Report

1. Scrapping - I have used beautifulsoup for scrapping the wallet addresses of 7 different currencies namely bitcoin,'litecoin','bitcoin cash','dogecoin','dash','bitcoin gold','vertcoin'.

   Scrapping is done using https://bitinfocharts.com/top-100-richest-{ct}-addresses-{i}.html

2. Pre processing - After that character level dictionary has been made using the addresses. Then addresses are tokenized and necessary padding is done. Labels were converted to numerical representation using sklearn label encoder.

   After that using sklearn the data is splitted into train and validation split.

3. Dataset - Then a custom dataset is made to convert the training and validation set to torch data.

4. Model - LSTM model is chosen in order to exploit the character level dependencies in the wallet address. Length of wallet address is taken into account and concatenated with the output of the LSTM and then put through the MLP layer.

5. Train loop - Training has been done for 300 epochs using adam optimizer, cross entropy loss and cosine annealing scheduler.

6. Report - Classification report is generated using sklearn's classification report.

Epoch 300/300, tr Loss: 0.14286, val loss 0.15793

for training

	0	1	2	3	4
precision	0.983888	0.774804	0.997693	0.999614	0.999486
recall	0.713167	0.987939	1.000000	0.999228	0.998587
f1-score	0.826935	0.868486	0.998845	0.999421	0.999036
support	7792.0000	7794.0000	7785.0000	7772.0000	7786.000000

	5	6	accuracy	macro avg	weighted avg
precision	0.999229	0.998833	0.956478	0.964792	0.964714
recall	0.997308	0.999740	0.956478	0.956567	0.956478
f1-score	0.998268	0.999286	0.956478	0.955754	0.955659
support	7801.0000	7702.000	0.956478	54432.000	54432.000000

for val

	0	1	2	3	4	5
precision	0.805846	0.681291	0.997937	1.0	1.00	1.0
recall	0.600622	0.854621	1.000000	1.0	0.998449	1.0
f1-score	0.688262	0.758176	0.998967	1.0	0.999224	1.0
support	1928.000	1926.000	1935.000	1948.0	1934.00	1919.0

	6	accuracy	macro avg	weighted avg
precision	1.0	0.922619	0.926439	0.927090
recall	1.0	0.922619	0.921956	0.922619
f1-score	1.0	0.922619	0.920661	0.921349
support	2018.0	0.922619	13608.000	13608.000000