=0.3876
Round 5: 600 labels, accuracy=0.3322
Round 6: 700 labels, accuracy=0.3824
Round 7: 800 labels, accuracy=0.3721
Round 8: 900 labels, accuracy=0.3676
Round 9: 1000 labels, accuracy=0.4272
Round 10: 1100 labels, accuracy=0.4087
Round 11: 1200 labels, accuracy=0.3962
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Round 12: 1300 labels, accuracy=0.4280
Round 13: 1400 labels, accuracy=0.3977
Round 14: 1500 labels, accuracy=0.4390
Round 15: 1600 labels, accuracy=0.4168
Round 16: 1700 labels, accuracy=0.4507
Round 17: 1800 labels, accuracy=0.4510
Round 18: 1900 labels, accuracy=0.4716
  Early stopping at epoch 9
Round 19: 2000 labels, accuracy=0.4667
    Completed in 584.0s
    Progress: 29/60 (48.3%)
    Rough ETA (minutes): 236.9
  Rep 5/5, Strategy: diversity, eps=0.0500
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1615
Round 1: 200 labels, accuracy=0.2580
Round 2: 300 labels, accuracy=0.3131
Round 3: 400 labels, accuracy=0.3511
Round 4: 500 labels, accuracy=0.4121
Round 5: 600 labels, accuracy=0.4009
  Early stopping at epoch 10
Round 6: 700 labels, accuracy=0.3764
Round 7: 800 labels, accuracy=0.4121
Round 8: 900 labels, accuracy=0.4115
Round 9: 1000 labels, accuracy=0.4359
Round 10: 1100 labels, accuracy=0.4639
Round 11: 1200 labels, accuracy=0.4569
Round 12: 1300 labels, accuracy=0.4010
Round 13: 1400 labels, accuracy=0.4574
Round 14: 1500 labels, accuracy=0.4713
Round 15: 1600 labels, accuracy=0.4783
Round 16: 1700 labels, accuracy=0.4725
Round 17: 1800 labels, accuracy=0.4996
Round 18: 1900 labels, accuracy=0.4652
Round 19: 2000 labels, accuracy=0.4773
    Completed in 584.2s
    Progress: 30/60 (50.0%)
    Rough ETA (minutes): 231.4
✓ Saved: /content/drive/MyDrive/AL_Results/al_results_e5.pkl
============================================================
Running epsilon = 0.1
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  Rep 1/5, Strategy: random, eps=0.1000
  Early stopping at epoch 7
Round 0: 100 labels, accuracy=0.1477
Round 1: 200 labels, accuracy=0.2280
Round 2: 300 labels, accuracy=0.2869
Round 3: 400 labels, accuracy=0.3406
Round 4: 500 labels, accuracy=0.3814
Round 5: 600 labels, accuracy=0.3692
Round 6: 700 labels, accuracy=0.4128
Round 7: 800 labels, accuracy=0.3615
Round 8: 900 labels, accuracy=0.3447
Round 9: 1000 labels, accuracy=0.4172
Round 10: 1100 labels, accuracy=0.4253
Round 11: 1200 labels, accuracy=0.4520
Round 12: 1300 labels, accuracy=0.4571
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Round 13: 1400 labels, accuracy=0.4649
Round 14: 1500 labels, accuracy=0.4485
Round 15: 1600 labels, accuracy=0.4762
Round 16: 1700 labels, accuracy=0.4518
Round 17: 1800 labels, accuracy=0.4997
Round 18: 1900 labels, accuracy=0.4558
Round 19: 2000 labels, accuracy=0.5006
    Completed in 222.4s
    Progress: 31/60 (51.7%)
    Rough ETA (minutes): 219.9
  Rep 1/5, Strategy: uncertainty, eps=0.1000
  Early stopping at epoch 7
Round 0: 100 labels, accuracy=0.1477
Round 1: 200 labels, accuracy=0.1777
Round 2: 300 labels, accuracy=0.2351
Round 3: 400 labels, accuracy=0.2971
Round 4: 500 labels, accuracy=0.3005
Round 5: 600 labels, accuracy=0.3287
  Early stopping at epoch 10
Round 6: 700 labels, accuracy=0.3246
Round 7: 800 labels, accuracy=0.3942
Round 8: 900 labels, accuracy=0.3751
Round 9: 1000 labels, accuracy=0.4458
Round 10: 1100 labels, accuracy=0.3962
Round 11: 1200 labels, accuracy=0.4191
Round 12: 1300 labels, accuracy=0.3715
Round 13: 1400 labels, accuracy=0.4671
Round 14: 1500 labels, accuracy=0.4545
Round 15: 1600 labels, accuracy=0.4786
Round 16: 1700 labels, accuracy=0.4411
Round 17: 1800 labels, accuracy=0.4525
Round 18: 1900 labels, accuracy=0.4184
Round 19: 2000 labels, accuracy=0.4930
    Completed in 577.7s
    Progress: 32/60 (53.3%)
    Rough ETA (minutes): 214.1
  Rep 1/5, Strategy: diversity, eps=0.1000
  Early stopping at epoch 7
Round 0: 100 labels, accuracy=0.1477
Round 1: 200 labels, accuracy=0.2085
Round 2: 300 labels, accuracy=0.3034
Round 3: 400 labels, accuracy=0.3524
Round 4: 500 labels, accuracy=0.3599
Round 5: 600 labels, accuracy=0.3752
Round 6: 700 labels, accuracy=0.3778
Round 7: 800 labels, accuracy=0.3743
Round 8: 900 labels, accuracy=0.3609
Round 9: 1000 labels, accuracy=0.3970
Round 10: 1100 labels, accuracy=0.4208
  Early stopping at epoch 9
Round 11: 1200 labels, accuracy=0.3778
Round 12: 1300 labels, accuracy=0.4520
Round 13: 1400 labels, accuracy=0.4241
Round 14: 1500 labels, accuracy=0.4459
Round 15: 1600 labels, accuracy=0.4327
Round 16: 1700 labels, accuracy=0.4438
Round 17: 1800 labels, accuracy=0.4541
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Round 18: 1900 labels, accuracy=0.4437
Round 19: 2000 labels, accuracy=0.4616
    Completed in 582.3s
    Progress: 33/60 (55.0%)
    Rough ETA (minutes): 208.2
  Rep 2/5, Strategy: random, eps=0.1000
  Early stopping at epoch 10
Round 0: 100 labels, accuracy=0.1878
Round 1: 200 labels, accuracy=0.2582
Round 2: 300 labels, accuracy=0.2249
Round 3: 400 labels, accuracy=0.3490
Round 4: 500 labels, accuracy=0.3885
  Early stopping at epoch 10
Round 5: 600 labels, accuracy=0.3731
Round 6: 700 labels, accuracy=0.3775
  Early stopping at epoch 10
Round 7: 800 labels, accuracy=0.3838
Round 8: 900 labels, accuracy=0.3621
Round 9: 1000 labels, accuracy=0.4301
Round 10: 1100 labels, accuracy=0.4092
Round 11: 1200 labels, accuracy=0.4445
Round 12: 1300 labels, accuracy=0.4079
Round 13: 1400 labels, accuracy=0.4589
Round 14: 1500 labels, accuracy=0.4473
Round 15: 1600 labels, accuracy=0.4643
Round 16: 1700 labels, accuracy=0.4643
Round 17: 1800 labels, accuracy=0.4410
Round 18: 1900 labels, accuracy=0.4648
Round 19: 2000 labels, accuracy=0.4508
    Completed in 221.5s
    Progress: 34/60 (56.7%)
    Rough ETA (minutes): 197.4
  Rep 2/5, Strategy: uncertainty, eps=0.1000
  Early stopping at epoch 10
Round 0: 100 labels, accuracy=0.1878
  Early stopping at epoch 7
Round 1: 200 labels, accuracy=0.2467
Round 2: 300 labels, accuracy=0.2447
Round 3: 400 labels, accuracy=0.3049
Round 4: 500 labels, accuracy=0.3719
  Early stopping at epoch 9
Round 5: 600 labels, accuracy=0.3006
Round 6: 700 labels, accuracy=0.3819
  Early stopping at epoch 7
Round 7: 800 labels, accuracy=0.3634
Round 8: 900 labels, accuracy=0.3529
Round 9: 1000 labels, accuracy=0.4151
Round 10: 1100 labels, accuracy=0.4041
Round 11: 1200 labels, accuracy=0.4204
Round 12: 1300 labels, accuracy=0.4073
Round 13: 1400 labels, accuracy=0.3967
Round 14: 1500 labels, accuracy=0.4229
  Early stopping at epoch 10
Round 15: 1600 labels, accuracy=0.4245
  Early stopping at epoch 9
Round 16: 1700 labels, accuracy=0.4182
Round 17: 1800 labels, accuracy=0.4170
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Round 18: 1900 labels, accuracy=0.4568
Round 19: 2000 labels, accuracy=0.4752
    Completed in 571.6s
    Progress: 35/60 (58.3%)
    Rough ETA (minutes): 191.2
  Rep 2/5, Strategy: diversity, eps=0.1000
  Early stopping at epoch 10
Round 0: 100 labels, accuracy=0.1878
  Early stopping at epoch 6
Round 1: 200 labels, accuracy=0.2120
Round 2: 300 labels, accuracy=0.2938
Round 3: 400 labels, accuracy=0.3574
Round 4: 500 labels, accuracy=0.3853
Round 5: 600 labels, accuracy=0.3874
  Early stopping at epoch 10
Round 6: 700 labels, accuracy=0.4129
Round 7: 800 labels, accuracy=0.4138
Round 8: 900 labels, accuracy=0.4113
Round 9: 1000 labels, accuracy=0.4389
  Early stopping at epoch 8
Round 10: 1100 labels, accuracy=0.3859
Round 11: 1200 labels, accuracy=0.4375
Round 12: 1300 labels, accuracy=0.4420
  Early stopping at epoch 10
Round 13: 1400 labels, accuracy=0.4196
Round 14: 1500 labels, accuracy=0.4112
Round 15: 1600 labels, accuracy=0.4147
Round 16: 1700 labels, accuracy=0.4560
Round 17: 1800 labels, accuracy=0.4363
Round 18: 1900 labels, accuracy=0.4612
Round 19: 2000 labels, accuracy=0.4855
    Completed in 590.2s
    Progress: 36/60 (60.0%)
    Rough ETA (minutes): 185.0
  Rep 3/5, Strategy: random, eps=0.1000
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1108
Round 1: 200 labels, accuracy=0.2569
Round 2: 300 labels, accuracy=0.3015
Round 3: 400 labels, accuracy=0.3880
Round 4: 500 labels, accuracy=0.3926
Round 5: 600 labels, accuracy=0.4324
Round 6: 700 labels, accuracy=0.4274
Round 7: 800 labels, accuracy=0.4024
Round 8: 900 labels, accuracy=0.4187
Round 9: 1000 labels, accuracy=0.4560
Round 10: 1100 labels, accuracy=0.4636
Round 11: 1200 labels, accuracy=0.4244
Round 12: 1300 labels, accuracy=0.4060
Round 13: 1400 labels, accuracy=0.4594
Round 14: 1500 labels, accuracy=0.4695
Round 15: 1600 labels, accuracy=0.4519
Round 16: 1700 labels, accuracy=0.4504
Round 17: 1800 labels, accuracy=0.4732
Round 18: 1900 labels, accuracy=0.4833
Round 19: 2000 labels, accuracy=0.4684
    Completed in 224.9s
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        Progress: 37/60 (61.7%)
        Rough ETA (minutes): 174.8
      Rep 3/5, Strategy: uncertainty, eps=0.1000
      Early stopping at epoch 6
    Round 0: 100 labels, accuracy=0.1108
    Round 1: 200 labels, accuracy=0.2270
    Round 2: 300 labels, accuracy=0.2764
    Round 3: 400 labels, accuracy=0.3008
    Round 4: 500 labels, accuracy=0.3412
    Round 5: 600 labels, accuracy=0.3862
    Round 6: 700 labels, accuracy=0.3648
    Round 7: 800 labels, accuracy=0.3764
      Early stopping at epoch 10
    Round 8: 900 labels, accuracy=0.3627
    Round 9: 1000 labels, accuracy=0.3969
    Round 10: 1100 labels, accuracy=0.3798
    Round 11: 1200 labels, accuracy=0.4601
    Round 12: 1300 labels, accuracy=0.4519
    Round 13: 1400 labels, accuracy=0.3935
    Round 14: 1500 labels, accuracy=0.4538
    Round 15: 1600 labels, accuracy=0.4895
    Round 16: 1700 labels, accuracy=0.4654
      Early stopping at epoch 10
    Round 17: 1800 labels, accuracy=0.4824
    Round 18: 1900 labels, accuracy=0.4665
    Round 19: 2000 labels, accuracy=0.4624
        Completed in 582.0s
        Progress: 38/60 (63.3%)
        Rough ETA (minutes): 168.4
      Rep 3/5, Strategy: diversity, eps=0.1000
      Early stopping at epoch 6
    Round 0: 100 labels, accuracy=0.1108
    Round 1: 200 labels, accuracy=0.2408
    Round 2: 300 labels, accuracy=0.2835
    Round 3: 400 labels, accuracy=0.3646
    Round 4: 500 labels, accuracy=0.4053
    Round 5: 600 labels, accuracy=0.3799
    Round 6: 700 labels, accuracy=0.4265
    Round 7: 800 labels, accuracy=0.4214
    Round 8: 900 labels, accuracy=0.4163
    Round 9: 1000 labels, accuracy=0.4301
    Round 10: 1100 labels, accuracy=0.4613
    Round 11: 1200 labels, accuracy=0.4586
    Round 12: 1300 labels, accuracy=0.4249
    Round 13: 1400 labels, accuracy=0.4445
    Round 14: 1500 labels, accuracy=0.4345
    Round 15: 1600 labels, accuracy=0.4655
    Round 16: 1700 labels, accuracy=0.4679
    Round 17: 1800 labels, accuracy=0.4783
    Round 18: 1900 labels, accuracy=0.4332
    Round 19: 2000 labels, accuracy=0.4771
        Completed in 584.6s
        Progress: 39/60 (65.0%)
        Rough ETA (minutes): 161.9
      Rep 4/5, Strategy: random, eps=0.1000
      Early stopping at epoch 6
    Round 0: 100 labels, accuracy=0.1299
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Round 1: 200 labels, accuracy=0.2363
  Early stopping at epoch 6
Round 2: 300 labels, accuracy=0.1928
Round 3: 400 labels, accuracy=0.3576
Round 4: 500 labels, accuracy=0.3815
Round 5: 600 labels, accuracy=0.3968
Round 6: 700 labels, accuracy=0.4237
Round 7: 800 labels, accuracy=0.4332
Round 8: 900 labels, accuracy=0.3999
Round 9: 1000 labels, accuracy=0.4232
Round 10: 1100 labels, accuracy=0.4431
Round 11: 1200 labels, accuracy=0.4295
Round 12: 1300 labels, accuracy=0.4533
Round 13: 1400 labels, accuracy=0.4686
Round 14: 1500 labels, accuracy=0.4840
Round 15: 1600 labels, accuracy=0.5055
Round 16: 1700 labels, accuracy=0.4771
Round 17: 1800 labels, accuracy=0.5083
Round 18: 1900 labels, accuracy=0.4948
Round 19: 2000 labels, accuracy=0.4830
    Completed in 221.3s
    Progress: 40/60 (66.7%)
    Rough ETA (minutes): 152.2
  Rep 4/5, Strategy: uncertainty, eps=0.1000
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1299
Round 1: 200 labels, accuracy=0.2632
  Early stopping at epoch 6
Round 2: 300 labels, accuracy=0.2094
Round 3: 400 labels, accuracy=0.3384
Round 4: 500 labels, accuracy=0.3894
Round 5: 600 labels, accuracy=0.3633
Round 6: 700 labels, accuracy=0.3688
Round 7: 800 labels, accuracy=0.3922
Round 8: 900 labels, accuracy=0.3437
Round 9: 1000 labels, accuracy=0.4150
Round 10: 1100 labels, accuracy=0.3579
Round 11: 1200 labels, accuracy=0.4311
Round 12: 1300 labels, accuracy=0.4409
Round 13: 1400 labels, accuracy=0.4209
Round 14: 1500 labels, accuracy=0.4310
Round 15: 1600 labels, accuracy=0.4240
Round 16: 1700 labels, accuracy=0.4768
Round 17: 1800 labels, accuracy=0.4417
  Early stopping at epoch 10
Round 18: 1900 labels, accuracy=0.4286
Round 19: 2000 labels, accuracy=0.4580
    Completed in 574.9s
    Progress: 41/60 (68.3%)
    Rough ETA (minutes): 145.5
  Rep 4/5, Strategy: diversity, eps=0.1000
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1299
Round 1: 200 labels, accuracy=0.2138
Round 2: 300 labels, accuracy=0.2959
Round 3: 400 labels, accuracy=0.3714
Round 4: 500 labels, accuracy=0.3758
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Round 5: 600 labels, accuracy=0.3622
Round 6: 700 labels, accuracy=0.3855
Round 7: 800 labels, accuracy=0.4026
Round 8: 900 labels, accuracy=0.3710
Round 9: 1000 labels, accuracy=0.4197
Round 10: 1100 labels, accuracy=0.4405
Round 11: 1200 labels, accuracy=0.3960
Round 12: 1300 labels, accuracy=0.4408
Round 13: 1400 labels, accuracy=0.4383
Round 14: 1500 labels, accuracy=0.4513
Round 15: 1600 labels, accuracy=0.4714
Round 16: 1700 labels, accuracy=0.4808
Round 17: 1800 labels, accuracy=0.4911
  Early stopping at epoch 10
Round 18: 1900 labels, accuracy=0.4777
Round 19: 2000 labels, accuracy=0.4716
    Completed in 586.3s
    Progress: 42/60 (70.0%)
    Rough ETA (minutes): 138.7
  Rep 5/5, Strategy: random, eps=0.1000
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1615
Round 1: 200 labels, accuracy=0.2216
Round 2: 300 labels, accuracy=0.3310
  Early stopping at epoch 10
Round 3: 400 labels, accuracy=0.3058
Round 4: 500 labels, accuracy=0.3302
Round 5: 600 labels, accuracy=0.3883
Round 6: 700 labels, accuracy=0.3833
Round 7: 800 labels, accuracy=0.3873
Round 8: 900 labels, accuracy=0.3937
Round 9: 1000 labels, accuracy=0.4411
Round 10: 1100 labels, accuracy=0.4519
Round 11: 1200 labels, accuracy=0.4413
Round 12: 1300 labels, accuracy=0.4260
Round 13: 1400 labels, accuracy=0.4427
Round 14: 1500 labels, accuracy=0.4874
Round 15: 1600 labels, accuracy=0.4563
Round 16: 1700 labels, accuracy=0.4778
Round 17: 1800 labels, accuracy=0.4861
Round 18: 1900 labels, accuracy=0.4984
Round 19: 2000 labels, accuracy=0.4815
    Completed in 226.8s
    Progress: 43/60 (71.7%)
    Rough ETA (minutes): 129.5
  Rep 5/5, Strategy: uncertainty, eps=0.1000
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1615
Round 1: 200 labels, accuracy=0.2090
Round 2: 300 labels, accuracy=0.3045
Round 3: 400 labels, accuracy=0.3009
Round 4: 500 labels, accuracy=0.3342
Round 5: 600 labels, accuracy=0.3673
Round 6: 700 labels, accuracy=0.3565
  Early stopping at epoch 9
Round 7: 800 labels, accuracy=0.3601
Round 8: 900 labels, accuracy=0.3639
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Round 9: 1000 labels, accuracy=0.4072
Round 10: 1100 labels, accuracy=0.3591
Round 11: 1200 labels, accuracy=0.4250
Round 12: 1300 labels, accuracy=0.4041
Round 13: 1400 labels, accuracy=0.3500
Round 14: 1500 labels, accuracy=0.4426
Round 15: 1600 labels, accuracy=0.4166
Round 16: 1700 labels, accuracy=0.4456
Round 17: 1800 labels, accuracy=0.4494
Round 18: 1900 labels, accuracy=0.4440
Round 19: 2000 labels, accuracy=0.4052
    Completed in 589.6s
    Progress: 44/60 (73.3%)
    Rough ETA (minutes): 122.7
  Rep 5/5, Strategy: diversity, eps=0.1000
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1615
Round 1: 200 labels, accuracy=0.2432
Round 2: 300 labels, accuracy=0.2837
Round 3: 400 labels, accuracy=0.3519
Round 4: 500 labels, accuracy=0.3790
  Early stopping at epoch 8
Round 5: 600 labels, accuracy=0.3693
Round 6: 700 labels, accuracy=0.3876
Round 7: 800 labels, accuracy=0.4041
Round 8: 900 labels, accuracy=0.3926
Round 9: 1000 labels, accuracy=0.4135
Round 10: 1100 labels, accuracy=0.4350
Round 11: 1200 labels, accuracy=0.4405
Round 12: 1300 labels, accuracy=0.4161
Round 13: 1400 labels, accuracy=0.4729
Round 14: 1500 labels, accuracy=0.4805
Round 15: 1600 labels, accuracy=0.4655
Round 16: 1700 labels, accuracy=0.4447
Round 17: 1800 labels, accuracy=0.4785
Round 18: 1900 labels, accuracy=0.4652
Round 19: 2000 labels, accuracy=0.5024
    Completed in 584.1s
    Progress: 45/60 (75.0%)
    Rough ETA (minutes): 115.7
✓ Saved: /content/drive/MyDrive/AL_Results/al_results_e10.pkl
============================================================
Running epsilon = 0.15
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  Rep 1/5, Strategy: random, eps=0.1500
  Early stopping at epoch 7
Round 0: 100 labels, accuracy=0.1477
Round 1: 200 labels, accuracy=0.1910
Round 2: 300 labels, accuracy=0.3150
Round 3: 400 labels, accuracy=0.3470
Round 4: 500 labels, accuracy=0.3396
Round 5: 600 labels, accuracy=0.3713
Round 6: 700 labels, accuracy=0.3793
Round 7: 800 labels, accuracy=0.3973
Round 8: 900 labels, accuracy=0.3807
Round 9: 1000 labels, accuracy=0.4379
Round 10: 1100 labels, accuracy=0.3883
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Round 11: 1200 labels, accuracy=0.4363
Round 12: 1300 labels, accuracy=0.4514
Round 13: 1400 labels, accuracy=0.4692
Round 14: 1500 labels, accuracy=0.4701
Round 15: 1600 labels, accuracy=0.4626
Round 16: 1700 labels, accuracy=0.4526
Round 17: 1800 labels, accuracy=0.4682
Round 18: 1900 labels, accuracy=0.4611
Round 19: 2000 labels, accuracy=0.4826
    Completed in 222.6s
    Progress: 46/60 (76.7%)
    Rough ETA (minutes): 106.8
  Rep 1/5, Strategy: uncertainty, eps=0.1500
  Early stopping at epoch 7
Round 0: 100 labels, accuracy=0.1477
Round 1: 200 labels, accuracy=0.1977
Round 2: 300 labels, accuracy=0.2476
Round 3: 400 labels, accuracy=0.2898
Round 4: 500 labels, accuracy=0.3069
Round 5: 600 labels, accuracy=0.3528
Round 6: 700 labels, accuracy=0.3778
Round 7: 800 labels, accuracy=0.3599
  Early stopping at epoch 10
Round 8: 900 labels, accuracy=0.3482
Round 9: 1000 labels, accuracy=0.4084
Round 10: 1100 labels, accuracy=0.4170
Round 11: 1200 labels, accuracy=0.4177
Round 12: 1300 labels, accuracy=0.3749
Round 13: 1400 labels, accuracy=0.3967
Round 14: 1500 labels, accuracy=0.4111
Round 15: 1600 labels, accuracy=0.4357
Round 16: 1700 labels, accuracy=0.4083
Round 17: 1800 labels, accuracy=0.4056
Round 18: 1900 labels, accuracy=0.4230
Round 19: 2000 labels, accuracy=0.4564
    Completed in 580.1s
    Progress: 47/60 (78.3%)
    Rough ETA (minutes): 99.7
  Rep 1/5, Strategy: diversity, eps=0.1500
  Early stopping at epoch 7
Round 0: 100 labels, accuracy=0.1477
Round 1: 200 labels, accuracy=0.2208
  Early stopping at epoch 6
Round 2: 300 labels, accuracy=0.2299
Round 3: 400 labels, accuracy=0.3197
Round 4: 500 labels, accuracy=0.3562
Round 5: 600 labels, accuracy=0.3878
Round 6: 700 labels, accuracy=0.3756
Round 7: 800 labels, accuracy=0.3995
Round 8: 900 labels, accuracy=0.3954
Round 9: 1000 labels, accuracy=0.3988
Round 10: 1100 labels, accuracy=0.4109
Round 11: 1200 labels, accuracy=0.4454
Round 12: 1300 labels, accuracy=0.4379
Round 13: 1400 labels, accuracy=0.4536
Round 14: 1500 labels, accuracy=0.4341
Round 15: 1600 labels, accuracy=0.4439
```

```
Round 16: 1700 labels, accuracy=0.4680
Round 17: 1800 labels, accuracy=0.4746
Round 18: 1900 labels, accuracy=0.4749
Round 19: 2000 labels, accuracy=0.4818
    Completed in 584.4s
    Progress: 48/60 (80.0%)
    Rough ETA (minutes): 92.5
  Rep 2/5, Strategy: random, eps=0.1500
  Early stopping at epoch 10
Round 0: 100 labels, accuracy=0.1878
Round 1: 200 labels, accuracy=0.2743
  Early stopping at epoch 6
Round 2: 300 labels, accuracy=0.1688
Round 3: 400 labels, accuracy=0.3344
Round 4: 500 labels, accuracy=0.3525
Round 5: 600 labels, accuracy=0.3958
Round 6: 700 labels, accuracy=0.3727
Round 7: 800 labels, accuracy=0.3352
Round 8: 900 labels, accuracy=0.3846
Round 9: 1000 labels, accuracy=0.4137
Round 10: 1100 labels, accuracy=0.4243
Round 11: 1200 labels, accuracy=0.4458
Round 12: 1300 labels, accuracy=0.4409
Round 13: 1400 labels, accuracy=0.4514
Round 14: 1500 labels, accuracy=0.4006
Round 15: 1600 labels, accuracy=0.4578
Round 16: 1700 labels, accuracy=0.4425
Round 17: 1800 labels, accuracy=0.4781
Round 18: 1900 labels, accuracy=0.4360
Round 19: 2000 labels, accuracy=0.4470
    Completed in 221.4s
    Progress: 49/60 (81.7%)
    Rough ETA (minutes): 83.9
  Rep 2/5, Strategy: uncertainty, eps=0.1500
  Early stopping at epoch 10
Round 0: 100 labels, accuracy=0.1878
  Early stopping at epoch 6
Round 1: 200 labels, accuracy=0.2096
Round 2: 300 labels, accuracy=0.2374
Round 3: 400 labels, accuracy=0.3012
Round 4: 500 labels, accuracy=0.3296
Round 5: 600 labels, accuracy=0.3719
Round 6: 700 labels, accuracy=0.3523
Round 7: 800 labels, accuracy=0.3820
Round 8: 900 labels, accuracy=0.3883
Round 9: 1000 labels, accuracy=0.4382
  Early stopping at epoch 10
Round 10: 1100 labels, accuracy=0.3713
Round 11: 1200 labels, accuracy=0.4289
Round 12: 1300 labels, accuracy=0.4101
Round 13: 1400 labels, accuracy=0.4532
Round 14: 1500 labels, accuracy=0.3886
Round 15: 1600 labels, accuracy=0.3998
Round 16: 1700 labels, accuracy=0.4529
Round 17: 1800 labels, accuracy=0.4471
Round 18: 1900 labels, accuracy=0.4267
Round 19: 2000 labels, accuracy=0.4453
```

```
        Completed in 580.8s
        Progress: 50/60 (83.3%)
        Rough ETA (minutes): 76.7
      Rep 2/5, Strategy: diversity, eps=0.1500
      Early stopping at epoch 10
    Round 0: 100 labels, accuracy=0.1878
      Early stopping at epoch 6
    Round 1: 200 labels, accuracy=0.2331
    Round 2: 300 labels, accuracy=0.2960
    Round 3: 400 labels, accuracy=0.3236
    Round 4: 500 labels, accuracy=0.3487
    Round 5: 600 labels, accuracy=0.3725
    Round 6: 700 labels, accuracy=0.3651
    Round 7: 800 labels, accuracy=0.3799
    Round 8: 900 labels, accuracy=0.3681
    Round 9: 1000 labels, accuracy=0.4127
    Round 10: 1100 labels, accuracy=0.4190
      Early stopping at epoch 7
    Round 11: 1200 labels, accuracy=0.3327
    Round 12: 1300 labels, accuracy=0.4132
    Round 13: 1400 labels, accuracy=0.4325
    Round 14: 1500 labels, accuracy=0.4319
    Round 15: 1600 labels, accuracy=0.4268
    Round 16: 1700 labels, accuracy=0.4610
    Round 17: 1800 labels, accuracy=0.4320
    Round 18: 1900 labels, accuracy=0.4674
    Round 19: 2000 labels, accuracy=0.4742
        Completed in 582.1s
        Progress: 51/60 (85.0%)
        Rough ETA (minutes): 69.4
      Rep 3/5, Strategy: random, eps=0.1500
      Early stopping at epoch 6
    Round 0: 100 labels, accuracy=0.1108
    Round 1: 200 labels, accuracy=0.2514
    Round 2: 300 labels, accuracy=0.2889
    Round 3: 400 labels, accuracy=0.3305
    Round 4: 500 labels, accuracy=0.3729
    Round 5: 600 labels, accuracy=0.3475
    Round 6: 700 labels, accuracy=0.4107
    Round 7: 800 labels, accuracy=0.3880
    Round 8: 900 labels, accuracy=0.3624
    Round 9: 1000 labels, accuracy=0.4042
    Round 10: 1100 labels, accuracy=0.4185
    Round 11: 1200 labels, accuracy=0.4441
      Early stopping at epoch 10
    Round 12: 1300 labels, accuracy=0.4165
    Round 13: 1400 labels, accuracy=0.4667
    Round 14: 1500 labels, accuracy=0.4388
    Round 15: 1600 labels, accuracy=0.4743
    Round 16: 1700 labels, accuracy=0.4726
    Round 17: 1800 labels, accuracy=0.4707
    Round 18: 1900 labels, accuracy=0.4921
    Round 19: 2000 labels, accuracy=0.4664
        Completed in 222.8s
        Progress: 52/60 (86.7%)
        Rough ETA (minutes): 61.1
      Rep 3/5, Strategy: uncertainty, eps=0.1500
```

```
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1108
Round 1: 200 labels, accuracy=0.2294
Round 2: 300 labels, accuracy=0.2293
Round 3: 400 labels, accuracy=0.3047
Round 4: 500 labels, accuracy=0.3861
Round 5: 600 labels, accuracy=0.3594
Round 6: 700 labels, accuracy=0.3314
Round 7: 800 labels, accuracy=0.3942
Round 8: 900 labels, accuracy=0.3573
Round 9: 1000 labels, accuracy=0.3692
Round 10: 1100 labels, accuracy=0.3657
Round 11: 1200 labels, accuracy=0.4059
Round 12: 1300 labels, accuracy=0.4052
Round 13: 1400 labels, accuracy=0.4389
Round 14: 1500 labels, accuracy=0.4257
Round 15: 1600 labels, accuracy=0.4578
Round 16: 1700 labels, accuracy=0.4408
Round 17: 1800 labels, accuracy=0.4490
Round 18: 1900 labels, accuracy=0.4507
Round 19: 2000 labels, accuracy=0.4622
    Completed in 586.9s
    Progress: 53/60 (88.3%)
    Rough ETA (minutes): 53.7
  Rep 3/5, Strategy: diversity, eps=0.1500
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1108
Round 1: 200 labels, accuracy=0.2614
Round 2: 300 labels, accuracy=0.2999
  Early stopping at epoch 10
Round 3: 400 labels, accuracy=0.3623
Round 4: 500 labels, accuracy=0.3974
Round 5: 600 labels, accuracy=0.3955
Round 6: 700 labels, accuracy=0.4243
Round 7: 800 labels, accuracy=0.4383
Round 8: 900 labels, accuracy=0.4336
Round 9: 1000 labels, accuracy=0.4083
Round 10: 1100 labels, accuracy=0.4356
Round 11: 1200 labels, accuracy=0.4552
Round 12: 1300 labels, accuracy=0.4711
Round 13: 1400 labels, accuracy=0.4698
Round 14: 1500 labels, accuracy=0.4491
Round 15: 1600 labels, accuracy=0.4688
Round 16: 1700 labels, accuracy=0.4679
Round 17: 1800 labels, accuracy=0.4455
Round 18: 1900 labels, accuracy=0.4913
Round 19: 2000 labels, accuracy=0.4702
    Completed in 591.3s
    Progress: 54/60 (90.0%)
    Rough ETA (minutes): 46.3
  Rep 4/5, Strategy: random, eps=0.1500
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1299
Round 1: 200 labels, accuracy=0.2516
Round 2: 300 labels, accuracy=0.3250
  Early stopping at epoch 10
Round 3: 400 labels, accuracy=0.2804
```

```
Round 4: 500 labels, accuracy=0.3742
  Early stopping at epoch 10
Round 5: 600 labels, accuracy=0.3636
Round 6: 700 labels, accuracy=0.3727
Round 7: 800 labels, accuracy=0.4088
Round 8: 900 labels, accuracy=0.3866
Round 9: 1000 labels, accuracy=0.3812
Round 10: 1100 labels, accuracy=0.4086
Round 11: 1200 labels, accuracy=0.3831
Round 12: 1300 labels, accuracy=0.4258
Round 13: 1400 labels, accuracy=0.4386
Round 14: 1500 labels, accuracy=0.4485
Round 15: 1600 labels, accuracy=0.4508
Round 16: 1700 labels, accuracy=0.4292
Round 17: 1800 labels, accuracy=0.4332
Round 18: 1900 labels, accuracy=0.4379
Round 19: 2000 labels, accuracy=0.4516
    Completed in 223.6s
    Progress: 55/60 (91.7%)
    Rough ETA (minutes): 38.2
  Rep 4/5, Strategy: uncertainty, eps=0.1500
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1299
Round 1: 200 labels, accuracy=0.2634
Round 2: 300 labels, accuracy=0.2909
Round 3: 400 labels, accuracy=0.3067
Round 4: 500 labels, accuracy=0.3600
Round 5: 600 labels, accuracy=0.3608
Round 6: 700 labels, accuracy=0.3331
Round 7: 800 labels, accuracy=0.3805
Round 8: 900 labels, accuracy=0.3441
Round 9: 1000 labels, accuracy=0.4189
Round 10: 1100 labels, accuracy=0.3905
Round 11: 1200 labels, accuracy=0.3787
Round 12: 1300 labels, accuracy=0.4282
Round 13: 1400 labels, accuracy=0.4254
Round 14: 1500 labels, accuracy=0.3578
Round 15: 1600 labels, accuracy=0.4621
Round 16: 1700 labels, accuracy=0.3788
Round 17: 1800 labels, accuracy=0.4176
Round 18: 1900 labels, accuracy=0.4094
Round 19: 2000 labels, accuracy=0.4592
    Completed in 582.4s
    Progress: 56/60 (93.3%)
    Rough ETA (minutes): 30.7
  Rep 4/5, Strategy: diversity, eps=0.1500
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1299
Round 1: 200 labels, accuracy=0.2034
Round 2: 300 labels, accuracy=0.3018
  Early stopping at epoch 10
Round 3: 400 labels, accuracy=0.3478
Round 4: 500 labels, accuracy=0.3934
Round 5: 600 labels, accuracy=0.3982
Round 6: 700 labels, accuracy=0.4154
Round 7: 800 labels, accuracy=0.3850
Round 8: 900 labels, accuracy=0.3429
```

```
  Early stopping at epoch 9
Round 9: 1000 labels, accuracy=0.3923
Round 10: 1100 labels, accuracy=0.3881
Round 11: 1200 labels, accuracy=0.4373
  Early stopping at epoch 10
Round 12: 1300 labels, accuracy=0.4451
Round 13: 1400 labels, accuracy=0.4336
Round 14: 1500 labels, accuracy=0.4067
Round 15: 1600 labels, accuracy=0.4669
Round 16: 1700 labels, accuracy=0.4490
Round 17: 1800 labels, accuracy=0.4461
Round 18: 1900 labels, accuracy=0.4741
Round 19: 2000 labels, accuracy=0.4403
    Completed in 584.2s
    Progress: 57/60 (95.0%)
    Rough ETA (minutes): 23.1
  Rep 5/5, Strategy: random, eps=0.1500
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1615
Round 1: 200 labels, accuracy=0.2104
Round 2: 300 labels, accuracy=0.2900
Round 3: 400 labels, accuracy=0.2915
Round 4: 500 labels, accuracy=0.3041
Round 5: 600 labels, accuracy=0.3548
Round 6: 700 labels, accuracy=0.3798
Round 7: 800 labels, accuracy=0.4044
Round 8: 900 labels, accuracy=0.3912
Round 9: 1000 labels, accuracy=0.4301
Round 10: 1100 labels, accuracy=0.4440
Round 11: 1200 labels, accuracy=0.4121
Round 12: 1300 labels, accuracy=0.4509
Round 13: 1400 labels, accuracy=0.4443
Round 14: 1500 labels, accuracy=0.4490
Round 15: 1600 labels, accuracy=0.4673
Round 16: 1700 labels, accuracy=0.4085
Round 17: 1800 labels, accuracy=0.4057
Round 18: 1900 labels, accuracy=0.4477
Round 19: 2000 labels, accuracy=0.4874
    Completed in 223.3s
    Progress: 58/60 (96.7%)
    Rough ETA (minutes): 15.3
  Rep 5/5, Strategy: uncertainty, eps=0.1500
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1615
Round 1: 200 labels, accuracy=0.2382
Round 2: 300 labels, accuracy=0.2769
Round 3: 400 labels, accuracy=0.3127
Round 4: 500 labels, accuracy=0.3608
Round 5: 600 labels, accuracy=0.3347
Round 6: 700 labels, accuracy=0.3687
Round 7: 800 labels, accuracy=0.3854
Round 8: 900 labels, accuracy=0.3451
Round 9: 1000 labels, accuracy=0.3832
Round 10: 1100 labels, accuracy=0.3641
Round 11: 1200 labels, accuracy=0.3965
Round 12: 1300 labels, accuracy=0.3845
Round 13: 1400 labels, accuracy=0.3936
```

```
Round 14: 1500 labels, accuracy=0.4251
Round 15: 1600 labels, accuracy=0.3740
Round 16: 1700 labels, accuracy=0.4356
Round 17: 1800 labels, accuracy=0.4185
Round 18: 1900 labels, accuracy=0.4563
Round 19: 2000 labels, accuracy=0.4427
    Completed in 585.7s
    Progress: 59/60 (98.3%)
    Rough ETA (minutes): 7.7
  Rep 5/5, Strategy: diversity, eps=0.1500
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1615
Round 1: 200 labels, accuracy=0.2252
Round 2: 300 labels, accuracy=0.2874
Round 3: 400 labels, accuracy=0.3676
Round 4: 500 labels, accuracy=0.3754
Round 5: 600 labels, accuracy=0.4017
Round 6: 700 labels, accuracy=0.3795
Round 7: 800 labels, accuracy=0.3949
Round 8: 900 labels, accuracy=0.3815
Round 9: 1000 labels, accuracy=0.4192
Round 10: 1100 labels, accuracy=0.4273
Round 11: 1200 labels, accuracy=0.4208
Round 12: 1300 labels, accuracy=0.4503
Round 13: 1400 labels, accuracy=0.4580
Round 14: 1500 labels, accuracy=0.4257
Round 15: 1600 labels, accuracy=0.4262
Round 16: 1700 labels, accuracy=0.4432
Round 17: 1800 labels, accuracy=0.4646
Round 18: 1900 labels, accuracy=0.4558
Round 19: 2000 labels, accuracy=0.4796
    Completed in 589.5s
    Progress: 60/60 (100.0%)
    Rough ETA (minutes): 0.0
✓ Saved: /content/drive/MyDrive/AL_Results/al_results_e15.pkl
============================================================
All experiments completed! Total time: 7.72 hours
Results saved to: /content/drive/MyDrive/AL_Results
============================================================
✓ Results saved to: /content/drive/MyDrive/AL_Results
```

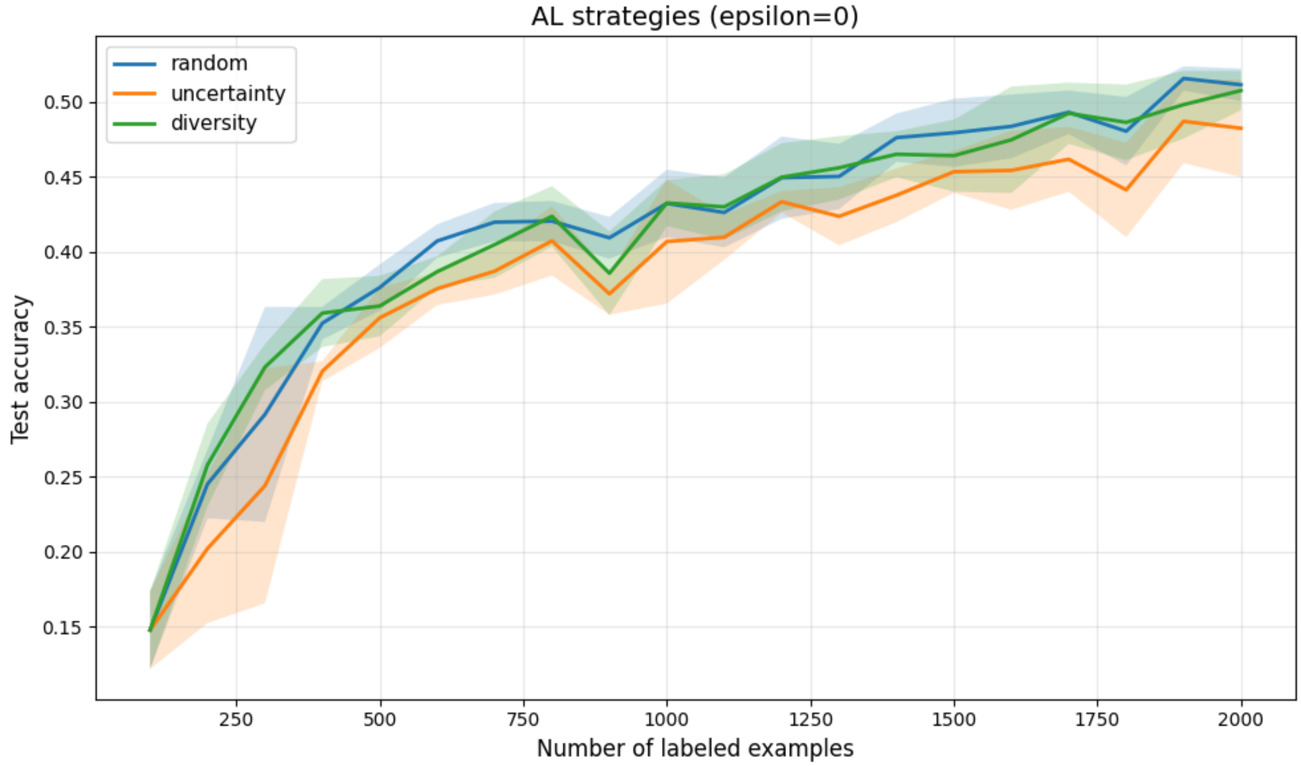
In [ ]:

```
# ============================================================
# CELL 5: Post-process and visualize
# ============================================================
import pickle
import json
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import os

SAVE_DIR = SAVE_DIR  # already defined

# helper to load result file for a given epsilon (int percent)
def load_results_for_epsilon(save_dir, e_percent):
```

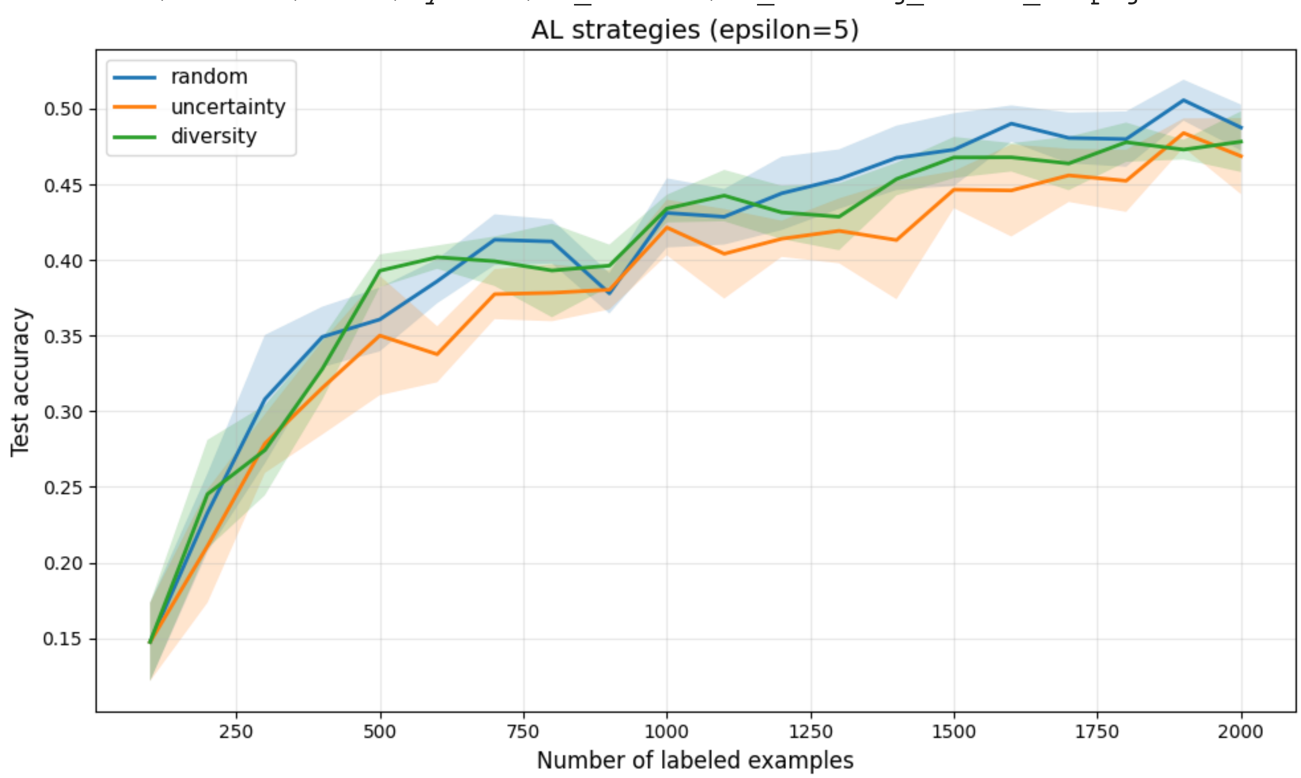
```
    fname = os.path.join(save_dir, f"al_results_e{e_percent}.pkl")
    if not os.path.exists(fname):
        raise FileNotFoundError(f"{fname} not found")
    with open(fname, "rb") as f:
        all_results = pickle.load(f)
    return all_results

# process all saved result files found in SAVE_DIR matching pattern al_result
files = [f for f in os.listdir(SAVE_DIR) if f.startswith('al_results_e') and
print(f"Found result files: {files}")

for f in files:
    path = os.path.join(SAVE_DIR, f)
    with open(path, "rb") as fh:
        all_results = pickle.load(fh)
    e_str = f.split('al_results_e')[-1].split('.pkl')[0]
    # normalize e label
    try:
        e_val = int(e_str)
    except Exception:
        e_val = e_str

    summary = {}
    for s in all_results:
        # collect all label counts from all reps
        labels_grid = sorted({n for rep in all_results[s] for n,_ in rep})
        mats = []
        for rep in all_results[s]:
            acc_map = {n:acc for n,acc in rep}
            # create accs aligned to labels_grid by forward-fill using last a
            accs = []
            for n in labels_grid:
                if n in acc_map:
                    accs.append(acc_map[n])
                else:
                    # find the largest key <= n
                    keys = [k for k in acc_map.keys() if k <= n]
                    if len(keys) == 0:
                        accs.append(0.0)
                    else:
                        accs.append(acc_map[max(keys)])
            mats.append(accs)
        mats = np.array(mats)
        mean = mats.mean(0)
        ci95 = 1.96 * mats.std(0, ddof=1) / np.sqrt(max(1, mats.shape[0]))
        summary[s] = {'labels': labels_grid, 'mean': mean.tolist(), 'ci': ci9

    # Save JSON
    json_path = os.path.join(SAVE_DIR, f"summary_e{e_val}.json")
    with open(json_path, "w") as fjson:
        json.dump(summary, fjson, indent=2)

    # Save CSV
```

```
    rows = []
    for s in summary:
        for n, m, c in zip(summary[s]['labels'], summary[s]['mean'], summary[
            rows.append({"strategy": s, "labels": n, "accuracy_mean": m, "acc
    csv_path = os.path.join(SAVE_DIR, f"summary_e{e_val}.csv")
    pd.DataFrame(rows).to_csv(csv_path, index=False)

    # Plot
    plt.figure(figsize=(10, 6))
    for s in summary:
        x = summary[s]['labels']
        y = summary[s]['mean']
        ci = summary[s]['ci']
        plt.plot(x, y, label=s, linewidth=2)
        plt.fill_between(x, np.array(y) - np.array(ci), np.array(y) + np.arra
    plt.xlabel("Number of labeled examples", fontsize=12)
    plt.ylabel("Test accuracy", fontsize=12)
    plt.title(f"AL strategies (epsilon={e_val})", fontsize=14)
    plt.legend(fontsize=11)
    plt.grid(True, alpha=0.3)
    plt.tight_layout()

    plot_path = os.path.join(SAVE_DIR, f"al_learning_curves_e{e_val}.png")
    plt.savefig(plot_path, dpi=200, bbox_inches='tight')
    plt.show()

    print(f"✓ Saved: {json_path}")
    print(f"✓ Saved: {csv_path}")
    print(f"✓ Saved: {plot_path}")

print(f"{'='*60}")
print(f"All summaries generated and saved to: {SAVE_DIR}")
print(f"{'='*60}")
```

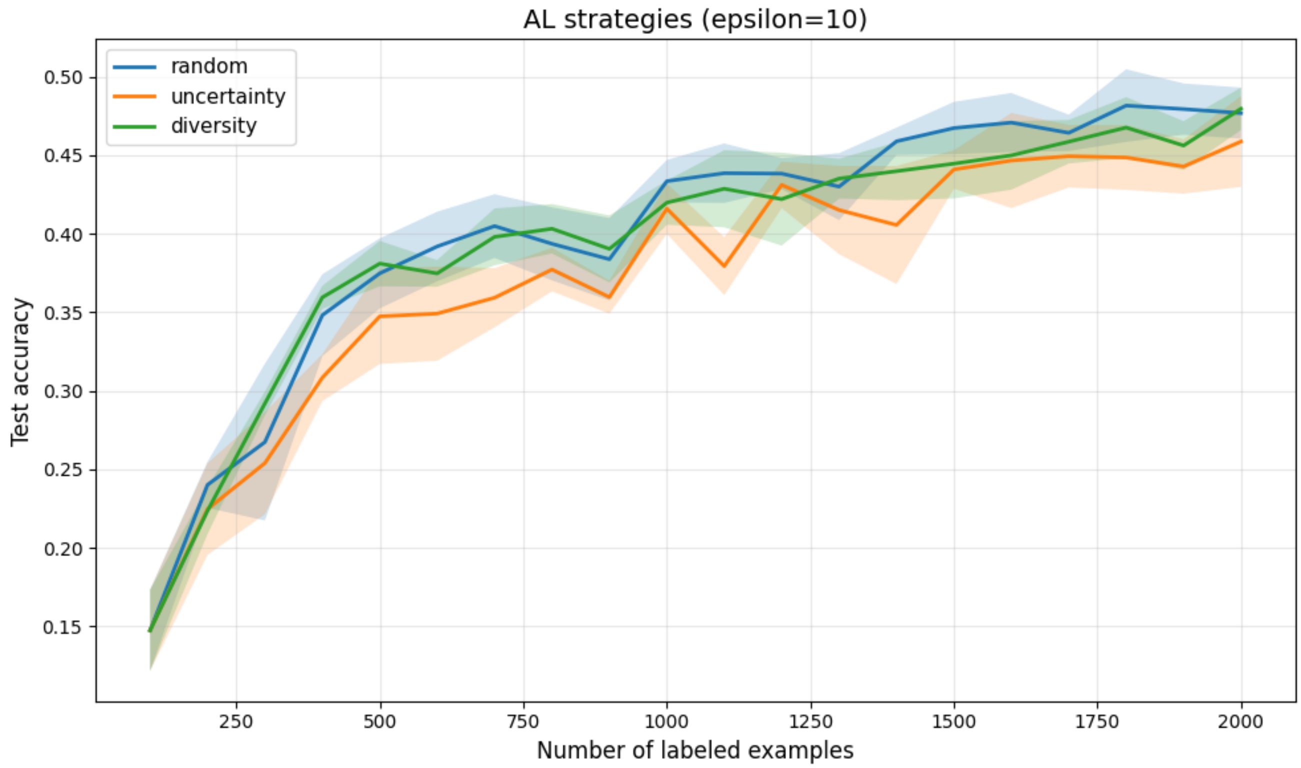
```
Found result files: ['al_results_e0.pkl', 'al_results_e5.pkl', 'al_results_e1
0.pkl', 'al_results_e15.pkl']
```



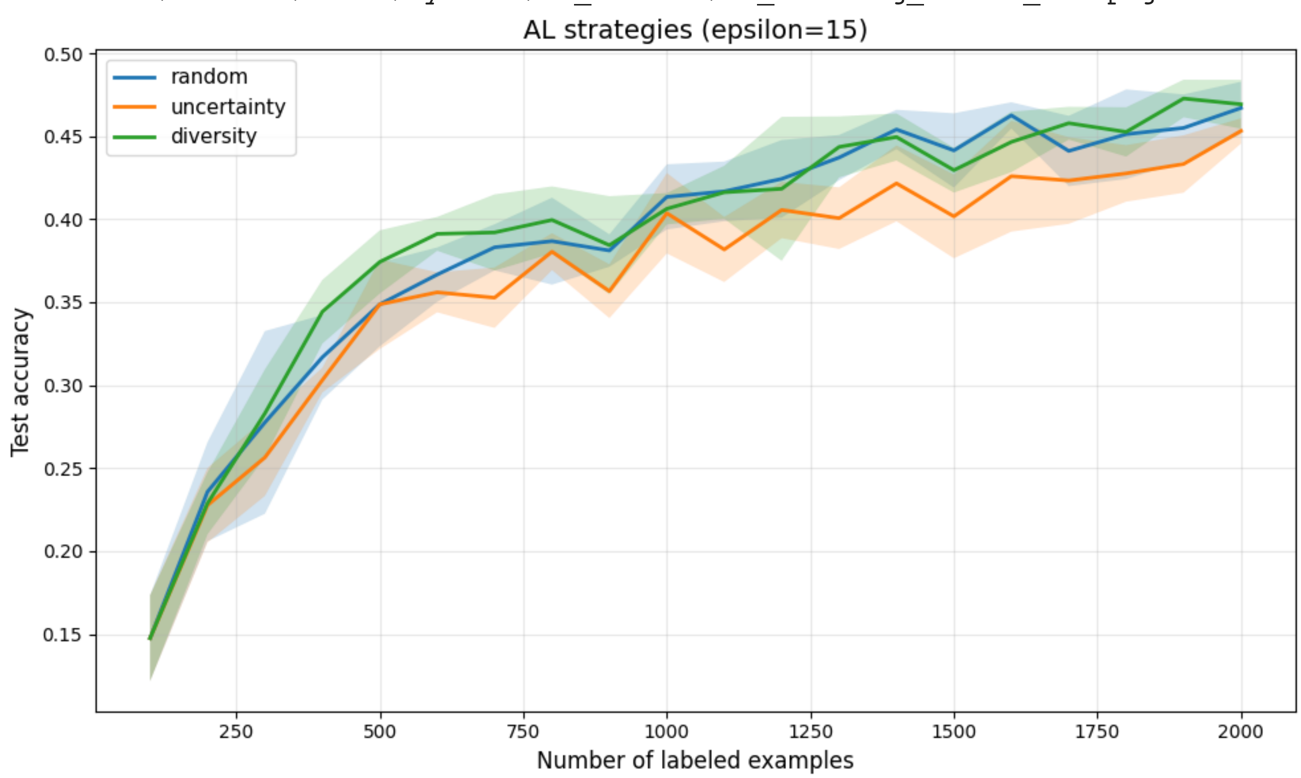
✓ Saved: /content/drive/MyDrive/AL_Results/summary_e0.json
✓ Saved: /content/drive/MyDrive/AL_Results/summary_e0.csv
✓ Saved: /content/drive/MyDrive/AL_Results/al_learning_curves_e0.png



✓ Saved: /content/drive/MyDrive/AL_Results/summary_e5.json
✓ Saved: /content/drive/MyDrive/AL_Results/summary_e5.csv
✓ Saved: /content/drive/MyDrive/AL_Results/al_learning_curves_e5.png




```
✓ Saved: /content/drive/MyDrive/AL_Results/summary_e10.json
✓ Saved: /content/drive/MyDrive/AL_Results/summary_e10.csv
✓ Saved: /content/drive/MyDrive/AL_Results/al_learning_curves_e10.png
```



```
✓ Saved: /content/drive/MyDrive/AL_Results/summary_e15.json
✓ Saved: /content/drive/MyDrive/AL_Results/summary_e15.csv
✓ Saved: /content/drive/MyDrive/AL_Results/al_learning_curves_e15.png
============================================================
All summaries generated and saved to: /content/drive/MyDrive/AL_Results
============================================================
```

My last message before I go to sleep. Hopefully it disconnects at a convenient point lol.

In [ ]:

```
!pip install pingouin
```

```
Collecting pingouin
  Downloading pingouin-0.5.5-py3-none-any.whl.metadata (19 kB)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.12/dist-pa
ckages (from pingouin) (3.10.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.12/dist-package
s (from pingouin) (2.0.2)
Requirement already satisfied: pandas>=1.5 in /usr/local/lib/python3.12/dist-p
ackages (from pingouin) (2.2.2)
Collecting pandas-flavor (from pingouin)
  Downloading pandas_flavor-0.8.1-py3-none-any.whl.metadata (6.6 kB)
Requirement already satisfied: scikit-learn>=1.2 in /usr/local/lib/python3.12/
dist-packages (from pingouin) (1.6.1)
Requirement already satisfied: scipy in /usr/local/lib/python3.12/dist-package
s (from pingouin) (1.16.3)
Requirement already satisfied: seaborn in /usr/local/lib/python3.12/dist-packa
ges (from pingouin) (0.13.2)
Requirement already satisfied: statsmodels in /usr/local/lib/python3.12/dist-p
ackages (from pingouin) (0.14.5)
Requirement already satisfied: tabulate in /usr/local/lib/python3.12/dist-pack
ages (from pingouin) (0.9.0)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python
3.12/dist-packages (from pandas>=1.5->pingouin) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.12/dist-
packages (from pandas>=1.5->pingouin) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.12/dis
t-packages (from pandas>=1.5->pingouin) (2025.2)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.12/dist
-packages (from scikit-learn>=1.2->pingouin) (1.5.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.
12/dist-packages (from scikit-learn>=1.2->pingouin) (3.6.0)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.12/d
ist-packages (from matplotlib->pingouin) (1.3.3)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.12/dist-
packages (from matplotlib->pingouin) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.12/
dist-packages (from matplotlib->pingouin) (4.61.0)
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python3.12/
dist-packages (from matplotlib->pingouin) (1.4.9)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.12/di
st-packages (from matplotlib->pingouin) (25.0)
Requirement already satisfied: pillow>=8 in /usr/local/lib/python3.12/dist-pac
kages (from matplotlib->pingouin) (11.3.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.12/d
ist-packages (from matplotlib->pingouin) (3.2.5)
Requirement already satisfied: xarray in /usr/local/lib/python3.12/dist-packag
es (from pandas-flavor->pingouin) (2025.11.0)
Requirement already satisfied: patsy>=0.5.6 in /usr/local/lib/python3.12/dist-
packages (from statsmodels->pingouin) (1.0.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.12/dist-pack
ages (from python-dateutil>=2.8.2->pandas>=1.5->pingouin) (1.17.0)
Downloading pingouin-0.5.5-py3-none-any.whl (204 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 204.4/204.4 kB 16.4 MB/s eta 0:0
0:00
Downloading pandas_flavor-0.8.1-py3-none-any.whl (8.5 kB)
Installing collected packages: pandas-flavor, pingouin
Successfully installed pandas-flavor-0.8.1 pingouin-0.5.5
```

In [ ]:

```
# ============================================================
# CELL 6: READ + EXTRACT METRICS FROM PKL FILES
# ============================================================

import pickle
import pandas as pd
import os

SAVE_DIR = SAVE_DIR

pkl_files = [f for f in os.listdir(SAVE_DIR) if f.startswith("al_results_e") a
print("Found PKL files:", pkl_files)

records = []

for fname in pkl_files:
    # Extract epsilon from filename
    e_str = fname.split("al_results_e")[-1].split(".pkl")[0]
    epsilon = float(e_str)

    path = os.path.join(SAVE_DIR, fname)   # <-- FIXED HERE

    with open(path, "rb") as f:
        all_results = pickle.load(f)
        # structure: all_results[strategy] = [ replication -> list of (n_labe

    for strategy, reps in all_results.items():
        for rep_id, rep_data in enumerate(reps):
            for (n_labels, acc) in rep_data:
                records.append({
                    "epsilon": epsilon,
                    "strategy": strategy,
                    "rep": rep_id,
                    "labels": n_labels,
                    "accuracy": acc
                })

df = pd.DataFrame(records)
print(df.head())
print(df.shape)
```

```
Found PKL files: ['al_results_e0.pkl', 'al_results_e5.pkl', 'al_results_e10.pk
l', 'al_results_e15.pkl']
   epsilon strategy  rep  labels  accuracy
0      0.0   random    0     100    0.1477
1      0.0   random    0     200    0.2115
2      0.0   random    0     300    0.2934
3      0.0   random    0     400    0.3467
4      0.0   random    0     500    0.3758
(1200, 5)
```

In [ ]:

```
# ============================================================
```

```python
# CELL 7: Statistical analysis of AL strategies
# ===============================================================

import numpy as np
import pandas as pd
from scipy import stats
import statsmodels.api as sm
from statsmodels.formula.api import ols
from statsmodels.stats.multicomp import pairwise_tukeyhsd

print("Computing AULC for each strategy / epsilon / replication...")

# ---- Compute AULC per replication ----
aulc_rows = []
for (eps, strat, rep), g in df.groupby(["epsilon", "strategy", "rep"]):
    g_sorted = g.sort_values("labels")
    auc_val = np.trapz(g_sorted["accuracy"], g_sorted["labels"])
    aulc_rows.append({
        "epsilon": eps,
        "strategy": strat,
        "replication": rep,
        "aulc": auc_val
    })

aulc_df = pd.DataFrame(aulc_rows)
aulc_path = os.path.join(SAVE_DIR, "aulc_results.csv")
aulc_df.to_csv(aulc_path, index=False)
print("✓ Saved:", aulc_path)

# ---- Run ANOVA per epsilon level ----
anova_results = {}
tukey_results = {}

print("\n============================")
print("ANOVA PER EPSILON")
print("============================")

for eps, g in aulc_df.groupby("epsilon"):
    print(f"\n--- Epsilon = {eps:.2f} ---")

    model = ols("aulc ~ C(strategy)", data=g).fit()
    anova_table = sm.stats.anova_lm(model, typ=2)
    anova_results[eps] = anova_table

    print(anova_table)

    # Tukey HSD
    tukey = pairwise_tukeyhsd(g["aulc"], g["strategy"])
    tukey_results[eps] = tukey
    print("\nPost-hoc Tukey HSD:")
    print(tukey)

# ---- Compute effect sizes ----
```

```python
def etasquared(anova):
    return anova.loc["C(strategy)", "sum_sq"] / anova["sum_sq"].sum()

def cohend(x, y):
    return (np.mean(x) - np.mean(y)) / np.sqrt((np.var(x) + np.var(y)) / 2)

print("\n============================")
print("Effect Sizes")
print("============================")

for eps, g in aulc_df.groupby("epsilon"):
    print(f"\n--- Epsilon = {eps:.2f} ---")
    anova = anova_results[eps]
    eta2 = etasquared(anova)
    print(f"η² (effect size of strategy): {eta2:.3f}")

    for s1 in g["strategy"].unique():
        for s2 in g["strategy"].unique():
            if s1 >= s2:
                continue
            d = cohend(
                g[g.strategy == s1]["aulc"],
                g[g.strategy == s2]["aulc"]
            )
            print(f"Cohen's d ({s1} vs {s2}): {d:.3f}")
```

```
Computing AULC for each strategy / epsilon / replication...
✓ Saved: /content/drive/MyDrive/AL_Results/aulc_results.csv

============================
ANOVA PER EPSILON
============================

--- Epsilon = 0.00 ---
                  sum_sq    df         F    PR(>F)
C(strategy)  9147.43213   2.0  9.768867  0.003035
Residual     5618.31701  12.0       NaN       NaN
/tmp/ipython-input-1524081169.py:18: DeprecationWarning: `trapz` is deprecate
d. Use `trapezoid` instead, or one of the numerical integration functions in `
scipy.integrate`.
  auc_val = np.trapz(g_sorted["accuracy"], g_sorted["labels"])
Post-hoc Tukey HSD:
     Multiple Comparison of Means - Tukey HSD, FWER=0.05
==============================================================
  group1     group2   meandiff p-adj   lower    upper   reject
--------------------------------------------------------------
diversity      random     5.63 0.9116 -30.8795  42.1395  False
diversity uncertainty  -49.343 0.0093 -85.8525 -12.8335   True
   random uncertainty  -54.973 0.0045 -91.4825 -18.4635   True
--------------------------------------------------------------

--- Epsilon = 5.00 ---
                   sum_sq    df          F    PR(>F)
```

```
C(strategy)  7290.050623   2.0  12.142397  0.001308
Residual     3602.279310  12.0        NaN       NaN

Post-hoc Tukey HSD:
     Multiple Comparison of Means - Tukey HSD, FWER=0.05
===============================================================
  group1     group2   meandiff p-adj   lower    upper   reject
---------------------------------------------------------------
diversity      random   12.787 0.4939 -16.4472  42.0212  False
diversity uncertainty  -39.042 0.0101 -68.2762  -9.8078   True
   random uncertainty  -51.829 0.0013 -81.0632 -22.5948   True
---------------------------------------------------------------

--- Epsilon = 10.00 ---
                  sum_sq    df          F    PR(>F)
C(strategy)  7440.199163   2.0  16.146435  0.000395
Residual     2764.770960  12.0        NaN       NaN

Post-hoc Tukey HSD:
     Multiple Comparison of Means - Tukey HSD, FWER=0.05
===============================================================
  group1     group2   meandiff p-adj   lower    upper   reject
---------------------------------------------------------------
diversity      random   12.097 0.4428 -13.5144  37.7084  False
diversity uncertainty   -40.02 0.0034 -65.6314 -14.4086   True
   random uncertainty  -52.117 0.0004 -77.7284 -26.5056   True
---------------------------------------------------------------

--- Epsilon = 15.00 ---
                 sum_sq    df          F    PR(>F)
C(strategy)  6782.32123   2.0  13.261875  0.000914
Residual     3068.48971  12.0        NaN       NaN

Post-hoc Tukey HSD:
     Multiple Comparison of Means - Tukey HSD, FWER=0.05
===============================================================
  group1     group2   meandiff p-adj   lower    upper   reject
---------------------------------------------------------------
diversity      random   -9.815 0.6084 -36.7965  17.1665  False
diversity uncertainty  -49.207  0.001 -76.1885 -22.2255   True
   random uncertainty  -39.392 0.0056 -66.3735 -12.4105   True
---------------------------------------------------------------

============================
Effect Sizes
============================

--- Epsilon = 0.00 ---
η² (effect size of strategy): 0.620
Cohen's d (diversity vs random): -0.271
Cohen's d (diversity vs uncertainty): 2.364
Cohen's d (random vs uncertainty): 3.428

--- Epsilon = 5.00 ---
η² (effect size of strategy): 0.669
Cohen's d (diversity vs random): -0.832
Cohen's d (diversity vs uncertainty): 2.805
```

```
Cohen's d (random vs uncertainty): 3.041

--- Epsilon = 10.00 ---
η² (effect size of strategy): 0.729
Cohen's d (diversity vs random): -0.851
Cohen's d (diversity vs uncertainty): 2.994
Cohen's d (random vs uncertainty): 3.972

--- Epsilon = 15.00 ---
η² (effect size of strategy): 0.689
Cohen's d (diversity vs random): 0.595
Cohen's d (diversity vs uncertainty): 3.150
Cohen's d (random vs uncertainty): 3.991
```

In [ ]:

```
# ============================================================
# CELL 8: Secondary Experiment: Uniform Random Epsilon per Rep
# ============================================================

# Use a small subset for quick testing
config_secondary = {
    'save_dir': SAVE_DIR + "/secondary",  # separate folder to avoid overwrit
    'subset': 2000,                       # small subset
    'initial_labels': 50,
    'labeling_budget': 500,
    'query_batch': 50,
    'max_epochs': 5,                       # fewer epochs for speed
    'strategies': ['random', 'uncertainty', 'diversity'],
    'epsilons': [0.10],                    # pick a single epsilon
    'replications': 3,                     # small number of reps
    'seed': 123,
    'early_stopping': True,
    'patience': 2,
    'verbose': True,
    'sample_epsilon_per_rep': True         # uniform random epsilon per repli
}

os.makedirs(config_secondary['save_dir'], exist_ok=True)

# Run the experiment
save_dir_secondary = run_experiment(config_secondary)
print(f"Secondary experiment completed. Results saved to: {save_dir_secondary

# ============================================================
# Load and inspect
# ============================================================
import pickle, json, os, numpy as np, pandas as pd

# Load results
files = [f for f in os.listdir(save_dir_secondary) if f.startswith('al_result
for f in files:
    path = os.path.join(save_dir_secondary, f)
    with open(path, "rb") as fh:
        all_results = pickle.load(fh)
    print(f"\nResults for file: {f}")
    for strat, reps in all_results.items():
        accs = [r[-1][1] for r in reps]  # final accuracy of each replication
        print(f"  Strategy: {strat}, mean final accuracy: {np.mean(accs):.3f}
```

```
Using device: cuda
100%|██████████| 170M/170M [00:02<00:00, 77.7MB/s]
Experiment configuration:
  Dataset size: 2000
  Initial labels: 50
  Labeling budget: 500
  Max epochs: 5
  Strategies: ['random', 'uncertainty', 'diversity']
```

```
  Epsilon values: [0.1] (if sampling enabled, values may be drawn per-replicat
ion)
  Replications: 3
  Save directory: /content/drive/MyDrive/AL_Results/secondary
Total experiments (approx): 9
============================================================
Running epsilon = 0.1
============================================================
  Rep 1/3, Strategy: random, eps=0.0696
Round 0: 50 labels, accuracy=0.1680
Round 1: 100 labels, accuracy=0.1526
Round 2: 150 labels, accuracy=0.1389
Round 3: 200 labels, accuracy=0.1557
Round 4: 250 labels, accuracy=0.1297
Round 5: 300 labels, accuracy=0.1740
Round 6: 350 labels, accuracy=0.1693
Round 7: 400 labels, accuracy=0.2361
Round 8: 450 labels, accuracy=0.2127
Round 9: 500 labels, accuracy=0.2698
    Completed in 36.9s
    Progress: 1/9 (11.1%)
    Rough ETA (minutes): 5.0
  Rep 1/3, Strategy: uncertainty, eps=0.0696
Round 0: 50 labels, accuracy=0.1680
Round 1: 100 labels, accuracy=0.1443
Round 2: 150 labels, accuracy=0.1497
Round 3: 200 labels, accuracy=0.1492
Round 4: 250 labels, accuracy=0.1395
Round 5: 300 labels, accuracy=0.1769
Round 6: 350 labels, accuracy=0.1791
Round 7: 400 labels, accuracy=0.2042
Round 8: 450 labels, accuracy=0.2271
Round 9: 500 labels, accuracy=0.2196
    Completed in 41.3s
    Progress: 2/9 (22.2%)
    Rough ETA (minutes): 4.6
  Rep 1/3, Strategy: diversity, eps=0.0696
Round 0: 50 labels, accuracy=0.1680
Round 1: 100 labels, accuracy=0.1458
Round 2: 150 labels, accuracy=0.1558
Round 3: 200 labels, accuracy=0.1883
Round 4: 250 labels, accuracy=0.1609
Round 5: 300 labels, accuracy=0.1659
Round 6: 350 labels, accuracy=0.1867
Round 7: 400 labels, accuracy=0.2250
Round 8: 450 labels, accuracy=0.2865
Round 9: 500 labels, accuracy=0.2305
    Completed in 42.4s
    Progress: 3/9 (33.3%)
    Rough ETA (minutes): 4.0
  Rep 2/3, Strategy: random, eps=0.0106
Round 0: 50 labels, accuracy=0.1373
Round 1: 100 labels, accuracy=0.2134
Round 2: 150 labels, accuracy=0.1831
Round 3: 200 labels, accuracy=0.1258
Round 4: 250 labels, accuracy=0.1313
Round 5: 300 labels, accuracy=0.2224
```

```
        Round 6: 350 labels, accuracy=0.2011
        Round 7: 400 labels, accuracy=0.2345
        Round 8: 450 labels, accuracy=0.2569
        Round 9: 500 labels, accuracy=0.2639
            Completed in 35.4s
            Progress: 4/9 (44.4%)
            Rough ETA (minutes): 3.3
  Rep 2/3, Strategy: uncertainty, eps=0.0106
        Round 0: 50 labels, accuracy=0.1373
        Round 1: 100 labels, accuracy=0.1710
        Round 2: 150 labels, accuracy=0.1764
        Round 3: 200 labels, accuracy=0.1808
        Round 4: 250 labels, accuracy=0.1678
        Round 5: 300 labels, accuracy=0.1743
        Round 6: 350 labels, accuracy=0.2443
        Round 7: 400 labels, accuracy=0.2395
        Round 8: 450 labels, accuracy=0.2222
        Round 9: 500 labels, accuracy=0.2854
            Completed in 41.7s
            Progress: 5/9 (55.6%)
            Rough ETA (minutes): 2.6
  Rep 2/3, Strategy: diversity, eps=0.0106
        Round 0: 50 labels, accuracy=0.1373
        Round 1: 100 labels, accuracy=0.1665
        Round 2: 150 labels, accuracy=0.1674
        Round 3: 200 labels, accuracy=0.1539
        Round 4: 250 labels, accuracy=0.2154
        Round 5: 300 labels, accuracy=0.2123
        Round 6: 350 labels, accuracy=0.2464
        Round 7: 400 labels, accuracy=0.2661
        Round 8: 450 labels, accuracy=0.2478
        Round 9: 500 labels, accuracy=0.3016
            Completed in 42.6s
            Progress: 6/9 (66.7%)
            Rough ETA (minutes): 2.0
  Rep 3/3, Strategy: random, eps=0.0507
        Round 0: 50 labels, accuracy=0.1746
        Round 1: 100 labels, accuracy=0.1411
        Round 2: 150 labels, accuracy=0.1546
        Round 3: 200 labels, accuracy=0.1946
        Round 4: 250 labels, accuracy=0.1525
        Round 5: 300 labels, accuracy=0.1844
        Round 6: 350 labels, accuracy=0.2149
        Round 7: 400 labels, accuracy=0.2306
        Round 8: 450 labels, accuracy=0.2793
        Round 9: 500 labels, accuracy=0.3005
            Completed in 35.2s
            Progress: 7/9 (77.8%)
            Rough ETA (minutes): 1.3
  Rep 3/3, Strategy: uncertainty, eps=0.0507
        Round 0: 50 labels, accuracy=0.1746
        Round 1: 100 labels, accuracy=0.1696
        Round 2: 150 labels, accuracy=0.1592
        Round 3: 200 labels, accuracy=0.1585
        Round 4: 250 labels, accuracy=0.1859
        Round 5: 300 labels, accuracy=0.1951
        Round 6: 350 labels, accuracy=0.2465
```

```
Round 7: 400 labels, accuracy=0.2317
Round 8: 450 labels, accuracy=0.2597
Round 9: 500 labels, accuracy=0.2969
    Completed in 41.4s
    Progress: 8/9 (88.9%)
    Rough ETA (minutes): 0.7
  Rep 3/3, Strategy: diversity, eps=0.0507
Round 0: 50 labels, accuracy=0.1746
Round 1: 100 labels, accuracy=0.1876
Round 2: 150 labels, accuracy=0.2143
Round 3: 200 labels, accuracy=0.2190
Round 4: 250 labels, accuracy=0.2139
Round 5: 300 labels, accuracy=0.2162
Round 6: 350 labels, accuracy=0.2769
Round 7: 400 labels, accuracy=0.2820
Round 8: 450 labels, accuracy=0.3242
Round 9: 500 labels, accuracy=0.3221
    Completed in 42.0s
    Progress: 9/9 (100.0%)
    Rough ETA (minutes): 0.0
✓ Saved: /content/drive/MyDrive/AL_Results/secondary/al_results_e10.pkl
============================================================
All experiments completed! Total time: 0.10 hours
Results saved to: /content/drive/MyDrive/AL_Results/secondary
============================================================
Secondary experiment completed. Results saved to: /content/drive/MyDrive/AL_Re
sults/secondary

Results for file: al_results_e10.pkl
  Strategy: random, mean final accuracy: 0.278, std: 0.016
  Strategy: uncertainty, mean final accuracy: 0.267, std: 0.034
  Strategy: diversity, mean final accuracy: 0.285, std: 0.039
```

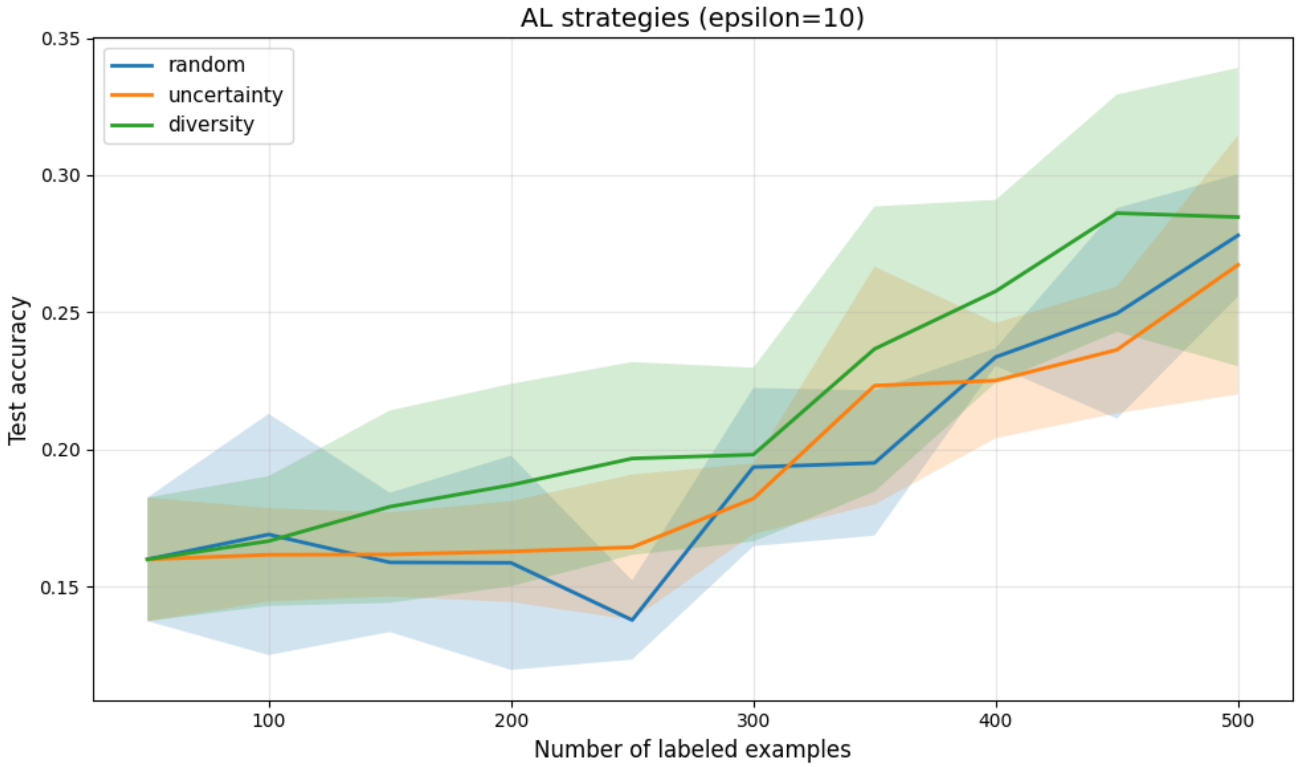
In [ ]:

```
# ============================================================
# CELL 9: Post-process and visualize
# ============================================================
import pickle
import json
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import os

DIR = SAVE_DIR + "/secondary"  # already defined

# helper to load result file for a given epsilon (int percent)
def load_results_for_epsilon(save_dir, e_percent):
    fname = os.path.join(save_dir, f"al_results_e{e_percent}.pkl")
    if not os.path.exists(fname):
        raise FileNotFoundError(f"{fname} not found")
    with open(fname, "rb") as f:
        all_results = pickle.load(f)
    return all_results

# process all saved result files found in SAVE_DIR matching pattern al_result
```

```
files = [f for f in os.listdir(DIR) if f.startswith('al_results_e') and f.end
print(f"Found result files: {files}")

for f in files:
    path = os.path.join(DIR, f)
    with open(path, "rb") as fh:
        all_results = pickle.load(fh)
    e_str = f.split('al_results_e')[-1].split('.pkl')[0]
    # normalize e label
    try:
        e_val = int(e_str)
    except Exception:
        e_val = e_str

    summary = {}
    for s in all_results:
        # collect all label counts from all reps
        labels_grid = sorted({n for rep in all_results[s] for n,_ in rep})
        mats = []
        for rep in all_results[s]:
            acc_map = {n:acc for n,acc in rep}
            # create accs aligned to labels_grid by forward-fill using last a
            accs = []
            for n in labels_grid:
                if n in acc_map:
                    accs.append(acc_map[n])
                else:
                    # find the largest key <= n
                    keys = [k for k in acc_map.keys() if k <= n]
                    if len(keys) == 0:
                        accs.append(0.0)
                    else:
                        accs.append(acc_map[max(keys)])
            mats.append(accs)
        mats = np.array(mats)
        mean = mats.mean(0)
        ci95 = 1.96 * mats.std(0, ddof=1) / np.sqrt(max(1, mats.shape[0]))
        summary[s] = {'labels': labels_grid, 'mean': mean.tolist(), 'ci': ci9

    # Save JSON
    json_path = os.path.join(DIR, f"summary_e{e_val}.json")
    with open(json_path, "w") as fjson:
        json.dump(summary, fjson, indent=2)

    # Save CSV
    rows = []
    for s in summary:
        for n, m, c in zip(summary[s]['labels'], summary[s]['mean'], summary[
            rows.append({"strategy": s, "labels": n, "accuracy_mean": m, "acc
    csv_path = os.path.join(DIR, f"summary_e{e_val}.csv")
    pd.DataFrame(rows).to_csv(csv_path, index=False)

    # Plot
```

```
    plt.figure(figsize=(10, 6))
    for s in summary:
        x = summary[s]['labels']
        y = summary[s]['mean']
        ci = summary[s]['ci']
        plt.plot(x, y, label=s, linewidth=2)
        plt.fill_between(x, np.array(y) - np.array(ci), np.array(y) + np.arra
    plt.xlabel("Number of labeled examples", fontsize=12)
    plt.ylabel("Test accuracy", fontsize=12)
    plt.title(f"AL strategies (epsilon={e_val})", fontsize=14)
    plt.legend(fontsize=11)
    plt.grid(True, alpha=0.3)
    plt.tight_layout()

    plot_path = os.path.join(DIR, f"al_learning_curves_e{e_val}.png")
    plt.savefig(plot_path, dpi=200, bbox_inches='tight')
    plt.show()

    print(f"✓ Saved: {json_path}")
    print(f"✓ Saved: {csv_path}")
    print(f"✓ Saved: {plot_path}")

print(f"{'='*60}")
print(f"All summaries generated and saved to: {DIR}")
print(f"{'='*60}")
```

```
Found result files: ['al_results_e10.pkl']
```




```
✓ Saved: /content/drive/MyDrive/AL_Results/secondary/summary_e10.json
✓ Saved: /content/drive/MyDrive/AL_Results/secondary/summary_e10.csv
✓ Saved: /content/drive/MyDrive/AL_Results/secondary/al_learning_curves_e10.pn
g
============================================================
All summaries generated and saved to: /content/drive/MyDrive/AL_Results/second
ary
============================================================
```

In [ ]:

```
# ============================================================
# CELL 10: Secondary Experiment: Uniform Random Epsilon per Rep
# ============================================================

# Use a small subset for quick testing
config_secondary = {
    'save_dir': SAVE_DIR + "/tertiary",  # separate folder to avoid overwriti
    'subset': 4000,                       # small subset
    'initial_labels': 100,
    'labeling_budget': 1000,
    'query_batch': 50,
    'max_epochs': 5,                      # fewer epochs for speed
    'strategies': ['random', 'uncertainty', 'diversity'],
    'epsilons': [0.10, 0.15],                   # pick a single epsilon
    'replications': 3,                    # small number of reps
    'seed': 123,
    'early_stopping': True,
    'patience': 2,
    'verbose': True,
    'sample_epsilon_per_rep': True        # uniform random epsilon per repli
}

os.makedirs(config_secondary['save_dir'], exist_ok=True)

# Run the experiment
save_dir_secondary = run_experiment(config_secondary)
print(f"Secondary experiment completed. Results saved to: {save_dir_secondary

# ============================================================
# Load and inspect
# ============================================================
import pickle, json, os, numpy as np, pandas as pd

# Load results
files = [f for f in os.listdir(save_dir_secondary) if f.startswith('al_result
for f in files:
    path = os.path.join(save_dir_secondary, f)
    with open(path, "rb") as fh:
        all_results = pickle.load(fh)
    print(f"\nResults for file: {f}")
    for strat, reps in all_results.items():
        accs = [r[-1][1] for r in reps]  # final accuracy of each replication
        print(f"  Strategy: {strat}, mean final accuracy: {np.mean(accs):.3f}
```

```
Using device: cuda
Experiment configuration:
  Dataset size: 4000
  Initial labels: 100
  Labeling budget: 1000
  Max epochs: 5
  Strategies: ['random', 'uncertainty', 'diversity']
  Epsilon values: [0.1, 0.15] (if sampling enabled, values may be drawn per-re
```

```
plication)
  Replications: 3
  Save directory: /content/drive/MyDrive/AL_Results/tertiary
Total experiments (approx): 18
============================================================
Running epsilon = 0.1
============================================================
  Rep 1/3, Strategy: random, eps=0.0696
Round 0: 100 labels, accuracy=0.1381
Round 1: 150 labels, accuracy=0.1361
Round 2: 200 labels, accuracy=0.1219
Round 3: 250 labels, accuracy=0.1246
Round 4: 300 labels, accuracy=0.1433
Round 5: 350 labels, accuracy=0.1952
Round 6: 400 labels, accuracy=0.2360
Round 7: 450 labels, accuracy=0.2234
Round 8: 500 labels, accuracy=0.2167
Round 9: 550 labels, accuracy=0.2965
Round 10: 600 labels, accuracy=0.3380
Round 11: 650 labels, accuracy=0.3390
Round 12: 700 labels, accuracy=0.3107
Round 13: 750 labels, accuracy=0.3627
Round 14: 800 labels, accuracy=0.3643
Round 15: 850 labels, accuracy=0.3238
Round 16: 900 labels, accuracy=0.3374
Round 17: 950 labels, accuracy=0.3711
Round 18: 1000 labels, accuracy=0.3728
    Completed in 81.1s
    Progress: 1/18 (5.6%)
    Rough ETA (minutes): 23.0
  Rep 1/3, Strategy: uncertainty, eps=0.0696
Round 0: 100 labels, accuracy=0.1381
Round 1: 150 labels, accuracy=0.1125
Round 2: 200 labels, accuracy=0.1132
Round 3: 250 labels, accuracy=0.1410
Round 4: 300 labels, accuracy=0.1617
Round 5: 350 labels, accuracy=0.1590
Round 6: 400 labels, accuracy=0.2185
Round 7: 450 labels, accuracy=0.2265
Round 8: 500 labels, accuracy=0.2231
Round 9: 550 labels, accuracy=0.1650
Round 10: 600 labels, accuracy=0.2494
Round 11: 650 labels, accuracy=0.3302
Round 12: 700 labels, accuracy=0.2522
Round 13: 750 labels, accuracy=0.3046
Round 14: 800 labels, accuracy=0.3169
Round 15: 850 labels, accuracy=0.2863
Round 16: 900 labels, accuracy=0.3064
Round 17: 950 labels, accuracy=0.3592
Round 18: 1000 labels, accuracy=0.2713
    Completed in 103.8s
    Progress: 2/18 (11.1%)
    Rough ETA (minutes): 24.7
  Rep 1/3, Strategy: diversity, eps=0.0696
Round 0: 100 labels, accuracy=0.1381
Round 1: 150 labels, accuracy=0.1346
Round 2: 200 labels, accuracy=0.1114
```

```
            Round 3: 250 labels, accuracy=0.1338
            Round 4: 300 labels, accuracy=0.1622
            Round 5: 350 labels, accuracy=0.1666
            Round 6: 400 labels, accuracy=0.2208
            Round 7: 450 labels, accuracy=0.2325
            Round 8: 500 labels, accuracy=0.2688
            Round 9: 550 labels, accuracy=0.2409
            Round 10: 600 labels, accuracy=0.2791
            Round 11: 650 labels, accuracy=0.2808
            Round 12: 700 labels, accuracy=0.3002
            Round 13: 750 labels, accuracy=0.3092
            Round 14: 800 labels, accuracy=0.3651
            Round 15: 850 labels, accuracy=0.3750
            Round 16: 900 labels, accuracy=0.2706
            Round 17: 950 labels, accuracy=0.3647
            Round 18: 1000 labels, accuracy=0.3928
                Completed in 106.1s
                Progress: 3/18 (16.7%)
                Rough ETA (minutes): 24.3
              Rep 2/3, Strategy: random, eps=0.0106
            Round 0: 100 labels, accuracy=0.2135
            Round 1: 150 labels, accuracy=0.1963
            Round 2: 200 labels, accuracy=0.2161
            Round 3: 250 labels, accuracy=0.1804
            Round 4: 300 labels, accuracy=0.2043
            Round 5: 350 labels, accuracy=0.2138
            Round 6: 400 labels, accuracy=0.2772
            Round 7: 450 labels, accuracy=0.2761
            Round 8: 500 labels, accuracy=0.2701
            Round 9: 550 labels, accuracy=0.2529
            Round 10: 600 labels, accuracy=0.3287
            Round 11: 650 labels, accuracy=0.3489
            Round 12: 700 labels, accuracy=0.3394
            Round 13: 750 labels, accuracy=0.3017
            Round 14: 800 labels, accuracy=0.3375
            Round 15: 850 labels, accuracy=0.3661
            Round 16: 900 labels, accuracy=0.3914
            Round 17: 950 labels, accuracy=0.3696
            Round 18: 1000 labels, accuracy=0.3329
                Completed in 80.5s
                Progress: 4/18 (22.2%)
                Rough ETA (minutes): 21.7
              Rep 2/3, Strategy: uncertainty, eps=0.0106
            Round 0: 100 labels, accuracy=0.2135
            Round 1: 150 labels, accuracy=0.1841
            Round 2: 200 labels, accuracy=0.2134
            Round 3: 250 labels, accuracy=0.2153
            Round 4: 300 labels, accuracy=0.2272
            Round 5: 350 labels, accuracy=0.2636
            Round 6: 400 labels, accuracy=0.2234
            Round 7: 450 labels, accuracy=0.2781
            Round 8: 500 labels, accuracy=0.2419
            Round 9: 550 labels, accuracy=0.2348
            Round 10: 600 labels, accuracy=0.3054
            Round 11: 650 labels, accuracy=0.3173
            Round 12: 700 labels, accuracy=0.2911
            Round 13: 750 labels, accuracy=0.3327
```

```
Round 14: 800 labels, accuracy=0.3694
Round 15: 850 labels, accuracy=0.3276
Round 16: 900 labels, accuracy=0.3205
Round 17: 950 labels, accuracy=0.3749
Round 18: 1000 labels, accuracy=0.3908
    Completed in 104.8s
    Progress: 5/18 (27.8%)
    Rough ETA (minutes): 20.6
  Rep 2/3, Strategy: diversity, eps=0.0106
Round 0: 100 labels, accuracy=0.2135
Round 1: 150 labels, accuracy=0.2043
Round 2: 200 labels, accuracy=0.1874
Round 3: 250 labels, accuracy=0.1955
Round 4: 300 labels, accuracy=0.2264
Round 5: 350 labels, accuracy=0.2456
Round 6: 400 labels, accuracy=0.2505
Round 7: 450 labels, accuracy=0.2700
Round 8: 500 labels, accuracy=0.2818
Round 9: 550 labels, accuracy=0.3257
Round 10: 600 labels, accuracy=0.3705
Round 11: 650 labels, accuracy=0.3207
Round 12: 700 labels, accuracy=0.3429
Round 13: 750 labels, accuracy=0.3642
Round 14: 800 labels, accuracy=0.3762
Round 15: 850 labels, accuracy=0.3548
Round 16: 900 labels, accuracy=0.3583
Round 17: 950 labels, accuracy=0.4098
Round 18: 1000 labels, accuracy=0.3943
    Completed in 106.0s
    Progress: 6/18 (33.3%)
    Rough ETA (minutes): 19.4
  Rep 3/3, Strategy: random, eps=0.0507
Round 0: 100 labels, accuracy=0.1735
Round 1: 150 labels, accuracy=0.1861
Round 2: 200 labels, accuracy=0.1660
Round 3: 250 labels, accuracy=0.1653
Round 4: 300 labels, accuracy=0.2099
Round 5: 350 labels, accuracy=0.1977
Round 6: 400 labels, accuracy=0.2125
Round 7: 450 labels, accuracy=0.2290
Round 8: 500 labels, accuracy=0.3173
Round 9: 550 labels, accuracy=0.3253
Round 10: 600 labels, accuracy=0.3628
Round 11: 650 labels, accuracy=0.3331
Round 12: 700 labels, accuracy=0.3353
Round 13: 750 labels, accuracy=0.3676
Round 14: 800 labels, accuracy=0.3085
Round 15: 850 labels, accuracy=0.3221
Round 16: 900 labels, accuracy=0.3772
Round 17: 950 labels, accuracy=0.3899
Round 18: 1000 labels, accuracy=0.4101
    Completed in 80.6s
    Progress: 7/18 (38.9%)
    Rough ETA (minutes): 17.4
  Rep 3/3, Strategy: uncertainty, eps=0.0507
Round 0: 100 labels, accuracy=0.1735
Round 1: 150 labels, accuracy=0.1985
```

```
Round 2: 200 labels, accuracy=0.1512
Round 3: 250 labels, accuracy=0.1977
Round 4: 300 labels, accuracy=0.2541
Round 5: 350 labels, accuracy=0.2567
Round 6: 400 labels, accuracy=0.2690
Round 7: 450 labels, accuracy=0.2336
Round 8: 500 labels, accuracy=0.3079
Round 9: 550 labels, accuracy=0.3448
Round 10: 600 labels, accuracy=0.3976
Round 11: 650 labels, accuracy=0.3107
Round 12: 700 labels, accuracy=0.3517
Round 13: 750 labels, accuracy=0.3278
Round 14: 800 labels, accuracy=0.3630
Round 15: 850 labels, accuracy=0.3684
Round 16: 900 labels, accuracy=0.3363
Round 17: 950 labels, accuracy=0.3421
Round 18: 1000 labels, accuracy=0.3614
    Completed in 104.9s
    Progress: 8/18 (44.4%)
    Rough ETA (minutes): 16.0
  Rep 3/3, Strategy: diversity, eps=0.0507
Round 0: 100 labels, accuracy=0.1735
Round 1: 150 labels, accuracy=0.2108
Round 2: 200 labels, accuracy=0.2165
Round 3: 250 labels, accuracy=0.1935
Round 4: 300 labels, accuracy=0.2257
Round 5: 350 labels, accuracy=0.2364
Round 6: 400 labels, accuracy=0.2549
Round 7: 450 labels, accuracy=0.2801
Round 8: 500 labels, accuracy=0.2356
Round 9: 550 labels, accuracy=0.3413
Round 10: 600 labels, accuracy=0.2425
Round 11: 650 labels, accuracy=0.3261
Round 12: 700 labels, accuracy=0.3024
Round 13: 750 labels, accuracy=0.3296
Round 14: 800 labels, accuracy=0.3172
Round 15: 850 labels, accuracy=0.3776
Round 16: 900 labels, accuracy=0.3557
Round 17: 950 labels, accuracy=0.3427
Round 18: 1000 labels, accuracy=0.3642
    Completed in 106.6s
    Progress: 9/18 (50.0%)
    Rough ETA (minutes): 14.6
✓ Saved: /content/drive/MyDrive/AL_Results/tertiary/al_results_e10.pkl
============================================================
Running epsilon = 0.15
============================================================
  Rep 1/3, Strategy: random, eps=0.1045
Round 0: 100 labels, accuracy=0.1381
Round 1: 150 labels, accuracy=0.1428
Round 2: 200 labels, accuracy=0.1371
Round 3: 250 labels, accuracy=0.1681
Round 4: 300 labels, accuracy=0.1599
Round 5: 350 labels, accuracy=0.1911
Round 6: 400 labels, accuracy=0.2130
Round 7: 450 labels, accuracy=0.2071
Round 8: 500 labels, accuracy=0.1985
```

```
        Round 9: 550 labels, accuracy=0.2150
        Round 10: 600 labels, accuracy=0.2549
        Round 11: 650 labels, accuracy=0.2807
        Round 12: 700 labels, accuracy=0.2745
        Round 13: 750 labels, accuracy=0.2978
        Round 14: 800 labels, accuracy=0.3187
        Round 15: 850 labels, accuracy=0.3271
        Round 16: 900 labels, accuracy=0.3292
        Round 17: 950 labels, accuracy=0.3782
        Round 18: 1000 labels, accuracy=0.3578
            Completed in 81.4s
            Progress: 10/18 (55.6%)
            Rough ETA (minutes): 12.7
          Rep 1/3, Strategy: uncertainty, eps=0.1045
        Round 0: 100 labels, accuracy=0.1381
        Round 1: 150 labels, accuracy=0.1165
        Round 2: 200 labels, accuracy=0.1399
        Round 3: 250 labels, accuracy=0.1526
        Round 4: 300 labels, accuracy=0.1648
        Round 5: 350 labels, accuracy=0.1613
        Round 6: 400 labels, accuracy=0.2009
        Round 7: 450 labels, accuracy=0.2255
        Round 8: 500 labels, accuracy=0.2507
        Round 9: 550 labels, accuracy=0.2374
        Round 10: 600 labels, accuracy=0.2101
        Round 11: 650 labels, accuracy=0.2463
        Round 12: 700 labels, accuracy=0.2468
        Round 13: 750 labels, accuracy=0.3053
        Round 14: 800 labels, accuracy=0.3199
        Round 15: 850 labels, accuracy=0.2985
        Round 16: 900 labels, accuracy=0.2710
        Round 17: 950 labels, accuracy=0.2932
        Round 18: 1000 labels, accuracy=0.3387
            Completed in 105.0s
            Progress: 11/18 (61.1%)
            Rough ETA (minutes): 11.3
          Rep 1/3, Strategy: diversity, eps=0.1045
        Round 0: 100 labels, accuracy=0.1381
        Round 1: 150 labels, accuracy=0.1379
        Round 2: 200 labels, accuracy=0.1577
        Round 3: 250 labels, accuracy=0.1821
        Round 4: 300 labels, accuracy=0.1969
        Round 5: 350 labels, accuracy=0.1783
        Round 6: 400 labels, accuracy=0.2154
        Round 7: 450 labels, accuracy=0.2278
        Round 8: 500 labels, accuracy=0.2255
        Round 9: 550 labels, accuracy=0.2400
        Round 10: 600 labels, accuracy=0.2926
        Round 11: 650 labels, accuracy=0.2526
        Round 12: 700 labels, accuracy=0.3228
        Round 13: 750 labels, accuracy=0.3393
        Round 14: 800 labels, accuracy=0.3600
        Round 15: 850 labels, accuracy=0.3076
        Round 16: 900 labels, accuracy=0.3296
        Round 17: 950 labels, accuracy=0.3682
        Round 18: 1000 labels, accuracy=0.3315
            Completed in 107.2s
```

```
        Progress: 12/18 (66.7%)
        Rough ETA (minutes): 9.7
      Rep 2/3, Strategy: random, eps=0.0159
    Round 0: 100 labels, accuracy=0.2135
    Round 1: 150 labels, accuracy=0.1963
    Round 2: 200 labels, accuracy=0.2161
    Round 3: 250 labels, accuracy=0.1804
    Round 4: 300 labels, accuracy=0.2043
    Round 5: 350 labels, accuracy=0.2138
    Round 6: 400 labels, accuracy=0.2772
    Round 7: 450 labels, accuracy=0.2761
    Round 8: 500 labels, accuracy=0.2701
    Round 9: 550 labels, accuracy=0.2529
    Round 10: 600 labels, accuracy=0.3287
    Round 11: 650 labels, accuracy=0.3489
    Round 12: 700 labels, accuracy=0.3394
    Round 13: 750 labels, accuracy=0.3017
    Round 14: 800 labels, accuracy=0.3375
    Round 15: 850 labels, accuracy=0.3661
    Round 16: 900 labels, accuracy=0.3914
    Round 17: 950 labels, accuracy=0.3696
    Round 18: 1000 labels, accuracy=0.3329
        Completed in 81.9s
        Progress: 13/18 (72.2%)
        Rough ETA (minutes): 8.0
      Rep 2/3, Strategy: uncertainty, eps=0.0159
    Round 0: 100 labels, accuracy=0.2135
    Round 1: 150 labels, accuracy=0.1841
    Round 2: 200 labels, accuracy=0.2038
    Round 3: 250 labels, accuracy=0.2174
    Round 4: 300 labels, accuracy=0.2271
    Round 5: 350 labels, accuracy=0.2042
    Round 6: 400 labels, accuracy=0.2291
    Round 7: 450 labels, accuracy=0.2283
    Round 8: 500 labels, accuracy=0.2837
    Round 9: 550 labels, accuracy=0.2749
    Round 10: 600 labels, accuracy=0.3823
    Round 11: 650 labels, accuracy=0.3393
    Round 12: 700 labels, accuracy=0.2709
    Round 13: 750 labels, accuracy=0.3108
    Round 14: 800 labels, accuracy=0.3123
    Round 15: 850 labels, accuracy=0.3634
    Round 16: 900 labels, accuracy=0.3662
    Round 17: 950 labels, accuracy=0.3647
    Round 18: 1000 labels, accuracy=0.4146
        Completed in 105.7s
        Progress: 14/18 (77.8%)
        Rough ETA (minutes): 6.5
      Rep 2/3, Strategy: diversity, eps=0.0159
    Round 0: 100 labels, accuracy=0.2135
    Round 1: 150 labels, accuracy=0.2001
    Round 2: 200 labels, accuracy=0.1999
    Round 3: 250 labels, accuracy=0.2330
    Round 4: 300 labels, accuracy=0.2851
    Round 5: 350 labels, accuracy=0.3035
    Round 6: 400 labels, accuracy=0.2609
    Round 7: 450 labels, accuracy=0.2607
```

```
        Round 8: 500 labels, accuracy=0.2219
        Round 9: 550 labels, accuracy=0.3451
        Round 10: 600 labels, accuracy=0.3539
        Round 11: 650 labels, accuracy=0.3402
        Round 12: 700 labels, accuracy=0.3362
        Round 13: 750 labels, accuracy=0.3898
        Round 14: 800 labels, accuracy=0.3872
        Round 15: 850 labels, accuracy=0.3663
        Round 16: 900 labels, accuracy=0.3570
        Round 17: 950 labels, accuracy=0.3288
        Round 18: 1000 labels, accuracy=0.3876
    Completed in 106.4s
    Progress: 15/18 (83.3%)
    Rough ETA (minutes): 4.9
  Rep 3/3, Strategy: random, eps=0.0760
        Round 0: 100 labels, accuracy=0.1735
        Round 1: 150 labels, accuracy=0.1832
        Round 2: 200 labels, accuracy=0.1770
        Round 3: 250 labels, accuracy=0.1846
        Round 4: 300 labels, accuracy=0.2152
        Round 5: 350 labels, accuracy=0.1662
        Round 6: 400 labels, accuracy=0.2204
        Round 7: 450 labels, accuracy=0.2341
        Round 8: 500 labels, accuracy=0.2388
        Round 9: 550 labels, accuracy=0.3190
        Round 10: 600 labels, accuracy=0.2790
        Round 11: 650 labels, accuracy=0.2917
        Round 12: 700 labels, accuracy=0.3301
        Round 13: 750 labels, accuracy=0.3328
        Round 14: 800 labels, accuracy=0.3332
        Round 15: 850 labels, accuracy=0.3863
        Round 16: 900 labels, accuracy=0.3363
        Round 17: 950 labels, accuracy=0.3886
        Round 18: 1000 labels, accuracy=0.3801
    Completed in 81.8s
    Progress: 16/18 (88.9%)
    Rough ETA (minutes): 3.2
  Rep 3/3, Strategy: uncertainty, eps=0.0760
        Round 0: 100 labels, accuracy=0.1735
        Round 1: 150 labels, accuracy=0.1830
        Round 2: 200 labels, accuracy=0.1452
        Round 3: 250 labels, accuracy=0.2042
        Round 4: 300 labels, accuracy=0.2400
        Round 5: 350 labels, accuracy=0.2233
        Round 6: 400 labels, accuracy=0.2562
        Round 7: 450 labels, accuracy=0.2688
        Round 8: 500 labels, accuracy=0.2515
        Round 9: 550 labels, accuracy=0.2724
        Round 10: 600 labels, accuracy=0.3171
        Round 11: 650 labels, accuracy=0.3408
        Round 12: 700 labels, accuracy=0.3300
        Round 13: 750 labels, accuracy=0.3393
        Round 14: 800 labels, accuracy=0.3651
        Round 15: 850 labels, accuracy=0.3466
        Round 16: 900 labels, accuracy=0.3275
        Round 17: 950 labels, accuracy=0.3740
        Round 18: 1000 labels, accuracy=0.3605
```

```
    Completed in 104.6s
    Progress: 17/18 (94.4%)
    Rough ETA (minutes): 1.6
  Rep 3/3, Strategy: diversity, eps=0.0760
Round 0: 100 labels, accuracy=0.1735
Round 1: 150 labels, accuracy=0.1737
Round 2: 200 labels, accuracy=0.1885
Round 3: 250 labels, accuracy=0.1899
Round 4: 300 labels, accuracy=0.2284
Round 5: 350 labels, accuracy=0.2547
Round 6: 400 labels, accuracy=0.2988
Round 7: 450 labels, accuracy=0.2867
Round 8: 500 labels, accuracy=0.2807
Round 9: 550 labels, accuracy=0.3146
Round 10: 600 labels, accuracy=0.3399
Round 11: 650 labels, accuracy=0.3282
Round 12: 700 labels, accuracy=0.3406
Round 13: 750 labels, accuracy=0.3401
Round 14: 800 labels, accuracy=0.3361
Round 15: 850 labels, accuracy=0.3797
Round 16: 900 labels, accuracy=0.3574
Round 17: 950 labels, accuracy=0.3537
Round 18: 1000 labels, accuracy=0.3929
    Completed in 106.1s
    Progress: 18/18 (100.0%)
    Rough ETA (minutes): 0.0
✓ Saved: /content/drive/MyDrive/AL_Results/tertiary/al_results_e15.pkl
============================================================
All experiments completed! Total time: 0.49 hours
Results saved to: /content/drive/MyDrive/AL_Results/tertiary
============================================================
Secondary experiment completed. Results saved to: /content/drive/MyDrive/AL_Re
sults/tertiary

Results for file: al_results_e10.pkl
  Strategy: random, mean final accuracy: 0.372, std: 0.032
  Strategy: uncertainty, mean final accuracy: 0.341, std: 0.051
  Strategy: diversity, mean final accuracy: 0.384, std: 0.014

Results for file: al_results_e15.pkl
  Strategy: random, mean final accuracy: 0.357, std: 0.019
  Strategy: uncertainty, mean final accuracy: 0.371, std: 0.032
  Strategy: diversity, mean final accuracy: 0.371, std: 0.028
```

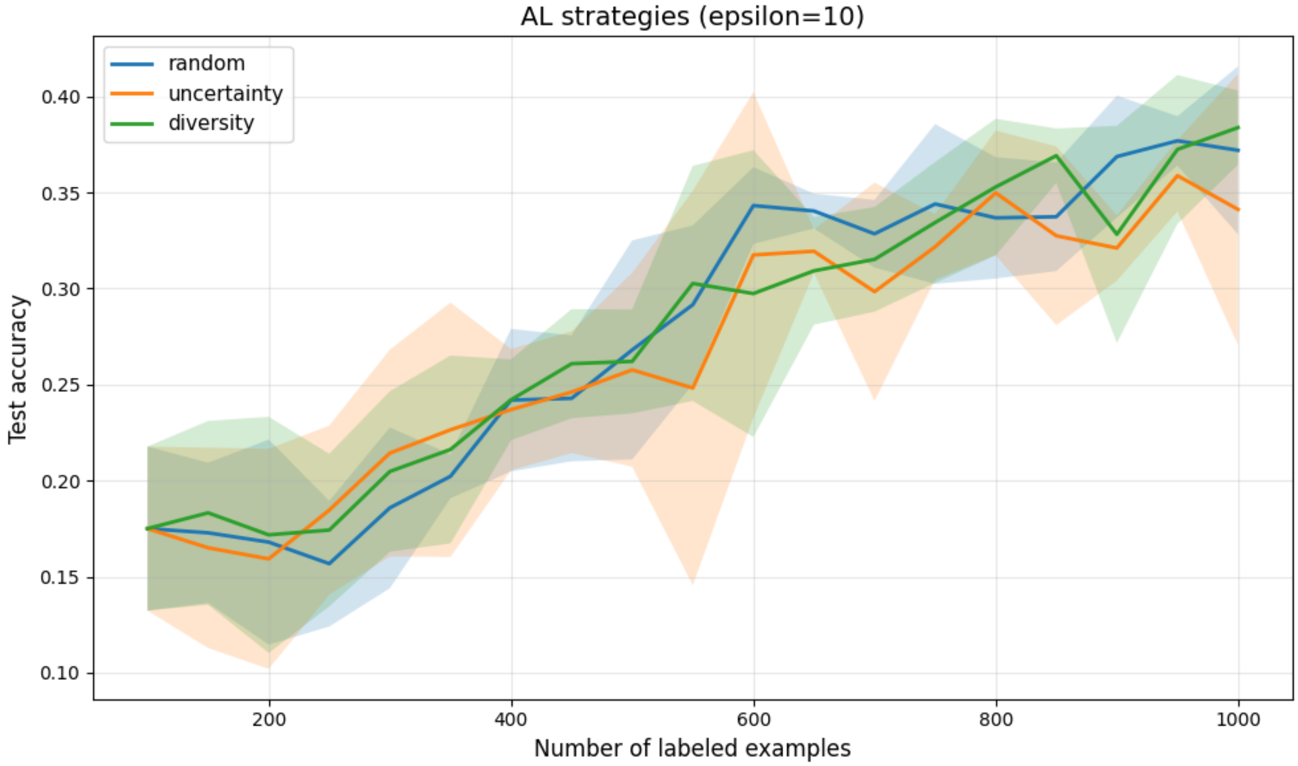
In [ ]:

```python
# ============================================================
# CELL 11: Post-process and visualize
# ============================================================
import pickle
import json
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import os

SUB_DIR = "/tertiary"
```

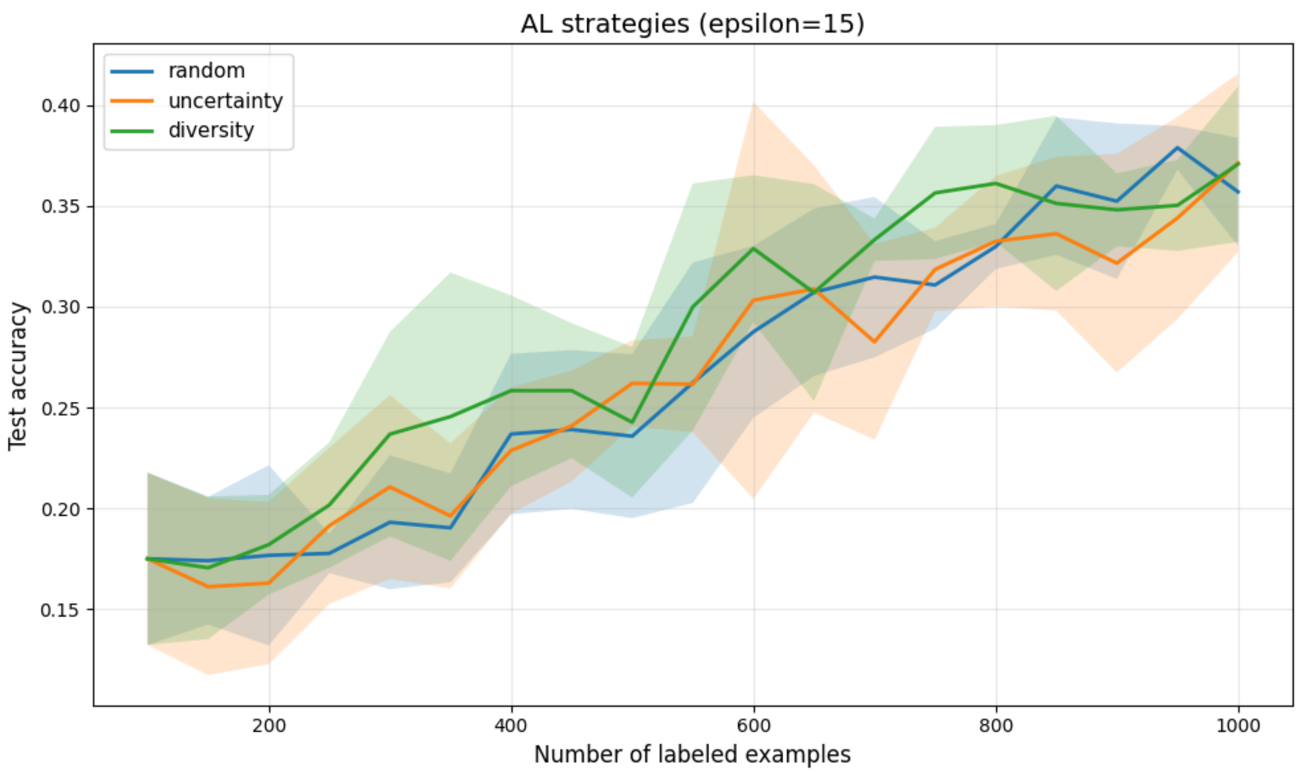
```
DIR = SAVE_DIR + SUB_DIR  # already defined

# helper to load result file for a given epsilon (int percent)
def load_results_for_epsilon(save_dir, e_percent):
    fname = os.path.join(save_dir, f"al_results_e{e_percent}.pkl")
    if not os.path.exists(fname):
        raise FileNotFoundError(f"{fname} not found")
    with open(fname, "rb") as f:
        all_results = pickle.load(f)
    return all_results

# process all saved result files found in SAVE_DIR matching pattern al_result
files = [f for f in os.listdir(DIR) if f.startswith('al_results_e') and f.end
print(f"Found result files: {files}")

for f in files:
    path = os.path.join(DIR, f)
    with open(path, "rb") as fh:
        all_results = pickle.load(fh)
    e_str = f.split('al_results_e')[-1].split('.pkl')[0]
    # normalize e label
    try:
        e_val = int(e_str)
    except Exception:
        e_val = e_str

    summary = {}
    for s in all_results:
        # collect all label counts from all reps
        labels_grid = sorted({n for rep in all_results[s] for n,_ in rep})
        mats = []
        for rep in all_results[s]:
            acc_map = {n:acc for n,acc in rep}
            # create accs aligned to labels_grid by forward-fill using last a
            accs = []
            for n in labels_grid:
                if n in acc_map:
                    accs.append(acc_map[n])
                else:
                    # find the largest key <= n
                    keys = [k for k in acc_map.keys() if k <= n]
                    if len(keys) == 0:
                        accs.append(0.0)
                    else:
                        accs.append(acc_map[max(keys)])
            mats.append(accs)
        mats = np.array(mats)
        mean = mats.mean(0)
        ci95 = 1.96 * mats.std(0, ddof=1) / np.sqrt(max(1, mats.shape[0]))
        summary[s] = {'labels': labels_grid, 'mean': mean.tolist(), 'ci': ci9

    # Save JSON
```

```
    json_path = os.path.join(DIR, f"summary_e{e_val}.json")
    with open(json_path, "w") as fjson:
        json.dump(summary, fjson, indent=2)

    # Save CSV
    rows = []
    for s in summary:
        for n, m, c in zip(summary[s]['labels'], summary[s]['mean'], summary[
            rows.append({"strategy": s, "labels": n, "accuracy_mean": m, "acc
    csv_path = os.path.join(DIR, f"summary_e{e_val}.csv")
    pd.DataFrame(rows).to_csv(csv_path, index=False)

    # Plot
    plt.figure(figsize=(10, 6))
    for s in summary:
        x = summary[s]['labels']
        y = summary[s]['mean']
        ci = summary[s]['ci']
        plt.plot(x, y, label=s, linewidth=2)
        plt.fill_between(x, np.array(y) - np.array(ci), np.array(y) + np.arra
    plt.xlabel("Number of labeled examples", fontsize=12)
    plt.ylabel("Test accuracy", fontsize=12)
    plt.title(f"AL strategies (epsilon={e_val})", fontsize=14)
    plt.legend(fontsize=11)
    plt.grid(True, alpha=0.3)
    plt.tight_layout()

    plot_path = os.path.join(DIR, f"al_learning_curves_e{e_val}.png")
    plt.savefig(plot_path, dpi=200, bbox_inches='tight')
    plt.show()

    print(f"✓ Saved: {json_path}")
    print(f"✓ Saved: {csv_path}")
    print(f"✓ Saved: {plot_path}")

print(f"{'='*60}")
print(f"All summaries generated and saved to: {DIR}")
print(f"{'='*60}")
```

```
Found result files: ['al_results_e10.pkl', 'al_results_e15.pkl']
```




```
✓ Saved: /content/drive/MyDrive/AL_Results/tertiary/summary_e10.json
✓ Saved: /content/drive/MyDrive/AL_Results/tertiary/summary_e10.csv
✓ Saved: /content/drive/MyDrive/AL_Results/tertiary/al_learning_curves_e10.png
```



```
✓ Saved: /content/drive/MyDrive/AL_Results/tertiary/summary_e15.json
✓ Saved: /content/drive/MyDrive/AL_Results/tertiary/summary_e15.csv
✓ Saved: /content/drive/MyDrive/AL_Results/tertiary/al_learning_curves_e15.png
============================================================
All summaries generated and saved to: /content/drive/MyDrive/AL_Results/tertia
ry
============================================================
```

In [ ]:

```python
# ============================================================
# CELL 12: Final Robust Experiment (Full Scale, Stochastic Noise)
# ============================================================

config_robust = {
    'save_dir': SAVE_DIR + "/robust_stochastic",
    'subset': None,
    'initial_labels': 100,
    'labeling_budget': 2000,
    'query_batch': 100,
    'max_epochs': 10,
    'strategies': ['random', 'uncertainty', 'diversity'],
    'epsilons': [0.15],
    'sample_epsilon_per_rep': True,
    'replications': 5,
    'seed': 999, # New seed to ensure independence
    'early_stopping': True,
    'patience': 3,
    'verbose': True
}

# Run it
print(f"Starting Robust Stochastic Run...")
results_dir = run_experiment(config_robust)
print(f"\n✓ Robust results saved to: {results_dir}")
```

```
Starting Robust Stochastic Run...
Using device: cuda
100%|██████████| 170M/170M [00:13<00:00, 12.5MB/s]
Experiment configuration:
  Dataset size: 50000
  Initial labels: 100
  Labeling budget: 2000
  Max epochs: 10
  Strategies: ['random', 'uncertainty', 'diversity']
  Epsilon values: [0.15] (if sampling enabled, values may be drawn per-replica
tion)
  Replications: 5
  Save directory: /content/drive/MyDrive/AL_Results/robust_stochastic
Total experiments (approx): 15
============================================================
Running epsilon = 0.15
============================================================
  Rep 1/5, Strategy: random, eps=0.1205
  Early stopping at epoch 7
Round 0: 100 labels, accuracy=0.1669
```

```
Round 1: 200 labels, accuracy=0.2478
Round 2: 300 labels, accuracy=0.3061
Round 3: 400 labels, accuracy=0.3175
Round 4: 500 labels, accuracy=0.3476
Round 5: 600 labels, accuracy=0.3837
Round 6: 700 labels, accuracy=0.3837
Round 7: 800 labels, accuracy=0.3806
Round 8: 900 labels, accuracy=0.3920
Round 9: 1000 labels, accuracy=0.4130
Round 10: 1100 labels, accuracy=0.4281
Round 11: 1200 labels, accuracy=0.4663
Round 12: 1300 labels, accuracy=0.4686
Round 13: 1400 labels, accuracy=0.4358
Round 14: 1500 labels, accuracy=0.4888
Round 15: 1600 labels, accuracy=0.4935
Round 16: 1700 labels, accuracy=0.4627
Round 17: 1800 labels, accuracy=0.4420
Round 18: 1900 labels, accuracy=0.5060
Round 19: 2000 labels, accuracy=0.5006
    Completed in 209.2s
    Progress: 1/15 (6.7%)
    Rough ETA (minutes): 48.9
  Rep 1/5, Strategy: uncertainty, eps=0.1205
  Early stopping at epoch 7
Round 0: 100 labels, accuracy=0.1669
Round 1: 200 labels, accuracy=0.2160
Round 2: 300 labels, accuracy=0.2775
Round 3: 400 labels, accuracy=0.3345
Round 4: 500 labels, accuracy=0.3907
Round 5: 600 labels, accuracy=0.3720
Round 6: 700 labels, accuracy=0.2975
Round 7: 800 labels, accuracy=0.4333
Round 8: 900 labels, accuracy=0.3641
  Early stopping at epoch 9
Round 9: 1000 labels, accuracy=0.4042
Round 10: 1100 labels, accuracy=0.4231
Round 11: 1200 labels, accuracy=0.3981
Round 12: 1300 labels, accuracy=0.4236
Round 13: 1400 labels, accuracy=0.4505
Round 14: 1500 labels, accuracy=0.4770
Round 15: 1600 labels, accuracy=0.4257
Round 16: 1700 labels, accuracy=0.4106
Round 17: 1800 labels, accuracy=0.4407
Round 18: 1900 labels, accuracy=0.4661
  Early stopping at epoch 7
Round 19: 2000 labels, accuracy=0.3391
    Completed in 536.8s
    Progress: 2/15 (13.3%)
    Rough ETA (minutes): 80.8
  Rep 1/5, Strategy: diversity, eps=0.1205
  Early stopping at epoch 7
Round 0: 100 labels, accuracy=0.1669
Round 1: 200 labels, accuracy=0.2844
Round 2: 300 labels, accuracy=0.3139
Round 3: 400 labels, accuracy=0.3364
Round 4: 500 labels, accuracy=0.3692
Round 5: 600 labels, accuracy=0.3921
```

```
Round 6: 700 labels, accuracy=0.3717
Round 7: 800 labels, accuracy=0.3919
Round 8: 900 labels, accuracy=0.4058
Round 9: 1000 labels, accuracy=0.4121
Round 10: 1100 labels, accuracy=0.4139
Round 11: 1200 labels, accuracy=0.4503
Round 12: 1300 labels, accuracy=0.4337
Round 13: 1400 labels, accuracy=0.4793
Round 14: 1500 labels, accuracy=0.4368
Round 15: 1600 labels, accuracy=0.4800
Round 16: 1700 labels, accuracy=0.4662
Round 17: 1800 labels, accuracy=0.4659
Round 18: 1900 labels, accuracy=0.5012
Round 19: 2000 labels, accuracy=0.4632
    Completed in 547.0s
    Progress: 3/15 (20.0%)
    Rough ETA (minutes): 86.2
  Rep 2/5, Strategy: random, eps=0.0980
Round 0: 100 labels, accuracy=0.2347
Round 1: 200 labels, accuracy=0.2617
Round 2: 300 labels, accuracy=0.3170
Round 3: 400 labels, accuracy=0.3472
Round 4: 500 labels, accuracy=0.3245
Round 5: 600 labels, accuracy=0.3923
Round 6: 700 labels, accuracy=0.3678
Round 7: 800 labels, accuracy=0.4100
Round 8: 900 labels, accuracy=0.3762
Round 9: 1000 labels, accuracy=0.4102
Round 10: 1100 labels, accuracy=0.4357
Round 11: 1200 labels, accuracy=0.3852
Round 12: 1300 labels, accuracy=0.4385
Round 13: 1400 labels, accuracy=0.4173
  Early stopping at epoch 9
Round 14: 1500 labels, accuracy=0.3749
Round 15: 1600 labels, accuracy=0.4701
Round 16: 1700 labels, accuracy=0.4752
Round 17: 1800 labels, accuracy=0.4651
Round 18: 1900 labels, accuracy=0.4766
Round 19: 2000 labels, accuracy=0.5214
    Completed in 207.8s
    Progress: 4/15 (26.7%)
    Rough ETA (minutes): 68.8
  Rep 2/5, Strategy: uncertainty, eps=0.0980
Round 0: 100 labels, accuracy=0.2347
  Early stopping at epoch 8
Round 1: 200 labels, accuracy=0.1806
Round 2: 300 labels, accuracy=0.3159
Round 3: 400 labels, accuracy=0.2657
Round 4: 500 labels, accuracy=0.3334
Round 5: 600 labels, accuracy=0.3650
Round 6: 700 labels, accuracy=0.3940
Round 7: 800 labels, accuracy=0.3418
Round 8: 900 labels, accuracy=0.3657
Round 9: 1000 labels, accuracy=0.3351
Round 10: 1100 labels, accuracy=0.3863
Round 11: 1200 labels, accuracy=0.4016
Round 12: 1300 labels, accuracy=0.3992
```

```
Round 13: 1400 labels, accuracy=0.3916
Round 14: 1500 labels, accuracy=0.3919
Round 15: 1600 labels, accuracy=0.4479
Round 16: 1700 labels, accuracy=0.4592
Round 17: 1800 labels, accuracy=0.4212
Round 18: 1900 labels, accuracy=0.4452
Round 19: 2000 labels, accuracy=0.4687
    Completed in 549.1s
    Progress: 5/15 (33.3%)
    Rough ETA (minutes): 68.3
  Rep 2/5, Strategy: diversity, eps=0.0980
Round 0: 100 labels, accuracy=0.2347
Round 1: 200 labels, accuracy=0.2069
Round 2: 300 labels, accuracy=0.2974
Round 3: 400 labels, accuracy=0.3147
Round 4: 500 labels, accuracy=0.3702
Round 5: 600 labels, accuracy=0.3782
Round 6: 700 labels, accuracy=0.4048
Round 7: 800 labels, accuracy=0.4076
Round 8: 900 labels, accuracy=0.3971
Round 9: 1000 labels, accuracy=0.4214
  Early stopping at epoch 9
Round 10: 1100 labels, accuracy=0.3882
Round 11: 1200 labels, accuracy=0.4145
Round 12: 1300 labels, accuracy=0.4385
Round 13: 1400 labels, accuracy=0.4444
Round 14: 1500 labels, accuracy=0.4485
Round 15: 1600 labels, accuracy=0.4628
Round 16: 1700 labels, accuracy=0.4658
Round 17: 1800 labels, accuracy=0.4309
Round 18: 1900 labels, accuracy=0.4744
Round 19: 2000 labels, accuracy=0.4817
    Completed in 550.2s
    Progress: 6/15 (40.0%)
    Rough ETA (minutes): 65.0
  Rep 3/5, Strategy: random, eps=0.0459
  Early stopping at epoch 6
Round 0: 100 labels, accuracy=0.1361
Round 1: 200 labels, accuracy=0.2892
Round 2: 300 labels, accuracy=0.3358
Round 3: 400 labels, accuracy=0.3397
Round 4: 500 labels, accuracy=0.3708
Round 5: 600 labels, accuracy=0.4012
Round 6: 700 labels, accuracy=0.4036
Round 7: 800 labels, accuracy=0.4356
Round 8: 900 labels, accuracy=0.4047
Round 9: 1000 labels, accuracy=0.4300
Round 10: 1100 labels, accuracy=0.4331
Round 11: 1200 labels, accuracy=0.4577
Round 12: 1300 labels, accuracy=0.4840
Round 13: 1400 labels, accuracy=0.3687
Round 14: 1500 labels, accuracy=0.4744
Round 15: 1600 labels, accuracy=0.4483
Round 16: 1700 labels, accuracy=0.4964
Round 17: 1800 labels, accuracy=0.4910
Round 18: 1900 labels, accuracy=0.5160
Round 19: 2000 labels, accuracy=0.5137
```

```
        Completed in 207.3s
        Progress: 7/15 (46.7%)
        Rough ETA (minutes): 53.5
      Rep 3/5, Strategy: uncertainty, eps=0.0459
      Early stopping at epoch 6
    Round 0: 100 labels, accuracy=0.1361
      Early stopping at epoch 6
    Round 1: 200 labels, accuracy=0.1838
    Round 2: 300 labels, accuracy=0.2890
    Round 3: 400 labels, accuracy=0.3022
    Round 4: 500 labels, accuracy=0.3376
      Early stopping at epoch 8
    Round 5: 600 labels, accuracy=0.3116
      Early stopping at epoch 8
    Round 6: 700 labels, accuracy=0.3002
    Round 7: 800 labels, accuracy=0.3891
    Round 8: 900 labels, accuracy=0.3929
    Round 9: 1000 labels, accuracy=0.4029
    Round 10: 1100 labels, accuracy=0.3985
    Round 11: 1200 labels, accuracy=0.4114
    Round 12: 1300 labels, accuracy=0.3740
    Round 13: 1400 labels, accuracy=0.4421
    Round 14: 1500 labels, accuracy=0.4829
    Round 15: 1600 labels, accuracy=0.4688
    Round 16: 1700 labels, accuracy=0.4751
    Round 17: 1800 labels, accuracy=0.4531
    Round 18: 1900 labels, accuracy=0.5175
    Round 19: 2000 labels, accuracy=0.5023
        Completed in 534.2s
        Progress: 8/15 (53.3%)
        Rough ETA (minutes): 48.7
      Rep 3/5, Strategy: diversity, eps=0.0459
      Early stopping at epoch 6
    Round 0: 100 labels, accuracy=0.1361
    Round 1: 200 labels, accuracy=0.2350
    Round 2: 300 labels, accuracy=0.2990
    Round 3: 400 labels, accuracy=0.3454
    Round 4: 500 labels, accuracy=0.3577
    Round 5: 600 labels, accuracy=0.4000
    Round 6: 700 labels, accuracy=0.4256
    Round 7: 800 labels, accuracy=0.4328
    Round 8: 900 labels, accuracy=0.4277
    Round 9: 1000 labels, accuracy=0.4395
      Early stopping at epoch 10
    Round 10: 1100 labels, accuracy=0.4183
    Round 11: 1200 labels, accuracy=0.4458
      Early stopping at epoch 7
    Round 12: 1300 labels, accuracy=0.3622
    Round 13: 1400 labels, accuracy=0.4472
    Round 14: 1500 labels, accuracy=0.4790
    Round 15: 1600 labels, accuracy=0.3959
    Round 16: 1700 labels, accuracy=0.4874
    Round 17: 1800 labels, accuracy=0.4673
    Round 18: 1900 labels, accuracy=0.4858
    Round 19: 2000 labels, accuracy=0.4773
        Completed in 537.3s
        Progress: 9/15 (60.0%)
```

```
    Rough ETA (minutes): 43.1
  Rep 4/5, Strategy: random, eps=0.0193
  Early stopping at epoch 9
Round 0: 100 labels, accuracy=0.2202
Round 1: 200 labels, accuracy=0.2511
Round 2: 300 labels, accuracy=0.3573
Round 3: 400 labels, accuracy=0.3928
Round 4: 500 labels, accuracy=0.4237
Round 5: 600 labels, accuracy=0.4013
Round 6: 700 labels, accuracy=0.4447
  Early stopping at epoch 9
Round 7: 800 labels, accuracy=0.4279
Round 8: 900 labels, accuracy=0.4119
Round 9: 1000 labels, accuracy=0.4500
Round 10: 1100 labels, accuracy=0.4331
Round 11: 1200 labels, accuracy=0.4708
Round 12: 1300 labels, accuracy=0.4984
Round 13: 1400 labels, accuracy=0.4782
Round 14: 1500 labels, accuracy=0.4731
Round 15: 1600 labels, accuracy=0.4992
Round 16: 1700 labels, accuracy=0.4957
Round 17: 1800 labels, accuracy=0.4976
Round 18: 1900 labels, accuracy=0.5376
Round 19: 2000 labels, accuracy=0.5199
    Completed in 205.4s
    Progress: 10/15 (66.7%)
    Rough ETA (minutes): 34.0
  Rep 4/5, Strategy: uncertainty, eps=0.0193
  Early stopping at epoch 9
Round 0: 100 labels, accuracy=0.2202
Round 1: 200 labels, accuracy=0.2084
  Early stopping at epoch 6
Round 2: 300 labels, accuracy=0.1645
Round 3: 400 labels, accuracy=0.3179
Round 4: 500 labels, accuracy=0.4033
  Early stopping at epoch 9
Round 5: 600 labels, accuracy=0.3852
Round 6: 700 labels, accuracy=0.3954
Round 7: 800 labels, accuracy=0.3725
Round 8: 900 labels, accuracy=0.3790
Round 9: 1000 labels, accuracy=0.3979
Round 10: 1100 labels, accuracy=0.3607
Round 11: 1200 labels, accuracy=0.4551
Round 12: 1300 labels, accuracy=0.4593
Round 13: 1400 labels, accuracy=0.4244
Round 14: 1500 labels, accuracy=0.4321
```

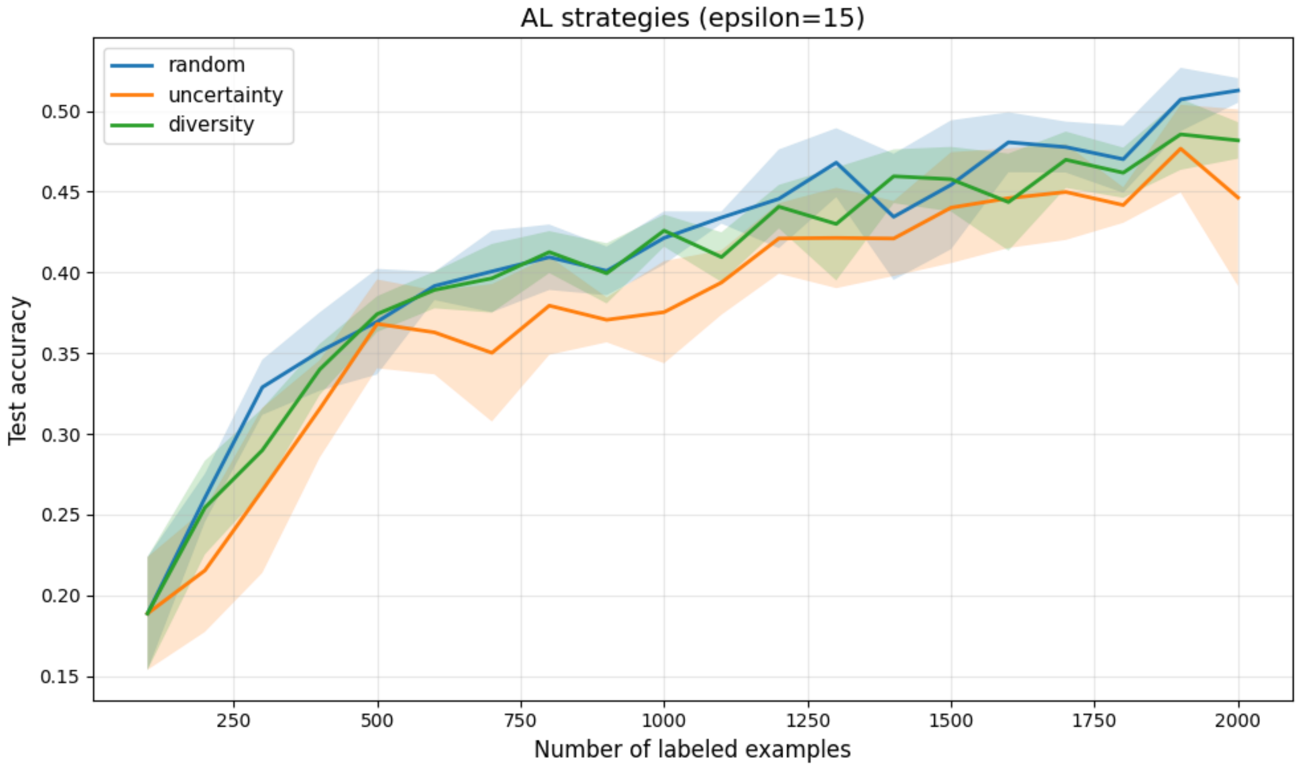
In [ ]:

```python
# ============================================================
# CELL 13: Post-process and visualize
# ============================================================
import pickle
import json
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

```
import os

SUB_DIR = "/robust_stochastic"

DIR = SAVE_DIR + SUB_DIR

# Process all saved result files found in SAVE_DIR matching pattern al_result
files = [f for f in os.listdir(DIR) if f.startswith('al_results_e') and f.end
print(f"Found result files: {files}")

for f in files:
    path = os.path.join(DIR, f)
    with open(path, "rb") as fh:
        all_results = pickle.load(fh)
    e_str = f.split('al_results_e')[-1].split('.pkl')[0]
    try:
        e_val = int(e_str)
    except Exception:
        e_val = e_str

    summary = {}
    for s in all_results:
        labels_grid = sorted({n for rep in all_results[s] for n,_ in rep})
        mats = []
        for rep in all_results[s]:
            acc_map = {n:acc for n,acc in rep}
            accs = []
            for n in labels_grid:
                if n in acc_map:
                    accs.append(acc_map[n])
                else:
                    keys = [k for k in acc_map.keys() if k <= n]
                    if len(keys) == 0:
                        accs.append(0.0)
                    else:
                        accs.append(acc_map[max(keys)])
            mats.append(accs)
        mats = np.array(mats)
        mean = mats.mean(0)
        ci95 = 1.96 * mats.std(0, ddof=1) / np.sqrt(max(1, mats.shape[0]))
        summary[s] = {'labels': labels_grid, 'mean': mean.tolist(), 'ci': ci9

    # Save JSON
    json_path = os.path.join(DIR, f"summary_e{e_val}.json")
    with open(json_path, "w") as fjson:
        json.dump(summary, fjson, indent=2)

    # Save CSV
    rows = []
    for s in summary:
        for n, m, c in zip(summary[s]['labels'], summary[s]['mean'], summary[
            rows.append({"strategy": s, "labels": n, "accuracy_mean": m, "acc
    csv_path = os.path.join(DIR, f"summary_e{e_val}.csv")
```

```
    pd.DataFrame(rows).to_csv(csv_path, index=False)

    # Plot
    plt.figure(figsize=(10, 6))
    for s in summary:
        x = summary[s]['labels']
        y = summary[s]['mean']
        ci = summary[s]['ci']
        plt.plot(x, y, label=s, linewidth=2)
        plt.fill_between(x, np.array(y) - np.array(ci), np.array(y) + np.arra
    plt.xlabel("Number of labeled examples", fontsize=12)
    plt.ylabel("Test accuracy", fontsize=12)
    plt.title(f"AL strategies (epsilon={e_val})", fontsize=14)
    plt.legend(fontsize=11)
    plt.grid(True, alpha=0.3)
    plt.tight_layout()

    plot_path = os.path.join(DIR, f"al_learning_curves_e{e_val}.png")
    plt.savefig(plot_path, dpi=200, bbox_inches='tight')
    plt.show()

    print(f"✓ Saved: {json_path}")
    print(f"✓ Saved: {csv_path}")
    print(f"✓ Saved: {plot_path}")

print(f"{'='*60}")
print(f"All summaries generated and saved to: {DIR}")
print(f"{'='*60}")
```

```
Found result files: ['al_results_e15.pkl']
```




```
✓ Saved: /content/drive/MyDrive/AL_Results/robust_stochastic/summary_e15.json
✓ Saved: /content/drive/MyDrive/AL_Results/robust_stochastic/summary_e15.csv
✓ Saved: /content/drive/MyDrive/AL_Results/robust_stochastic/al_learning_curve
s_e15.png
============================================================
All summaries generated and saved to: /content/drive/MyDrive/AL_Results/robust
_stochastic
============================================================
```

In [ ]:

```python
# ============================================================
# CELL 14: Statistical Analysis of Full Scale, Stochastic Noise Experiment
# ============================================================

import numpy as np
import pandas as pd
import pickle
import os
from scipy import stats
import statsmodels.api as sm
from statsmodels.formula.api import ols
from statsmodels.stats.multicomp import pairwise_tukeyhsd

# Load the specific stochastic results
# Note: The file is named 'e15' because 0.15 was the upper bound config param
stochastic_path = os.path.join(SAVE_DIR, "robust_stochastic", "al_results_e15
print(f"Loading results from: {stochastic_path}")

with open(stochastic_path, "rb") as f:
    all_results = pickle.load(f)
```

```
# Parse into DataFrame
data_rows = []
for strat, reps in all_results.items():
    for rep_idx, rep_data in enumerate(reps):
        for labels, acc in rep_data:
            data_rows.append({
                "strategy": strat,
                "rep": rep_idx,
                "labels": labels,
                "accuracy": acc,
                "condition": "Stochastic (0-15%)"
            })

df = pd.DataFrame(data_rows)
print(f"Data loaded: {len(df)} rows across {len(df['rep'].unique())} replicat

# Compute AULC (Area Under Learning Curve)
print("\nComputing AULC per replication...")
aulc_rows = []
# Group by strategy and replication (condition is constant)
for (strat, rep), g in df.groupby(["strategy", "rep"]):
    g_sorted = g.sort_values("labels")
    # Trapz computes area under the curve
    auc_val = np.trapz(g_sorted["accuracy"], g_sorted["labels"])
    aulc_rows.append({
        "strategy": strat,
        "rep": rep,
        "aulc": auc_val
    })

aulc_df = pd.DataFrame(aulc_rows)
print(aulc_df.head())

# Run One-Way ANOVA (Strategy)
print("\n=============================")
print("ANOVA: Stochastic Noise Condition")
print("=============================")

model = ols("aulc ~ C(strategy)", data=aulc_df).fit()
anova_table = sm.stats.anova_lm(model, typ=2)
print(anova_table)

# Tukey HSD Post-Hoc Test
print("\nPost-hoc Tukey HSD:")
tukey = pairwise_tukeyhsd(aulc_df["aulc"], aulc_df["strategy"])
print(tukey)

# Effect Sizes (Eta-squared & Cohen's d)
def etasquared(anova_tbl):
    return anova_tbl.loc["C(strategy)", "sum_sq"] / anova_tbl["sum_sq"].sum()

def cohend(x, y):
```

```
    # Pooled standard deviation
    n1, n2 = len(x), len(y)
    var1, var2 = np.var(x, ddof=1), np.var(y, ddof=1)
    pool_sd = np.sqrt(((n1-1)*var1 + (n2-1)*var2) / (n1+n2-2))
    return (np.mean(x) - np.mean(y)) / pool_sd

print("\n===============================")
print("Effect Sizes")
print("===============================")

eta2 = etasquared(anova_table)
print(f"η² (Global effect size of strategy): {eta2:.3f}")
print("Interpretation: <0.06 (small), 0.06-0.14 (medium), >0.14 (large)\n")

strategies = aulc_df["strategy"].unique()
for i, s1 in enumerate(strategies):
    for s2 in strategies[i+1:]:
        group1 = aulc_df[aulc_df.strategy == s1]["aulc"]
        group2 = aulc_df[aulc_df.strategy == s2]["aulc"]

        d = cohend(group1, group2)
        print(f"Cohen's d ({s1} vs {s2}): {d:.3f}")
```

```
Loading results from: /content/drive/MyDrive/AL_Results/robust_stochastic/al_r
esults_e15.pkl
Data loaded: 300 rows across 5 replications.

Computing AULC per replication...
    strategy  rep     aulc
0  diversity    0  771.985
1  diversity    1  752.450
2  diversity    2  765.830
3  diversity    3  782.105
4  diversity    4  764.910

============================
ANOVA: Stochastic Noise Condition
============================
                   sum_sq    df          F    PR(>F)
C(strategy)  10329.653303   2.0  12.74649  0.001075
Residual      4862.352020  12.0       NaN       NaN

Post-hoc Tukey HSD:
/tmp/ipython-input-1321323608.py:45: DeprecationWarning: `trapz` is deprecate
d. Use `trapezoid` instead, or one of the numerical integration functions in `
scipy.integrate`.
  auc_val = np.trapz(g_sorted["accuracy"], g_sorted["labels"])
     Multiple Comparison of Means - Tukey HSD, FWER=0.05
==============================================================
  group1     group2   meandiff p-adj   lower    upper   reject
--------------------------------------------------------------
diversity      random   18.099 0.3612 -15.8656  52.0636  False
diversity uncertainty  -44.366 0.0116 -78.3306 -10.4014   True
   random uncertainty  -62.465  0.001 -96.4296 -28.5004   True
--------------------------------------------------------------

============================
Effect Sizes
============================
η² (Global effect size of strategy): 0.680
Interpretation: <0.06 (small), 0.06-0.14 (medium), >0.14 (large)

Cohen's d (diversity vs random): -0.814
Cohen's d (diversity vs uncertainty): 3.382
Cohen's d (random vs uncertainty): 2.666
```