

SRSML24: STM Machine Learning Module

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Overview

This module provides tools for machine learning analysis of scanning tunnelling microscopy (STM) data, including autoencoder models, clustering tools, and STM-specific preprocessing.

Getting the Code

Clone the repository from GitHub:

```
git clone https://github.com/srschofield/SRSML24.git
```

Installation

It is recommended to create a clean Python environment using `conda`. The following steps assume you are working on a macOS system with Apple Silicon:

```
# create and activate environment
conda create --name srsml24 python=3.8 -y
conda activate srsml24
```

```
# install packages
pip install -r requirements-macos.txt
```

Known Working Configuration

This module has been tested and is known to work with the following configuration on macOS 15.0.1 (Apple Silicon, M3 Pro chip):

Package	Version
python	3.8
tensorflow-macos	2.13.0
tensorflow-metal	1.0.1
numpy	1.24.3
pandas	2.0.3
matplotlib	3.7.5
scikit-learn	1.3.2
scipy	1.10.1
opencv-python	4.11.0.86
Pillow	10.4.0
joblib	1.4.2
jupyter	1.1.1
ipykernel	6.29.5
keras-core	0.1.5
spiepy	0.2.1
access2thetmatrix	0.4.4

Table 1: Verified package versions for macOS (Apple Silicon) environment

These packages can be installed using the `requirements-macos.txt` file. The Python version is critical: other versions may cause compatibility issues with TensorFlow or other packages on Apple Silicon.

Python Files

- `data_prep.py` – Functions for data preparation, including slicing STM images into windows and saving them in efficient formats.
- `model.py` – Defines convolutional autoencoder and UNET-style models.
- `utils.py` – Utility functions for loading/saving models, feature arrays, and results.

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Parameter Summary

Parameter	Description
General	
job_name	Label for the run, it will be the folder name for output.
verbose	If True , enables more detailed print output.
Matrix data file processing	
flatten_method	Method used to flatten STM images before analysis. Options are 'none', 'iterate_mask', 'poly_xy'.
pixel_density	All images will be converted to this pixel density (px/nm).
pixel_ratio	Images that have ratio of fast/slow scan direction less than this will be discarded. Setting to 1 means only complete (square) images are kept.
data_scaling	Multiplicative factor for z-height data. Setting to 1.e9 means that the range 0–1 (used for training) corresponds to 1 nm.
Window generation	
window_size	Side length of square image windows (in pixels).
window_pitch	Spacing between adjacent windows during tiling.
Data saving	
(Should remain defaults but options can be useful for examining data manually.)	
save_windows	If True , saves image windows as .npy files (True).
together	If True , saves windows per image in a single file (True).
save_jpg	If True , saves full STM images as JPGs (False).
collate	If True , flattens directory structure into one folder. (False).
save_window_jpgs	If True , saves image windows as JPGs. (False)
Autoencoder	
model_name	Label used to save and load the trained autoencoder model.
batch_size	Number of windows per training batch.
buffer_size	Size of shuffle buffer.
learning_rate	Learning rate for the optimizer.
epochs	Number of training epochs.
Clustering	
cluster_model_name	Name used when saving the clustering model.
cluster_batch_size	Number of latent vectors per clustering batch.
cluster_buffer_size	Size of buffer for clustering shuffle.
num_clusters	Number of clusters to form using KMeans.
n_init	Number of initializations for KMeans.
max_iter	Max iterations for KMeans convergence.
reassignment_ratio	Fraction of centroids reassigned each step.
Image prediction	
predict_window_pitch	Window spacing during prediction step.
mtrx_train_data_limit	Max number of training MTRX files to use.
mtrx_test_data_limit	Max number of validation MTRX files to use.
train_data_limit	Limit on number of training windows.
test_data_limit	Limit on number of validation windows.

Step 1: Converting MATRIX STM Data Files

The initial step in utilizing the SRSML24 module involves converting raw STM data files from the Scienta Omicron MATRIX format into a standardized format suitable for machine learning analysis. This is accomplished using the `process_mtrx_files` function.

Function Overview

`process_mtrx_files(mtrx_paths, save_data_path, **kwargs)` is designed to batch process a list of MATRIX (`.mtrx`) files, performing the following operations:

- **Loading Data:** Reads each `.mtrx` file and extracts image data along with associated meta-data.
- **Preprocessing:** Applies flattening methods to correct for background variations and rescales images to a consistent pixel density.
- **Window Extraction:** Divides images into smaller windows of specified size and pitch, facilitating training of machine learning models.
- **Saving Outputs:** Stores processed windows and optional JPEG representations in a structured directory hierarchy under `save_data_path`.

This function ensures that STM data is preprocessed consistently, facilitating reliable training and evaluation of machine learning models within the SRSML24 framework. It will create a new directory called “windows” and subfolders under that with the names corresponding to the folders the matrix data was stored in (e.g., “training” or “testing”). Unless the “collate” variable is set, the windowed data will retain the full directory structure (dates, days, etc) of the matrix data. The individual windows for a given folder of matrix data are all stored within a single `.numpy` file, rather than separate `.numpy` files for each window, since this is much more efficient for data saving and retrieving. Two text files are also saved, one has the meta data (STM bias voltage, current, etc.). The other has the coordinates for each window in the dataset. This is useful since these are not uniform at two edges of the original image for the general case where the full image is not perfectly divided by the dimensions of the individual windows.

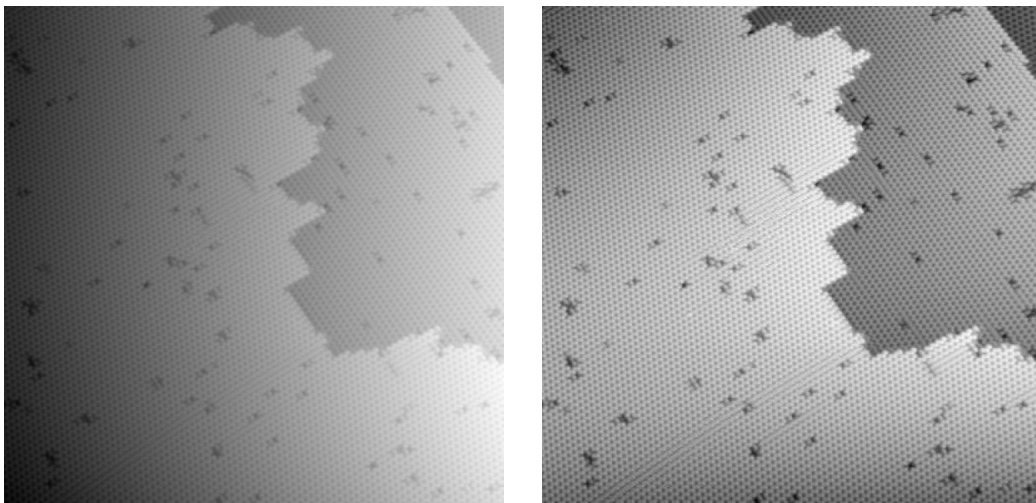


Figure 1: Typical scanning tunnelling microscopy (STM) image. (Left) raw data. (Right) After `poly_xy` background subtraction.



Figure 2: A sequence of 30×30 pixel windows extracted from the STM image in Fig. 1 with an 8 pixel pitch.

Step 2: Preparing Datasets and Training the Autoencoder

With windowed STM data in place, the next stage is to set up efficient TensorFlow data pipelines and train a convolutional autoencoder. This step handles the full model lifecycle, from data loading and batching to model training and saving the model and training history. These tools are provided by `model.py`, which we import as `m`, i.e., `import SRSML24.model as m`.

Preparing Datasets with `tf.data`

To begin, window data stored as `.npy` files in `windows_train_path` and `windows_test_path` are listed. If it is possible to choose a truncated subset of this list, e.g., to train on less data while optimising; this is done by setting the `train_data_limit` and `test_data_limit` parameters. These files are then loaded into TensorFlow `Dataset` objects for training and validation.

The function `m.create_tf_dataset_batched(file_paths, batch_size, buffer_size, window_size, is_autoencoder, shuffle)` constructs a pipeline that:

- **Loads image batches:** Reads window data from `.npy` files located at the specified paths.
- **Shuffles window order:** When `shuffle=True`, randomizes input order to enhance model generalization.
- **Batches the data:** Groups windows into batches of size `batch_size`.
- **Prefetches data:** Uses `prefetch(buffer_size)` to improve throughput by overlapping data preparation with model training.

- **Pairs inputs and targets:** For autoencoder training, each window is used as both the input and target.

Model Building and Training

Once the datasets are ready, the autoencoder can be constructed, compiled, and trained using the following workflow:

- **Model instantiation:**
 - Use `m.build_autoencoder(window_size, model_name)` to define the encoder–decoder architecture.
 - Call `model.summary()` to inspect the model structure.
- **Optimizer selection:**
 - On Apple Silicon/macOS systems, use `tf.keras.optimizers.legacy.RMSprop` for TensorFlow-metal compatibility.
 - On other systems, use the standard `tf.keras.optimizers.RMSprop`.
- **Compilation:** Compile the model with:
 - `loss='mean_squared_error'`
 - Metrics: `['mse', 'mae']`
 - Learning rate: from the `learning_rate` parameter.
- **Training:** Fit the model using:
 - `train_dataset` with `shuffle=True`
 - `validation_data=test_dataset`
 - The number of `epochs`
- **Saving outputs and diagnostics:**
 - Save the trained model using `m.save_model(..., model_train_time)`.
 - Plot and save the training history with `m.plot_history_from_file(...), m.save_history(...)`.

This produces a trained autoencoder model along with detailed training logs and performance plots, ready for use in clustering or anomaly detection tasks.

Layer (type)	Output Shape	Param #	Connected to
input (InputLayer)	[(None, 32, 32, 1)]	0	[]
conv1 (Conv2D)	(None, 32, 32, 32)	320	['input[0][0]']
drop1 (Dropout)	(None, 32, 32, 32)	0	['conv1[0][0]']
pool1 (MaxPooling2D)	(None, 16, 16, 32)	0	['drop1[0][0]']
conv2 (Conv2D)	(None, 16, 16, 64)	18496	['pool1[0][0]']
drop2 (Dropout)	(None, 16, 16, 64)	0	['conv2[0][0]']
pool2 (MaxPooling2D)	(None, 8, 8, 64)	0	['drop2[0][0]']
conv3 (Conv2D)	(None, 8, 8, 128)	73856	['pool2[0][0]']
drop3 (Dropout)	(None, 8, 8, 128)	0	['conv3[0][0]']
pool3 (MaxPooling2D)	(None, 4, 4, 128)	0	['drop3[0][0]']
bottleneck (Conv2D)	(None, 4, 4, 256)	295168	['pool3[0][0]']
up1 (UpSampling2D)	(None, 8, 8, 256)	0	['bottleneck[0][0]']
upconv1 (Conv2D)	(None, 8, 8, 128)	295040	['up1[0][0]']
skip1 (Concatenate)	(None, 8, 8, 256)	0	['upconv1[0][0]', 'conv3[0][0]']
conv4 (Conv2D)	(None, 8, 8, 128)	295040	['skip1[0][0]']
up2 (UpSampling2D)	(None, 16, 16, 128)	0	['conv4[0][0]']
upconv2 (Conv2D)	(None, 16, 16, 64)	73792	['up2[0][0]']
skip2 (Concatenate)	(None, 16, 16, 128)	0	['upconv2[0][0]', 'conv2[0][0]']
conv5 (Conv2D)	(None, 16, 16, 64)	73792	['skip2[0][0]']
up3 (UpSampling2D)	(None, 32, 32, 64)	0	['conv5[0][0]']
upconv3 (Conv2D)	(None, 32, 32, 32)	18464	['up3[0][0]']
skip3 (Concatenate)	(None, 32, 32, 64)	0	['upconv3[0][0]', 'conv1[0][0]']
conv6 (Conv2D)	(None, 32, 32, 32)	18464	['skip3[0][0]']
output (Conv2D)	(None, 32, 32, 1)	33	['conv6[0][0]']
=====			
Total params: 1162465 (4.43 MB)			
Trainable params: 1162465 (4.43 MB)			
Non-trainable params: 0 (0.00 Byte)			

Figure 3: Example UNET autoencoder model summary.