3 Requirement and Analysis

3.1 Problem Definition

3.1.1 Problem Analysis

The goal is to build a system that converts **input text** into **human-like handwriting** by generating a continuous sequence of pen strokes. The key challenges are:

- **Sequence generation:** handwriting is a long, variable-length time series with dependencies across timesteps.
- **Continuous outputs:** pen motion is continuous (x/y) plus a discrete pen-up/pen-down state.
- **Alignment:** text characters must be aligned to stroke segments (often unknown a priori), requiring attention-like mechanisms.
- **Style variability:** handwriting style differs per writer and even within the same writer; controlling style and “neatness” matters.
- **Rendering:** generated offsets must be converted into readable SVG/graphics.

In this ref/ implementation, these challenges are addressed with:

- **RNN-based model** with LSTM layers and an attention window over characters.
- **Mixture Density Network (MDN / GMM head)** to model continuous coordinates.
- **Style priming** via pre-saved style samples (styles/style-*-strokes.npy, styles/style-*-chars.npy).
- **Bias parameter** to control output neatness/diversity.

3.1.2 Existing Problem

Traditional approaches (fonts / rule-based stroke synthesis) often produce:

- Unnatural strokes and spacing,
- Lack of personalization,
- Limited variability and poor realism.

3.1.3 Proposed System

The proposed system is a stroke-based handwriting generator:

1. **Input:** text lines (ASCII) + optional (style, bias)
2. **Encoding:** convert text to integer IDs (drawing.encode_ascii)
3. **Generation:** RNN + attention + MDN predicts stroke offsets and pen state
4. **Post-process:** denoise + align + convert offsets → coordinates
5. **Render:** export SVG via svgwrite

3.2 Requirement Specification

Functional Requirements

- **FR1:** Accept one or more text lines as input (max length constraint enforced in demo.py).
- **FR2:** Generate stroke sequences $(\Delta x, \Delta y, eos)$ for each line.
- **FR3:** Support **bias** as a controllable parameter affecting neatness/diversity.
- **FR4:** Support **style priming** using a small set of reference strokes/characters.
- **FR5:** Render generated handwriting into **SVG** output.
- **FR6:** Allow training from processed dataset arrays (data/processed/*.npy).
- **FR7:** Save and restore model checkpoints.
- **FR8:** Record training logs.

Non-Functional Requirements

- **NFR1 (Performance):** Training/inference should run on CPU; GPU is optional.
- **NFR2 (Reproducibility):** Config and checkpoints allow runs to be reproduced.
- **NFR3 (Usability):** Provide simple scripts for training and demo generation.
- **NFR4 (Maintainability):** Modular separation of data, model, and rendering utilities.

3.3 Planning and Scheduling

An implementation-ready plan aligned to this repository's workflow:

1. **Dataset setup**
- Collect raw handwriting strokes + transcripts (or use provided processed data)
- Run preprocessing to produce x.npy, x_len.npy, c.npy, c_len.npy
2. **Model training**
- Run train_model.py for a fixed number of steps
- Monitor logs; periodically save checkpoints
3. **Sampling & demo**
- Restore a checkpoint
- Generate samples with/without priming; tune bias
- Render SVG outputs
4. **Testing & validation**
- Visual inspection of SVGs
- Sanity checks on data shapes and lengths

3.4 Software and Hardware Requirements

Software Requirements

- **Operating System:** Windows / Linux
- **Python:** 3.x (commonly used with TF 1.x codebases)
- **Core Libraries:**
  - TensorFlow 1.x compatible runtime
  - NumPy
  - svgwrite
  - Matplotlib (for visualization)

Hardware Requirements

- **Minimum:** CPU-only machine, 8GB RAM (more recommended for training)
- **Recommended:** NVIDIA GPU + CUDA-compatible setup for faster training
- **Storage:** enough for datasets + checkpoints + logs (hundreds of MB to GB depending on dataset)

3.5 Preliminary Product Description

The system provides two main capabilities:

- **Training:** learns a handwriting synthesis model from stroke/text sequences and saves checkpoints.
- **Generation:** synthesizes handwriting from new text, with:
  - **Priming** (style imitation via reference samples)
  - **Bias control** (neatness vs diversity)
  - **SVG export** for downstream use

The output is a set of SVG files containing realistic stroke paths suitable for preview, printing, or embedding in documents.

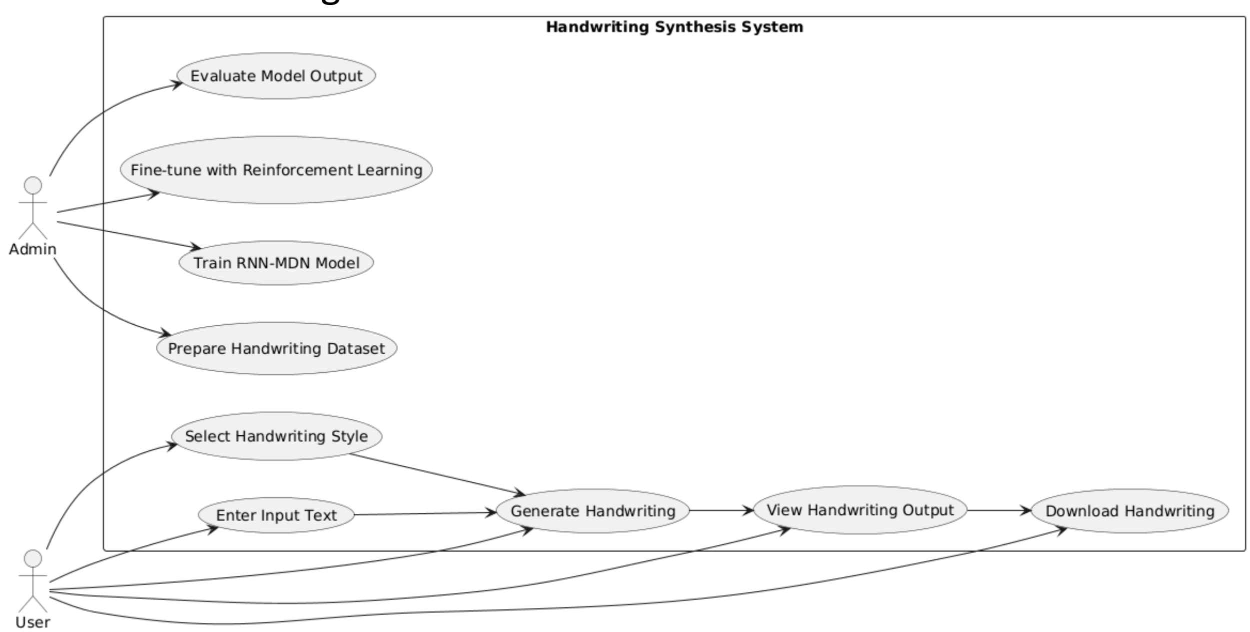
3.6 Conceptual Diagrams

The following diagrams describe the same system visually.

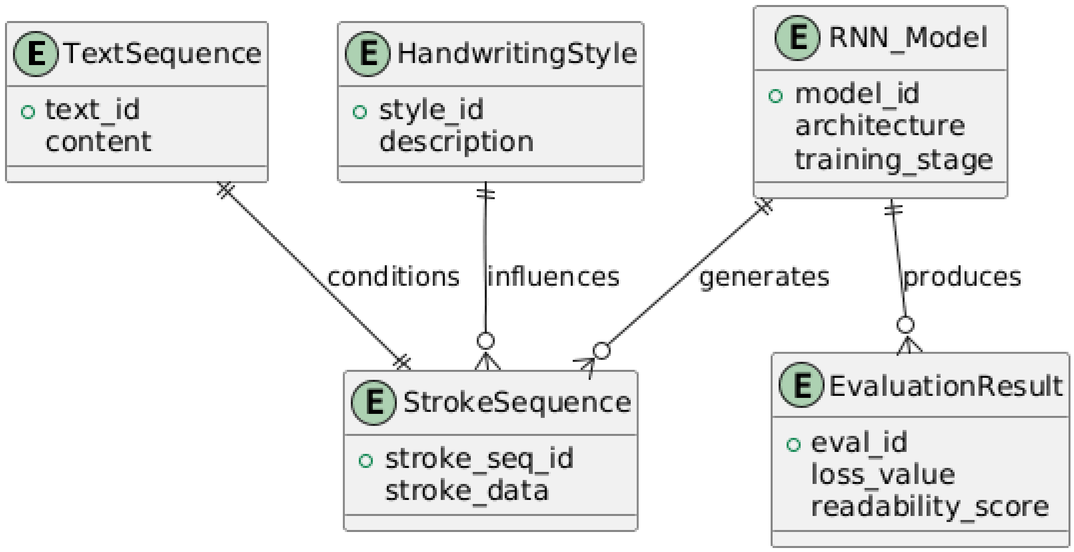
3.6.1 Event Table

Event ID	Trigger / Event	Input	Processing (High-level)	Output
E1	Generate synthetic data	--num_samples	synthesize_training_data.py creates stroke/text arrays	data/processed/*.npy
E2	Prepare/validate dataset	raw strokes + ascii	prepare_data.py normalizes/splits/serializes	processed .npy
E3	Train model	processed .npy	train_model.py → rnn.fit() training loop	checkpoints + logs
E4	Generate handwriting	text lines (+ style/bias)	demo.py samples nn.sampled_sequence	stroke sequences
E5	Render/export	strokes	drawing.py + svgwrite renders strokes	.svg images

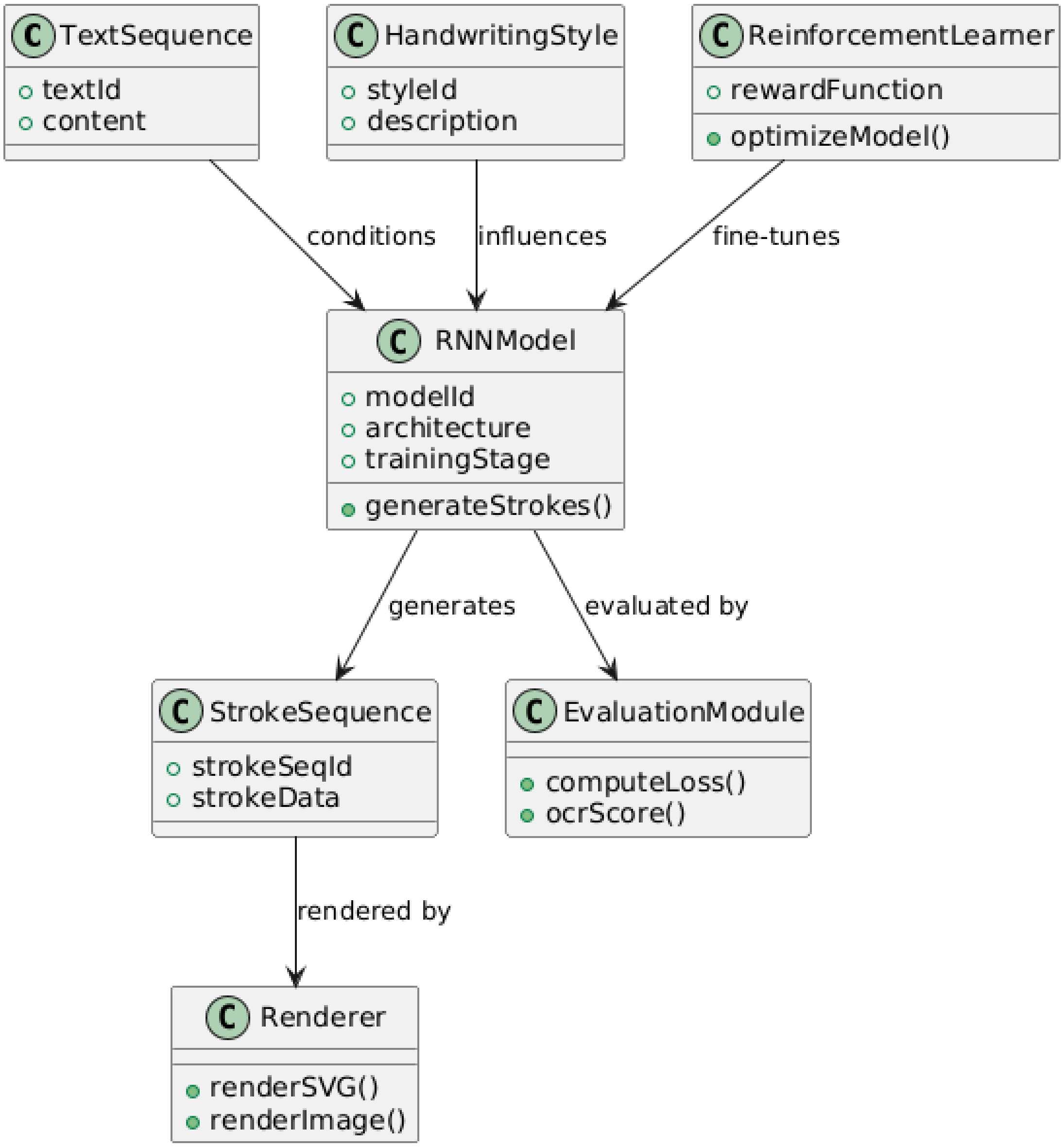
3.6.2 Use Case Diagram



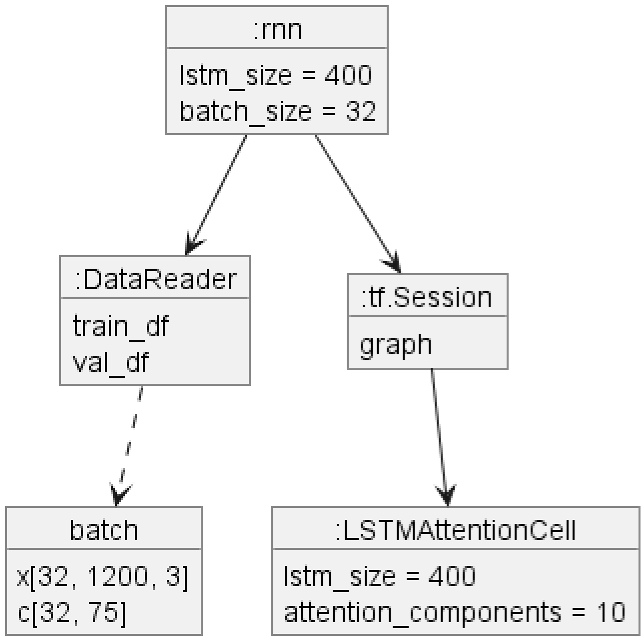
3.6.3 ER Diagram



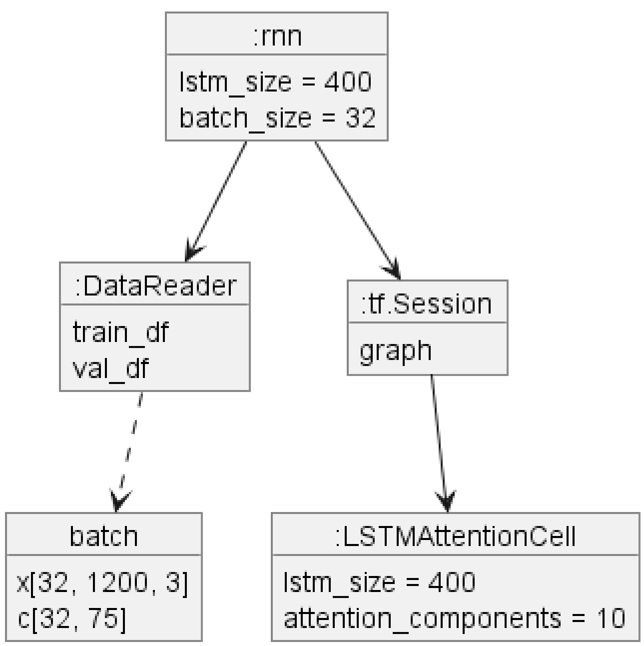
3.6.4 Class Diagram



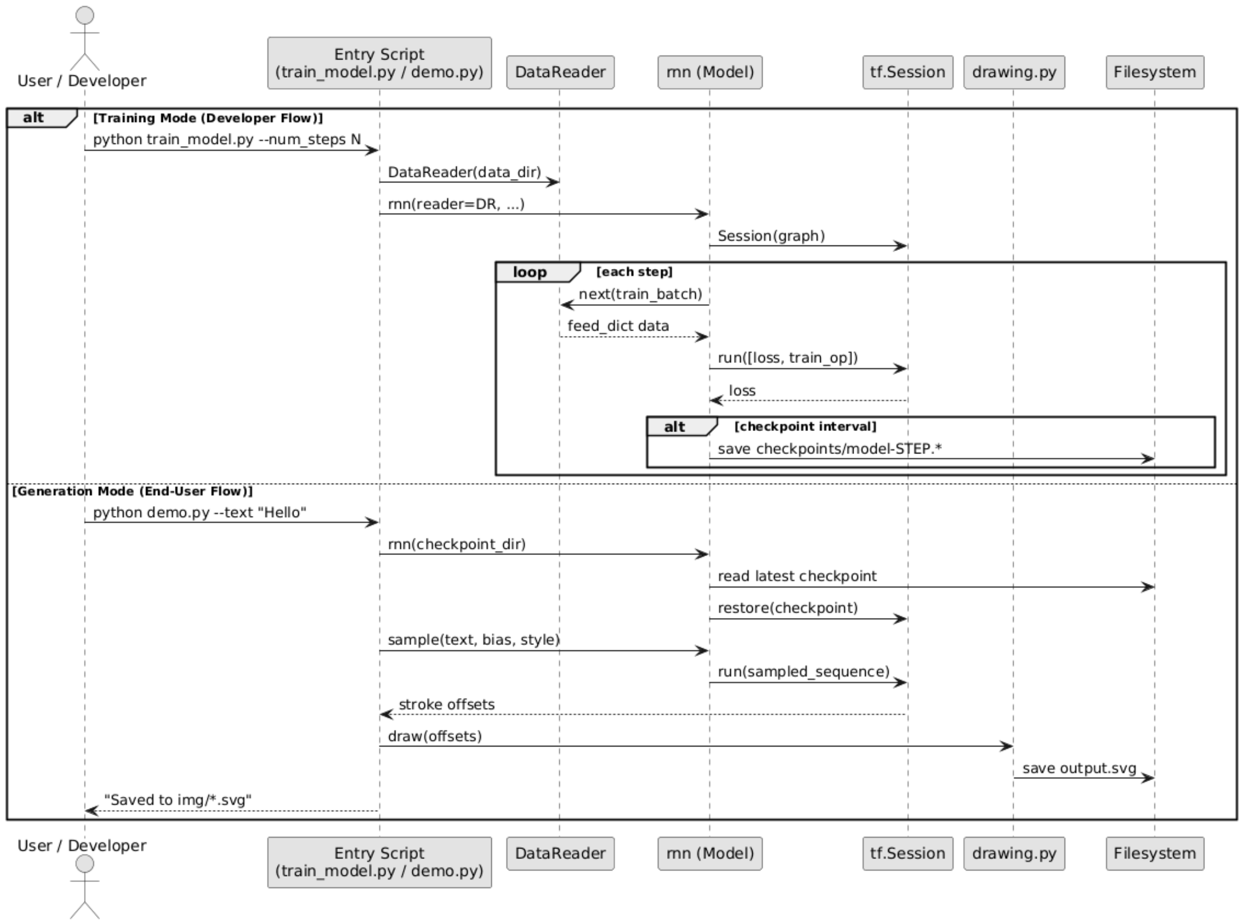
3.6.5 Object Diagram



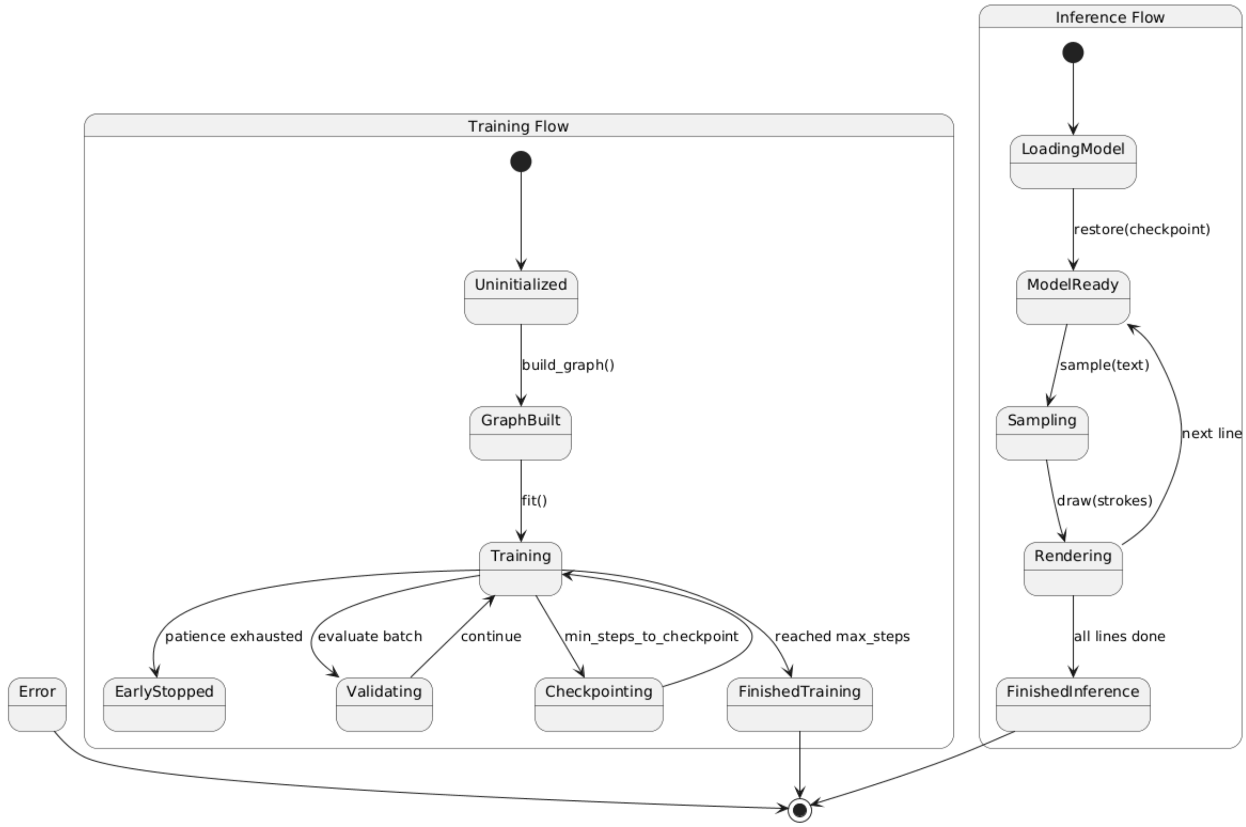
3.6.6 Activity Diagram



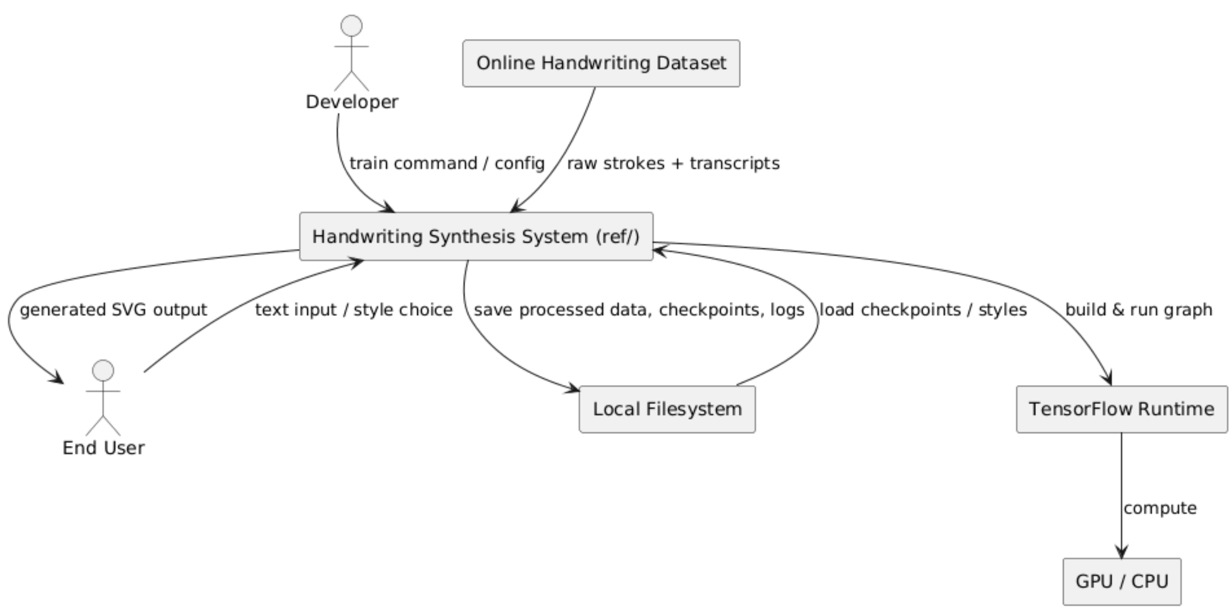
3.6.7 Sequence Diagram



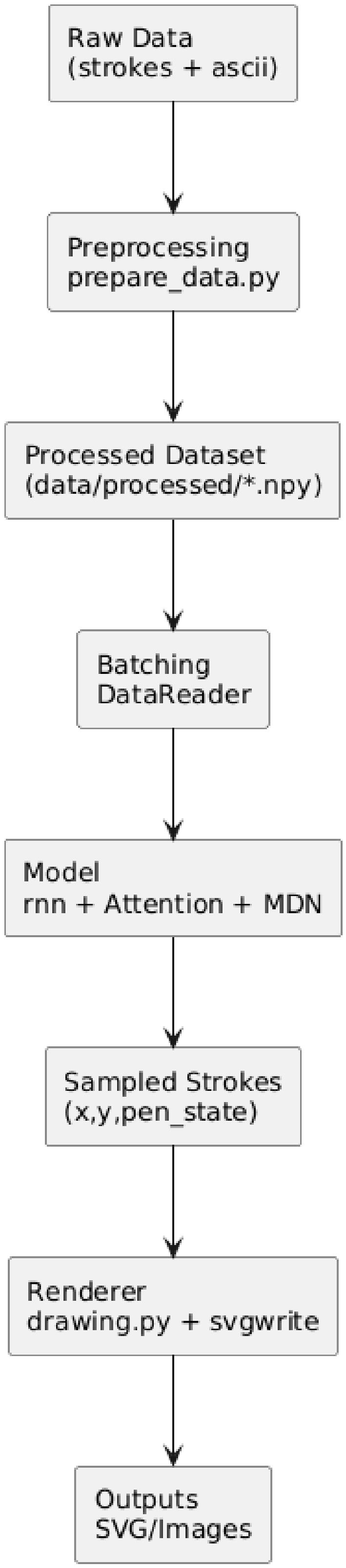
3.6.8 State-Flow Diagram



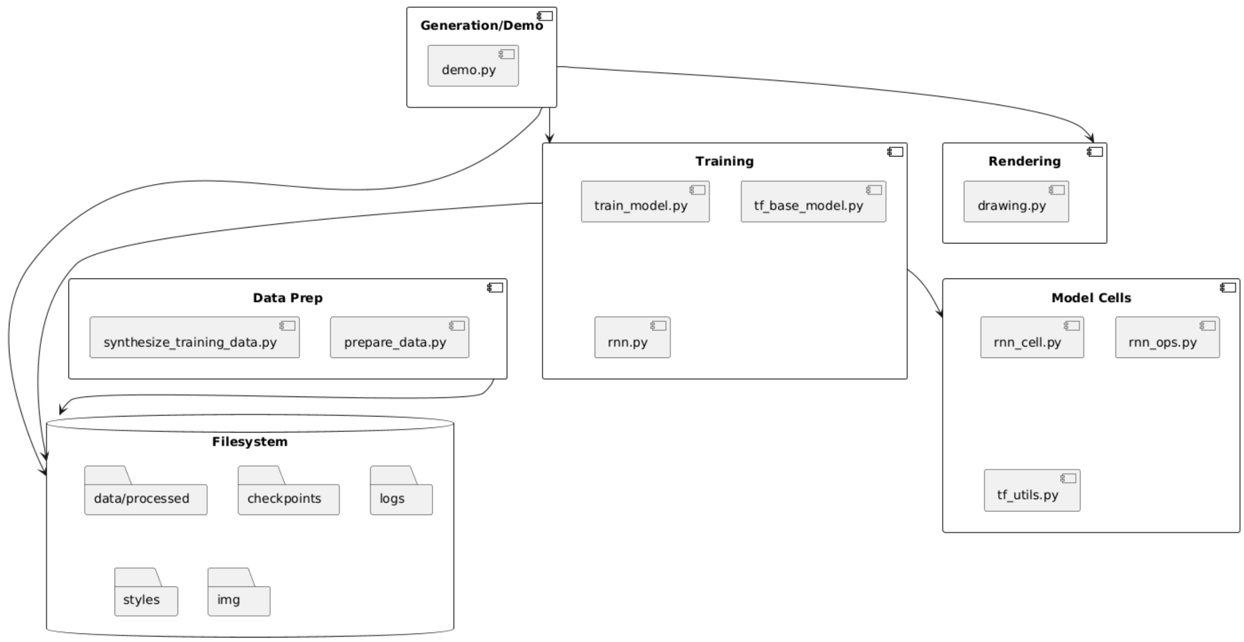
3.6.9 Context Diagram



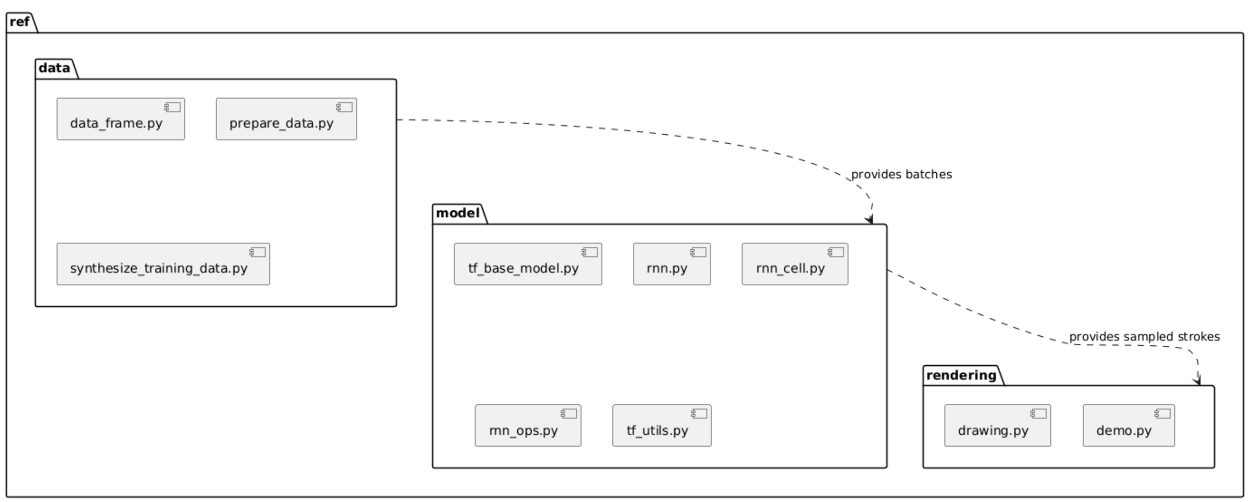
3.6.10 Data Flow Diagram



3.6.10 Component Diagram



3.6.12 Package Diagram



3.6.9 Depolyment Diagram