Report: Active Learning for Power Grid Security Classification

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1. Introduction

- Brief description of the problem (e.g., power grid security assessment)
- Objective of the task: using active learning to improve binary classification efficiency

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2. Dataset Description

- **Source**: Dataset created using `prepare_dataset.py` by combining:
  - `distributed_generators.csv`
  - `distributed_loads_uniform.csv`
- **Size**: 8769 rows × 273 columns
- **Features**:
  - `timestamp`: simulation timestamp (not a real time series)
  - `status`: secure/insecure label
  - `max_line_loading_percent_*`: highest line loading
  - `min/max_bus_voltage_pu_*`: voltage limits
  - `load_*`, `gen_*`, `sgen_*`: active power (in MW) for loads, generators, and static generators

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3. Simulation Context

- Each row represents an **independent N-1 contingency simulation**
- Simulations are **short-term synthetic events** (seconds to minutes)
- **No real-world chronological time** — data is **not a time series**

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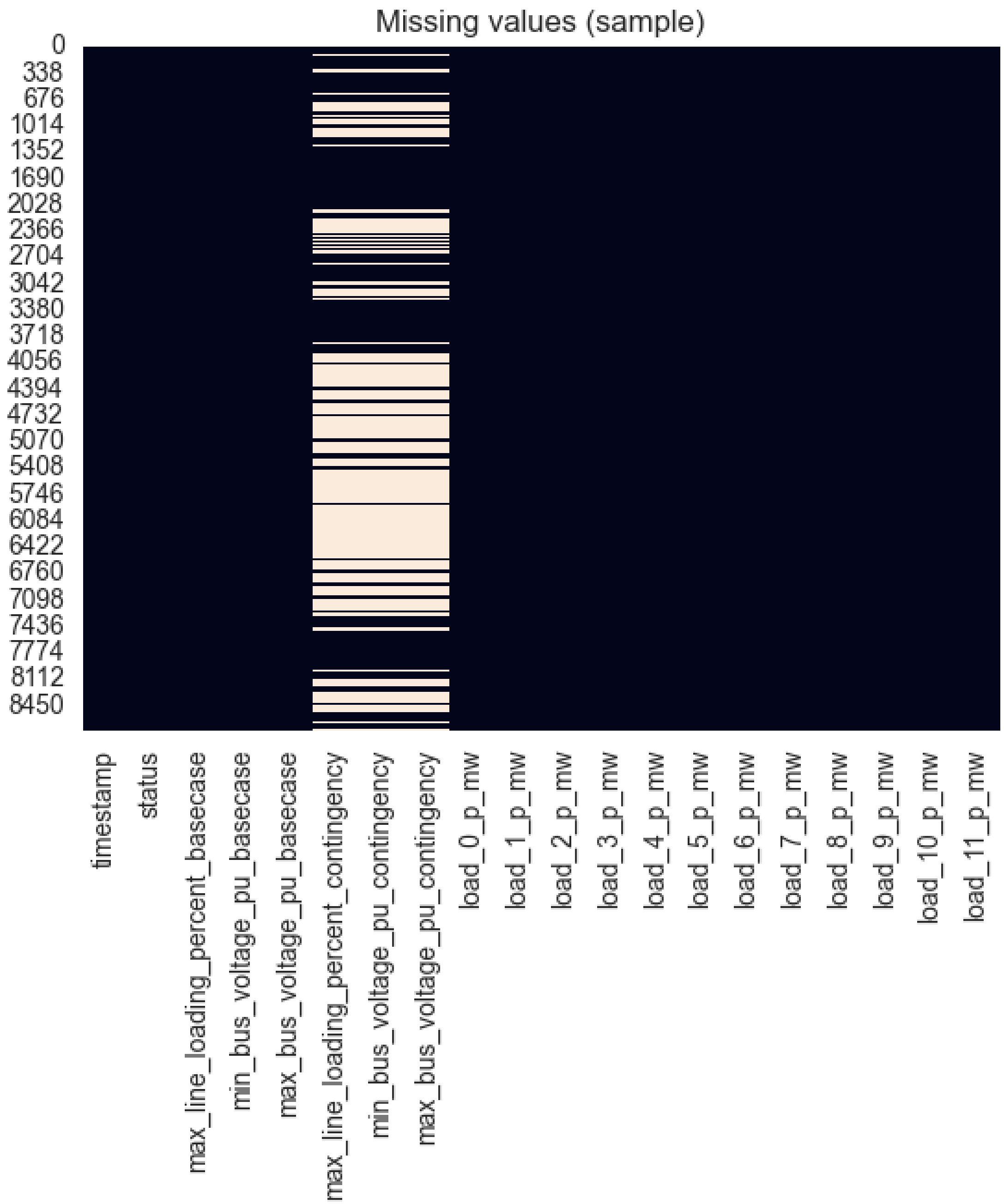
4. Exploratory Data Analysis (EDA)

Class Distribution

- `secure`: 4497 samples
- `insecure`: 4272 samples

Missing Values

- Only 3 features contain missing values:
  - `max_line_loading_percent_contingency`
  - `min_bus_voltage_pu_contingency`
  - `max_bus_voltage_pu_contingency`



For more detailed analysis and visualizations related to the dataset, refer to the full EDA report:

EDA Report
Path: `smart-energy-ml-analysis-jsi/reports/eda_classifier_report.md`

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5. Data Preparation

Two data splitting approaches were used in the experiments:

Manual Temporal Split (more frequent)

- First 90% of the dataset used as **training pool** (`X_pool`, `y_pool`)
- Last 10% used as the **validation set** (`X_val`, `y_val`)
- While the dataset has a `timestamp` column, it **does not reflect real-world temporal dependence**, so a manual chronological split was used for simulation consistency.

Random Train/Test Split

- Used `train_test_split()` from scikit-learn with a 90/10 split ratio
- Enabled **random shuffling**, suitable because data samples are independent simulation runs

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Additional Notes

- **Label Encoding**:
  - Column `status` was converted to `status_binary`:
    `"secure"` → `1`, `"insecure"` → `0`
- **Feature Selection**:
  - The following columns were removed:
    `timestamp`, `status`, `status_binary`, and contingency/basecase voltage/loading features.
- **Normalization**:
  - Not applied, since **Random Forests** are insensitive to feature scales.

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6. Active Learning Setup

Strategies Compared

- `random`
- `uncertainty sampling`
- `entropy-based`
- `margin sampling`

Parameters

- `initial_size`: e.g., 100
- `batch_size`: e.g., 50
- `test_size`: 10%
- Up to 100 **iterations** used
- **Metrics tracked**:
  - Final accuracy
  - Accuracy mean and standard deviation
  - Execution time

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7. Results

7.1 Overview Table

The full table with all active learning runs and evaluation metrics is available here:

active_learning_runs_v1.csv
Path: `smart-energy-ml-analysis-jsi/tables/active_learning_runs_v1.csv`

7.2 Visualizations

Two folders contain the generated figures, depending on the data splitting strategy used:

Figures from Train/Test Split

Path: `smart-energy-ml-analysis-jsi/figures/al_train_test_split/`

Contains plots generated using random `train_test_split`.

Figures from Manual Temporal Split

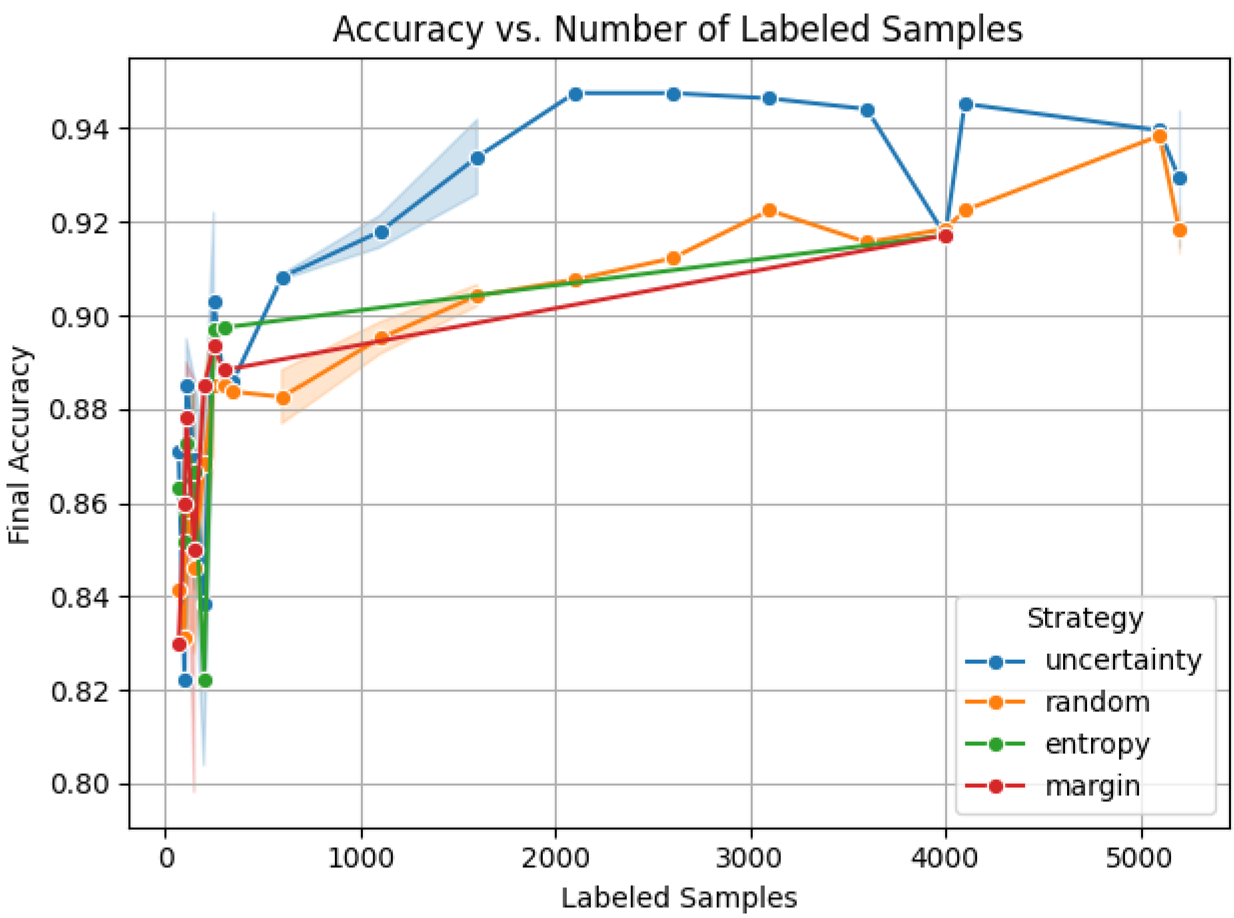
Path: `smart-energy-ml-analysis-jsi/figures/al_temporal_split/`

Contains similar visualizations, but generated using **manual temporal splitting**, where earlier data is used for training and later for validation.

7.2 Visualizations

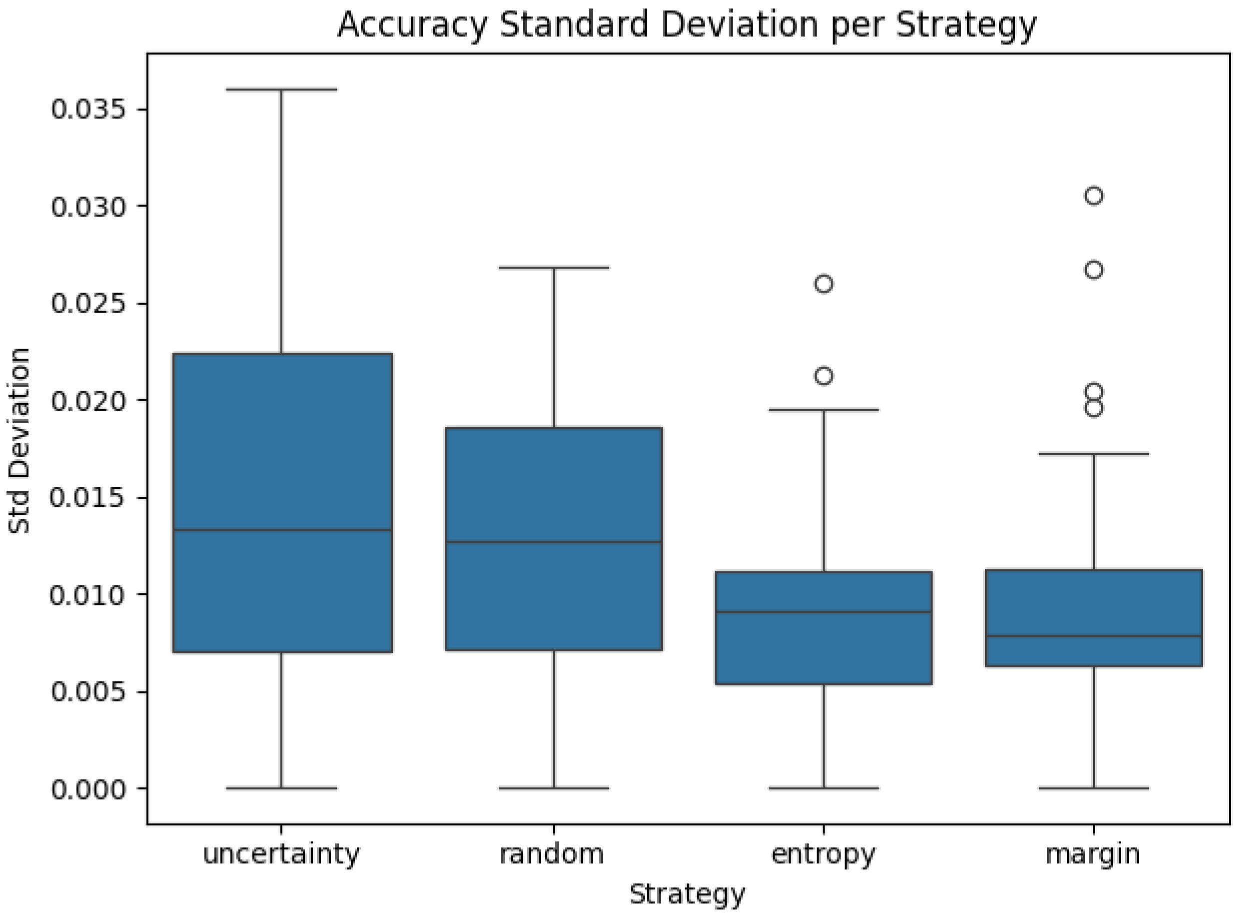
Accuracy vs. Number of Labeled Samples

Shows how accuracy evolves as more samples are labeled.



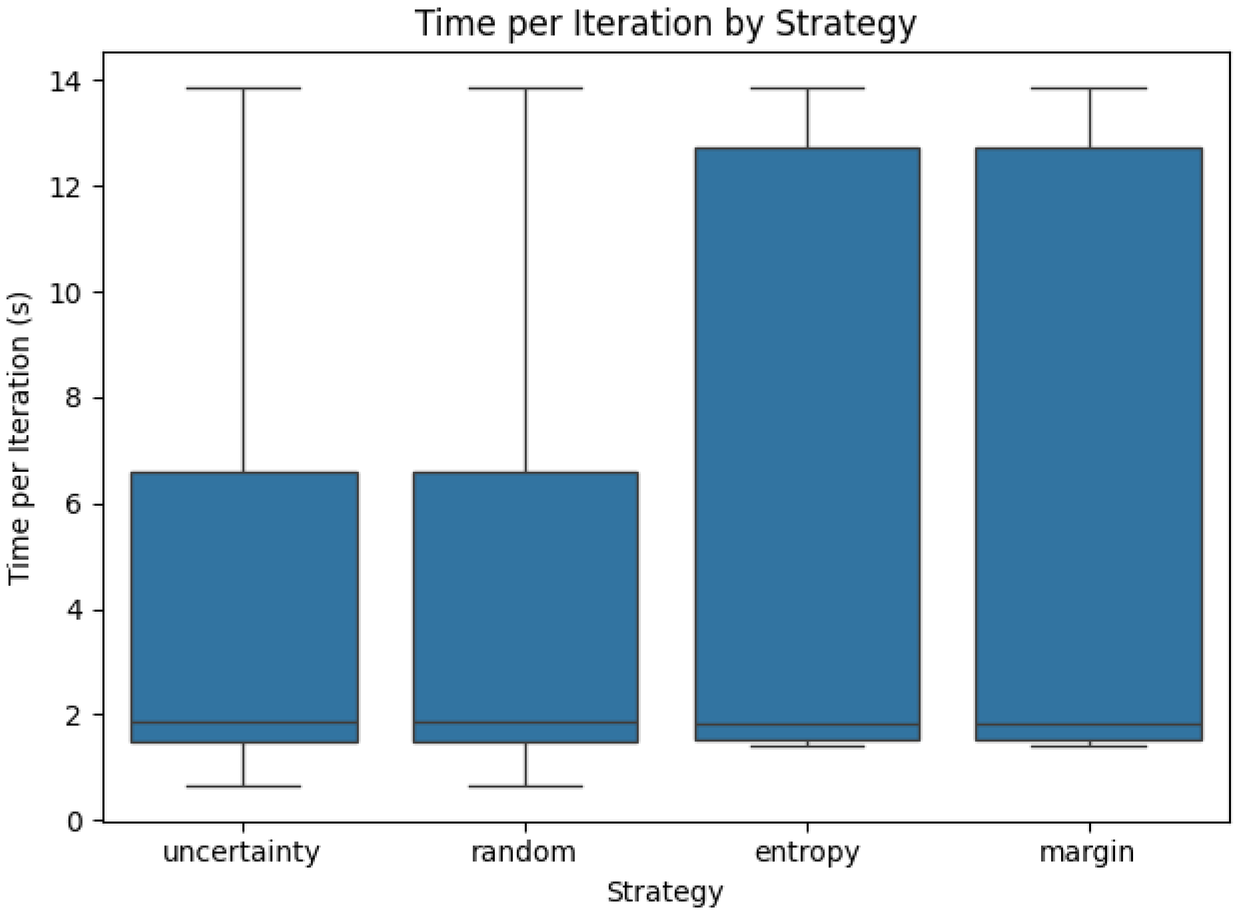
Accuracy Standard Deviation per Strategy

Boxplot showing the variability of accuracy across different runs for each strategy.



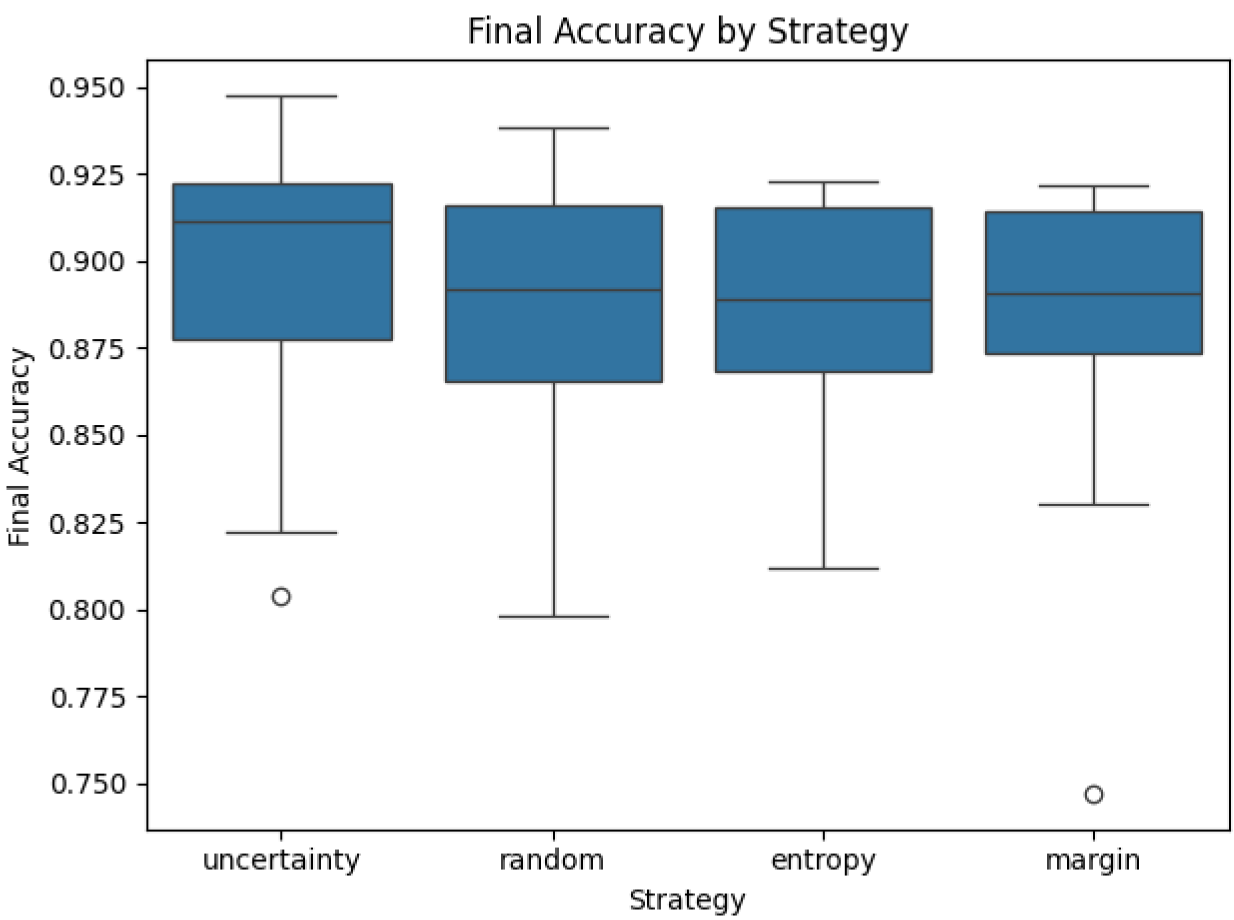
Time per Iteration by Strategy

Shows average time per iteration for each strategy, highlighting computational differences.



Final Accuracy Comparison

Distribution of final accuracy scores per strategy.



7.3 Key Observations

Which strategy was most accurate and stable?

- **Most accurate**:
  - Under both splitting strategies, **Margin sampling** and **Uncertainty sampling** consistently reached the highest final accuracies.
    - Example (Manual Temporal Split): `margin` reached up to **0.9190**
    - Example (Train/Test Split): `uncertainty` reached **0.9475**
- **Most stable** (lowest `accuracy_std`):
  - **Margin** and **Entropy** achieved the lowest standard deviation, indicating consistent results across different runs.

Which strategy was fastest?

- **Random** and **Uncertainty** sampling were **consistently faster** per iteration.
- **Entropy** and **Margin** strategies required more computation time, likely due to additional scoring mechanisms.
  - See: `time_per_iteration.png`

Did active learning outperform random?

- **Yes**, especially with more iterations.

- Under **Train/Test Split** at 100 iterations:
    - `uncertainty`: **0.9374**
    - `random`: **0.9130**
- Under **Manual Temporal Split** at 100 iterations:
    - `uncertainty`: **0.9164**
    - `random`: **0.9106**

- In early iterations (1–5), differences were small or negligible.
- Over time, active learning strategie (especially **uncertainty**) showed more consistent improvement.

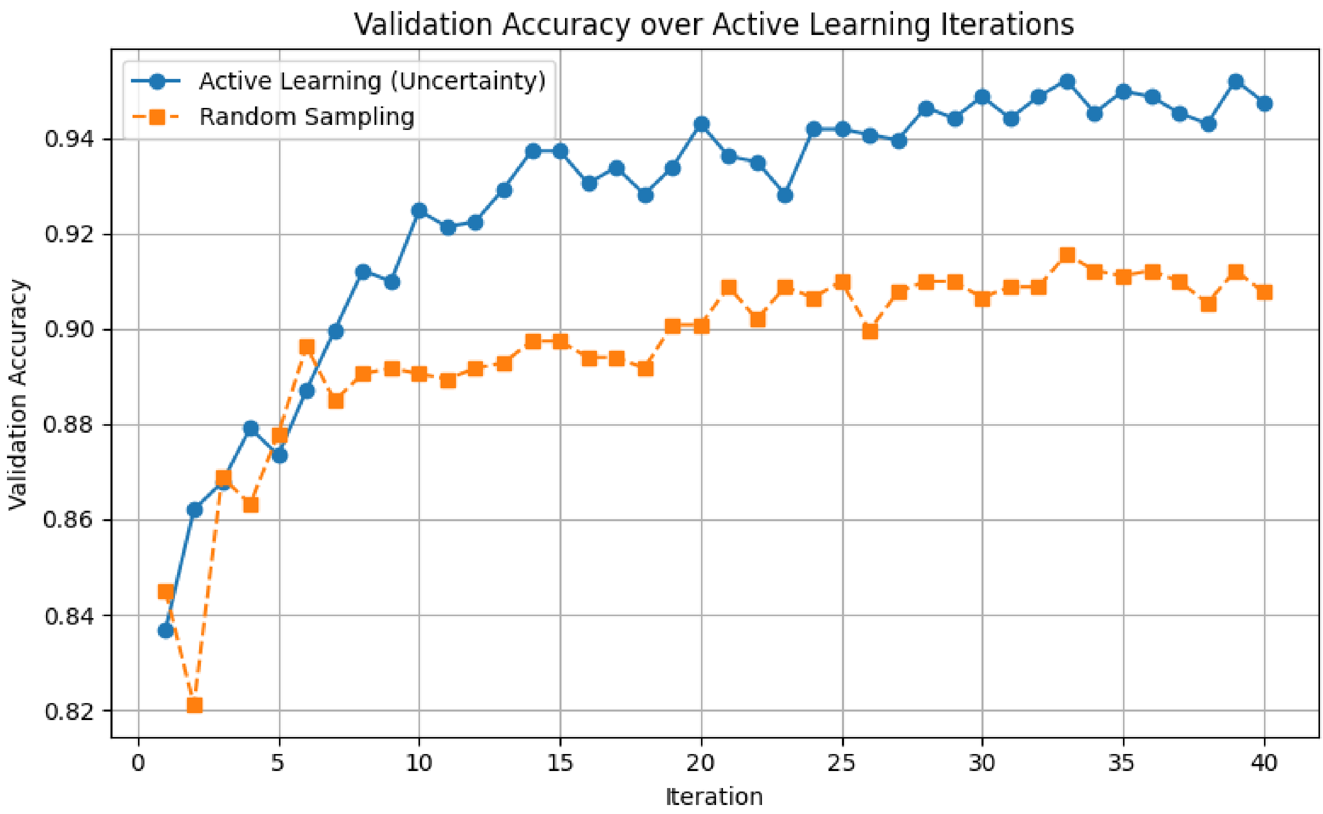
Best Overall Result - Train/Test Split

- The **highest recorded accuracy** across all experiments was:

> **Final Accuracy**: `0.9475`
> **Strategy**: `Uncertainty Sampling`
> **Data Splitting**: `Train/Test Split`
> **Parameters**:
>
> - `initial_size`: 100
> - `batch_size`: 50
> - `iterations`: 40
> - `total_labeled_samples`: 2100

- This suggests that:
    - **Uncertainty sampling** with a **moderate batch size** (50) and **sufficient iterations** (40) is highly effective.
    - The **Train/Test Split** setup led to a slightly better top score than Manual Temporal Split, possibly due to less strict data separation.

Supporting Visualization:



You can find this result in the table under timestamp `20250513_183415`.

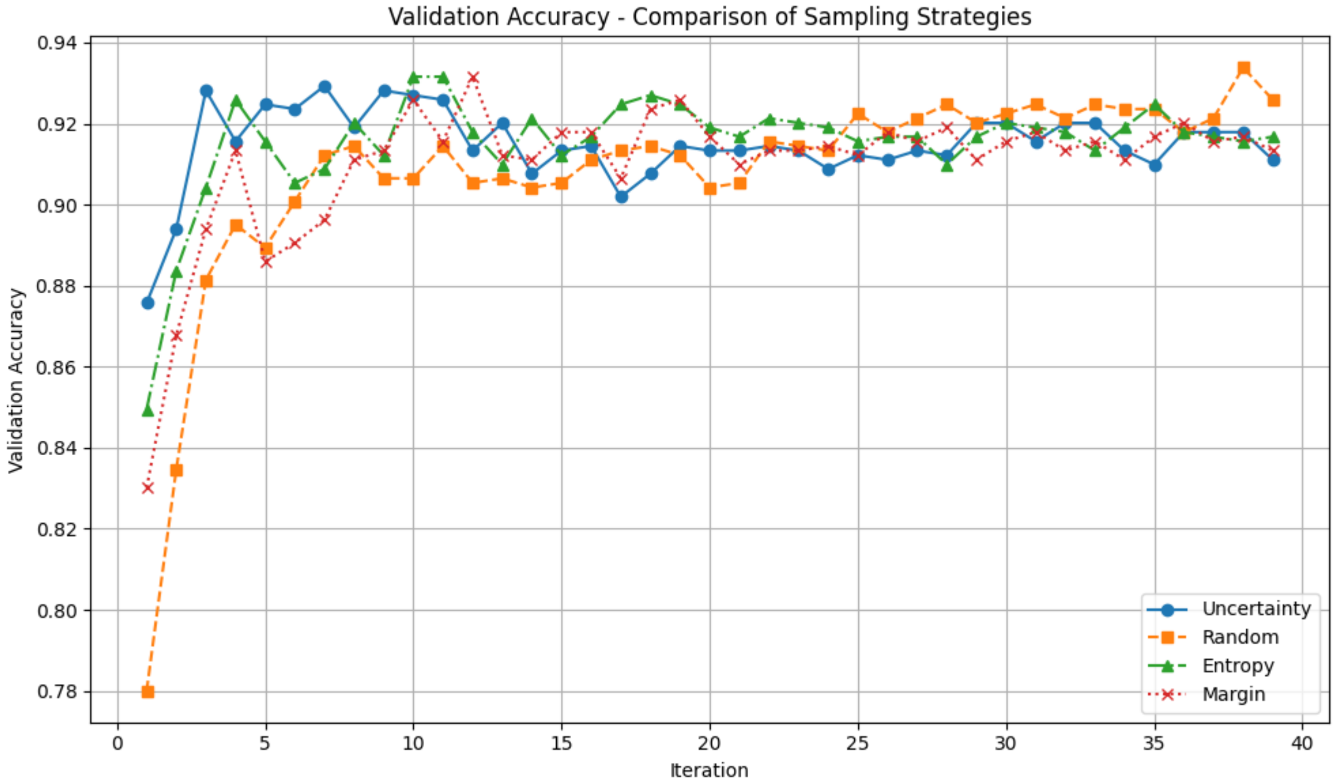
Best Result – Manual Temporal Split

- **Highest final accuracy** using the **Manual Temporal Split**:

  > **Final Accuracy**: `0.9259`
  > **Strategy**: `Random Sampling`
  > **Data Splitting**: `Manual Temporal Split`
  > **Parameters**:
  >
  > - `initial_size`: 100
  > - `batch_size`: 100
  > - `iterations`: 39
  > - `total_labeled_samples`: 4000
  > - `timestamp`: `20250513_210537`

- Although uncertainty-based methods performed well, in this case, **random sampling** achieved the top accuracy with the manual time split.

Supporting Visualization:



You can find this result in the table under timestamp `20250513_210537`.