

CSE574 PA2, Spring 2021
Group # 36
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Report 1:

1. The results when Part2 is evaluated for the default setting with a number of units in hidden layers units (M) = 50 and $\lambda = 0.5$ are as follows:

Training completed in 18.95 seconds.

Training set Accuracy: 67.66%

Test set Accuracy: 64.34%

2. The number of units in hidden layers (M) is increased from 10 to 100, with increments of 10 keeping the same value of $\lambda = 0$. We can observe that the training and test accuracy increase as M 's value increases until M reaches 100. Hence, **M 's optimal value is chosen as 100**, based on both train and test sets' performance (Fig. 1(a)). In Fig. 1(b), training time (in seconds) vs. No. of hidden units (M). At $M = 100$, train and test accuracies are 72.02% and 67.73%, respectively. Based on the training and test accuracies, we have chosen the optimal $M = 100$ and carried out the rest of the analysis accordingly.

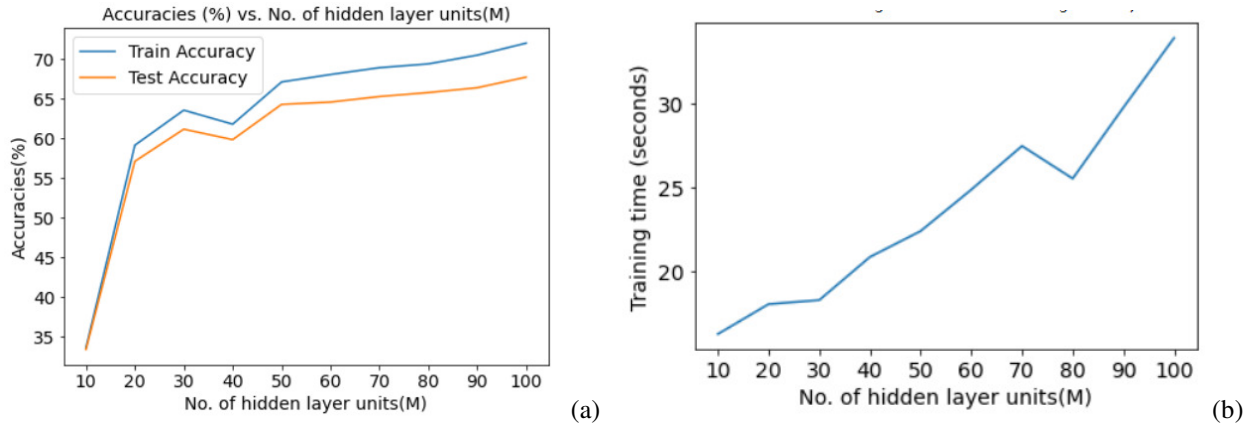


Fig. 1 (a) Accuracies (%) vs. No. of hidden layer units (M), and (b) Training Time (Seconds) vs. No of hidden units (M)

3. Now, with the optimal value of M (units in hidden layer) = 100, the value of λ (the regularization coefficient) is varied from 2 to 20, in steps of 2. The variation of train and test accuracy and the training time is plotted in Fig. 2(a) and (b), respectively. Hence, **the optimal value of the Regularization coefficient (λ) is chosen as 20**, based on both train and test sets' performance (Fig. 2(a)). At $\lambda = 20$, train and test accuracies are 72.33% and 64.84%, respectively, which is found to be highest among the range of λ das $[0, 20]$.

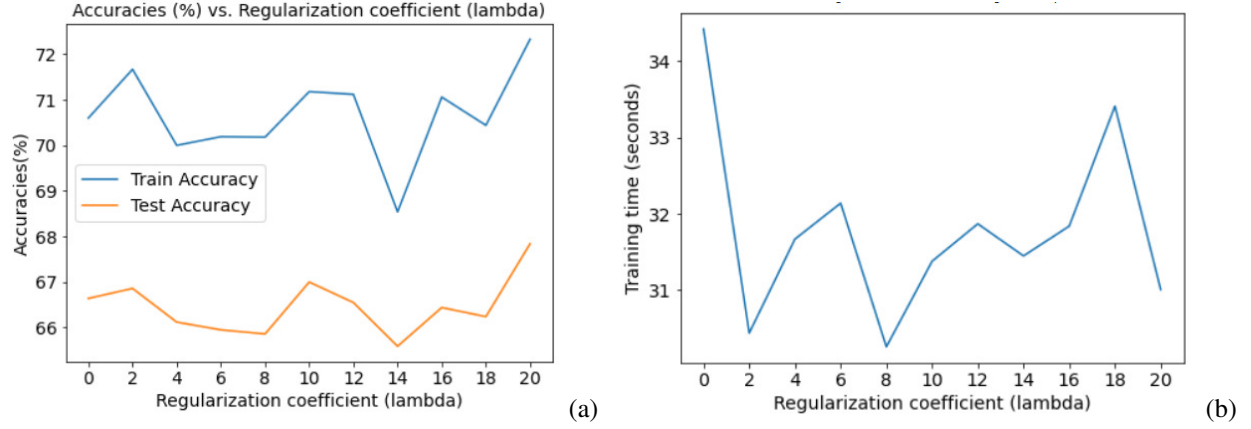


Fig. 2 (a) Accuracies (%) vs. Regularization coefficient (lambda), and (b) Training Time (Seconds) vs. Regularization coefficient (lambda).

- For the optimal values of $M=100$ and $\lambda=20$, the test data's performance has been investigated, and confusion matrices (CMs) have been plotted in Fig. 3. In Fig. 3(a), the deterministic CM has been plotted for a particular class, and the #of samples that have been correctly labeled is shown by the diagonal elements of the 10×10 matrix. In Fig. 3(b), each class's probabilistic performance could be investigated on the test set. Similarly, the correctly predicted labels would be the diagonal elements for each class. For each class, there are 2500 observations to be predicted on the test set. The true prediction accuracy for 'Class 6' is the lowest among all classes, i.e., 27% only. However, 'Class 0' has the highest prediction accuracy of 90% on the test set. The overall accuracy on the test set is 67.7% from considering $M=100$ and $\lambda=20$.

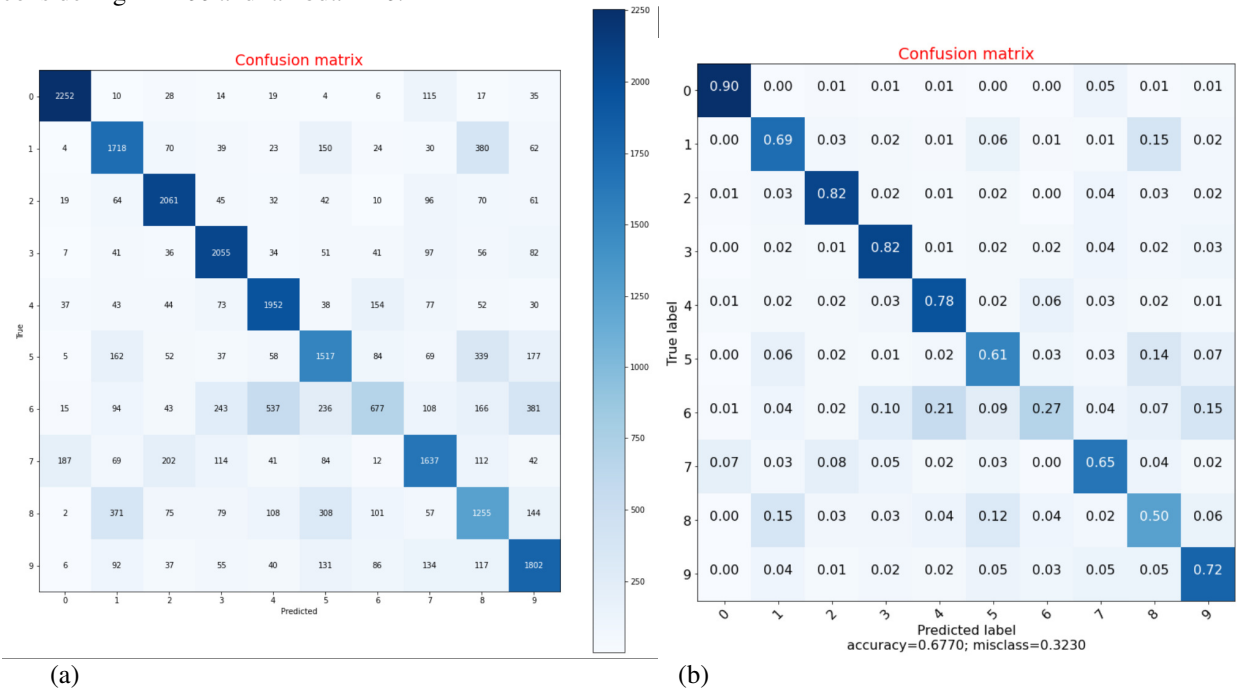


Fig. 3 (a) Deterministic CM and (b) Probabilistic CM from test set where optimal $M = 100$ and $\lambda = 20$.

Briefly discuss how your model's performance can be improved further: The following ways could improve the ANN model's performance:

- Modifying the model's architecture, adding more hidden layers in the network if the model is under-fitting during training.
- Exploring other suitable activation functions than sigmoid can improve the model performance.
- Applying some efficient weight initialization procedure other than random weight initialization. Often random weight initialization won't be as effective as pre-trained weights.
- Applying dropout on the input layer and hidden layers as the #of training parameters increases. Dropouts often help perform better on deep learning model, and it's a hyperparameter that is very problem-specific.

All the approaches mentioned above could be used to improve the performance of the model for image classification.

Report 2:

1. Train and test set accuracy vs. #of layers (L) plot have been given in Fig. 4(a). It has been seen from the figure that for $L=3$, the train and test accuracies are optimal, i.e., 80.16% and 75.83%, respectively. Thus, the model performs at best with three hidden layers of 100 hidden units (M) each. The training time (second) has been plotted for different values of $L = [1,5]$ in Fig. 4(b). the training time is increasing as the L increases.

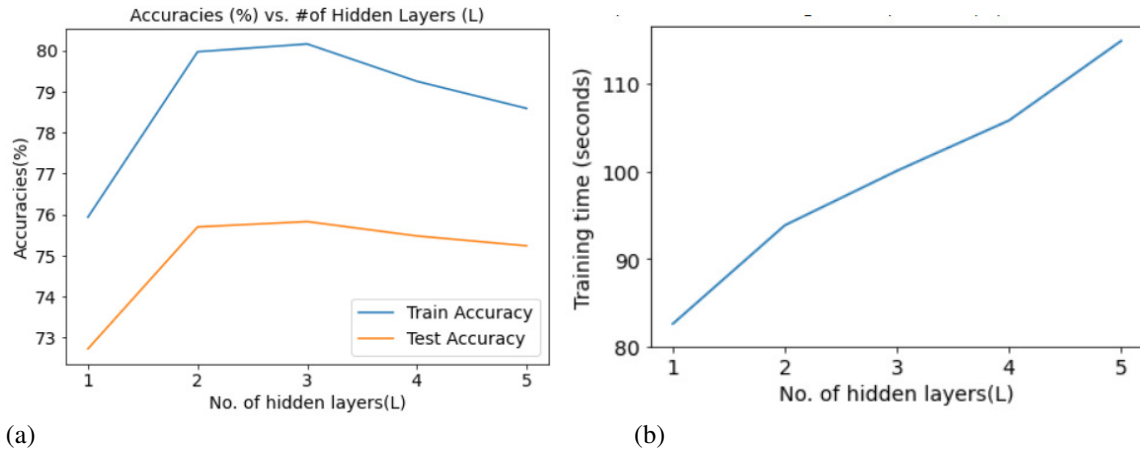


Fig. 4 (a) Accuracies (%) vs. No. of hidden layers (L), and (b) Training Time (Seconds) vs. No of hidden layers (L)

2. Using the optimal $M=100$ and $L=3$ from the previous part (Report 2.1), the performance of the model (in terms of training and testing accuracies and the training time) for different choices of the activation function (*sigmoid*, *tanh*, and *relu*) has been compared in Fig. 5 (a) and (b), respectively. It has been shown in Fig. 5(a), optimal accuracies for train and test sets are for *sigmoid* activation function, i.e., 83.68% and 75.83%, respectively. The *relu* activation function overfits the model on the train set; thus, the test set's performance drops. So, the best choice would be *sigmoid* activation function as its performing best on the test set. In Fig. 5(b), the best(least) training time (s) is for *relu* activation function, i.e., 95.51s, but due to overfitting on the train set, it would not be a good choice for this analysis. So the best choice for the image classification would be $M=100$, $\lambda = 20$, $L=3$, and activation function = *sigmoid*.

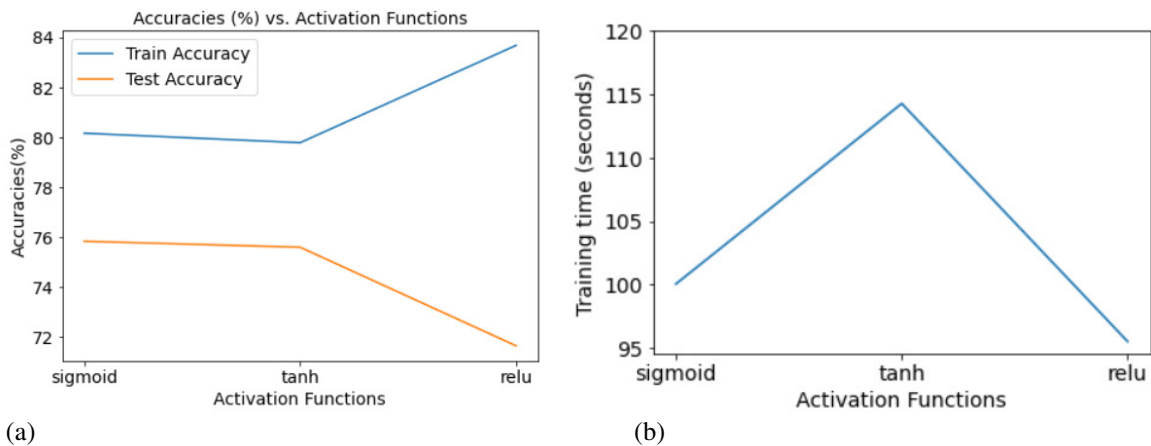


Fig. 5 (a) Accuracies (%) vs Activation Functions and (b) Training Time (Seconds) vs. Activation Functions