

# MLCV Coursework 1 Report

Shinyoung Yu  
20200405

School of Computing  
sahaa0918@kaist.ac.kr

Jiyoung Park  
20210263

School of Computing  
jiyun02@kaist.ac.kr

## 1. Eigenfaces

Face data is the base dataset for our experiment. This consists of 520 data with 52 classes and 10 data for each class. We will conduct the upcoming experiments by dividing the data for each class into an 8:2 train-test split.

### 1.1. Eigenfaces

There are two method to conduct PCA:  $PCA(S = AA^T)$  and low dimensional  $PCA(S = A^T A)$ . We compare two methods on training dataset with size  $2576 \times 416 (D \times N)$ .

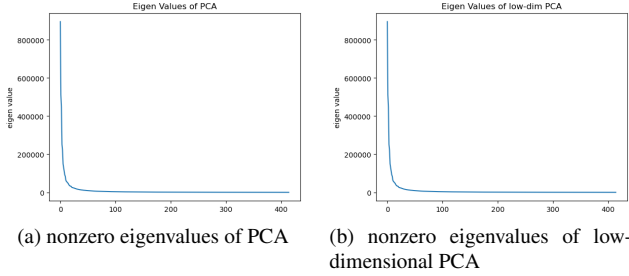


Figure 1. Comparison between eigenvalues of PCA methods

As shown in Fig. 1 both methods have the same nonzero eigenvalues. Specifically, PCA has 2576 nonzero eigenvalues, and low-dimensional PCA has 416. However, when selecting values bigger than  $\frac{1}{100}$ , both methods yield 415 eigenvalues. This is because, given matrix sizes of  $2576 \times 2576$  and  $416 \times 416$ , the maximum ranks are 2576 and 416, respectively. But since we have 416 data points, the PCA projection subspace can at most capture 415 meaningful dimensions, resulting in 415 eigenvalues larger than  $\frac{1}{100}$ . From this comparison (Fig. 1), we conclude that both methods yield the same eigenvalues, and their top 415 eigenvectors are also identical.

The only difference between them is computation time: PCA takes 8.015s, while low-dimensional PCA takes 1.092s. Low-dimensional PCA is faster because, in our case, the data dimension exceeds the number of data points, making its covariance matrix smaller than that of PCA.

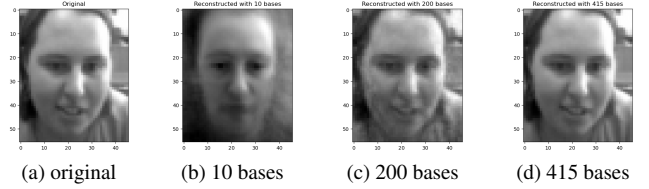


Figure 2. Training data reconstruction results

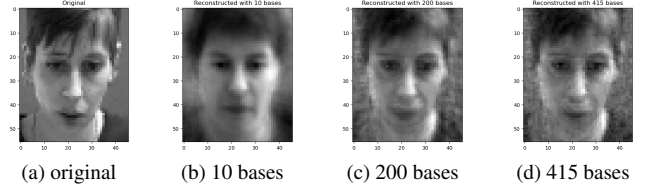


Figure 3. Test data reconstruction results

Based on this time efficiency, we use low-dimensional PCA going forward.

### 1.2. Image reconstruction using Eigenfaces

Using pca basis from above, we perform face reconstruction. Fig. 2 and Fig. 3 shows reconstruction results using different numbers of PCA bases. As seen in the images, the reconstruction become more accurate with more bases. When using only 10 bases, the results resemble the mean face(Fig. 13) of training data. This occurs because the PCA basis is oriented to capture common features by maximizing data variance. Thus, with a small number of bases, the reconstruction reflects common features of the dataset more strongly than specific details of each image.

For more detailed analysis, we computed the reconstruction error. The theoretical error is given by  $\sum_{i=n+1}^M \lambda_i$  where  $n$  is the number of bases we used for the reconstruction,  $M$  is total number of PCA bases, and  $\lambda_i$  is eigenvalues of unused eigenvectors. The actual reconstruction error can be calculated using L2-norm of difference between the original and reconstructed data.

As shown in Fig. 4, the reconstruction error from the

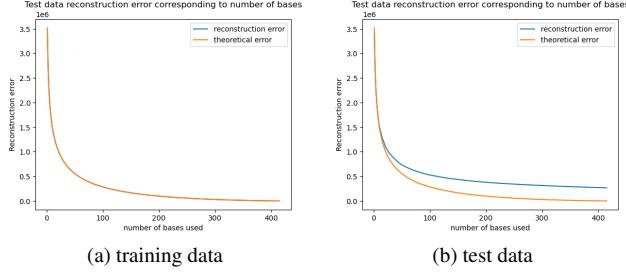


Figure 4. PCA reconstruction error

training data matched the theoretical result. However, for the test data, while the graph’s shape was similar to the theoretical result, the actual values differed slightly. This may be because the PCA bases used for reconstruction were derived from the training data, not the test data.

### 1.3. KNN classification using Eigenfaces

We can also perform classification using PCA with NN classifier. As shown in Fig. 5a, accuracy improves with more PCA bases and fewer neighbors( $k$ ). More PCA bases preserve more data information, leading to accurate projections in the PCA subspace. For the number of neighbors, using fewer makes the classifier more sensitive to local information and better at preserving class boundaries, thus increasing classification accuracy.

In terms of time and memory, the number of neighbors made no significant difference. However, as shown in Fig. 5b and Fig. 5c, the execution time and memory usage of the  $k$ -NN classifier linearly increase with the number of PCA bases increase. This is because, the execution time and memory usage is  $O(N \cdot M)$  where  $N$  is the number of total data and  $M$  is the number of PCA bases we used. Since  $k$  only affects on final selection process, its impact during the computation is very small.

However, its overall prediction accuracy is about 0.6, which is not that high. This might because, PCA is not very sophisticated model to capture all the detailed features of data. As we also check from the confusion matrix(Fig. 14), there are many components outside the diagonal, that failed to be predicted.

Detailed prediction examples can be found in Appendix B, C.

## 2. Incremental PCA

### 2.1. Important parameter in implementation: $d_3$

To implement incremental PCA, we utilized the algorithm from the "Online Learning" slides presented in class. Here, a key parameter is  $d_2$  and  $d_3$ . When new data arrives in incremental PCA, computing the eigenspace model for this subset requires  $O(\min(D, N')^3)$  time, where  $N'$  is the

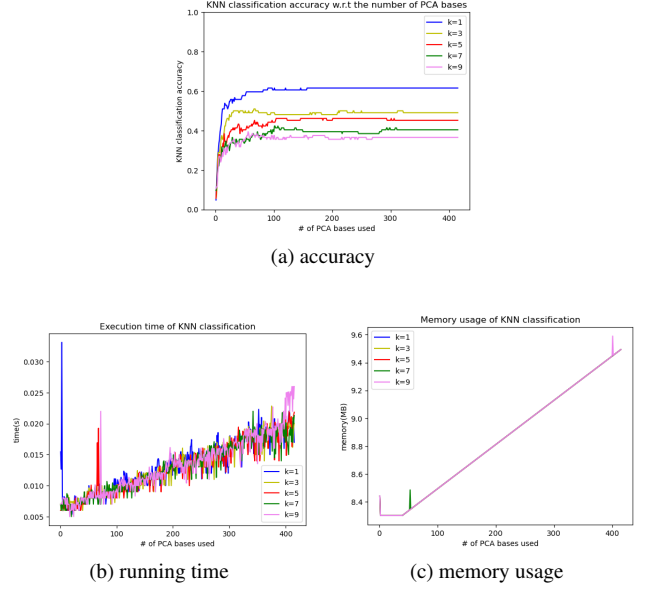


Figure 5. Analysis on KNN classification using PCA

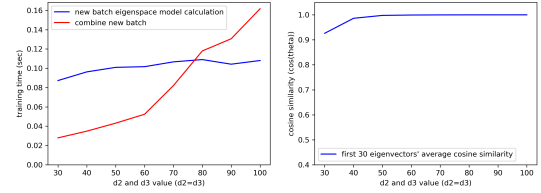


Figure 6. Incremental PCA’s time-accuracy tradeoff according to the value of  $d_3$

number of data points in the subset. Additionally, merging this new eigenspace model with the existing data takes  $O((d_1 + d_2 + 1)^3)$  time, where  $d_1$  is equal to the previously computed eigenspace model’s  $d_3$  value. Therefore, to enhance time efficiency in incremental PCA, it is essential to keep  $d_3$  small, although this results in a time-accuracy tradeoff by dropping less-significant eigenvector information, which is represented by our experiment result Fig. 6

### 2.2. Comparison with other PCA

We compared the results of each incremental PCA stage (i.e.adding training data in four batches) with the results of batch PCA in the following four aspects. In summary, incremental PCA is a good approximation of batch PCA, and even requires less training time.

- Training time: For batch PCA, we measured training time by re-training the model each time new data was added. The results are shown in Fig. 7a. Using one subset, the training time is approximately the same for both methods. However, as we add more data, the value of  $N$  increases for batch PCA, while the values of  $N'$  and  $d_3$  remain con-

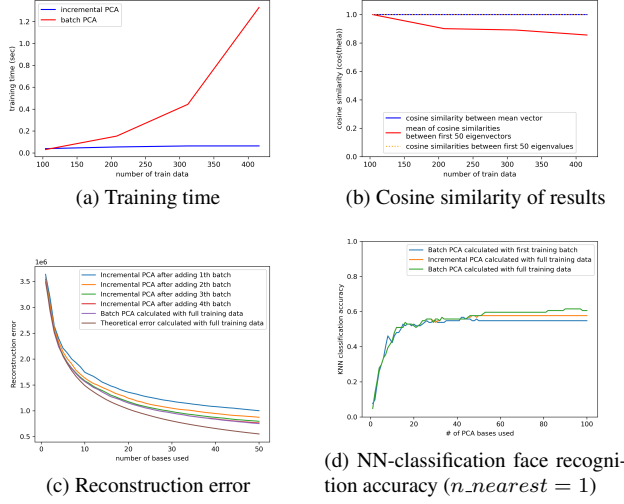


Figure 7. Comparison between Incremental and Batch PCA methods

stant for incremental PCA, maintaining constant time and improving time-wise efficiency.

- **Accuracy of incremental PCA:** In incremental PCA, time-accuracy tradeoff occurs since less-significant eigenvectors are dropped during  $d_1 + d_2$  merging, retaining only the top  $d_3$  eigenvectors. We calculated the cosine similarity of eigenvectors, eigenvalues, and mean vectors between incremental PCA at each stage and batch PCA calculated by corresponding data, as shown in Fig. 7b. As more training data is added, the number of discarded less-significant eigenvectors increases, resulting in decreased similarity between eigenvectors; the similarity after adding the last subset is 0.856. For mean vectors and eigenvalues, cosine similarities are 1 and close to 1 respectively, indicating that the incremental PCA is a good approximation.
- **Reconstruction error:** Referring to Fig. 7c, the reconstruction error for incremental PCA using all training data (i.e., after adding the 4th batch) is almost identical to that of batch PCA with the same amount of data. This also demonstrates that incremental PCA gives similar result to batch PCA.
- **Face recognition accuracy:** In the optimal settings of batch PCA found in Question1 (i.e.  $K=1$  and  $bases=90$ ) the accuracy ranks as follows: full-data batch PCA > full-data incremental PCA > PCA using only the first training set. This indicates that classification accuracy improves progressively with the increase in training data. Additionally, using incremental PCA in place of batch PCA results in an accuracy drop of approximately 6.67%, also indicating a time-accuracy tradeoff.

### 3. LDA Ensemble for Face Recognition

PCA can effectively reduce the dimension of input data preserving important features. And LDA can maximize the variance of between-class while minimize between-class. Thus, using PCA-LDA is expected to increase computing efficiency and classification accuracy. In this section, we try to figure out the effect of PCA-LDA via some experiments.

#### 3.1. Recognition accuracy of PCA-LDA

To implement PCA-LDA, we set  $M_{pca}$  and  $M_{lda}$  by measuring classification accuracy with  $M_{pca}$  from 1 to 415 and  $M_{lda}$  from 1 to  $\min(M_{pca} - 1, 51)$ . This is because, the maximum possible projection dimension for PCA is  $N - 1$  since the total number of principal components can not be larger than overall data, and for LDA is  $n_{class} - 1$  since the number of direction for maximizing the distance of between-class and minimizing within-class cannot be larger than the total number of classes. As shown in Fig. 8, accuracy peaked at  $M_{pca} = 150$  and  $M_{lda} = 50$ . Higher  $M_{lda}$  improves performance by enhancing data discrimination, while optimal  $M_{pca}$  is between 100 and 200, balancing information retention and overfitting risk.

In LDA, the rank of within-class scatter matrix( $S_w$ ) is  $\min(364, M_{pca})$ , where  $N - n_{class} = 416 - 52 = 364$  and the rank of between-class scatter matrix( $S_b$ ) is  $n_{class} - 1 = 51$ . Since  $\sum_{x \in D_i} (x - m_i) = 0$ , each class is linearly dependent, so,  $S_w = \sum_{i=1}^c \sum_{x \in D_i} (x - m_i)(x - m_i)^T$  has at most  $N - n_{class}$  linearly independent row vectors. After reducing dimensions using PCA, the rank of  $S_w$  cannot exceed  $M_{pca}$  as the vectors are confined to the PCA subspace. For  $S_b$  defined as  $S_b = \sum_{i=1}^c (m_i - m)(m_i - m)^T$ , it depends only on class means, and since their relationship of class mean does not change after PCA projection since their relationships remain unchanged under PCA (a linear transformation), the maximum possible rank for  $S_b$  is  $N - n_{class}$ .

Based on this observation, we decided to fix  $M_{pca} = 150$  and  $M_{lda} = 50$  for further experiments.

#### 3.2. Result of PCA-LDA

Fig. 15 is the confusion matrix of PCA-LDA classification result. As most of prediction result is on the diagonal entry, it indicates that most of prediction is successful. We take a closer look at success and failure cases. Fig. 19 shows successfully predicted cases. Despite the different angles of the faces, the model infer the class accurately. Fig. 20 is failure cases. It seems that the prediction failed because of the similar glasses and face expression.

#### 3.3. PCA-LDA Ensemble

There are 3 hyperparameter that we can handle randomness: the number of random vector in feature space, the proportion of training data for subsampling, and the number of

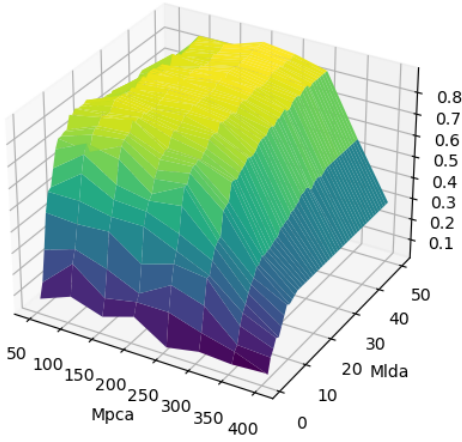


Figure 8. Classification accuracy varying Mpca and Mlda

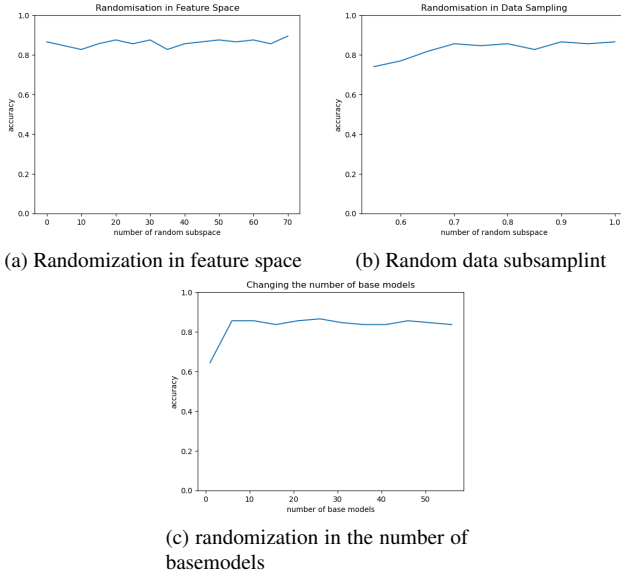


Figure 9. Accuracy comparison between randomness parameters

models for the ensemble. We will examine the impact of each one one by one.

First, we look into randomization in feature space ( $M1$ ). As Fig. 9a indicates, the accuracy is almost highest when the number of random samples is around 30. This is because if the number of random vectors is too large, important features cannot be preserved, and if it is too small, overfitting occurs. Therefore, it is estimated that optimization occurred when the number of random vectors was 30.

Next, we observe the impact of data subsampling proportion ( $\alpha$ ). Fig. 9b shows the accuracy with respect to the proportion of sub-sampled data. The more data we use, the better accuracy we get. This is quite predictable since

the more data you have, the easier it is to generalize.

Lastly, regarding the effect of the number of base models ( $n_{model}$ ), we varied the number from 1 to 60, as shown in Fig. 9c. When there are fewer than 30 models, the results are similar to a single PCA-LDA model. However, with more than 30 models, performance improves significantly, though further increases beyond 30 yield minimal gains. This is because up to 30 models, the ensemble can capture diverse features for generalization, but the PCA-LDA model's limited ability to capture complex patterns prevents substantial improvement beyond that point. We used "majority voting" for combining predictions, as it's most suitable for classification tasks where each class lacks numeric meaning, making it more appropriate than methods like averaging or maximum selection.

Considering both accuracy and computation cost, we conclude that the ensemble model with  $M1 = 30$ ,  $\alpha = 0.9$ ,  $n_{model} = 30$  has the best performance.

### 3.4. Result of PCA-LDA Ensemble

The accuracy of committee machine, which gather all prediction results from each base models from ensemble model, is 0.846. And the average of individual models in ensemble model is 0.736. From this result, we can check that the performance of committee machine is better than individual as we learned. (Ensemble Learning LN, p.11-13)

In addition, Fig. 16 shows the confusion matrix of ensemble model. Compared to Fig. 15, since Fig. 16 has less components outside the diagonal, we can visually check that the accuracy of classification of ensemble model is higher than single PCA-LDA model.

## 4. Generative and Discriminative Subspace Learning

PCA is a generative model, which aims to reconstruct the input. And LDA is a discriminative model, which conducts classification. If we want to take advantages of both methods, it is inevitable to redesign the objective function.

### 4.1. Objective function

To achieve our goal, it is natural to think of a function that combine objective functions from PCA and LDA.

$$J(W) = \alpha W^T S W + (1 - \alpha) \frac{W^T S_b W}{W^T S_w W} \quad (1)$$

Eq. (1) is identical to PCA objective function when  $\alpha = 1$  and to LDA objective function when  $\alpha = 0$ . Our goal is to find  $W$  that maximizes  $J(W)$  since reconstruction error is reduced and subspaces become more discriminative when PCA, LDA objective functions are maximized. Such  $W$  must satisfy Eq. (2) for some constant  $\lambda$ .

$$(\alpha S + (1 - \alpha) S_b) W = \lambda (\alpha I + (1 - \alpha) S_w) W \quad (2)$$

If  $\alpha I + (1 - \alpha)S_w$  is invertible, we can easily get  $W$  using eigenvector-eigenvalue method. Detailed derivation can be found in Appendix D.

## 5. RF classifier

The random forest model has several key parameters, and testing them all simultaneously would require excessive effort and time. Therefore, we configured the optimal parameters in the sequence described below. Also, to ensure result stability, each test was executed 10 times, with the average result displayed in a graph, and the confusion matrix representing the best result among the 10 runs is recorded in Appendix.

1. Number of Trees & Tree Depth: We tested using an axis-aligned weak learner with the split number fixed at 10.
2. Split Number (Randomness Parameter): Using the optimal number of trees and tree depth derived in step 1, with an axis-aligned weak learner.
3. Type of Weak Learner: With the optimal values for other parameters determined in steps 1 and 2, we tested different weak learners.

### 5.1. Number of trees & The depth of trees

We varied the number of trees and their depths, obtaining the results shown in Fig. 10a. In the graph, the best accuracy 0.625 occurred at  $N(\text{number of trees}) = 250$  and  $D(\text{depth}) = 10$ , explained as follows:

- Number of Trees: A single tree in random forests tends to overfit to data; therefore, we can generalize the model using ensembles of trees. As shown in Fig. 10a, the accuracy converges near  $N = 250$ , which is selected as optimal parameter.
- Tree Depth: When depth is  $D$ , maximum of  $2^D - 1$  nodes are generated. As shown in Fig. 10a, for a given  $N$ , accuracy initially increases with tree depth but later decreases due to overfitting. Notably, the optimal depth  $D$  increases with  $N$ , indicating that a larger  $N$  result in less overfitting. Also, we chose  $D = 8$  as the later experiment's standard value, accuracy of 0.610, which is sufficiently high.

The theoretical training/testing time when adjusting the number of trees and tree depth is as follows, and our testing time results align with theoretical predictions Fig. 10b, Fig. 10c. However, due to the small size of the training data, some splits stop prematurely, not reaching the maximum tree depth, resulting in less training time than theory.

- Number of Trees  $N$ :  $O(N)$  time
- Tree Depth  $D$ :  $O(2^D)$  time

Moreover, our code do not utilize parallelization of each tree's growth. Based on theoretical insights from course materials, training each tree in parallel could reduce the time for the tree numbers to  $O(1)$ , not  $O(N)$ .

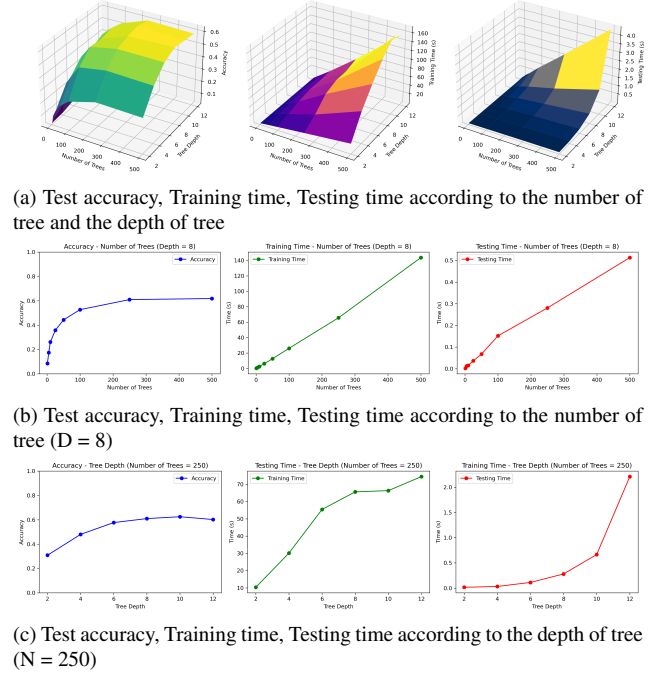


Figure 10. Test accuracy, training/testing time according to the number and depth of trees

### 5.2. Randomness parameter

Due to the high dimension image data, we randomly select dimensions and threshold values to create the split function. For each split function, we attempt  $\rho$  random splits and choose the one with the highest information gain. There is a trade-off in the magnitude of  $\rho$  value: If the  $\rho$  value is too low, fewer splits are attempted, which reduces similarity between trees but increases the risk of the less-optimal split. Conversely, as  $\rho$  increases, more various split functions are tested, leading to greater similarity among trees, which decreases the advantage of ensemble multiple trees. As shown in Fig. 11a, accuracy initially increases with higher  $\rho$  values until  $\rho = 10$  and then decreases, as expected. In Fig. 11b, training time is same as expected,  $O(\rho)$ . However, since  $\rho$  does not affect the resulting tree structure in training, it has constant testing time.

### 5.3. Impact of the different types of weak-learners

The impact of the weak learner are shown in Fig. 12. As expected, the axis-aligned method provides sufficiently good testing accuracy along with the shorter training and testing times. However, even with all other parameters being the same, the accuracy when using the two-pixel test is approximately 8.32% higher. Therefore, the two-points test's information gain per split is greater than that of the axis-aligned method. Although other weak learners, such as linear and non-linear methods, were also implemented and tested, they



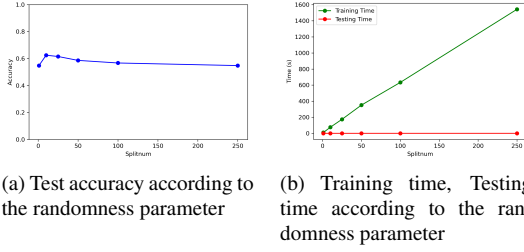


Figure 11. Test accuracy, training/testing time according to the randomness parameter

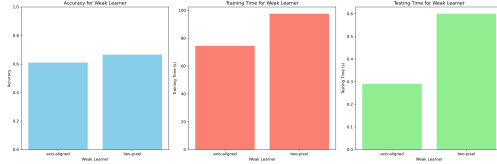


Figure 12. Axis-aligned vs Two-pixel test

took so long to measure training and testing times that it was expected impractical for real-time training/testing, and thus they were not included in the report.

#### 5.4. Confusion matrix, Example success/failures, Information gain histogram

The main results' confusion matrix, example success/failures, example node's histogram representing information gain along splitting are written in Appendix: E, F

#### 5.5. Comparison with PCA and PCA-LDA method

Since parallel programming was not used our random forest, both the training and testing times are significantly large compared to the PCA and PCA-LDA methods. In addition, for PCA and PCA-LDA, the differences are further amplified due to Python NumPy's parallelization for matrix operations and scikit-learn's optimized KNN classification, which is well-tuned for handling multiple data points efficiently. About the accuracy, because raw pixel values were used directly as inputs, the optimal accuracy of Q1 PCA is almost identical to random forest's result. Overall, the accuracy is much lower compared to the PCA-LDA method, indicating that in situations where the size of the training dataset is small ( $N \ll D$ ), applying the random forest with no PCA is relatively less suitable. Additionally, similar to the PCA-LDA ensemble, as the number of base models (tree) increases, there is a tendency for accuracy to improve, indicating that the 'ensemble models' is beneficial.

# Appendix

## A. Mean face

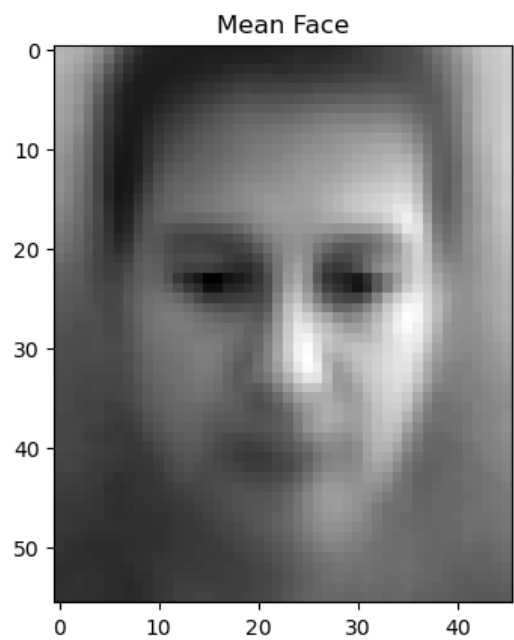


Figure 13. Mean face of training data

## B. Confusion matrix

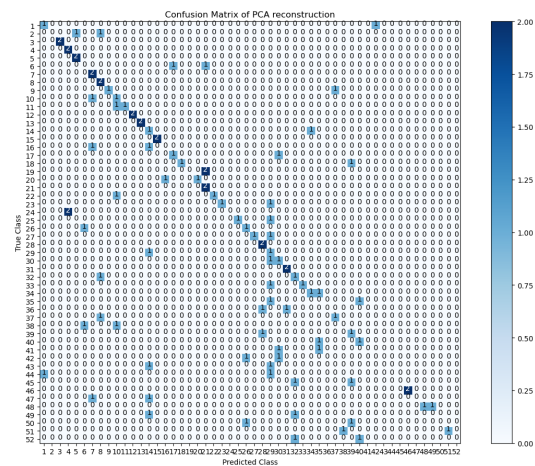


Figure 14. Confusion matrix of PCA

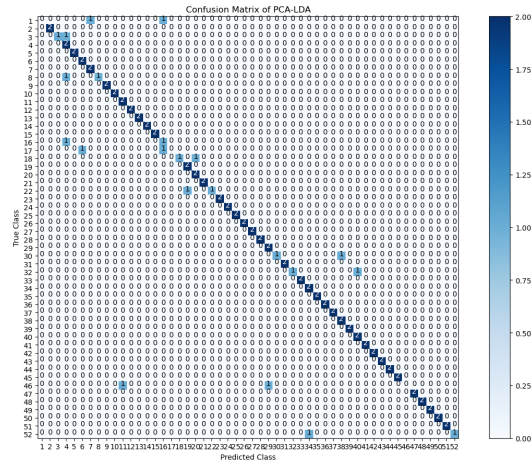


Figure 15. Confusion matrix of PCA-LDA

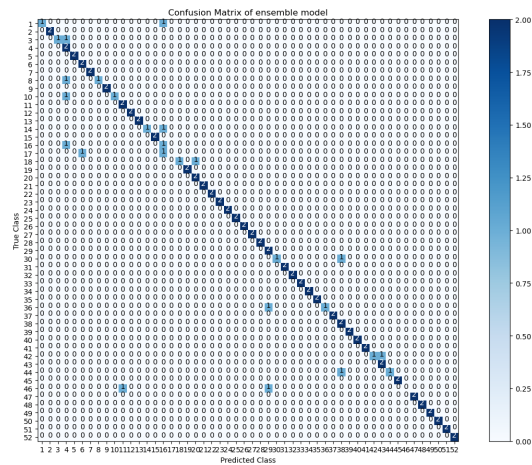


Figure 16. Confusion matrix of Ensemble model



Figure 17. PCA classification success example





Figure 18. PCA classification failure example



Figure 19. PCA-LDA classification success example



Figure 20. PCA-LDA classification failure example

## C. Prediction examples

## D. Generative and Discriminative Subspace Learning

Below is the objective function for generative and discriminative subspace learning. Our goal is to find  $W$  that maximizes  $J(W)$

$$J(W) = \alpha W^T S W + (1 - \alpha) \frac{W^T S_b W}{W^T S_w W} \quad (3)$$

Eq. (3) can be changed as Eq. (4) since  $W^T W = I$ . (This is because,  $W$  is a projection matrix, hence  $W^T W$  indicates re-projection after projection to the subspace. Therefore, projected vector returns to itself after applying  $W^T W$ .)

$$J(W) = \alpha \frac{W^T S W}{W^T W} + (1 - \alpha) \frac{W^T S_b W}{W^T S_w W} = \frac{W^T (\alpha S + (1 - \alpha) S_b) W}{W^T (\alpha I + (1 - \alpha) S_w) W} \quad (4)$$

If we keep the denominator constant, the problem we have to solve changes to the problem to maximize the numerator. Let the denominator  $k(\text{constant})$  and use Lagrange-multiplier. (Eq. (5))

$$W^T (\alpha I + (1 - \alpha) S_w) W = k \quad (5)$$

$$L(W, \lambda) = W^T (\alpha S + (1 - \alpha) S_b) W + \lambda (k - W^T (\alpha I + (1 - \alpha) S_w) W) \quad (6)$$

To get the solution, each partial derivatives of  $L(W, \lambda)$  with respect to  $W$  and  $\lambda$  must be 0.

$$\frac{\partial L}{\partial W} = 2 * W (\alpha S + (1 - \alpha) S_b - \lambda (\alpha I + (1 - \alpha) S_w)) = 0 \quad (7)$$

$$\frac{\partial L}{\partial \lambda} = k - W^T (\alpha I + (1 - \alpha) S_w) W = 0 \quad (8)$$

Eq. (8) is satisfied from our assumption of the denominator. Now, the only thing we have to consider is Eq. (7). If we organize Eq. (7), we can get Eq. (9).

$$(\alpha S + (1 - \alpha) S_b) W = \lambda (\alpha I + (1 - \alpha) S_w) W \quad (9)$$

If  $\alpha I + (1 - \alpha) S_w$  is invertible, the equation becomes as below.(Eq. (10))

$$(\alpha I + (1 - \alpha) S_w)^{-1} (\alpha S + (1 - \alpha) S_b) W = \lambda W \quad (10)$$

Since  $\lambda$  is some constants, we can regard Eq. (10) as a eigenvector-eigenvalue problem where  $W$  is an eigenvector matrix and  $\lambda$  is an eigenvalue matrix.

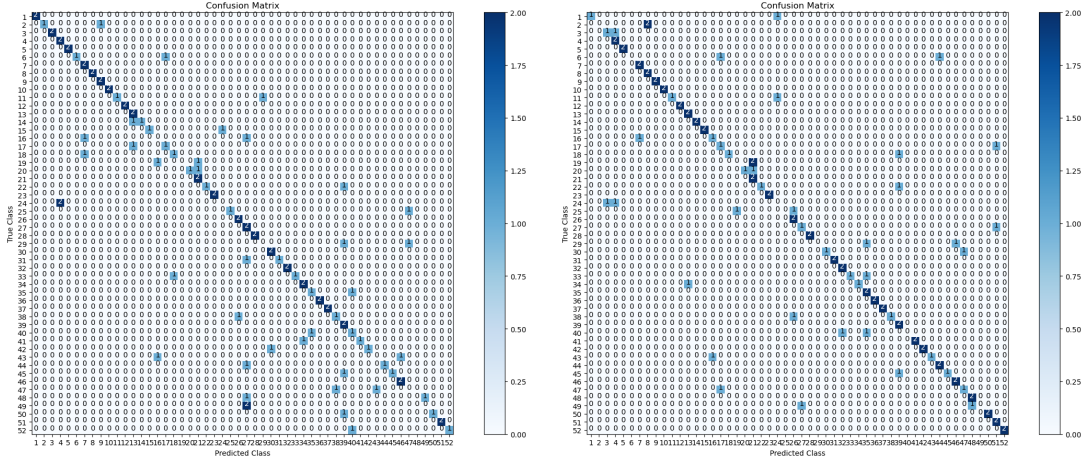
## E. Q5: Test result's confusion matrix and success/failure cases

The optimal parameters determined for the random forest through experiments are  $N = 250$ ,  $D = 8$ , and  $\text{splitnum} = 10$ . With this configuration, each real-time executable weak learner—axis-aligned and two-pixel tests—each was trained 10 times. The confusion matrix results below represent the best test accuracy among the 10 repetitive train results.

Additionally, the example success and failure cases based on the confusion matrix results above are shown below. Compared to the success cases, the failure cases show a higher similarity between the failed image and the predicted class, meaning that our model is reasonable.

## F. Q5: Visualization of random forest's information gain process

## References



(a) Axis-aligned weak learner, test accuracy=0.644

(b) Two-pixel test weak learner, test accuracy=0.692

Figure 21. Confusion matrix of optimal cases ( $N = 250$ ,  $D = 8$ , and splitnum = 10)

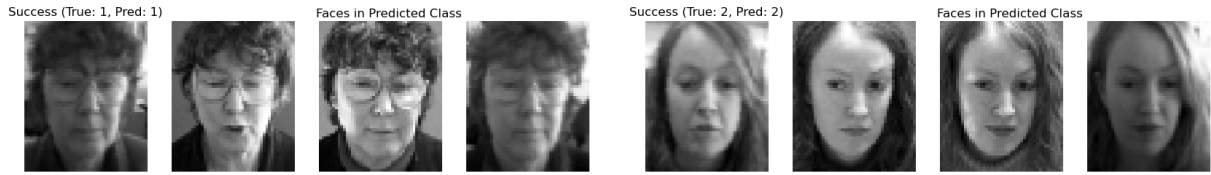


Figure 22. Axis-aligned weak learner: Example success case



Figure 23. Axis-aligned weak learner: Example failure case



Figure 24. Two-pixel test weak learner: Example success case



Figure 25. Two-pixel test weak learner: Example failure case