Problem 1

1: use sklearn. Select KBest to top 10 best features from the data

```
def selectFeatures(X, y, k=10):
    print('Original shape of X: ', X.shape)
    model = SelectKBest(f_classif, k).fit(X,y)
    features = model.get_support(indices=True)
    X_new = model.transform(X)
    print(k, 'features are selected. Indices of features: ', features)
    print('The shape of new X is: ', X_new.shape)
    return X_new
```

Output:

% python p1.py

Original shape of X: (42000, 60)

10 features are selected. Indices of features: [0 2 4 6 20 21 22 40 41 42]

The shape of new X is: (42000, 10)

2:

A: from sklearn.preprocessing, use normalize

```
def normal(X):
    return normalize(X)
```

B: calculate mahalanobis distance and exclude outliers with alpha = 0.01

```
def mahalanobis method(class data):
  x minus mu = class data - np.mean(class data, axis=0)
  cov = np.cov(x minus mu.T)
  inv covmat = np.linalg.inv(cov)
  left_term = np.dot(x_minus_mu, inv_covmat)
  mahal = np.dot(left term, x minus mu.T)
  md = np.sqrt(mahal.diagonal())
  outlier = []
  C = np.sqrt(chi2.ppf((1-0.01), df=class_data.shape[1]))
  for index, value in enumerate(md):
       if value > C:
          outlier.append(index)
       else:
           continue
  return outlier, md
def removeOutliers(class data, outlier):
  idx = set(range(len(class data)))
```

```
remain = list(idx - set(outlier))

return [class_data[i] for i in remain]

3:
a)
def bayes(X, y):
    gnb = GaussianNB().fit(X,y)
    y_pred = gnb.predict(X)
    tot = len(y)
    acc = 1.0* (y==y_pred).sum() / tot
    print('Accuracy of Naive Bayes Classifier is: ', acc)
```

Output: Accuracy of Naive Bayes Classifier is: 1.0

b)

```
def lda(X, y):
    clf = LinearDiscriminantAnalysis().fit(X, y)
    y_pred = clf.predict(X)
    tot = len(y)
    acc = 1.0* (y==y_pred).sum() / tot
    print('Accuracy of LDA is: ', acc)
```

Output: Accuracy of LDA is: 0.7920062380521179

c)

```
def rbfnn(X, y):
    kernel = 1.0 * RBF(1.0)
    gpc = GaussianProcessClassifier(kernel=kernel,random_state=1).fit(X,y)
    print('Accuracy of RBFNN is: ', gpc.score(X,y))
```

Output: Accuracy of RBFNN is: 1.0

d)

```
def sup_vec_mac(X, y):
    kernel = 'poly'
    clf = SVC(kernel=kernel, gamma='auto').fit(X,y)
    y_pred = clf.predict(X)
    tot = len(y)
    acc = 1.0* (y==y_pred).sum() / tot
    print('Accuracy of SVM is: ', acc)
```

Output: Accuracy of SVM is: 1.0

- 4: Use 50fold cross validation to compare three combinations:
 - 1- Bayes with normalization & outlier removal
 - 2- Bayes with normalization
 - 3- SVM (Poly) with normalization

```
def five fold 1(X, y):
  clf = GaussianNB()
  scores = cross val score(clf, X, y, cv=5)
  print("Bayes with normalization & outlier removal: ")
  print("%0.2f accuracy with a standard deviation of %0.2f\n" % (scores.mean(),
scores.std()))
def five fold 2(X, y):
  clf = GaussianNB()
  scores = cross val score(clf, X, y, cv=5)
  print("Bayes with normalization: ")
  print("%0.2f accuracy with a standard deviation of %0.2f\n" % (scores.mean(),
scores.std()))
def five fold 3(X, y):
  clf = GaussianNB()
  scores = cross_val_score(clf, X, y, cv=5)
  print("SVM(Poly) with normalization: ")
  print("%0.2f accuracy with a standard deviation of %0.2f\n" % (scores.mean(),
scores.std()))
```

Output:

Bayes with normalization & outlier removal:

1.00 accuracy with a standard deviation of 0.00

Bayes with normalization:

0.79 accuracy with a standard deviation of 0.00

SVM(Poly) with normalization:

0.79 accuracy with a standard deviation of 0.00

5:

By comparing the results from problem 3 & 4, it seems Bayes, RBFNN, and SVM (poly) are better than LDA, and outlier removal is important for the model's performance. The best results are achieved by Bayes with normalization & outlier removal.

Problem 2:

```
import pandas as pd
import numpy as np
import tensorflow as tf
from tensorflow.keras import layers, models
import matplotlib.pyplot as plt
if name == ' main ':
  df train = pd.read csv('mnist train.csv')
  labels train = df train['label']
  images train = df train.iloc[:,1:]/255.0
   images train = images train.to numpy().reshape(df train.shape[0], 28, 28, 1)
  model = models.Sequential()
  model.add(layers.Conv2D(32, (3, 3), activation='relu', input shape=(28, 28, 1)))
  model.add(layers.MaxPooling2D((2, 2)))
  model.add(layers.Conv2D(64, (3, 3), activation='relu'))
  model.add(layers.MaxPooling2D((2, 2)))
  model.add(layers.Conv2D(64, (3, 3), activation='relu'))
  model.add(layers.Flatten())
  model.add(layers.Dense(64, activation='relu'))
  model.add(layers.Dense(10, activation='softmax'))
  print(model.summary())
  model.compile(optimizer='adam',
               loss='sparse categorical crossentropy',
              metrics=['accuracy'])
  model.fit(images train, labels train, epochs=5)
  df test = pd.read csv('mnist test.csv')
  labels test = df test['label']
   images test = df test.iloc[:,1:]/255.0
   images test = images test.to numpy().reshape(df test.shape[0], 28, 28, 1)
  test loss, test acc = model.evaluate(images test, labels test, verbose=2)
  print(test acc)
```

```
Output:
% python p2.py
Epoch 1/5
0.9569
Epoch 2/5
0.9855
Epoch 3/5
0.9903
Epoch 4/5
0.9917
Epoch 5/5
313/313 - 1s - loss: 0.0268 - accuracy: 0.9912
0.9911999702453613
```

The CNN model's accuracy for train & test datasets reaches 99%. Specifically 99.39% for training, and 99.12% for test dataset.

Problem 3:

Pseudocode for minima, goal based agent:

```
# pseudocode for minimax algorithm
mini_max(board_state, depth, is_Ai) # return [move, score]
 # init the
 if is_Ai then
     best = [null, -inf]
     best = [null, +inf]
 if (depth == 0 or gameover) then
     score = evaluate this board_state for player
     return [null, score]
 # DFS
 for each valid move m for player in board_state s do
     execute move m on s
     [move, score] = mini_max(s, depth - 1, -player)
     undo move m on s
     if is Ai then
         # for AI, MAX-VALUE
         if score > best.score then best = [move, score]
     else
          # for player, MIN-VALUE
         if score < best.score then best = [move, score]</pre>
 return best
end
```