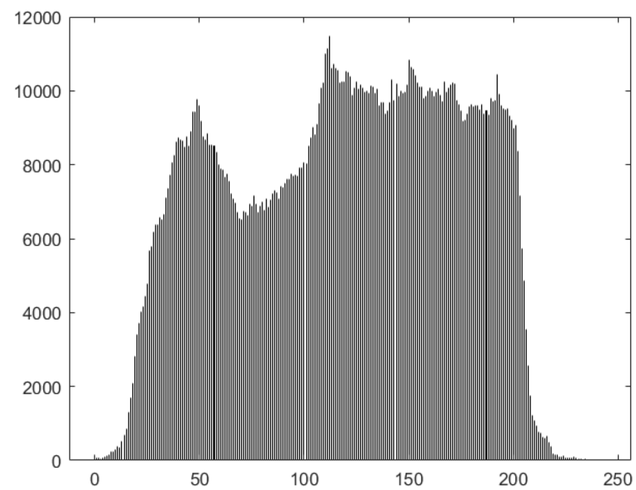
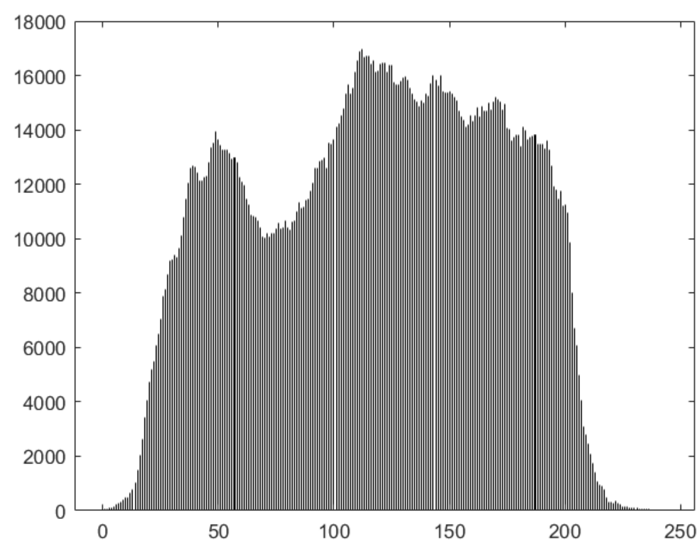
- Original image data, only change X.
- Value of Data:
  - X_test : 160x112x92 single (160x10304 double)
  - X_train : 249x112x92 single (240x10304 double)
  - Y_test: 160x20 double
  - Y_train: 240x20 double

Step 1: Run the model with unconstrained ORL_faces

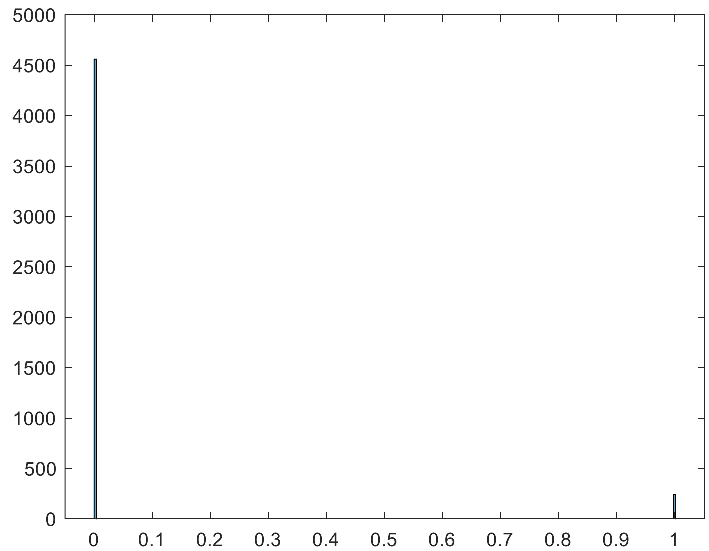


Histogram của X_test

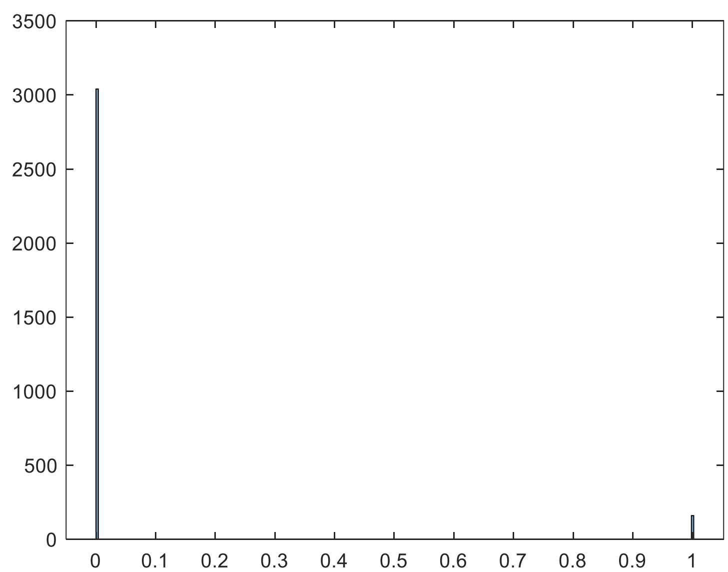


Histogram của X_train

The figure above illustrates two histograms representing the distribution of pixel values in the test dataset (X_test) and the training dataset (X_train). The horizontal axis represents pixel values (assumed to range from 0 to 255 for grayscale images), while the vertical axis indicates the number of pixels with corresponding values. The histogram of X_test (Figure 3.2.2) shows a fairly uniform distribution with a few prominent peaks at specific pixel values. Similarly, the histogram of X_train (Figure 3.2.3) has a comparable shape but with a larger scale, as the pixel count peaks near 18,000, reflecting the larger size of the training set. The X_test dataset consists of 160 image samples, initially sized 112x92 (3-dimensional), which are flattened into vectors of size 160x10304. Meanwhile, the X_train dataset contains 240 image samples, also flattened into vectors of size 240x10304. The corresponding labels are Y_test (160 samples, each with 20 dimensions) and Y_train (240 samples, each with 20 dimensions).



Histogram của y_train ()



Histogram của y_test

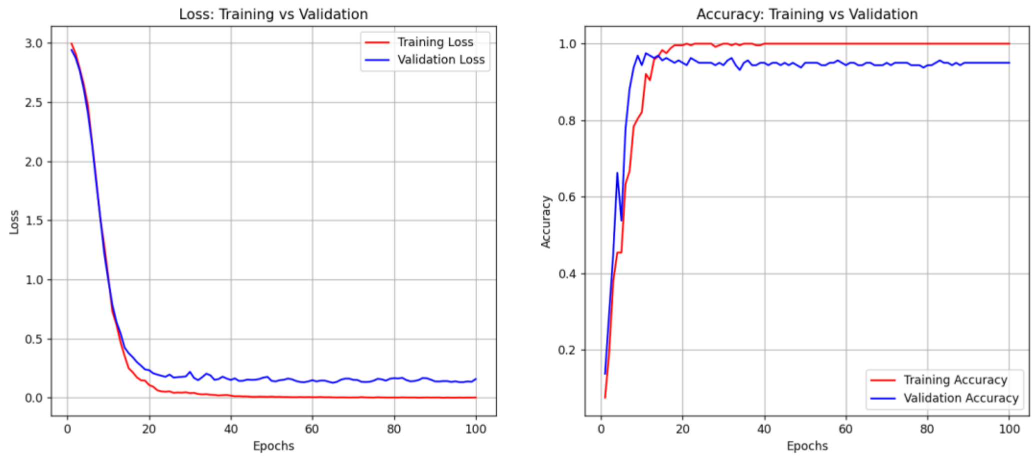
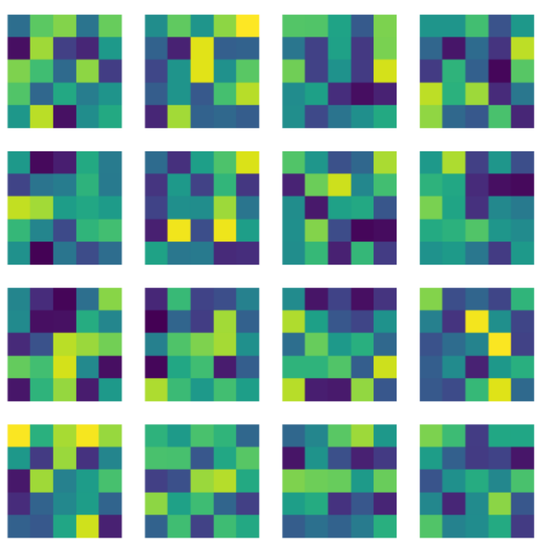


Fig. 3.4 The loss and accuracy between training and validation

Figure 3.4 presents the results of training a machine learning model, covering two aspects: loss and accuracy over the number of epochs. In the left chart, the loss values for both the training and validation datasets decrease rapidly during the initial phase (around the first 20 epochs) and stabilize at a low level as the number of epochs increases. The curves for both datasets align closely, indicating that the model does not suffer from overfitting. In the right chart, the accuracy for both the training and validation datasets increases rapidly during the early epochs, reaching near-maximum values (approximately 1.0) and remaining stable after around 20 epochs. The similarity between the accuracy and loss curves for both datasets demonstrates that the model has effectively learned and generalized well, ensuring good performance on both the validation data and potentially unseen test data.



First Layer

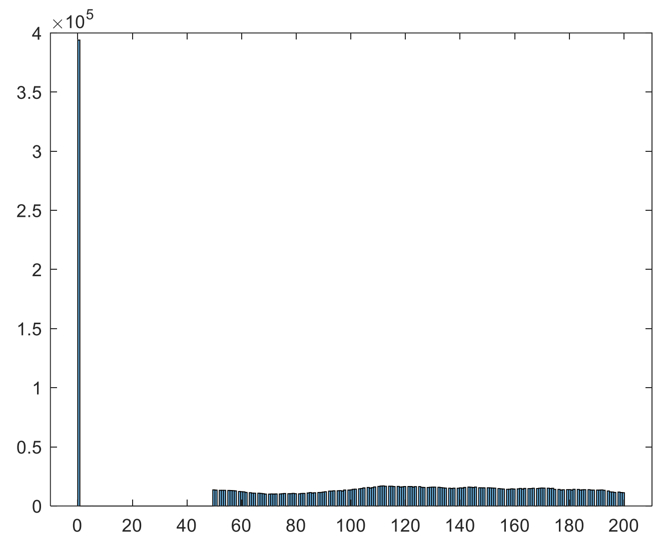
Test Accuracy: 95.00%

The histograms of X_test and X_train reveal a similar distribution after training, with input values ranging from 0 to 255. However, the majority of the input data is concentrated within the range of 10 to 225, as indicated by the figure. This concentrated distribution suggests that most of the significant input values fall within this range.

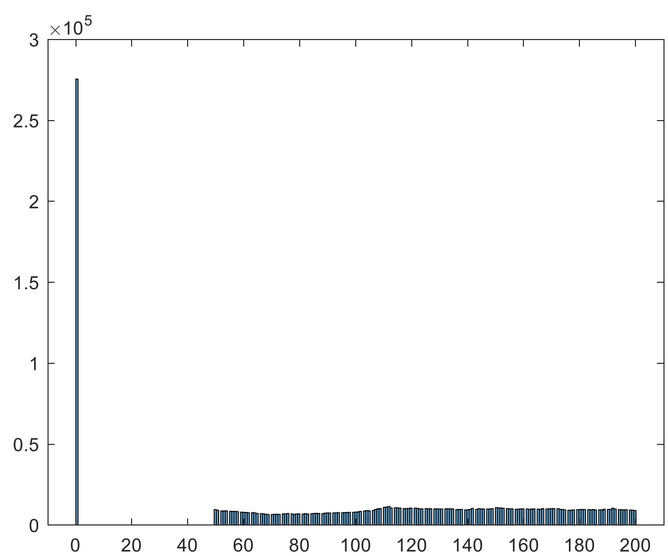
After training the model with this input distribution, the recognition accuracy reaches an impressive **95%**, demonstrating the effectiveness of the training process. This highlights that the data's natural distribution plays a crucial role in optimizing the model's performance, ensuring high accuracy while effectively utilizing the input range.

Step 2. Adjust data

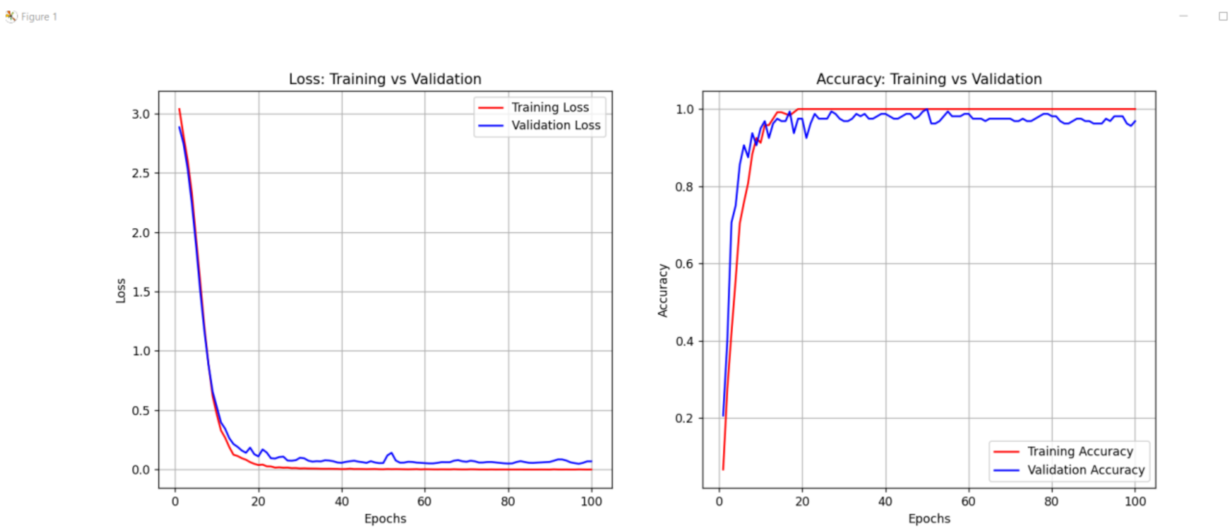
Case 1: If data of X < 50 and X > 200, values outside the range will be 0.

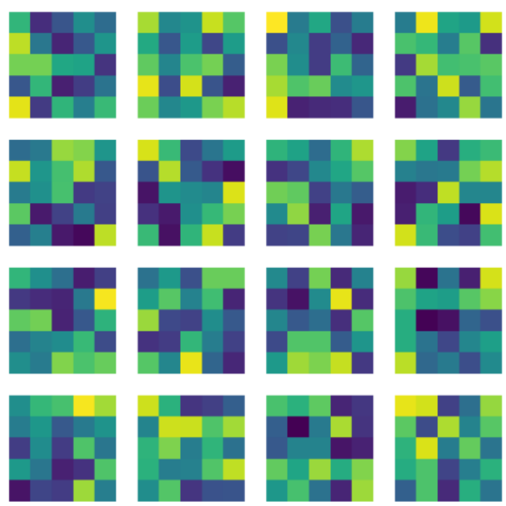


Histogram of X_train



Histogram of X_test



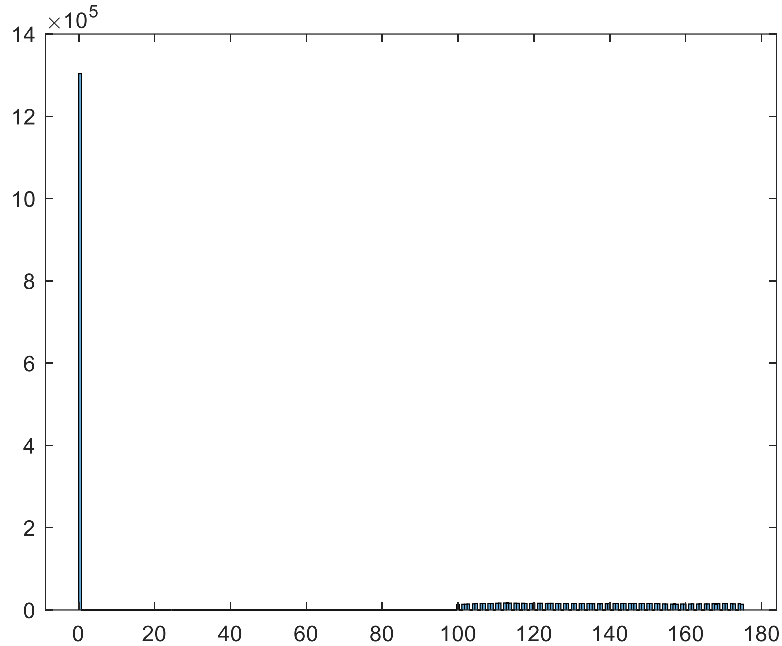


Test Accuracy: 96.88%

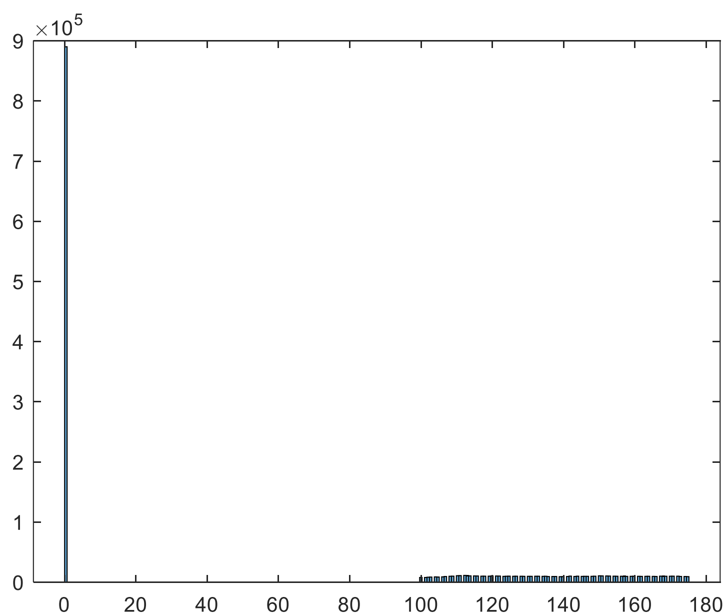
By limiting the input range to values between 50 and 200, we observed that the values within this range remained unchanged, while those outside the range were set to 0. After applying this limitation and retraining the model, the recognition accuracy improved significantly, reaching nearly 97%, which is 2% higher than the accuracy achieved during the original training.

To further analyze the impact of different input ranges, we experimented with ranges from 100 to 175 and 150 to 220. However, in both cases, the recognition accuracy dropped below 93%, indicating a noticeable decline compared to the original training results. These findings suggest that the range from 50 to 200 is optimal for selecting inputs for the multiplier, as it achieves the best balance between accuracy and performance. This range aligns closely with the input distribution most relevant to the application, highlighting its effectiveness in ensuring higher recognition accuracy.

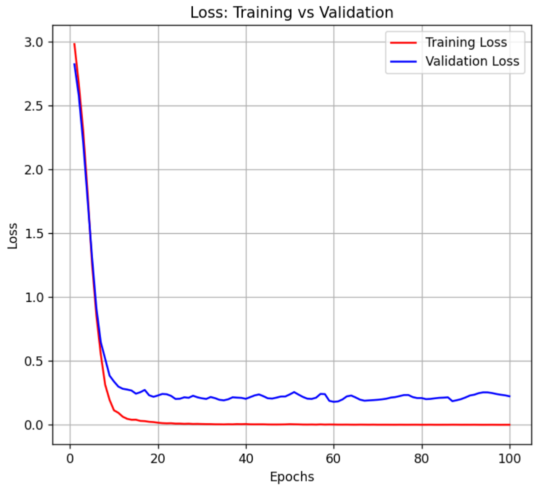
Case 2: If data of X < 100 and X > 175, values outside the range will be 0.

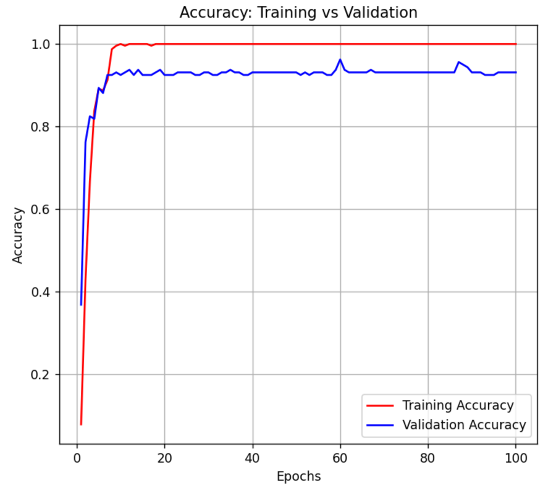


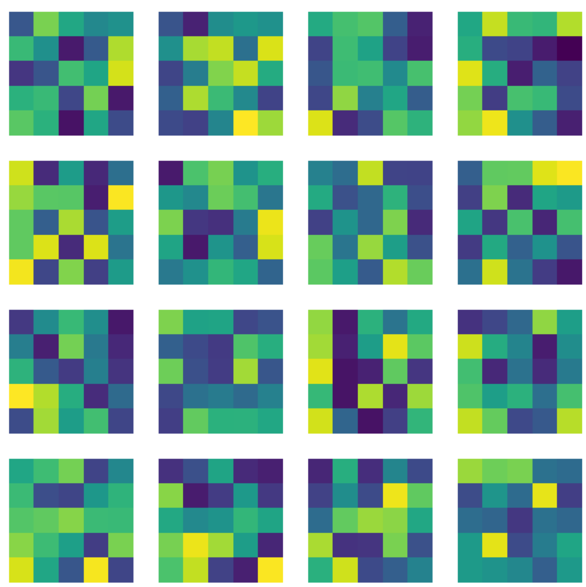
Histogram của X_train



Histogram của X_test



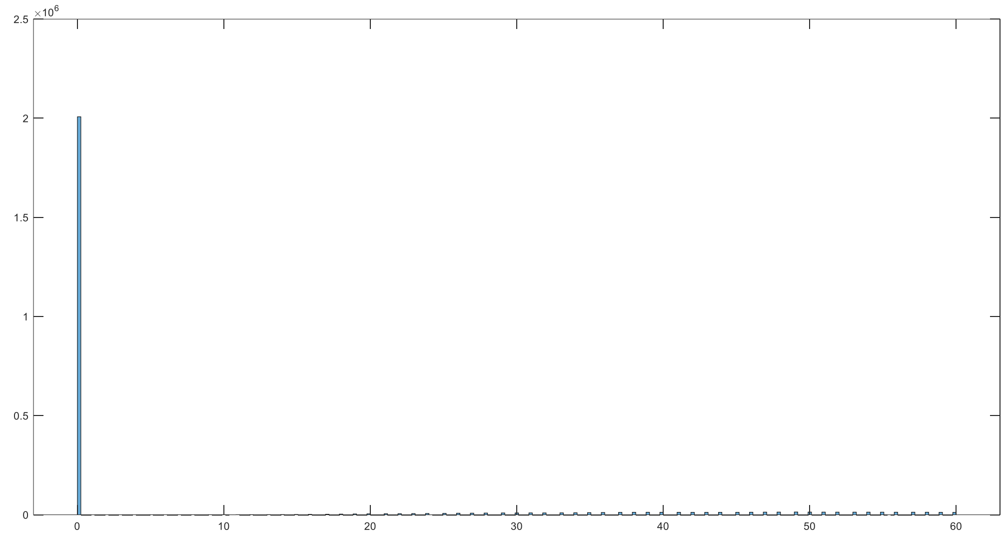




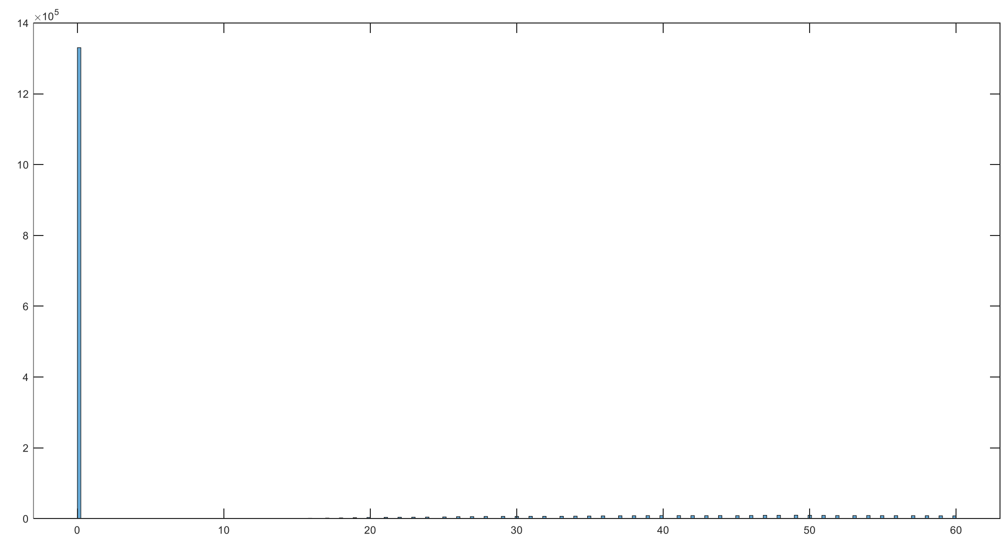
Test Accuracy: 93.12%

Limiting it to [100,175] (outside the range = 0), the accuracy after training is less than 94%, lower than not limiting it to [0,255].

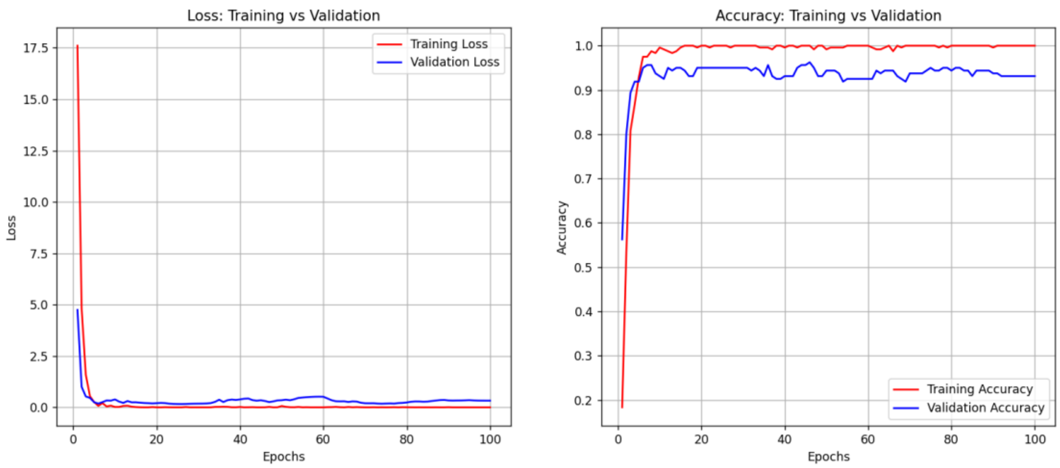
Case 3: If X's data > 60, values outside the range will be 0.

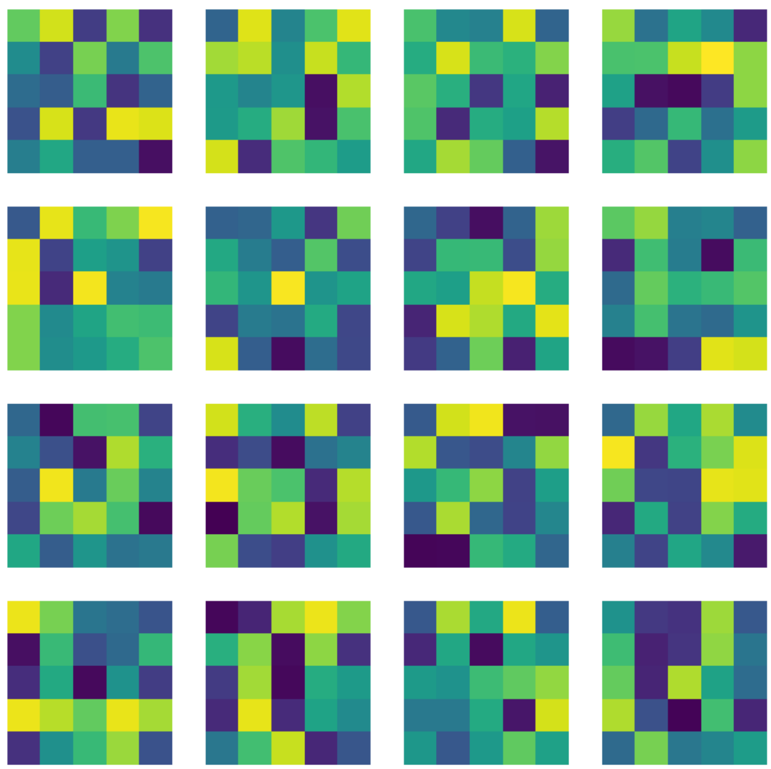


Histogram của X_train



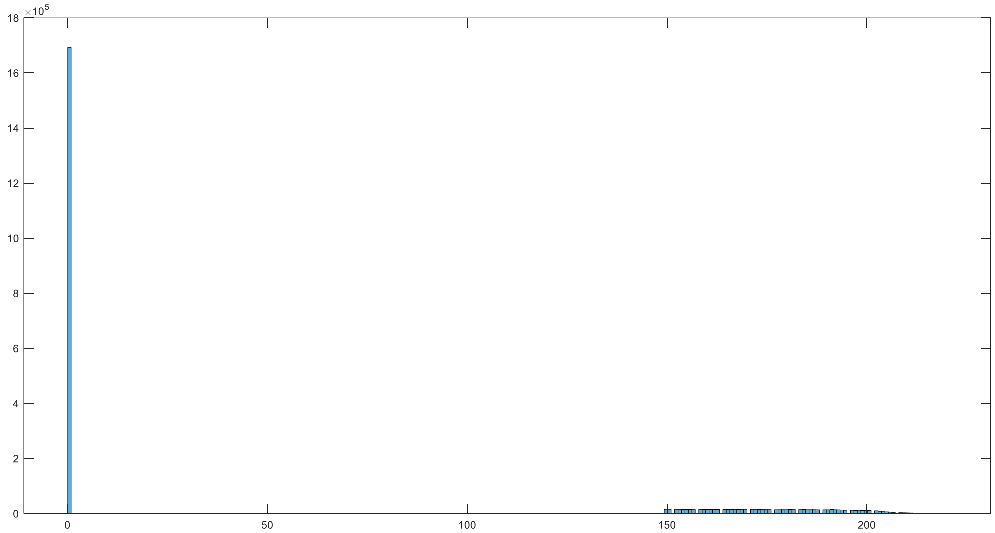
Histogram của X_test



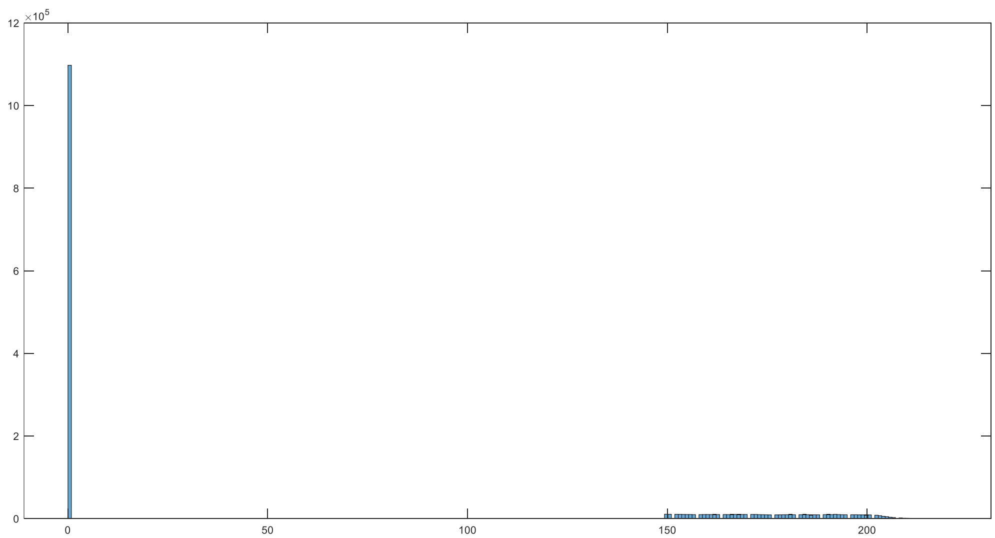


Test Accuracy: 93.12%

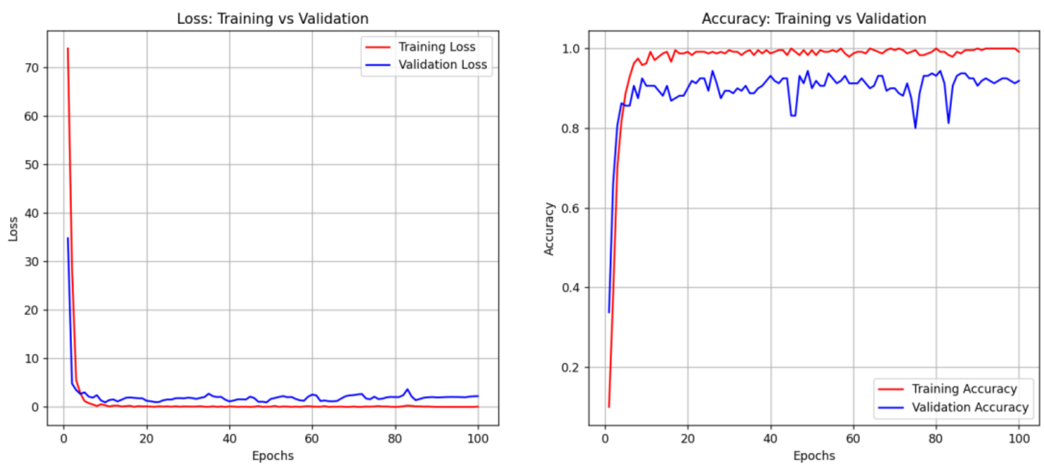
Case 4: If data of X > 150 and X > 220, values outside the range will be 0.

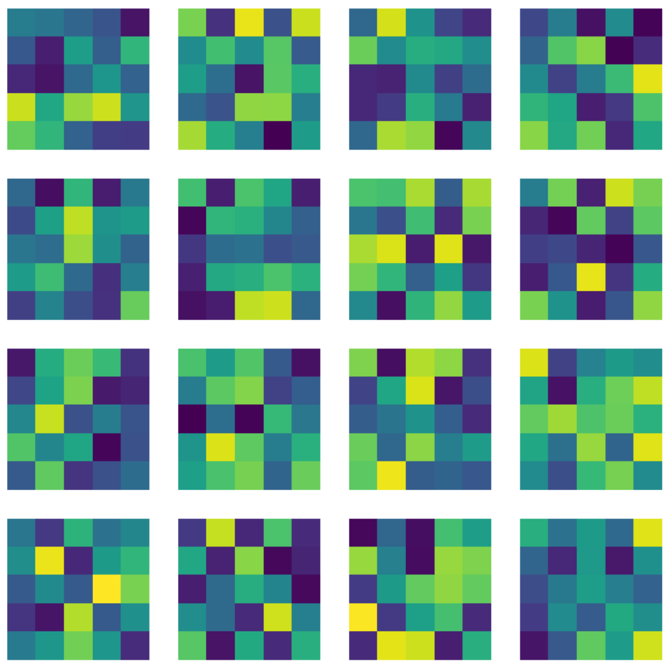


Histogram của X_train



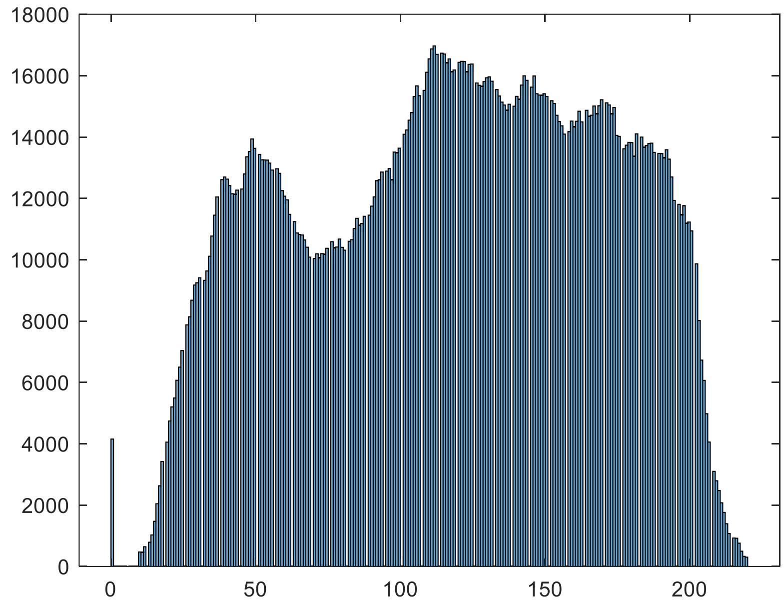
Histogram của X_test



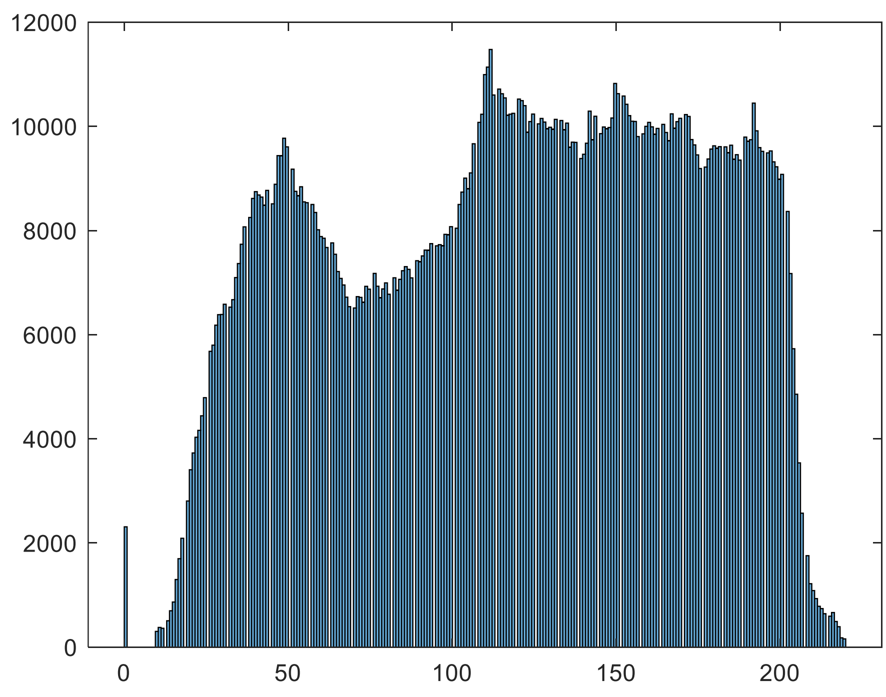


Test Accuracy: 91.87%

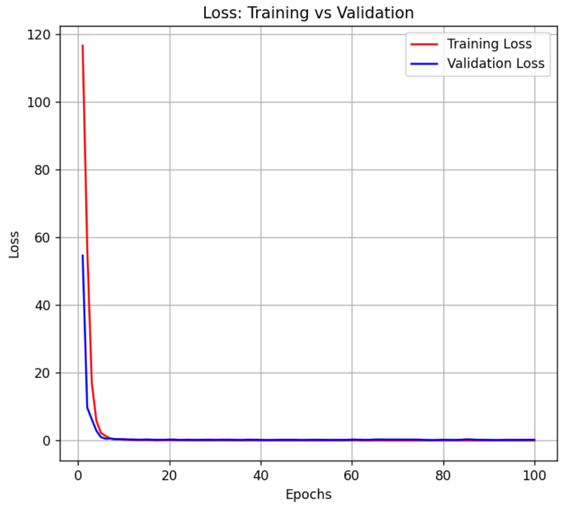
Case 5: If data of X < 10 and X > 220, values outside the range will be 0.

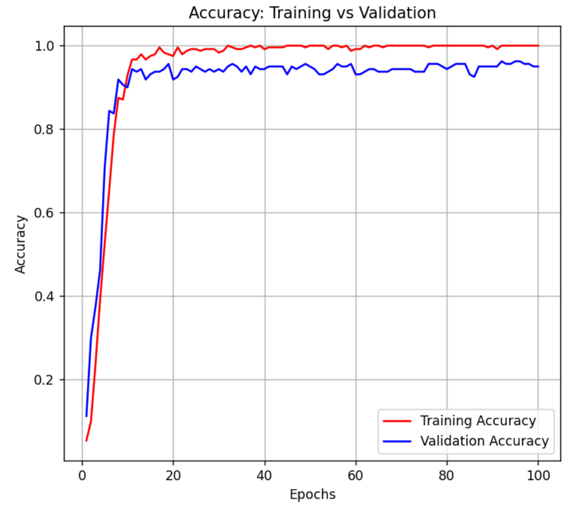


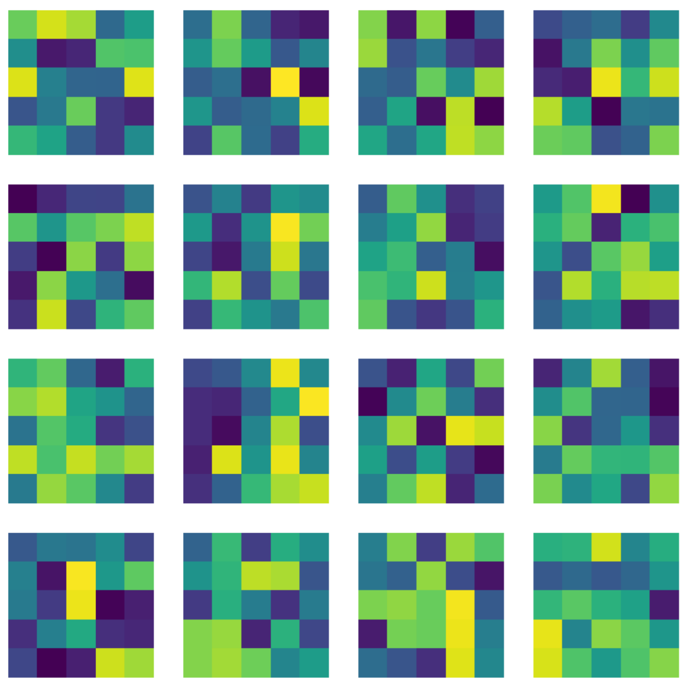
Histogram của X_train



Histogram của X_test







Test Accuracy: 95.00%