1.

a. Done in python

b. Done in Python

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Epoch 1/5
1875/1875 [
Epoch 2/5
1875/1875
                        ======] - 10s 5ms/step - loss: 0.0803 - accuracy: 0.9744
Epoch 3/5
                     =======] - 10s 5ms/step - loss: 0.0556 - accuracy: 0.9823
Epoch 4/5
1875/1875
Epoch 5/5
1875/1875 [=====
Evaluating MLP2 on test set 1
313/313 [====
                    ========] - 1s 3ms/step - loss: 0.0875 - accuracy: 0.9766
Evaluating MLP2 on test set 2
Epoch 1/5
Epoch 2/5
                  =========] - 90s 48ms/step - loss: 0.0387 - accuracy: 0.9880
                  ========] - 89s 48ms/step - loss: 0.0236 - accuracy: 0.9924
1875/1875 [==
Epoch 4/5
                  =========] - 90s 48ms/step - loss: 0.0189 - accuracy: 0.9941
1875/1875 [=
Epoch 5/5
Evaluating CNN on test set 1
                          ==] - 4s 13ms/step - loss: 0.0361 - accuracy: 0.9895
Evaluating CNN on test set 2
```

- c. For test set 1, the accuracy was 0.9766 while for test set 2, the accuracy was 0.5935
- d. For test set 1, the accuracy was 0.9895 while for test set 2, the accuracy was 0.9029
- e. For me, the CNN proved to have a better accuracy on both tests in comparison to the Feedforward network. This is because for a CNN, we are using fewer parameters and have sparser connections between nodes which leads to our network being more efficient at classifying the images than a feedforward network which will need a lot more calculations due to the larger number of parameters it will take.

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3. Here we use Bayes Rules to get the Posterior Model Probability.
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Recall Bayes Rules is P(\theta|D) = \frac{p(D|\theta)P(\theta)}{p(D)}

P(\theta_1) = P(\theta_2) and P(\theta_3) = 3 P(\theta_1).

Therefore: P(\theta_1) = 1

P(\theta_1) = P(\theta_2) = 0.2 and P(\theta_3) = 0.6

P(D) = \sum_{i=\{1,2,3\}} P(\theta_i)P(D|\theta_i) = P(\theta_1)P(D|\theta_1) + P(\theta_2)P(D|\theta_2) + P(\theta_3)P(D|\theta_3)

P(D) = 0.2 = 0.00084 + 0.2 = 0.00105 = 0.6 = 0.00007

P(D) = 0.00042
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Therefore, the Posterior Probabilities for each model are $p(\theta_1 \mid D) = \frac{P(\theta_1)P(D \mid \theta_1)}{p(D)} = 0.2*\ 0.00084\ /\ 0.00042 = 0.4$

$$\begin{split} &p(\theta_2 \mid D) = \frac{P(\theta_2)P(D|\theta_2)}{p(D)} = 0.2*\ 0.00105\ /\ 0.00042 = 0.5 \\ &p(\theta_3 \mid D) = \frac{P(\theta_3)P(D|\theta_3)}{p(D)} = 0.6*\ 0.00007\ /\ 0.00042 = 0.1 \end{split}$$

- 4. You would be better of selling as we first take the argmax θ $P(\theta|D)$ to get our selected θ which, based off the previous question, is θ_2 . Given theta two, the prediction we get is p(y_{t+1} | y_t, θ_2) = .4 . As 0.4<0.5, it would be better to sell.
- 5. Based on the posterior predictive distribution, we would be better off buying as to get the posterior predictive distribution, we first do the calculation $\sum_{\theta} p(\theta|D)p(y_{t+1}|y_t,\theta) = 0.75*0.4+0.5*0.5+0.1*0.6=0.56.$ As 0.56>0.5, we would be better of buying.