

ELEC 478 HW5

December 2, 2022

Data

This dataset contains data from approximately 40,000 recipes. Each recipe is labeled with a cuisine of origin, and the list of ingredients used in that recipe are included as well. There are 6713 unique ingredients included in the entire dataset, and 20 different cuisines of origin are represented. The exact number of recipes from each cuisine is visualized below.

Task

The first task is to predict which recipes are from asian cuisines. For the purpose of this task, the following cuisines will be labeled as asian: 'indian', 'japanese', 'chinese', 'filipino', 'thai', 'korean', and 'vietnamese'. In other words, a classification model will be trained on the data and evaluated on a holdout test set, and the classification accuracy will be reported. The 1000 most frequently occurring ingredients will be used as features for this problem, and the values in the feature matrix will be indicators as to whether an ingredient is present in a given recipe.

The second task is to identify which ingredients are most important when determining whether a recipe is asian or not. Many cuisines include similar ingredients. For example, onions may be used in Chinese stir fries, French sauces, and Mexican tacos. However, other ingredients are more unique to certain cuisines. For example, one would not expect Mexican masa to appear in a Thai dish. Thus, the goal of this task is to discover the most defining ingredients in asian cuisine.

Data Preperation

```
[2]: import pandas as pd
import numpy as np

from sklearn import decomposition
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
from sklearn.model_selection import train_test_split, cross_val_score, \
    GridSearchCV, KFold
import warnings
warnings.filterwarnings('ignore')

import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap
```

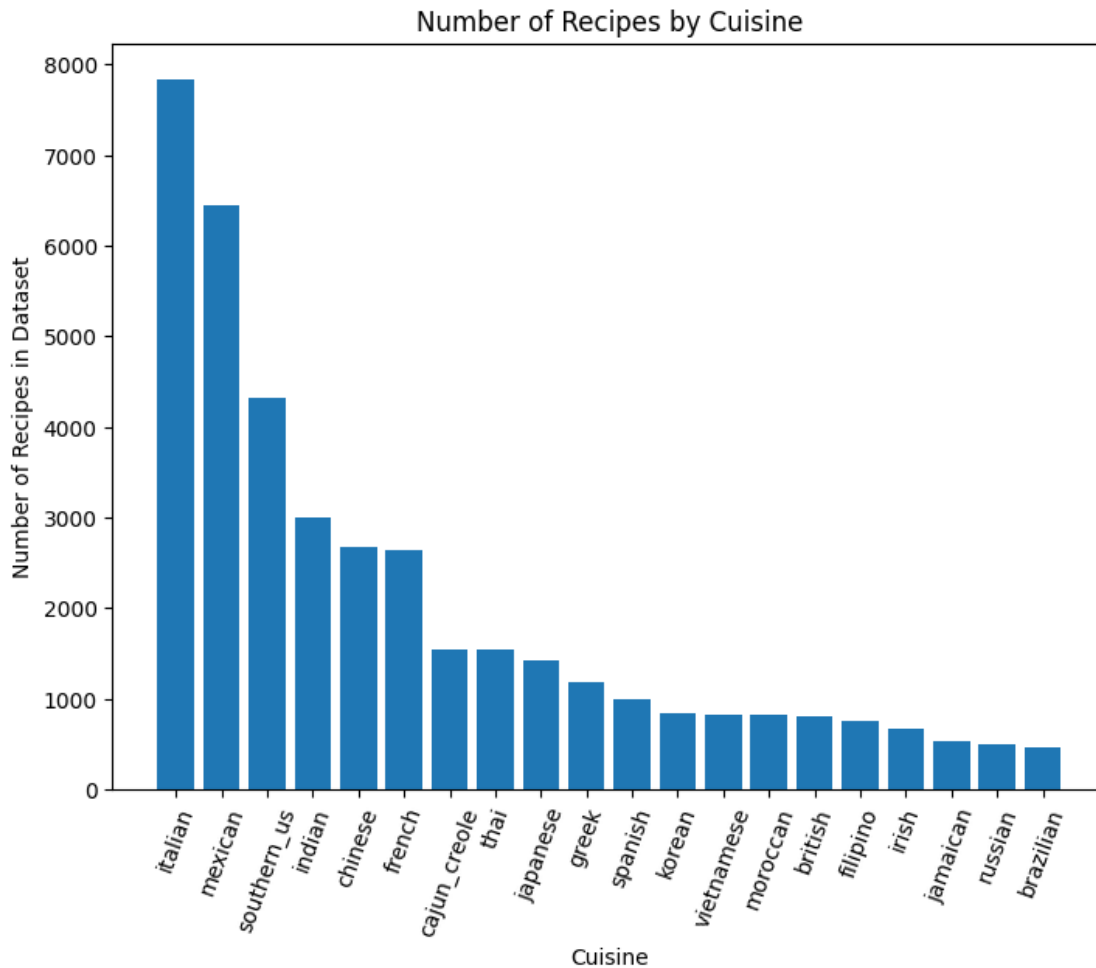
```
[77]: # The test data has no labels, so a train/test split will be performed on the \
    training data
```

```
{'italian', 'russian', 'korean', 'moroccan', 'greek', 'filipino', 'japanese',  
'mexican', 'jamaican', 'vietnamese', 'brazilian', 'spanish', 'british',  
'southern_us', 'cajun_creole', 'irish', 'thai', 'indian', 'french', 'chinese'}
```

```
[78]: Counter({'greek': 1175,
               'southern_us': 4320,
               'filipino': 755,
               'indian': 3003,
               'jamaican': 526,
               'spanish': 989,
               'italian': 7838,
               'mexican': 6438,
               'chinese': 2673,
               'british': 804,
               'thai': 1539,
               'vietnamese': 825,
               'cajun_creole': 1546,
               'brazilian': 467,
               'french': 2646,
               'japanese': 1423,
               'irish': 667,
               'korean': 830,
               'moroccan': 821,
               'russian': 489})
```

2

```
plt.title("Number of Recipes by Cuisine")
plt.xlabel("Cuisine")
plt.ylabel("Number of Recipes in Dataset")
plt.xticks(rotation = 70) # Rotates X-Axis Ticks by 45-degrees
plt.show()
```



```
[90]: # Convert the data to a binary classification problem: asian cuisine or not
asian_cuisines = ['indian', 'japanese', 'chinese', 'filipino', 'thai',
                  ↪ 'korean', 'vietnamese']

df['cuisine'] = df['cuisine'].map(lambda x: 'Asian' if x in asian_cuisines else
                                  ↪ 'Not Asian')
print(set(df['cuisine']))
cuisines = list(set(df['cuisine']))
```

```
{'Asian', 'Not Asian'}
```

```
[92]: # Slightly imbalanced classes
Counter(df['cuisine'])
```

```
[92]: Counter({'Not Asian': 28726, 'Asian': 11048})
```

```
[5]: # Ingredient counts sorted by frequency
countIngredients
```

```
[5]:
```

	Ingredient	weight
0	salt	18049
1	olive oil	7972
2	onions	7972
3	water	7457
4	garlic	7380
...
6709	sauerkraut juice	1
6710	no-calorie sweetener	1
6711	Bob Evans Italian Sausage	1
6712	extra firm silken tofu	1
6713	crushed cheese crackers	1

```
[6714 rows x 2 columns]
```

```
[6]: # Build a feature matrix using top 1000 most common ingredients
topIngredients = countIngredients[:1000]['Ingredient']
topIngredients
for i in topIngredients:
    df[i] = df['ingredients'].apply(lambda x: 1 if i in x else 0)
```

```
[7]: df.drop(columns='ingredients', inplace=True)
labels = df['cuisine']
df.drop(columns='cuisine', inplace=True)
df.drop(columns='id', inplace=True)

features = df
features
```

```
[7]:
```

	salt	olive oil	onions	water	garlic	sugar	garlic cloves	butter	\
0	0	0	0	0	1	0	0	0	
1	1	0	0	0	0	0	0	0	
2	1	0	0	0	0	0	0	1	
3	1	0	0	1	0	0	0	0	
4	1	0	1	1	0	0	0	1	
...	
39769	1	0	0	0	0	0	0	1	
39770	0	0	0	0	0	0	0	0	
39771	1	0	0	0	0	1	0	1	

39772	0	0	0	0	0	1	0	0
39773	1	0	1	0	1	0	0	0

	ground black pepper	all-purpose flour	...	gari	fruit	\
0	0	0	...	0	0	
1	1	0	...	0	0	
2	0	0	...	0	0	
3	0	0	...	0	0	
4	0	0	...	0	0	
...		
39769	0	1	...	0	0	
39770	0	0	...	0	0	
39771	0	0	...	0	0	
39772	0	0	...	0	0	
39773	1	0	...	0	0	

	plain low-fat yogurt	thai green curry paste	great northern beans	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	
...	
39769	0	0	0	
39770	0	0	0	
39771	0	0	0	
39772	0	0	0	
39773	0	0	0	

	seedless cucumber	salad greens	organic vegetable broth	duck	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	
...	
39769	0	0	0	0	
39770	0	0	0	0	
39771	0	0	0	0	
39772	0	0	0	0	
39773	0	0	0	0	

	file powder
0	0
1	0
2	0
3	0

```

4          0
...
39769      0
39770      0
39771      0
39772      0
39773      0

```

[39774 rows x 1000 columns]

Unsupervised Techniques

```

[8]: from sklearn import decomposition
import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap
from sklearn.manifold import TSNE

pca = decomposition.PCA(n_components=2)
X = pca.fit_transform(features)

NUM_COLORS = len(cuisines)
cm = plt.get_cmap('gist_rainbow')

# Build the plot
vals = {cuisine: i for i, cuisine in enumerate(cuisines)}
c = list(map(lambda x: vals[x], labels))
cmap = ListedColormap(['red', 'blue'])
fig, ax = plt.subplots()
scatter = ax.scatter(X[:,0], X[:,1], c=c, cmap=cmap)

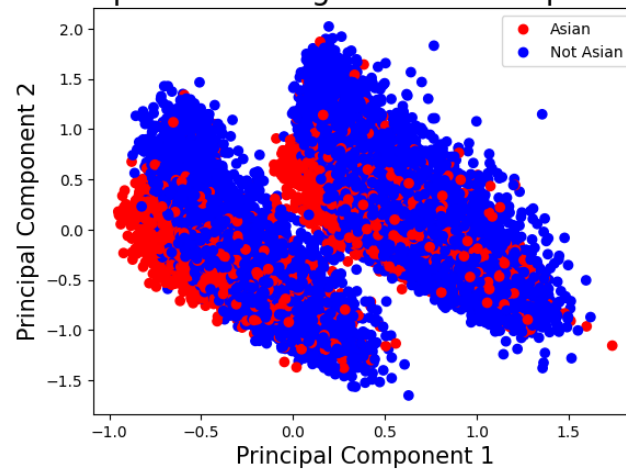
# Add labels
ax.set_xlabel('Principal Component 1', fontsize = 15)
ax.set_ylabel('Principal Component 2', fontsize = 15)
ax.set_title('Top 2 Principal Components Using 1000 Most Popular Recipe_
↳Ingredients', fontsize = 20)

plt.legend(handles=scatter.legend_elements()[0], labels=cuisines)

plt.show()

```

Top 2 Principal Components Using 1000 Most Popular Recipe Ingredients



```
[44]: from sklearn import decomposition
import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap
from sklearn.manifold import TSNE

pca = decomposition.PCA(n_components=10)
pca_result = pca.fit_transform(features)
tsne = TSNE(n_components=2, n_iter=300)
X = tsne.fit_transform(pca_result)

NUM_COLORS = len(cuisines)
cm = plt.get_cmap('gist_rainbow')

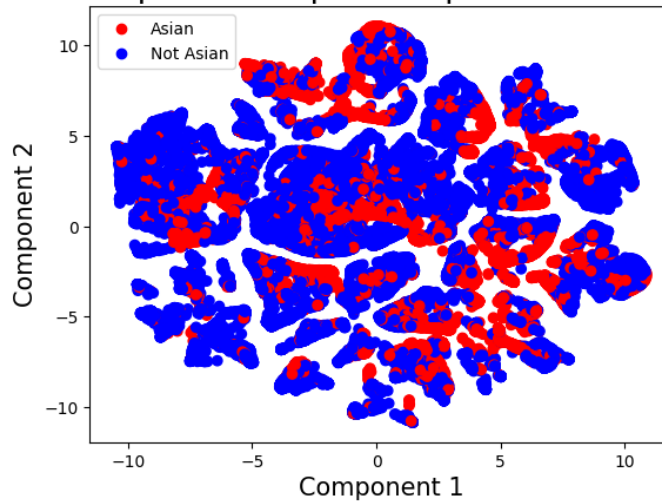
# Build the plot
vals = {cuisine: i for i, cuisine in enumerate(cuisines)}
c = list(map(lambda x: vals[x], labels))
cmap = ListedColormap(['red', 'blue'])
fig, ax = plt.subplots()
scatter = ax.scatter(X[:,0], X[:,1], c=c, cmap=cmap)

# Add labels
ax.set_xlabel('Component 1', fontsize = 15)
ax.set_ylabel('Component 2', fontsize = 15)
ax.set_title('TSNE Applied to Top 10 Principal Components of Recipe_
↳Ingredients', fontsize = 20)

plt.legend(handles=scatter.legend_elements()[0], labels=cuisines)

plt.show()
```

TSNE Applied to Top 10 Principal Components of Recipe Ingredients



Comparison of at least 3 ML models

Logistic Regression, Random Forests, Gradient Boosting, and Multi-Layer Perceptrons will be used to train classifiers and predict whether recipes originate from Asian cuisines or not.

Logistic Regression was selected for a few reasons. First, unlike Bayesian classifiers, it makes no assumptions about the distribution of the classes in the space of the features. Second, logistic regression is known to perform well on linear problems, and predicting recipe cuisines based on ingredient lists may be such a problem. Third, logistic regression produces interpretable models, as the coefficients of the features are rough indicators of feature importance.

Random Forests were selected for their strong predictive power. They are able to learn non-linear patterns in the data, and they perform well even without extensive hyperparameter tuning. Additionally, random forests are unlikely to overfit, as they use a subset of observations and features to train each individual tree, and use “wisdom of the crowd” to make a prediction. Thus, the model is expected to have a relatively low variance. They also produce relatively interpretable feature importance scores, which will assist in task 2.

Gradient Boosting was selected because it is also known to be a strong learner. Specifically, gradient boosting greedily improves on models in an iterative manner, meaning it is likely to produce a model with a high prediction accuracy as well. Similarly to trees, feature importance scores can be obtained from gradient boosting for interpretability.

Multi-Layer Perceptrons were selected because there is a significant amount of data (>10000 observations per class), and they have the ability to solve complex nonlinear problems. However, their usefulness is likely limited to task 1 alone, as the weights in a MLP are difficult to interpret.

```
[9]: # Separate into train and test data
X = features
y = labels.map(lambda x: 1 if x == 'Asian' else 0)
```



```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20,
↳random_state=0)
```

```
[11]: # Logistic Regression
from sklearn.linear_model import LogisticRegressionCV

# Tune hyperparameters using 5-fold CV
fit_logistic_regression = LogisticRegressionCV(cv=5, solver='saga', n_jobs=-1,
↳random_state=0).fit(X_train, y_train)
logistic_regression_score = fit_logistic_regression.score(X_test, y_test)
logistic_regression_score
```

```
[11]: 0.9587680703959773
```

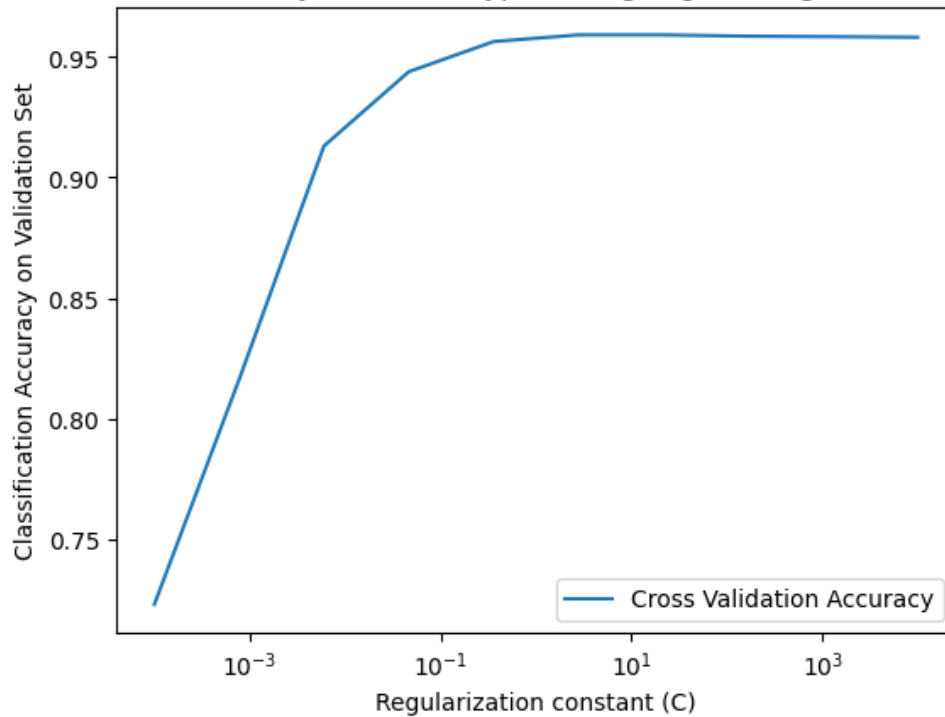
```
[12]: # Aggregate the cross validation accuracies for each C value tested by the
↳library function
scores = fit_logistic_regression.scores_[1]
k = len(scores)
Cs = fit_logistic_regression.Cs_
cv_accuracy = [0 for i in range(len(Cs))]

for i in range(len(scores)):
    for j in range(len(scores[0])):
        cv_accuracy[j] += scores[i][j] / k

# Plot lines
plt.plot(Cs, cv_accuracy, label = "Cross Validation Accuracy")
plt.xscale('log')

# Set labels
plt.xlabel('Regularization constant (C)')
plt.ylabel('Classification Accuracy on Validation Set')
plt.title('Classification Accuracy of Cuisine Types Using Logistic Regression,
↳(5-Fold CV)')
plt.legend()
plt.show()
```

Classification Accuracy of Cuisine Types Using Logistic Regression (5-Fold CV)



```
[21]: from sklearn.ensemble import RandomForestClassifier
import time

# Tuning for Random Forests
start = time.time()
n_estimators = range(50, 400, 100)
max_samples = np.arange(0.25, 1.25, 0.25)
best_estimators, best_oob, best_samples = -1, -1, -1
best_fit = None

for i in n_estimators:
    for k in max_samples:
        fit = RandomForestClassifier(n_estimators=i, max_samples=k,
                                     oob_score=True, n_jobs=-1).fit(X_train, y_train)
        if fit.oob_score_ > best_oob:
            best_estimators = i
            best_samples = k
            best_oob = fit.oob_score_
            best_fit = fit

end = time.time()
print('Best number of estimators in ensemble: ', str(best_estimators))
```

```

print('Best proportion of observations in each base estimator: ',
      str(best_samples))
print('Best oob score: ', str(best_oob))
print('Test Accuracy: ', str(best_fit.score(X_test, y_test)))
print('Time Taken: ', str(end - start))

```

Best number of estimators in ensemble: 350
 Best proportion of observations in each base estimator: 1.0
 Best oob score: 0.9509412615104184
 Test Accuracy: 0.9508485229415462
 Time Taken: 530.6455409526825

```

[23]: from sklearn.ensemble import GradientBoostingClassifier

# Gradient Boosting
start = time.time()
learning_rates = np.logspace(-1.0, 3.0, num=5, base=10.0)
subsample = np.arange(0.1, 1.1, 0.1)
n_estimators = [int(i) for i in np.logspace(0.0, 2.0, num=3, base=10.0)]
parameters = {'learning_rate': learning_rates, 'n_estimators': n_estimators,
              'subsample': subsample}
fit_gdb = GridSearchCV(GradientBoostingClassifier(random_state=0), parameters,
                       n_jobs=-1).fit(X_train, y_train)
end = time.time()

print('Best model: ' + str(fit_gdb.best_estimator_), fit_gdb.best_params_)
print('Best CV Accuracy: ', str(fit_gdb.best_score_))
print('Test Accuracy: ', str(fit_gdb.score(X_test, y_test)))
print('Time Taken: ', str(end - start))

```

Best model: GradientBoostingClassifier(learning_rate=1.0, random_state=0)
 {'learning_rate': 1.0, 'n_estimators': 100, 'subsample': 1.0}
 Best CV Accuracy: 0.949495521968467
 Test Accuracy: 0.9518541797611565
 Time Taken: 1370.3905398845673

```

[24]: import tensorflow as tf
from keras import callbacks
from sklearn.metrics import plot_confusion_matrix

# Split the training data into training and validation
X_train2, X_val, y_train2, y_val = train_test_split(X_train, y_train,
                                                    test_size=0.25, random_state=0)

```

2022-11-30 15:42:26.428647: I tensorflow/core/platform/cpu_feature_guard.cc:193]
 This TensorFlow binary is optimized with oneAPI Deep Neural Network Library
 (oneDNN) to use the following CPU instructions in performance-critical

operations: AVX2 FMA

To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.

```
[25]: # Utils for plotting confusion matrices
```

```
class estimator:
    _estimator_type = ''
    classes_=[]
    def __init__(self, model, classes):
        self.model = model
        self._estimator_type = 'classifier'
        self.classes_ = classes
    def predict(self, X):
        y_prob= self.model.predict(X)
        y_pred = y_prob.argmax(axis=1)
        return y_pred
```

```
[31]: # MLP with 2 hidden layers
```

```
def evaluate_layersize(size1, size2, dropout, results):
    earlystopping = callbacks.EarlyStopping(monitor="val_loss",
                                             mode="min", patience = 5,
                                             restore_best_weights = True)

    model = tf.keras.Sequential([
        tf.keras.layers.Flatten(),
        tf.keras.layers.Dense(size1, activation='relu'),
        tf.keras.layers.Dropout(dropout),
        tf.keras.layers.Dense(size2, activation='relu'),
        tf.keras.layers.Dropout(dropout),
        tf.keras.layers.Dense(10, activation='softmax')
    ])
    model.compile(optimizer='adam',
                  loss=tf.keras.losses.
    ↪SparseCategoricalCrossentropy(from_logits=True),
                  metrics=['accuracy'])
    model.fit(X_train2, y_train2, epochs=25, validation_data=(X_val, y_val),
    ↪callbacks=[earlystopping])

    # Evaluate results on the validation set
    val_loss, val_acc = model.evaluate(X_val, y_val, verbose=2)
    result = '\nValidation accuracy for layer sizes of ' + str(size1) + ' and '
    ↪+ str(size2) + 'with dropout ' + str(dropout) + ' : ' + str(val_acc)
    results.append(result)
    print(result)
    return val_acc, model
```

```
[35]: # Find the best hidden layer sizes for a MLP using grid search, including
      ↪ dropout layers
base_size = 1000
neuron_counts = [base_size // 100, base_size // 50, base_size // 10, base_size //
      ↪ 2]
dropouts = [0.2, 0.4, 0.5]

best_accuracy_mlp = 0
best_mlp = None
best_params_mlp = []
results_mlp = []

for i in neuron_counts:
    for j in neuron_counts:
        for k in dropouts:
            accuracy, model = evaluate_layersize(i, j, k, results_mlp)
            if accuracy > best_accuracy_mlp:
                best_accuracy_mlp = accuracy
                best_mlp = model
                best_params_mlp = [i, j, k]

# Plot CM
classifier = estimator(best_mlp, ['Not Asian', 'Asian'])
fig, ax = plt.subplots(figsize=(12,12))
plot_confusion_matrix(estimator=classifier, X=X_test, y_true=y_test,
      ↪ cmap='Blues', normalize='true', display_labels=['Not Asian', 'Asian'], ax=ax)
ax.set(xlabel='Predicted', ylabel='Actual', title='Confusion Matrix 2-Layer
      ↪ MLP')
```

Epoch 1/25

746/746 [=====] - 2s 2ms/step - loss: 0.6055 -
accuracy: 0.7831 - val_loss: 0.1528 - val_accuracy: 0.9490

Epoch 2/25

746/746 [=====] - 1s 2ms/step - loss: 0.1875 -
accuracy: 0.9425 - val_loss: 0.1313 - val_accuracy: 0.9540

Epoch 3/25

746/746 [=====] - 1s 2ms/step - loss: 0.1482 -
accuracy: 0.9543 - val_loss: 0.1283 - val_accuracy: 0.9565

Epoch 4/25

746/746 [=====] - 2s 2ms/step - loss: 0.1265 -
accuracy: 0.9603 - val_loss: 0.1243 - val_accuracy: 0.9578

Epoch 5/25

746/746 [=====] - 2s 2ms/step - loss: 0.1138 -
accuracy: 0.9639 - val_loss: 0.1260 - val_accuracy: 0.9580

Epoch 6/25

746/746 [=====] - 2s 2ms/step - loss: 0.1091 -
accuracy: 0.9661 - val_loss: 0.1242 - val_accuracy: 0.9595

Epoch 7/25
746/746 [=====] - 2s 2ms/step - loss: 0.1015 -
accuracy: 0.9667 - val_loss: 0.1278 - val_accuracy: 0.9580
Epoch 8/25
746/746 [=====] - 2s 2ms/step - loss: 0.0943 -
accuracy: 0.9696 - val_loss: 0.1295 - val_accuracy: 0.9569
Epoch 9/25
746/746 [=====] - 2s 2ms/step - loss: 0.0919 -
accuracy: 0.9692 - val_loss: 0.1304 - val_accuracy: 0.9583
Epoch 10/25
746/746 [=====] - 2s 2ms/step - loss: 0.0876 -
accuracy: 0.9718 - val_loss: 0.1341 - val_accuracy: 0.9585
Epoch 11/25
746/746 [=====] - 2s 2ms/step - loss: 0.0833 -
accuracy: 0.9726 - val_loss: 0.1360 - val_accuracy: 0.9571
249/249 - 0s - loss: 0.1242 - accuracy: 0.9595 - 238ms/epoch - 954us/step

Validation accuracy for layer sizes of 10 and 10with dropout 0.2 :
0.9595223069190979

Epoch 1/25
746/746 [=====] - 2s 3ms/step - loss: 0.8350 -
accuracy: 0.7559 - val_loss: 0.1569 - val_accuracy: 0.9452
Epoch 2/25
746/746 [=====] - 2s 2ms/step - loss: 0.2564 -
accuracy: 0.9174 - val_loss: 0.1306 - val_accuracy: 0.9529
Epoch 3/25
746/746 [=====] - 2s 2ms/step - loss: 0.2000 -
accuracy: 0.9383 - val_loss: 0.1256 - val_accuracy: 0.9549
Epoch 4/25
746/746 [=====] - 2s 2ms/step - loss: 0.1681 -
accuracy: 0.9462 - val_loss: 0.1246 - val_accuracy: 0.9571
Epoch 5/25
746/746 [=====] - 2s 2ms/step - loss: 0.1550 -
accuracy: 0.9463 - val_loss: 0.1269 - val_accuracy: 0.9571
Epoch 6/25
746/746 [=====] - 2s 2ms/step - loss: 0.1437 -
accuracy: 0.9516 - val_loss: 0.1271 - val_accuracy: 0.9581
Epoch 7/25
746/746 [=====] - 2s 2ms/step - loss: 0.1354 -
accuracy: 0.9516 - val_loss: 0.1289 - val_accuracy: 0.9566
Epoch 8/25
746/746 [=====] - 2s 2ms/step - loss: 0.1254 -
accuracy: 0.9547 - val_loss: 0.1319 - val_accuracy: 0.9574
Epoch 9/25
746/746 [=====] - 2s 2ms/step - loss: 0.1224 -
accuracy: 0.9561 - val_loss: 0.1377 - val_accuracy: 0.9583
249/249 - 0s - loss: 0.1246 - accuracy: 0.9571 - 212ms/epoch - 853us/step

Validation accuracy for layer sizes of 10 and 10with dropout 0.4 :
0.9571338891983032

Epoch 1/25

746/746 [=====] - 2s 2ms/step - loss: 0.8693 -
accuracy: 0.6652 - val_loss: 0.3450 - val_accuracy: 0.8001

Epoch 2/25

746/746 [=====] - 1s 2ms/step - loss: 0.3921 -
accuracy: 0.8390 - val_loss: 0.1853 - val_accuracy: 0.9480

Epoch 3/25

746/746 [=====] - 1s 2ms/step - loss: 0.2830 -
accuracy: 0.9076 - val_loss: 0.1487 - val_accuracy: 0.9531

Epoch 4/25

746/746 [=====] - 2s 2ms/step - loss: 0.2297 -
accuracy: 0.9334 - val_loss: 0.1405 - val_accuracy: 0.9547

Epoch 5/25

746/746 [=====] - 2s 2ms/step - loss: 0.2067 -
accuracy: 0.9400 - val_loss: 0.1351 - val_accuracy: 0.9560

Epoch 6/25

746/746 [=====] - 2s 2ms/step - loss: 0.1881 -
accuracy: 0.9453 - val_loss: 0.1375 - val_accuracy: 0.9565

Epoch 7/25

746/746 [=====] - 2s 2ms/step - loss: 0.1820 -
accuracy: 0.9463 - val_loss: 0.1336 - val_accuracy: 0.9565

Epoch 8/25

746/746 [=====] - 2s 2ms/step - loss: 0.1776 -
accuracy: 0.9474 - val_loss: 0.1368 - val_accuracy: 0.9583

Epoch 9/25

746/746 [=====] - 2s 2ms/step - loss: 0.1714 -
accuracy: 0.9497 - val_loss: 0.1425 - val_accuracy: 0.9584

Epoch 10/25

746/746 [=====] - 1s 1ms/step - loss: 0.1673 -
accuracy: 0.9511 - val_loss: 0.1431 - val_accuracy: 0.9584

Epoch 11/25

746/746 [=====] - 1s 2ms/step - loss: 0.1589 -
accuracy: 0.9501 - val_loss: 0.1417 - val_accuracy: 0.9568

Epoch 12/25

746/746 [=====] - 1s 2ms/step - loss: 0.1585 -
accuracy: 0.9503 - val_loss: 0.1449 - val_accuracy: 0.9578

249/249 - 0s - loss: 0.1336 - accuracy: 0.9565 - 244ms/epoch - 980us/step

Validation accuracy for layer sizes of 10 and 10with dropout 0.5 :
0.9565053582191467

Epoch 1/25

746/746 [=====] - 2s 2ms/step - loss: 0.4574 -
accuracy: 0.8615 - val_loss: 0.1387 - val_accuracy: 0.9530

Epoch 2/25

746/746 [=====] - 1s 2ms/step - loss: 0.1459 -
accuracy: 0.9515 - val_loss: 0.1343 - val_accuracy: 0.9542

Epoch 3/25
746/746 [=====] - 1s 1ms/step - loss: 0.1218 -
accuracy: 0.9620 - val_loss: 0.1226 - val_accuracy: 0.9586
Epoch 4/25
746/746 [=====] - 1s 1ms/step - loss: 0.1112 -
accuracy: 0.9647 - val_loss: 0.1247 - val_accuracy: 0.9588
Epoch 5/25
746/746 [=====] - 1s 1ms/step - loss: 0.0994 -
accuracy: 0.9674 - val_loss: 0.1230 - val_accuracy: 0.9589
Epoch 6/25
746/746 [=====] - 1s 1ms/step - loss: 0.0945 -
accuracy: 0.9687 - val_loss: 0.1256 - val_accuracy: 0.9586
Epoch 7/25
746/746 [=====] - 1s 1ms/step - loss: 0.0884 -
accuracy: 0.9712 - val_loss: 0.1268 - val_accuracy: 0.9570
Epoch 8/25
746/746 [=====] - 1s 1ms/step - loss: 0.0836 -
accuracy: 0.9728 - val_loss: 0.1306 - val_accuracy: 0.9596
249/249 - 0s - loss: 0.1226 - accuracy: 0.9586 - 210ms/epoch - 842us/step

Validation accuracy for layer sizes of 10 and 20with dropout 0.2 :
0.9586423635482788

Epoch 1/25
746/746 [=====] - 2s 2ms/step - loss: 0.5574 -
accuracy: 0.8283 - val_loss: 0.1477 - val_accuracy: 0.9495
Epoch 2/25
746/746 [=====] - 1s 1ms/step - loss: 0.1969 -
accuracy: 0.9354 - val_loss: 0.1288 - val_accuracy: 0.9542
Epoch 3/25
746/746 [=====] - 1s 1ms/step - loss: 0.1645 -
accuracy: 0.9490 - val_loss: 0.1228 - val_accuracy: 0.9576
Epoch 4/25
746/746 [=====] - 1s 2ms/step - loss: 0.1330 -
accuracy: 0.9578 - val_loss: 0.1237 - val_accuracy: 0.9578
Epoch 5/25
746/746 [=====] - 1s 1ms/step - loss: 0.1263 -
accuracy: 0.9611 - val_loss: 0.1251 - val_accuracy: 0.9584
Epoch 6/25
746/746 [=====] - 1s 1ms/step - loss: 0.1164 -
accuracy: 0.9635 - val_loss: 0.1270 - val_accuracy: 0.9584
Epoch 7/25
746/746 [=====] - 1s 1ms/step - loss: 0.1126 -
accuracy: 0.9643 - val_loss: 0.1307 - val_accuracy: 0.9585
Epoch 8/25
746/746 [=====] - 1s 1ms/step - loss: 0.1057 -
accuracy: 0.9655 - val_loss: 0.1326 - val_accuracy: 0.9575
249/249 - 0s - loss: 0.1228 - accuracy: 0.9576 - 211ms/epoch - 846us/step

Validation accuracy for layer sizes of 10 and 20with dropout 0.4 :
0.9576367139816284

Epoch 1/25

746/746 [=====] - 2s 2ms/step - loss: 0.6924 -
accuracy: 0.7884 - val_loss: 0.1632 - val_accuracy: 0.9454

Epoch 2/25

746/746 [=====] - 1s 1ms/step - loss: 0.2369 -
accuracy: 0.9170 - val_loss: 0.1317 - val_accuracy: 0.9526

Epoch 3/25

746/746 [=====] - 1s 1ms/step - loss: 0.1874 -
accuracy: 0.9363 - val_loss: 0.1299 - val_accuracy: 0.9546

Epoch 4/25

746/746 [=====] - 1s 1ms/step - loss: 0.1632 -
accuracy: 0.9441 - val_loss: 0.1262 - val_accuracy: 0.9554

Epoch 5/25

746/746 [=====] - 1s 1ms/step - loss: 0.1506 -
accuracy: 0.9463 - val_loss: 0.1287 - val_accuracy: 0.9560

Epoch 6/25

746/746 [=====] - 1s 1ms/step - loss: 0.1437 -
accuracy: 0.9483 - val_loss: 0.1283 - val_accuracy: 0.9573

Epoch 7/25

746/746 [=====] - 1s 1ms/step - loss: 0.1414 -
accuracy: 0.9465 - val_loss: 0.1314 - val_accuracy: 0.9578

Epoch 8/25

746/746 [=====] - 1s 1ms/step - loss: 0.1320 -
accuracy: 0.9501 - val_loss: 0.1323 - val_accuracy: 0.9573

Epoch 9/25

746/746 [=====] - 1s 1ms/step - loss: 0.1268 -
accuracy: 0.9513 - val_loss: 0.1383 - val_accuracy: 0.9569

249/249 - 0s - loss: 0.1262 - accuracy: 0.9554 - 210ms/epoch - 843us/step

Validation accuracy for layer sizes of 10 and 20with dropout 0.5 :
0.955374002456665

Epoch 1/25

746/746 [=====] - 2s 2ms/step - loss: 0.3338 -
accuracy: 0.9070 - val_loss: 0.1304 - val_accuracy: 0.9542

Epoch 2/25

746/746 [=====] - 1s 1ms/step - loss: 0.1242 -
accuracy: 0.9585 - val_loss: 0.1230 - val_accuracy: 0.9564

Epoch 3/25

746/746 [=====] - 1s 1ms/step - loss: 0.1081 -
accuracy: 0.9641 - val_loss: 0.1212 - val_accuracy: 0.9583

Epoch 4/25

746/746 [=====] - 1s 2ms/step - loss: 0.1003 -
accuracy: 0.9661 - val_loss: 0.1216 - val_accuracy: 0.9584

Epoch 5/25

746/746 [=====] - 2s 3ms/step - loss: 0.0936 -
accuracy: 0.9691 - val_loss: 0.1227 - val_accuracy: 0.9588

Epoch 6/25
746/746 [=====] - 2s 2ms/step - loss: 0.0862 - accuracy: 0.9718 - val_loss: 0.1208 - val_accuracy: 0.9591
Epoch 7/25
746/746 [=====] - 2s 2ms/step - loss: 0.0806 - accuracy: 0.9731 - val_loss: 0.1276 - val_accuracy: 0.9552
Epoch 8/25
746/746 [=====] - 2s 2ms/step - loss: 0.0758 - accuracy: 0.9750 - val_loss: 0.1325 - val_accuracy: 0.9584
Epoch 9/25
746/746 [=====] - 2s 2ms/step - loss: 0.0712 - accuracy: 0.9765 - val_loss: 0.1402 - val_accuracy: 0.9570
Epoch 10/25
746/746 [=====] - 2s 2ms/step - loss: 0.0679 - accuracy: 0.9780 - val_loss: 0.1422 - val_accuracy: 0.9551
Epoch 11/25
746/746 [=====] - 2s 2ms/step - loss: 0.0645 - accuracy: 0.9784 - val_loss: 0.1417 - val_accuracy: 0.9571
249/249 - 0s - loss: 0.1208 - accuracy: 0.9591 - 212ms/epoch - 851us/step

Validation accuracy for layer sizes of 10 and 100with dropout 0.2 :
0.959145188331604

Epoch 1/25
746/746 [=====] - 3s 2ms/step - loss: 0.4269 - accuracy: 0.8512 - val_loss: 0.1413 - val_accuracy: 0.9505
Epoch 2/25
746/746 [=====] - 2s 2ms/step - loss: 0.1582 - accuracy: 0.9437 - val_loss: 0.1248 - val_accuracy: 0.9571
Epoch 3/25
746/746 [=====] - 2s 2ms/step - loss: 0.1301 - accuracy: 0.9562 - val_loss: 0.1193 - val_accuracy: 0.9590
Epoch 4/25
746/746 [=====] - 2s 2ms/step - loss: 0.1177 - accuracy: 0.9585 - val_loss: 0.1237 - val_accuracy: 0.9575
Epoch 5/25
746/746 [=====] - 2s 2ms/step - loss: 0.1074 - accuracy: 0.9622 - val_loss: 0.1210 - val_accuracy: 0.9585
Epoch 6/25
746/746 [=====] - 2s 2ms/step - loss: 0.1043 - accuracy: 0.9621 - val_loss: 0.1200 - val_accuracy: 0.9583
Epoch 7/25
746/746 [=====] - 2s 2ms/step - loss: 0.1019 - accuracy: 0.9626 - val_loss: 0.1207 - val_accuracy: 0.9586
Epoch 8/25
746/746 [=====] - 2s 2ms/step - loss: 0.0941 - accuracy: 0.9656 - val_loss: 0.1224 - val_accuracy: 0.9573
249/249 - 0s - loss: 0.1193 - accuracy: 0.9590 - 214ms/epoch - 859us/step

Validation accuracy for layer sizes of 10 and 100with dropout 0.4 :
0.9590194821357727

Epoch 1/25

746/746 [=====] - 2s 3ms/step - loss: 0.4564 -
accuracy: 0.8343 - val_loss: 0.1478 - val_accuracy: 0.9506

Epoch 2/25

746/746 [=====] - 2s 2ms/step - loss: 0.1757 -
accuracy: 0.9405 - val_loss: 0.1265 - val_accuracy: 0.9549

Epoch 3/25

746/746 [=====] - 2s 2ms/step - loss: 0.1462 -
accuracy: 0.9504 - val_loss: 0.1214 - val_accuracy: 0.9559

Epoch 4/25

746/746 [=====] - 2s 2ms/step - loss: 0.1345 -
accuracy: 0.9549 - val_loss: 0.1210 - val_accuracy: 0.9570

Epoch 5/25

746/746 [=====] - 2s 3ms/step - loss: 0.1244 -
accuracy: 0.9576 - val_loss: 0.1195 - val_accuracy: 0.9579

Epoch 6/25

746/746 [=====] - 2s 2ms/step - loss: 0.1195 -
accuracy: 0.9600 - val_loss: 0.1197 - val_accuracy: 0.9578

Epoch 7/25

746/746 [=====] - 2s 2ms/step - loss: 0.1142 -
accuracy: 0.9619 - val_loss: 0.1202 - val_accuracy: 0.9579

Epoch 8/25

746/746 [=====] - 2s 2ms/step - loss: 0.1115 -
accuracy: 0.9621 - val_loss: 0.1222 - val_accuracy: 0.9568

Epoch 9/25

746/746 [=====] - 2s 2ms/step - loss: 0.1106 -
accuracy: 0.9614 - val_loss: 0.1221 - val_accuracy: 0.9569

Epoch 10/25

746/746 [=====] - 2s 2ms/step - loss: 0.1072 -
accuracy: 0.9633 - val_loss: 0.1228 - val_accuracy: 0.9568

249/249 - 0s - loss: 0.1195 - accuracy: 0.9579 - 215ms/epoch - 864us/step

Validation accuracy for layer sizes of 10 and 100with dropout 0.5 :
0.957888126373291

Epoch 1/25

746/746 [=====] - 2s 3ms/step - loss: 0.2783 -
accuracy: 0.9109 - val_loss: 0.1337 - val_accuracy: 0.9534

Epoch 2/25

746/746 [=====] - 2s 2ms/step - loss: 0.1188 -
accuracy: 0.9597 - val_loss: 0.1248 - val_accuracy: 0.9575

Epoch 3/25

746/746 [=====] - 2s 3ms/step - loss: 0.1035 -
accuracy: 0.9650 - val_loss: 0.1311 - val_accuracy: 0.9561

Epoch 4/25

746/746 [=====] - 2s 3ms/step - loss: 0.0925 -
accuracy: 0.9683 - val_loss: 0.1222 - val_accuracy: 0.9586

Epoch 5/25
 746/746 [=====] - 2s 3ms/step - loss: 0.0867 -
 accuracy: 0.9711 - val_loss: 0.1265 - val_accuracy: 0.9545
 Epoch 6/25
 746/746 [=====] - 2s 2ms/step - loss: 0.0800 -
 accuracy: 0.9739 - val_loss: 0.1313 - val_accuracy: 0.9573
 Epoch 7/25
 746/746 [=====] - 2s 2ms/step - loss: 0.0748 -
 accuracy: 0.9750 - val_loss: 0.1354 - val_accuracy: 0.9570
 Epoch 8/25
 746/746 [=====] - 2s 3ms/step - loss: 0.0705 -
 accuracy: 0.9771 - val_loss: 0.1326 - val_accuracy: 0.9576
 Epoch 9/25
 746/746 [=====] - 2s 3ms/step - loss: 0.0680 -
 accuracy: 0.9787 - val_loss: 0.1437 - val_accuracy: 0.9568
 249/249 - 0s - loss: 0.1222 - accuracy: 0.9586 - 222ms/epoch - 892us/step

Validation accuracy for layer sizes of 10 and 500with dropout 0.2 :
 0.9586423635482788

Epoch 1/25
 746/746 [=====] - 3s 3ms/step - loss: 0.3128 -
 accuracy: 0.8964 - val_loss: 0.1333 - val_accuracy: 0.9536
 Epoch 2/25
 746/746 [=====] - 2s 3ms/step - loss: 0.1363 -
 accuracy: 0.9547 - val_loss: 0.1235 - val_accuracy: 0.9559
 Epoch 3/25
 746/746 [=====] - 2s 3ms/step - loss: 0.1168 -
 accuracy: 0.9605 - val_loss: 0.1195 - val_accuracy: 0.9569
 Epoch 4/25
 746/746 [=====] - 2s 2ms/step - loss: 0.1098 -
 accuracy: 0.9627 - val_loss: 0.1200 - val_accuracy: 0.9571
 Epoch 5/25
 746/746 [=====] - 2s 2ms/step - loss: 0.1029 -
 accuracy: 0.9653 - val_loss: 0.1211 - val_accuracy: 0.9574
 Epoch 6/25
 746/746 [=====] - 2s 2ms/step - loss: 0.0985 -
 accuracy: 0.9664 - val_loss: 0.1199 - val_accuracy: 0.9585
 Epoch 7/25
 746/746 [=====] - 2s 2ms/step - loss: 0.0926 -
 accuracy: 0.9693 - val_loss: 0.1272 - val_accuracy: 0.9565
 Epoch 8/25
 746/746 [=====] - 2s 2ms/step - loss: 0.0890 -
 accuracy: 0.9700 - val_loss: 0.1238 - val_accuracy: 0.9581
 249/249 - 0s - loss: 0.1195 - accuracy: 0.9569 - 217ms/epoch - 872us/step

Validation accuracy for layer sizes of 10 and 500with dropout 0.4 :
 0.9568824768066406

Epoch 1/25

746/746 [=====] - 2s 3ms/step - loss: 0.3525 -
accuracy: 0.8778 - val_loss: 0.1361 - val_accuracy: 0.9525
Epoch 2/25
746/746 [=====] - 2s 2ms/step - loss: 0.1546 -
accuracy: 0.9480 - val_loss: 0.1247 - val_accuracy: 0.9542
Epoch 3/25
746/746 [=====] - 2s 2ms/step - loss: 0.1370 -
accuracy: 0.9543 - val_loss: 0.1217 - val_accuracy: 0.9580
Epoch 4/25
746/746 [=====] - 2s 2ms/step - loss: 0.1224 -
accuracy: 0.9583 - val_loss: 0.1209 - val_accuracy: 0.9581
Epoch 5/25
746/746 [=====] - 2s 3ms/step - loss: 0.1168 -
accuracy: 0.9596 - val_loss: 0.1210 - val_accuracy: 0.9588
Epoch 6/25
746/746 [=====] - 2s 3ms/step - loss: 0.1175 -
accuracy: 0.9594 - val_loss: 0.1205 - val_accuracy: 0.9583
Epoch 7/25
746/746 [=====] - 2s 3ms/step - loss: 0.1097 -
accuracy: 0.9614 - val_loss: 0.1215 - val_accuracy: 0.9590
Epoch 8/25
746/746 [=====] - 2s 3ms/step - loss: 0.1104 -
accuracy: 0.9615 - val_loss: 0.1222 - val_accuracy: 0.9588
Epoch 9/25
746/746 [=====] - 2s 3ms/step - loss: 0.1062 -
accuracy: 0.9627 - val_loss: 0.1235 - val_accuracy: 0.9579
Epoch 10/25
746/746 [=====] - 2s 3ms/step - loss: 0.1065 -
accuracy: 0.9621 - val_loss: 0.1267 - val_accuracy: 0.9574
Epoch 11/25
746/746 [=====] - 2s 3ms/step - loss: 0.1036 -
accuracy: 0.9623 - val_loss: 0.1251 - val_accuracy: 0.9586
249/249 - 0s - loss: 0.1205 - accuracy: 0.9583 - 221ms/epoch - 886us/step

Validation accuracy for layer sizes of 10 and 500 with dropout 0.5 :
0.9582652449607849

Epoch 1/25
746/746 [=====] - 2s 3ms/step - loss: 0.5170 -
accuracy: 0.8447 - val_loss: 0.1401 - val_accuracy: 0.9531
Epoch 2/25
746/746 [=====] - 2s 2ms/step - loss: 0.1466 -
accuracy: 0.9543 - val_loss: 0.1251 - val_accuracy: 0.9566
Epoch 3/25
746/746 [=====] - 2s 2ms/step - loss: 0.1208 -
accuracy: 0.9615 - val_loss: 0.1223 - val_accuracy: 0.9576
Epoch 4/25
746/746 [=====] - 2s 2ms/step - loss: 0.1090 -
accuracy: 0.9664 - val_loss: 0.1218 - val_accuracy: 0.9579

Epoch 5/25
746/746 [=====] - 2s 3ms/step - loss: 0.1031 - accuracy: 0.9670 - val_loss: 0.1225 - val_accuracy: 0.9591
Epoch 6/25
746/746 [=====] - 2s 2ms/step - loss: 0.0942 - accuracy: 0.9692 - val_loss: 0.1278 - val_accuracy: 0.9588
Epoch 7/25
746/746 [=====] - 2s 2ms/step - loss: 0.0840 - accuracy: 0.9726 - val_loss: 0.1323 - val_accuracy: 0.9590
Epoch 8/25
746/746 [=====] - 2s 2ms/step - loss: 0.0804 - accuracy: 0.9746 - val_loss: 0.1352 - val_accuracy: 0.9604
Epoch 9/25
746/746 [=====] - 2s 2ms/step - loss: 0.0726 - accuracy: 0.9769 - val_loss: 0.1457 - val_accuracy: 0.9560
249/249 - 0s - loss: 0.1218 - accuracy: 0.9579 - 225ms/epoch - 903us/step

Validation accuracy for layer sizes of 20 and 10with dropout 0.2 :
0.957888126373291

Epoch 1/25
746/746 [=====] - 2s 3ms/step - loss: 0.6186 - accuracy: 0.7984 - val_loss: 0.1513 - val_accuracy: 0.9492
Epoch 2/25
746/746 [=====] - 2s 2ms/step - loss: 0.2207 - accuracy: 0.9343 - val_loss: 0.1314 - val_accuracy: 0.9541
Epoch 3/25
746/746 [=====] - 2s 2ms/step - loss: 0.1794 - accuracy: 0.9460 - val_loss: 0.1268 - val_accuracy: 0.9555
Epoch 4/25
746/746 [=====] - 2s 3ms/step - loss: 0.1592 - accuracy: 0.9524 - val_loss: 0.1234 - val_accuracy: 0.9584
Epoch 5/25
746/746 [=====] - 2s 2ms/step - loss: 0.1425 - accuracy: 0.9573 - val_loss: 0.1238 - val_accuracy: 0.9571
Epoch 6/25
746/746 [=====] - 2s 2ms/step - loss: 0.1323 - accuracy: 0.9598 - val_loss: 0.1262 - val_accuracy: 0.9588
Epoch 7/25
746/746 [=====] - 2s 2ms/step - loss: 0.1212 - accuracy: 0.9612 - val_loss: 0.1283 - val_accuracy: 0.9593
Epoch 8/25
746/746 [=====] - 2s 2ms/step - loss: 0.1154 - accuracy: 0.9645 - val_loss: 0.1325 - val_accuracy: 0.9586
Epoch 9/25
746/746 [=====] - 2s 2ms/step - loss: 0.1073 - accuracy: 0.9683 - val_loss: 0.1344 - val_accuracy: 0.9594
249/249 - 0s - loss: 0.1234 - accuracy: 0.9584 - 228ms/epoch - 914us/step

Validation accuracy for layer sizes of 20 and 10with dropout 0.4 :
0.9583909511566162

Epoch 1/25

746/746 [=====] - 2s 3ms/step - loss: 0.7345 -
accuracy: 0.7506 - val_loss: 0.1624 - val_accuracy: 0.9432

Epoch 2/25

746/746 [=====] - 2s 2ms/step - loss: 0.2557 -
accuracy: 0.9235 - val_loss: 0.1353 - val_accuracy: 0.9525

Epoch 3/25

746/746 [=====] - 2s 2ms/step - loss: 0.2042 -
accuracy: 0.9381 - val_loss: 0.1256 - val_accuracy: 0.9564

Epoch 4/25

746/746 [=====] - 2s 2ms/step - loss: 0.1782 -
accuracy: 0.9438 - val_loss: 0.1209 - val_accuracy: 0.9580

Epoch 5/25

746/746 [=====] - 2s 2ms/step - loss: 0.1652 -
accuracy: 0.9467 - val_loss: 0.1242 - val_accuracy: 0.9574

Epoch 6/25

746/746 [=====] - 2s 2ms/step - loss: 0.1536 -
accuracy: 0.9492 - val_loss: 0.1219 - val_accuracy: 0.9571

Epoch 7/25

746/746 [=====] - 2s 2ms/step - loss: 0.1434 -
accuracy: 0.9511 - val_loss: 0.1226 - val_accuracy: 0.9573

Epoch 8/25

746/746 [=====] - 2s 2ms/step - loss: 0.1408 -
accuracy: 0.9493 - val_loss: 0.1291 - val_accuracy: 0.9574

Epoch 9/25

746/746 [=====] - 2s 3ms/step - loss: 0.1288 -
accuracy: 0.9524 - val_loss: 0.1349 - val_accuracy: 0.9571

249/249 - 0s - loss: 0.1209 - accuracy: 0.9580 - 229ms/epoch - 921us/step

Validation accuracy for layer sizes of 20 and 10with dropout 0.5 :
0.9580138325691223

Epoch 1/25

746/746 [=====] - 2s 3ms/step - loss: 0.3764 -
accuracy: 0.8791 - val_loss: 0.1338 - val_accuracy: 0.9550

Epoch 2/25

746/746 [=====] - 2s 2ms/step - loss: 0.1326 -
accuracy: 0.9565 - val_loss: 0.1235 - val_accuracy: 0.9583

Epoch 3/25

746/746 [=====] - 2s 2ms/step - loss: 0.1106 -
accuracy: 0.9642 - val_loss: 0.1249 - val_accuracy: 0.9581

Epoch 4/25

746/746 [=====] - 2s 2ms/step - loss: 0.1033 -
accuracy: 0.9661 - val_loss: 0.1224 - val_accuracy: 0.9584

Epoch 5/25

746/746 [=====] - 2s 2ms/step - loss: 0.0936 -
accuracy: 0.9683 - val_loss: 0.1249 - val_accuracy: 0.9586

Epoch 6/25
746/746 [=====] - 2s 2ms/step - loss: 0.0857 -
accuracy: 0.9715 - val_loss: 0.1277 - val_accuracy: 0.9571
Epoch 7/25
746/746 [=====] - 2s 2ms/step - loss: 0.0803 -
accuracy: 0.9728 - val_loss: 0.1335 - val_accuracy: 0.9591
Epoch 8/25
746/746 [=====] - 2s 2ms/step - loss: 0.0753 -
accuracy: 0.9757 - val_loss: 0.1323 - val_accuracy: 0.9575
Epoch 9/25
746/746 [=====] - 2s 2ms/step - loss: 0.0707 -
accuracy: 0.9768 - val_loss: 0.1405 - val_accuracy: 0.9561
249/249 - 0s - loss: 0.1224 - accuracy: 0.9584 - 225ms/epoch - 903us/step

Validation accuracy for layer sizes of 20 and 20with dropout 0.2 :
0.9583909511566162

Epoch 1/25
746/746 [=====] - 2s 3ms/step - loss: 0.4878 -
accuracy: 0.8452 - val_loss: 0.1475 - val_accuracy: 0.9483
Epoch 2/25
746/746 [=====] - 2s 2ms/step - loss: 0.1670 -
accuracy: 0.9488 - val_loss: 0.1285 - val_accuracy: 0.9559
Epoch 3/25
746/746 [=====] - 2s 2ms/step - loss: 0.1367 -
accuracy: 0.9561 - val_loss: 0.1283 - val_accuracy: 0.9563
Epoch 4/25
746/746 [=====] - 2s 3ms/step - loss: 0.1227 -
accuracy: 0.9630 - val_loss: 0.1227 - val_accuracy: 0.9581
Epoch 5/25
746/746 [=====] - 2s 2ms/step - loss: 0.1123 -
accuracy: 0.9646 - val_loss: 0.1251 - val_accuracy: 0.9580
Epoch 6/25
746/746 [=====] - 2s 2ms/step - loss: 0.1060 -
accuracy: 0.9669 - val_loss: 0.1369 - val_accuracy: 0.9579
Epoch 7/25
746/746 [=====] - 2s 2ms/step - loss: 0.1008 -
accuracy: 0.9690 - val_loss: 0.1336 - val_accuracy: 0.9584
Epoch 8/25
746/746 [=====] - 2s 2ms/step - loss: 0.0916 -
accuracy: 0.9720 - val_loss: 0.1294 - val_accuracy: 0.9566
Epoch 9/25
746/746 [=====] - 2s 2ms/step - loss: 0.0908 -
accuracy: 0.9707 - val_loss: 0.1317 - val_accuracy: 0.9584
249/249 - 0s - loss: 0.1227 - accuracy: 0.9581 - 226ms/epoch - 909us/step

Validation accuracy for layer sizes of 20 and 20with dropout 0.4 :
0.9581395387649536

Epoch 1/25

746/746 [=====] - 2s 3ms/step - loss: 0.6627 -
accuracy: 0.7950 - val_loss: 0.1501 - val_accuracy: 0.9468
Epoch 2/25
746/746 [=====] - 2s 3ms/step - loss: 0.1947 -
accuracy: 0.9399 - val_loss: 0.1308 - val_accuracy: 0.9549
Epoch 3/25
746/746 [=====] - 2s 2ms/step - loss: 0.1574 -
accuracy: 0.9507 - val_loss: 0.1308 - val_accuracy: 0.9558
Epoch 4/25
746/746 [=====] - 2s 2ms/step - loss: 0.1417 -
accuracy: 0.9545 - val_loss: 0.1255 - val_accuracy: 0.9583
Epoch 5/25
746/746 [=====] - 2s 2ms/step - loss: 0.1271 -
accuracy: 0.9601 - val_loss: 0.1297 - val_accuracy: 0.9586
Epoch 6/25
746/746 [=====] - 2s 2ms/step - loss: 0.1201 -
accuracy: 0.9627 - val_loss: 0.1280 - val_accuracy: 0.9580
Epoch 7/25
746/746 [=====] - 2s 3ms/step - loss: 0.1137 -
accuracy: 0.9642 - val_loss: 0.1301 - val_accuracy: 0.9576
Epoch 8/25
746/746 [=====] - 2s 2ms/step - loss: 0.1070 -
accuracy: 0.9645 - val_loss: 0.1305 - val_accuracy: 0.9583
Epoch 9/25
746/746 [=====] - 2s 2ms/step - loss: 0.1055 -
accuracy: 0.9656 - val_loss: 0.1328 - val_accuracy: 0.9578
249/249 - 0s - loss: 0.1255 - accuracy: 0.9583 - 232ms/epoch - 930us/step

Validation accuracy for layer sizes of 20 and 20with dropout 0.5 :

0.9582652449607849

Epoch 1/25
746/746 [=====] - 2s 3ms/step - loss: 0.2873 -
accuracy: 0.9142 - val_loss: 0.1276 - val_accuracy: 0.9555
Epoch 2/25
746/746 [=====] - 2s 2ms/step - loss: 0.1191 -
accuracy: 0.9585 - val_loss: 0.1239 - val_accuracy: 0.9573
Epoch 3/25
746/746 [=====] - 2s 3ms/step - loss: 0.1026 -
accuracy: 0.9653 - val_loss: 0.1201 - val_accuracy: 0.9594
Epoch 4/25
746/746 [=====] - 2s 3ms/step - loss: 0.0945 -
accuracy: 0.9679 - val_loss: 0.1212 - val_accuracy: 0.9574
Epoch 5/25
746/746 [=====] - 2s 2ms/step - loss: 0.0854 -
accuracy: 0.9714 - val_loss: 0.1308 - val_accuracy: 0.9580
Epoch 6/25
746/746 [=====] - 2s 2ms/step - loss: 0.0780 -
accuracy: 0.9725 - val_loss: 0.1279 - val_accuracy: 0.9565

Epoch 7/25

746/746 [=====] - 2s 2ms/step - loss: 0.0708 -
accuracy: 0.9757 - val_loss: 0.1367 - val_accuracy: 0.9578

Epoch 8/25

746/746 [=====] - 2s 2ms/step - loss: 0.0632 -
accuracy: 0.9786 - val_loss: 0.1470 - val_accuracy: 0.9565
249/249 - 0s - loss: 0.1201 - accuracy: 0.9594 - 239ms/epoch - 959us/step

Validation accuracy for layer sizes of 20 and 100with dropout 0.2 :
0.9593966007232666

Epoch 1/25

746/746 [=====] - 3s 3ms/step - loss: 0.3472 -
accuracy: 0.8939 - val_loss: 0.1360 - val_accuracy: 0.9531

Epoch 2/25

746/746 [=====] - 2s 2ms/step - loss: 0.1319 -
accuracy: 0.9569 - val_loss: 0.1337 - val_accuracy: 0.9545

Epoch 3/25

746/746 [=====] - 2s 2ms/step - loss: 0.1110 -
accuracy: 0.9630 - val_loss: 0.1234 - val_accuracy: 0.9570

Epoch 4/25

746/746 [=====] - 2s 3ms/step - loss: 0.1031 -
accuracy: 0.9652 - val_loss: 0.1186 - val_accuracy: 0.9590

Epoch 5/25

746/746 [=====] - 2s 3ms/step - loss: 0.0930 -
accuracy: 0.9687 - val_loss: 0.1221 - val_accuracy: 0.9591

Epoch 6/25

746/746 [=====] - 2s 2ms/step - loss: 0.0886 -
accuracy: 0.9705 - val_loss: 0.1216 - val_accuracy: 0.9586

Epoch 7/25

746/746 [=====] - 2s 2ms/step - loss: 0.0834 -
accuracy: 0.9726 - val_loss: 0.1281 - val_accuracy: 0.9583

Epoch 8/25

746/746 [=====] - 2s 2ms/step - loss: 0.0774 -
accuracy: 0.9747 - val_loss: 0.1290 - val_accuracy: 0.9594

Epoch 9/25

746/746 [=====] - 2s 2ms/step - loss: 0.0720 -
accuracy: 0.9755 - val_loss: 0.1350 - val_accuracy: 0.9574
249/249 - 0s - loss: 0.1186 - accuracy: 0.9590 - 248ms/epoch - 995us/step

Validation accuracy for layer sizes of 20 and 100with dropout 0.4 :
0.9590194821357727

Epoch 1/25

746/746 [=====] - 2s 3ms/step - loss: 0.3695 -
accuracy: 0.8827 - val_loss: 0.1409 - val_accuracy: 0.9510

Epoch 2/25

746/746 [=====] - 2s 3ms/step - loss: 0.1450 -
accuracy: 0.9527 - val_loss: 0.1236 - val_accuracy: 0.9565

Epoch 3/25

746/746 [=====] - 2s 2ms/step - loss: 0.1212 -
accuracy: 0.9604 - val_loss: 0.1267 - val_accuracy: 0.9558
Epoch 4/25
746/746 [=====] - 2s 3ms/step - loss: 0.1106 -
accuracy: 0.9649 - val_loss: 0.1253 - val_accuracy: 0.9581
Epoch 5/25
746/746 [=====] - 2s 3ms/step - loss: 0.1018 -
accuracy: 0.9657 - val_loss: 0.1268 - val_accuracy: 0.9584
Epoch 6/25
746/746 [=====] - 2s 2ms/step - loss: 0.0970 -
accuracy: 0.9677 - val_loss: 0.1247 - val_accuracy: 0.9588
Epoch 7/25
746/746 [=====] - 2s 2ms/step - loss: 0.0911 -
accuracy: 0.9706 - val_loss: 0.1278 - val_accuracy: 0.9575
249/249 - 0s - loss: 0.1236 - accuracy: 0.9565 - 239ms/epoch - 959us/step

Validation accuracy for layer sizes of 20 and 100with dropout 0.5 :
0.9565053582191467

Epoch 1/25
746/746 [=====] - 2s 3ms/step - loss: 0.2476 -
accuracy: 0.9209 - val_loss: 0.1319 - val_accuracy: 0.9535
Epoch 2/25
746/746 [=====] - 2s 3ms/step - loss: 0.1144 -
accuracy: 0.9606 - val_loss: 0.1248 - val_accuracy: 0.9563
Epoch 3/25
746/746 [=====] - 2s 3ms/step - loss: 0.1003 -
accuracy: 0.9648 - val_loss: 0.1200 - val_accuracy: 0.9575
Epoch 4/25
746/746 [=====] - 2s 2ms/step - loss: 0.0888 -
accuracy: 0.9690 - val_loss: 0.1233 - val_accuracy: 0.9583
Epoch 5/25
746/746 [=====] - 2s 3ms/step - loss: 0.0783 -
accuracy: 0.9741 - val_loss: 0.1272 - val_accuracy: 0.9580
Epoch 6/25
746/746 [=====] - 2s 3ms/step - loss: 0.0705 -
accuracy: 0.9760 - val_loss: 0.1297 - val_accuracy: 0.9560
Epoch 7/25
746/746 [=====] - 2s 3ms/step - loss: 0.0614 -
accuracy: 0.9796 - val_loss: 0.1377 - val_accuracy: 0.9578
Epoch 8/25
746/746 [=====] - 2s 3ms/step - loss: 0.0561 -
accuracy: 0.9811 - val_loss: 0.1537 - val_accuracy: 0.9575
249/249 - 0s - loss: 0.1200 - accuracy: 0.9575 - 234ms/epoch - 938us/step

Validation accuracy for layer sizes of 20 and 500with dropout 0.2 :
0.9575110077857971

Epoch 1/25
746/746 [=====] - 2s 3ms/step - loss: 0.2753 -

accuracy: 0.9117 - val_loss: 0.1342 - val_accuracy: 0.9554
 Epoch 2/25
 746/746 [=====] - 2s 3ms/step - loss: 0.1230 -
 accuracy: 0.9576 - val_loss: 0.1248 - val_accuracy: 0.9560
 Epoch 3/25
 746/746 [=====] - 2s 3ms/step - loss: 0.1076 -
 accuracy: 0.9633 - val_loss: 0.1229 - val_accuracy: 0.9575
 Epoch 4/25
 746/746 [=====] - 2s 3ms/step - loss: 0.0965 -
 accuracy: 0.9661 - val_loss: 0.1207 - val_accuracy: 0.9591
 Epoch 5/25
 746/746 [=====] - 2s 3ms/step - loss: 0.0892 -
 accuracy: 0.9698 - val_loss: 0.1222 - val_accuracy: 0.9576
 Epoch 6/25
 746/746 [=====] - 2s 3ms/step - loss: 0.0825 -
 accuracy: 0.9710 - val_loss: 0.1240 - val_accuracy: 0.9590
 Epoch 7/25
 746/746 [=====] - 2s 3ms/step - loss: 0.0766 -
 accuracy: 0.9742 - val_loss: 0.1286 - val_accuracy: 0.9581
 Epoch 8/25
 746/746 [=====] - 2s 3ms/step - loss: 0.0718 -
 accuracy: 0.9749 - val_loss: 0.1338 - val_accuracy: 0.9578
 Epoch 9/25
 746/746 [=====] - 2s 3ms/step - loss: 0.0641 -
 accuracy: 0.9774 - val_loss: 0.1445 - val_accuracy: 0.9574
 249/249 - 0s - loss: 0.1207 - accuracy: 0.9591 - 238ms/epoch - 957us/step

Validation accuracy for layer sizes of 20 and 500 with dropout 0.4 :
 0.959145188331604

Epoch 1/25
 746/746 [=====] - 3s 3ms/step - loss: 0.3016 -
 accuracy: 0.9022 - val_loss: 0.1309 - val_accuracy: 0.9532
 Epoch 2/25
 746/746 [=====] - 2s 3ms/step - loss: 0.1347 -
 accuracy: 0.9563 - val_loss: 0.1202 - val_accuracy: 0.9576
 Epoch 3/25
 746/746 [=====] - 2s 3ms/step - loss: 0.1153 -
 accuracy: 0.9605 - val_loss: 0.1214 - val_accuracy: 0.9574
 Epoch 4/25
 746/746 [=====] - 2s 3ms/step - loss: 0.1029 -
 accuracy: 0.9645 - val_loss: 0.1229 - val_accuracy: 0.9581
 Epoch 5/25
 746/746 [=====] - 2s 3ms/step - loss: 0.0956 -
 accuracy: 0.9671 - val_loss: 0.1208 - val_accuracy: 0.9571
 Epoch 6/25
 746/746 [=====] - 2s 3ms/step - loss: 0.0944 -
 accuracy: 0.9686 - val_loss: 0.1221 - val_accuracy: 0.9578
 Epoch 7/25

746/746 [=====] - 2s 3ms/step - loss: 0.0881 -
accuracy: 0.9709 - val_loss: 0.1311 - val_accuracy: 0.9580
249/249 - 0s - loss: 0.1202 - accuracy: 0.9576 - 252ms/epoch - 1ms/step

Validation accuracy for layer sizes of 20 and 500with dropout 0.5 :
0.9576367139816284

Epoch 1/25

746/746 [=====] - 3s 3ms/step - loss: 0.3362 -
accuracy: 0.9067 - val_loss: 0.1282 - val_accuracy: 0.9559

Epoch 2/25

746/746 [=====] - 2s 3ms/step - loss: 0.1315 -
accuracy: 0.9594 - val_loss: 0.1215 - val_accuracy: 0.9585

Epoch 3/25

746/746 [=====] - 2s 3ms/step - loss: 0.1089 -
accuracy: 0.9664 - val_loss: 0.1204 - val_accuracy: 0.9581

Epoch 4/25

746/746 [=====] - 2s 3ms/step - loss: 0.1018 -
accuracy: 0.9669 - val_loss: 0.1213 - val_accuracy: 0.9594

Epoch 5/25

746/746 [=====] - 2s 3ms/step - loss: 0.0873 -
accuracy: 0.9715 - val_loss: 0.1326 - val_accuracy: 0.9590

Epoch 6/25

746/746 [=====] - 2s 3ms/step - loss: 0.0745 -
accuracy: 0.9755 - val_loss: 0.1326 - val_accuracy: 0.9581

Epoch 7/25

746/746 [=====] - 2s 2ms/step - loss: 0.0663 -
accuracy: 0.9785 - val_loss: 0.1404 - val_accuracy: 0.9603

Epoch 8/25

746/746 [=====] - 2s 2ms/step - loss: 0.0554 -
accuracy: 0.9819 - val_loss: 0.1480 - val_accuracy: 0.9591
249/249 - 0s - loss: 0.1204 - accuracy: 0.9581 - 245ms/epoch - 983us/step

Validation accuracy for layer sizes of 100 and 10with dropout 0.2 :
0.9581395387649536

Epoch 1/25

746/746 [=====] - 2s 2ms/step - loss: 0.5272 -
accuracy: 0.8228 - val_loss: 0.1445 - val_accuracy: 0.9503

Epoch 2/25

746/746 [=====] - 2s 3ms/step - loss: 0.2200 -
accuracy: 0.9296 - val_loss: 0.1263 - val_accuracy: 0.9561

Epoch 3/25

746/746 [=====] - 2s 3ms/step - loss: 0.1896 -
accuracy: 0.9387 - val_loss: 0.1220 - val_accuracy: 0.9570

Epoch 4/25

746/746 [=====] - 2s 3ms/step - loss: 0.1651 -
accuracy: 0.9413 - val_loss: 0.1246 - val_accuracy: 0.9583

Epoch 5/25

746/746 [=====] - 2s 3ms/step - loss: 0.1497 -

accuracy: 0.9376 - val_loss: 0.1244 - val_accuracy: 0.9578
Epoch 6/25
746/746 [=====] - 2s 3ms/step - loss: 0.1371 -
accuracy: 0.9442 - val_loss: 0.1214 - val_accuracy: 0.9596
Epoch 7/25
746/746 [=====] - 2s 3ms/step - loss: 0.1254 -
accuracy: 0.9498 - val_loss: 0.1271 - val_accuracy: 0.9612
Epoch 8/25
746/746 [=====] - 2s 3ms/step - loss: 0.1155 -
accuracy: 0.9563 - val_loss: 0.1319 - val_accuracy: 0.9593
Epoch 9/25
746/746 [=====] - 2s 3ms/step - loss: 0.0932 -
accuracy: 0.9594 - val_loss: 0.1466 - val_accuracy: 0.9590
Epoch 10/25
746/746 [=====] - 2s 3ms/step - loss: 0.0780 -
accuracy: 0.9711 - val_loss: 0.1626 - val_accuracy: 0.9591
Epoch 11/25
746/746 [=====] - 2s 3ms/step - loss: 0.0659 -
accuracy: 0.9785 - val_loss: 0.1615 - val_accuracy: 0.9589
249/249 - 0s - loss: 0.1214 - accuracy: 0.9596 - 242ms/epoch - 974us/step

Validation accuracy for layer sizes of 100 and 10with dropout 0.4 :
0.9596480131149292

Epoch 1/25
746/746 [=====] - 3s 3ms/step - loss: 0.6151 -
accuracy: 0.8259 - val_loss: 0.1407 - val_accuracy: 0.9526
Epoch 2/25
746/746 [=====] - 2s 3ms/step - loss: 0.2787 -
accuracy: 0.9252 - val_loss: 0.1262 - val_accuracy: 0.9565
Epoch 3/25
746/746 [=====] - 2s 3ms/step - loss: 0.2378 -
accuracy: 0.9294 - val_loss: 0.1217 - val_accuracy: 0.9588
Epoch 4/25
746/746 [=====] - 2s 3ms/step - loss: 0.1842 -
accuracy: 0.9319 - val_loss: 0.1222 - val_accuracy: 0.9585
Epoch 5/25
746/746 [=====] - 2s 3ms/step - loss: 0.1679 -
accuracy: 0.9369 - val_loss: 0.1233 - val_accuracy: 0.9603
Epoch 6/25
746/746 [=====] - 2s 3ms/step - loss: 0.1489 -
accuracy: 0.9483 - val_loss: 0.1209 - val_accuracy: 0.9604
Epoch 7/25
746/746 [=====] - 2s 3ms/step - loss: 0.1279 -
accuracy: 0.9570 - val_loss: 0.1304 - val_accuracy: 0.9595
Epoch 8/25
746/746 [=====] - 2s 3ms/step - loss: 0.1205 -
accuracy: 0.9570 - val_loss: 0.1304 - val_accuracy: 0.9608
Epoch 9/25

746/746 [=====] - 2s 3ms/step - loss: 0.1096 -
 accuracy: 0.9625 - val_loss: 0.1336 - val_accuracy: 0.9617
 Epoch 10/25
 746/746 [=====] - 2s 3ms/step - loss: 0.0975 -
 accuracy: 0.9688 - val_loss: 0.1413 - val_accuracy: 0.9630
 Epoch 11/25
 746/746 [=====] - 2s 3ms/step - loss: 0.0867 -
 accuracy: 0.9714 - val_loss: 0.1511 - val_accuracy: 0.9610
 249/249 - 0s - loss: 0.1209 - accuracy: 0.9604 - 248ms/epoch - 996us/step

Validation accuracy for layer sizes of 100 and 10with dropout 0.5 :
 0.960402250289917

Epoch 1/25
 746/746 [=====] - 3s 3ms/step - loss: 0.2980 -
 accuracy: 0.9156 - val_loss: 0.1305 - val_accuracy: 0.9554
 Epoch 2/25
 746/746 [=====] - 2s 3ms/step - loss: 0.1187 -
 accuracy: 0.9604 - val_loss: 0.1260 - val_accuracy: 0.9564
 Epoch 3/25
 746/746 [=====] - 2s 3ms/step - loss: 0.1011 -
 accuracy: 0.9656 - val_loss: 0.1275 - val_accuracy: 0.9573
 Epoch 4/25
 746/746 [=====] - 2s 3ms/step - loss: 0.0877 -
 accuracy: 0.9697 - val_loss: 0.1279 - val_accuracy: 0.9576
 Epoch 5/25
 746/746 [=====] - 2s 3ms/step - loss: 0.0738 -
 accuracy: 0.9749 - val_loss: 0.1376 - val_accuracy: 0.9589
 Epoch 6/25
 746/746 [=====] - 2s 3ms/step - loss: 0.0616 -
 accuracy: 0.9791 - val_loss: 0.1377 - val_accuracy: 0.9586
 Epoch 7/25
 746/746 [=====] - 2s 3ms/step - loss: 0.0488 -
 accuracy: 0.9834 - val_loss: 0.1509 - val_accuracy: 0.9569
 249/249 - 0s - loss: 0.1260 - accuracy: 0.9564 - 248ms/epoch - 998us/step

Validation accuracy for layer sizes of 100 and 20with dropout 0.2 :
 0.9563796520233154

Epoch 1/25
 746/746 [=====] - 3s 3ms/step - loss: 0.4056 -
 accuracy: 0.8859 - val_loss: 0.1326 - val_accuracy: 0.9545
 Epoch 2/25
 746/746 [=====] - 2s 3ms/step - loss: 0.1504 -
 accuracy: 0.9552 - val_loss: 0.1278 - val_accuracy: 0.9586
 Epoch 3/25
 746/746 [=====] - 2s 3ms/step - loss: 0.1252 -
 accuracy: 0.9622 - val_loss: 0.1226 - val_accuracy: 0.9607
 Epoch 4/25
 746/746 [=====] - 2s 3ms/step - loss: 0.1092 -

accuracy: 0.9654 - val_loss: 0.1229 - val_accuracy: 0.9596
Epoch 5/25
746/746 [=====] - 2s 3ms/step - loss: 0.0968 -
accuracy: 0.9692 - val_loss: 0.1274 - val_accuracy: 0.9605
Epoch 6/25
746/746 [=====] - 2s 3ms/step - loss: 0.0855 -
accuracy: 0.9725 - val_loss: 0.1344 - val_accuracy: 0.9600
Epoch 7/25
746/746 [=====] - 3s 4ms/step - loss: 0.0757 -
accuracy: 0.9755 - val_loss: 0.1365 - val_accuracy: 0.9590
Epoch 8/25
746/746 [=====] - 2s 2ms/step - loss: 0.0671 -
accuracy: 0.9786 - val_loss: 0.1460 - val_accuracy: 0.9591
249/249 - 0s - loss: 0.1226 - accuracy: 0.9607 - 241ms/epoch - 970us/step

Validation accuracy for layer sizes of 100 and 20with dropout 0.4 :
0.9606536626815796

Epoch 1/25
746/746 [=====] - 2s 3ms/step - loss: 0.4363 -
accuracy: 0.8652 - val_loss: 0.1390 - val_accuracy: 0.9519
Epoch 2/25
746/746 [=====] - 2s 2ms/step - loss: 0.1689 -
accuracy: 0.9487 - val_loss: 0.1226 - val_accuracy: 0.9563
Epoch 3/25
746/746 [=====] - 2s 2ms/step - loss: 0.1403 -
accuracy: 0.9548 - val_loss: 0.1198 - val_accuracy: 0.9565
Epoch 4/25
746/746 [=====] - 2s 2ms/step - loss: 0.1234 -
accuracy: 0.9612 - val_loss: 0.1235 - val_accuracy: 0.9578
Epoch 5/25
746/746 [=====] - 2s 2ms/step - loss: 0.1113 -
accuracy: 0.9640 - val_loss: 0.1299 - val_accuracy: 0.9602
Epoch 6/25
746/746 [=====] - 2s 2ms/step - loss: 0.1017 -
accuracy: 0.9679 - val_loss: 0.1344 - val_accuracy: 0.9589
Epoch 7/25
746/746 [=====] - 2s 3ms/step - loss: 0.0944 -
accuracy: 0.9695 - val_loss: 0.1324 - val_accuracy: 0.9585
Epoch 8/25
746/746 [=====] - 2s 3ms/step - loss: 0.0904 -
accuracy: 0.9720 - val_loss: 0.1325 - val_accuracy: 0.9584
249/249 - 0s - loss: 0.1198 - accuracy: 0.9565 - 241ms/epoch - 966us/step

Validation accuracy for layer sizes of 100 and 20with dropout 0.5 :
0.9565053582191467

Epoch 1/25
746/746 [=====] - 3s 3ms/step - loss: 0.2342 -
accuracy: 0.9297 - val_loss: 0.1280 - val_accuracy: 0.9540

Epoch 2/25
746/746 [=====] - 2s 3ms/step - loss: 0.1071 - accuracy: 0.9627 - val_loss: 0.1225 - val_accuracy: 0.9583
Epoch 3/25
746/746 [=====] - 2s 3ms/step - loss: 0.0905 - accuracy: 0.9690 - val_loss: 0.1220 - val_accuracy: 0.9586
Epoch 4/25
746/746 [=====] - 2s 3ms/step - loss: 0.0746 - accuracy: 0.9752 - val_loss: 0.1311 - val_accuracy: 0.9541
Epoch 5/25
746/746 [=====] - 2s 3ms/step - loss: 0.0609 - accuracy: 0.9793 - val_loss: 0.1349 - val_accuracy: 0.9581
Epoch 6/25
746/746 [=====] - 2s 3ms/step - loss: 0.0472 - accuracy: 0.9842 - val_loss: 0.1483 - val_accuracy: 0.9576
Epoch 7/25
746/746 [=====] - 2s 3ms/step - loss: 0.0364 - accuracy: 0.9871 - val_loss: 0.1698 - val_accuracy: 0.9576
Epoch 8/25
746/746 [=====] - 2s 3ms/step - loss: 0.0298 - accuracy: 0.9886 - val_loss: 0.1890 - val_accuracy: 0.9569
249/249 - 0s - loss: 0.1220 - accuracy: 0.9586 - 244ms/epoch - 981us/step

Validation accuracy for layer sizes of 100 and 100with dropout 0.2 :
0.9586423635482788

Epoch 1/25
746/746 [=====] - 3s 3ms/step - loss: 0.2507 - accuracy: 0.9205 - val_loss: 0.1226 - val_accuracy: 0.9565
Epoch 2/25
746/746 [=====] - 2s 3ms/step - loss: 0.1155 - accuracy: 0.9628 - val_loss: 0.1196 - val_accuracy: 0.9583
Epoch 3/25
746/746 [=====] - 2s 3ms/step - loss: 0.1000 - accuracy: 0.9663 - val_loss: 0.1217 - val_accuracy: 0.9595
Epoch 4/25
746/746 [=====] - 2s 3ms/step - loss: 0.0838 - accuracy: 0.9718 - val_loss: 0.1299 - val_accuracy: 0.9594
Epoch 5/25
746/746 [=====] - 2s 3ms/step - loss: 0.0738 - accuracy: 0.9756 - val_loss: 0.1310 - val_accuracy: 0.9595
Epoch 6/25
746/746 [=====] - 2s 3ms/step - loss: 0.0619 - accuracy: 0.9788 - val_loss: 0.1313 - val_accuracy: 0.9586
Epoch 7/25
746/746 [=====] - 2s 3ms/step - loss: 0.0529 - accuracy: 0.9826 - val_loss: 0.1461 - val_accuracy: 0.9600
249/249 - 0s - loss: 0.1196 - accuracy: 0.9583 - 250ms/epoch - 1ms/step

Validation accuracy for layer sizes of 100 and 100with dropout 0.4 :
0.9582652449607849

Epoch 1/25
746/746 [=====] - 3s 3ms/step - loss: 0.2663 -
accuracy: 0.9157 - val_loss: 0.1387 - val_accuracy: 0.9521

Epoch 2/25
746/746 [=====] - 2s 3ms/step - loss: 0.1212 -
accuracy: 0.9586 - val_loss: 0.1226 - val_accuracy: 0.9574

Epoch 3/25
746/746 [=====] - 2s 3ms/step - loss: 0.1052 -
accuracy: 0.9658 - val_loss: 0.1188 - val_accuracy: 0.9596

Epoch 4/25
746/746 [=====] - 2s 3ms/step - loss: 0.0935 -
accuracy: 0.9695 - val_loss: 0.1224 - val_accuracy: 0.9598

Epoch 5/25
746/746 [=====] - 2s 3ms/step - loss: 0.0851 -
accuracy: 0.9726 - val_loss: 0.1216 - val_accuracy: 0.9600

Epoch 6/25
746/746 [=====] - 2s 3ms/step - loss: 0.0765 -
accuracy: 0.9762 - val_loss: 0.1321 - val_accuracy: 0.9612

Epoch 7/25
746/746 [=====] - 2s 3ms/step - loss: 0.0680 -
accuracy: 0.9769 - val_loss: 0.1315 - val_accuracy: 0.9615

Epoch 8/25
746/746 [=====] - 2s 3ms/step - loss: 0.0595 -
accuracy: 0.9803 - val_loss: 0.1467 - val_accuracy: 0.9576
249/249 - 0s - loss: 0.1188 - accuracy: 0.9596 - 253ms/epoch - 1ms/step

Validation accuracy for layer sizes of 100 and 100with dropout 0.5 :
0.9596480131149292

Epoch 1/25
746/746 [=====] - 3s 4ms/step - loss: 0.1940 -
accuracy: 0.9381 - val_loss: 0.1244 - val_accuracy: 0.9571

Epoch 2/25
746/746 [=====] - 3s 3ms/step - loss: 0.1022 -
accuracy: 0.9662 - val_loss: 0.1257 - val_accuracy: 0.9555

Epoch 3/25
746/746 [=====] - 2s 3ms/step - loss: 0.0848 -
accuracy: 0.9709 - val_loss: 0.1264 - val_accuracy: 0.9594

Epoch 4/25
746/746 [=====] - 3s 3ms/step - loss: 0.0673 -
accuracy: 0.9770 - val_loss: 0.1302 - val_accuracy: 0.9550

Epoch 5/25
746/746 [=====] - 3s 3ms/step - loss: 0.0521 -
accuracy: 0.9815 - val_loss: 0.1466 - val_accuracy: 0.9585

Epoch 6/25
746/746 [=====] - 3s 4ms/step - loss: 0.0388 -
accuracy: 0.9859 - val_loss: 0.1635 - val_accuracy: 0.9590

249/249 - 0s - loss: 0.1244 - accuracy: 0.9571 - 252ms/epoch - 1ms/step

Validation accuracy for layer sizes of 100 and 500with dropout 0.2 :

0.9571338891983032

Epoch 1/25

746/746 [=====] - 3s 4ms/step - loss: 0.2101 - accuracy: 0.9324 - val_loss: 0.1254 - val_accuracy: 0.9571

Epoch 2/25

746/746 [=====] - 2s 3ms/step - loss: 0.1097 - accuracy: 0.9627 - val_loss: 0.1186 - val_accuracy: 0.9594

Epoch 3/25

746/746 [=====] - 2s 3ms/step - loss: 0.0936 - accuracy: 0.9678 - val_loss: 0.1237 - val_accuracy: 0.9568

Epoch 4/25

746/746 [=====] - 2s 3ms/step - loss: 0.0795 - accuracy: 0.9723 - val_loss: 0.1204 - val_accuracy: 0.9594

Epoch 5/25

746/746 [=====] - 3s 4ms/step - loss: 0.0646 - accuracy: 0.9780 - val_loss: 0.1341 - val_accuracy: 0.9595

Epoch 6/25

746/746 [=====] - 3s 3ms/step - loss: 0.0544 - accuracy: 0.9818 - val_loss: 0.1440 - val_accuracy: 0.9594

Epoch 7/25

746/746 [=====] - 3s 3ms/step - loss: 0.0462 - accuracy: 0.9842 - val_loss: 0.1402 - val_accuracy: 0.9595

249/249 - 0s - loss: 0.1186 - accuracy: 0.9594 - 264ms/epoch - 1ms/step

Validation accuracy for layer sizes of 100 and 500with dropout 0.4 :

0.9593966007232666

Epoch 1/25

746/746 [=====] - 3s 4ms/step - loss: 0.2307 - accuracy: 0.9228 - val_loss: 0.1266 - val_accuracy: 0.9540

Epoch 2/25

746/746 [=====] - 2s 3ms/step - loss: 0.1169 - accuracy: 0.9610 - val_loss: 0.1208 - val_accuracy: 0.9574

Epoch 3/25

746/746 [=====] - 3s 4ms/step - loss: 0.0993 - accuracy: 0.9676 - val_loss: 0.1215 - val_accuracy: 0.9586

Epoch 4/25

746/746 [=====] - 2s 3ms/step - loss: 0.0869 - accuracy: 0.9706 - val_loss: 0.1215 - val_accuracy: 0.9594

Epoch 5/25

746/746 [=====] - 2s 3ms/step - loss: 0.0771 - accuracy: 0.9735 - val_loss: 0.1230 - val_accuracy: 0.9588

Epoch 6/25

746/746 [=====] - 3s 3ms/step - loss: 0.0651 - accuracy: 0.9777 - val_loss: 0.1245 - val_accuracy: 0.9594

Epoch 7/25

746/746 [=====] - 2s 3ms/step - loss: 0.0582 -
accuracy: 0.9801 - val_loss: 0.1444 - val_accuracy: 0.9589
249/249 - 0s - loss: 0.1208 - accuracy: 0.9574 - 263ms/epoch - 1ms/step

Validation accuracy for layer sizes of 100 and 500with dropout 0.5 :
0.9573853015899658

Epoch 1/25

746/746 [=====] - 4s 5ms/step - loss: 0.2694 -
accuracy: 0.9202 - val_loss: 0.1299 - val_accuracy: 0.9563

Epoch 2/25

746/746 [=====] - 3s 5ms/step - loss: 0.1274 -
accuracy: 0.9570 - val_loss: 0.1279 - val_accuracy: 0.9575

Epoch 3/25

746/746 [=====] - 3s 4ms/step - loss: 0.1094 -
accuracy: 0.9644 - val_loss: 0.1266 - val_accuracy: 0.9581

Epoch 4/25

746/746 [=====] - 3s 4ms/step - loss: 0.0862 -
accuracy: 0.9707 - val_loss: 0.1332 - val_accuracy: 0.9588

Epoch 5/25

746/746 [=====] - 3s 4ms/step - loss: 0.0660 -
accuracy: 0.9783 - val_loss: 0.1447 - val_accuracy: 0.9614

Epoch 6/25

746/746 [=====] - 4s 5ms/step - loss: 0.0493 -
accuracy: 0.9833 - val_loss: 0.1652 - val_accuracy: 0.9598

Epoch 7/25

746/746 [=====] - 3s 5ms/step - loss: 0.0355 -
accuracy: 0.9868 - val_loss: 0.1809 - val_accuracy: 0.9578

Epoch 8/25

746/746 [=====] - 3s 5ms/step - loss: 0.0248 -
accuracy: 0.9911 - val_loss: 0.2148 - val_accuracy: 0.9573

249/249 - 0s - loss: 0.1266 - accuracy: 0.9581 - 314ms/epoch - 1ms/step

Validation accuracy for layer sizes of 500 and 10with dropout 0.2 :
0.9581395387649536

Epoch 1/25

746/746 [=====] - 4s 5ms/step - loss: 0.4264 -
accuracy: 0.8461 - val_loss: 0.1322 - val_accuracy: 0.9531

Epoch 2/25

746/746 [=====] - 3s 4ms/step - loss: 0.2191 -
accuracy: 0.9124 - val_loss: 0.1237 - val_accuracy: 0.9560

Epoch 3/25

746/746 [=====] - 3s 5ms/step - loss: 0.1819 -
accuracy: 0.9228 - val_loss: 0.1243 - val_accuracy: 0.9576

Epoch 4/25

746/746 [=====] - 4s 5ms/step - loss: 0.1491 -
accuracy: 0.9357 - val_loss: 0.1270 - val_accuracy: 0.9585

Epoch 5/25

746/746 [=====] - 3s 5ms/step - loss: 0.1183 -

accuracy: 0.9514 - val_loss: 0.1248 - val_accuracy: 0.9579
Epoch 6/25
746/746 [=====] - 3s 5ms/step - loss: 0.1015 -
accuracy: 0.9564 - val_loss: 0.1483 - val_accuracy: 0.9598
Epoch 7/25
746/746 [=====] - 3s 5ms/step - loss: 0.0888 -
accuracy: 0.9602 - val_loss: 0.1620 - val_accuracy: 0.9603
249/249 - 0s - loss: 0.1237 - accuracy: 0.9560 - 318ms/epoch - 1ms/step

Validation accuracy for layer sizes of 500 and 10with dropout 0.4 :
0.9560025334358215

Epoch 1/25
746/746 [=====] - 4s 5ms/step - loss: 0.4101 -
accuracy: 0.8622 - val_loss: 0.1303 - val_accuracy: 0.9539
Epoch 2/25
746/746 [=====] - 3s 5ms/step - loss: 0.2087 -
accuracy: 0.9210 - val_loss: 0.1299 - val_accuracy: 0.9564
Epoch 3/25
746/746 [=====] - 3s 4ms/step - loss: 0.1744 -
accuracy: 0.9304 - val_loss: 0.1274 - val_accuracy: 0.9571
Epoch 4/25
746/746 [=====] - 3s 5ms/step - loss: 0.1556 -
accuracy: 0.9416 - val_loss: 0.1242 - val_accuracy: 0.9589
Epoch 5/25
746/746 [=====] - 3s 4ms/step - loss: 0.1407 -
accuracy: 0.9534 - val_loss: 0.1257 - val_accuracy: 0.9596
Epoch 6/25
746/746 [=====] - 4s 5ms/step - loss: 0.1261 -
accuracy: 0.9587 - val_loss: 0.1260 - val_accuracy: 0.9600
Epoch 7/25
746/746 [=====] - 3s 5ms/step - loss: 0.1103 -
accuracy: 0.9643 - val_loss: 0.1338 - val_accuracy: 0.9596
Epoch 8/25
746/746 [=====] - 3s 5ms/step - loss: 0.1017 -
accuracy: 0.9658 - val_loss: 0.1416 - val_accuracy: 0.9609
Epoch 9/25
746/746 [=====] - 3s 4ms/step - loss: 0.0873 -
accuracy: 0.9706 - val_loss: 0.1655 - val_accuracy: 0.9595
249/249 - 0s - loss: 0.1242 - accuracy: 0.9589 - 313ms/epoch - 1ms/step

Validation accuracy for layer sizes of 500 and 10with dropout 0.5 :
0.9588937759399414

Epoch 1/25
746/746 [=====] - 4s 5ms/step - loss: 0.2104 -
accuracy: 0.9368 - val_loss: 0.1288 - val_accuracy: 0.9552
Epoch 2/25
746/746 [=====] - 3s 5ms/step - loss: 0.1076 -
accuracy: 0.9655 - val_loss: 0.1251 - val_accuracy: 0.9581

Epoch 3/25
746/746 [=====] - 3s 5ms/step - loss: 0.0843 -
accuracy: 0.9730 - val_loss: 0.1235 - val_accuracy: 0.9610
Epoch 4/25
746/746 [=====] - 3s 5ms/step - loss: 0.0618 -
accuracy: 0.9802 - val_loss: 0.1350 - val_accuracy: 0.9575
Epoch 5/25
746/746 [=====] - 3s 5ms/step - loss: 0.0418 -
accuracy: 0.9866 - val_loss: 0.1493 - val_accuracy: 0.9584
Epoch 6/25
746/746 [=====] - 3s 5ms/step - loss: 0.0276 -
accuracy: 0.9900 - val_loss: 0.1786 - val_accuracy: 0.9574
Epoch 7/25
746/746 [=====] - 4s 5ms/step - loss: 0.0186 -
accuracy: 0.9932 - val_loss: 0.2073 - val_accuracy: 0.9563
Epoch 8/25
746/746 [=====] - 3s 5ms/step - loss: 0.0134 -
accuracy: 0.9952 - val_loss: 0.2303 - val_accuracy: 0.9556
249/249 - 0s - loss: 0.1235 - accuracy: 0.9610 - 324ms/epoch - 1ms/step

Validation accuracy for layer sizes of 500 and 20with dropout 0.2 :
0.9610307812690735

Epoch 1/25
746/746 [=====] - 4s 5ms/step - loss: 0.2884 -
accuracy: 0.9008 - val_loss: 0.1303 - val_accuracy: 0.9556
Epoch 2/25
746/746 [=====] - 3s 5ms/step - loss: 0.1392 -
accuracy: 0.9531 - val_loss: 0.1241 - val_accuracy: 0.9573
Epoch 3/25
746/746 [=====] - 3s 4ms/step - loss: 0.1147 -
accuracy: 0.9613 - val_loss: 0.1268 - val_accuracy: 0.9589
Epoch 4/25
746/746 [=====] - 4s 5ms/step - loss: 0.1001 -
accuracy: 0.9676 - val_loss: 0.1298 - val_accuracy: 0.9589
Epoch 5/25
746/746 [=====] - 3s 5ms/step - loss: 0.0826 -
accuracy: 0.9736 - val_loss: 0.1352 - val_accuracy: 0.9598
Epoch 6/25
746/746 [=====] - 3s 5ms/step - loss: 0.0666 -
accuracy: 0.9773 - val_loss: 0.1419 - val_accuracy: 0.9579
Epoch 7/25
746/746 [=====] - 3s 5ms/step - loss: 0.0532 -
accuracy: 0.9821 - val_loss: 0.1697 - val_accuracy: 0.9593
249/249 - 0s - loss: 0.1241 - accuracy: 0.9573 - 323ms/epoch - 1ms/step

Validation accuracy for layer sizes of 500 and 20with dropout 0.4 :
0.9572595953941345

Epoch 1/25

746/746 [=====] - 4s 5ms/step - loss: 0.3125 - accuracy: 0.9071 - val_loss: 0.1270 - val_accuracy: 0.9545
Epoch 2/25
746/746 [=====] - 3s 4ms/step - loss: 0.1512 - accuracy: 0.9545 - val_loss: 0.1328 - val_accuracy: 0.9563
Epoch 3/25
746/746 [=====] - 3s 5ms/step - loss: 0.1268 - accuracy: 0.9595 - val_loss: 0.1237 - val_accuracy: 0.9580
Epoch 4/25
746/746 [=====] - 3s 5ms/step - loss: 0.1119 - accuracy: 0.9632 - val_loss: 0.1268 - val_accuracy: 0.9594
Epoch 5/25
746/746 [=====] - 4s 5ms/step - loss: 0.0987 - accuracy: 0.9686 - val_loss: 0.1347 - val_accuracy: 0.9586
Epoch 6/25
746/746 [=====] - 4s 5ms/step - loss: 0.0852 - accuracy: 0.9724 - val_loss: 0.1453 - val_accuracy: 0.9591
Epoch 7/25
746/746 [=====] - 3s 5ms/step - loss: 0.0675 - accuracy: 0.9776 - val_loss: 0.1578 - val_accuracy: 0.9591
Epoch 8/25
746/746 [=====] - 4s 5ms/step - loss: 0.0583 - accuracy: 0.9799 - val_loss: 0.1599 - val_accuracy: 0.9589
249/249 - 0s - loss: 0.1237 - accuracy: 0.9580 - 422ms/epoch - 2ms/step

Validation accuracy for layer sizes of 500 and 20with dropout 0.5 :
0.9580138325691223

Epoch 1/25
746/746 [=====] - 4s 5ms/step - loss: 0.1870 - accuracy: 0.9405 - val_loss: 0.1264 - val_accuracy: 0.9560
Epoch 2/25
746/746 [=====] - 4s 5ms/step - loss: 0.0991 - accuracy: 0.9659 - val_loss: 0.1168 - val_accuracy: 0.9585
Epoch 3/25
746/746 [=====] - 4s 5ms/step - loss: 0.0707 - accuracy: 0.9754 - val_loss: 0.1292 - val_accuracy: 0.9584
Epoch 4/25
746/746 [=====] - 4s 5ms/step - loss: 0.0468 - accuracy: 0.9837 - val_loss: 0.1377 - val_accuracy: 0.9585
Epoch 5/25
746/746 [=====] - 4s 5ms/step - loss: 0.0276 - accuracy: 0.9894 - val_loss: 0.1940 - val_accuracy: 0.9569
Epoch 6/25
746/746 [=====] - 4s 5ms/step - loss: 0.0173 - accuracy: 0.9934 - val_loss: 0.2052 - val_accuracy: 0.9564
Epoch 7/25
746/746 [=====] - 4s 5ms/step - loss: 0.0116 - accuracy: 0.9955 - val_loss: 0.2441 - val_accuracy: 0.9536

249/249 - 0s - loss: 0.1168 - accuracy: 0.9585 - 340ms/epoch - 1ms/step

Validation accuracy for layer sizes of 500 and 100with dropout 0.2 :

0.9585166573524475

Epoch 1/25

746/746 [=====] - 4s 5ms/step - loss: 0.1975 -
accuracy: 0.9354 - val_loss: 0.1252 - val_accuracy: 0.9556

Epoch 2/25

746/746 [=====] - 4s 5ms/step - loss: 0.1047 -
accuracy: 0.9651 - val_loss: 0.1298 - val_accuracy: 0.9526

Epoch 3/25

746/746 [=====] - 4s 5ms/step - loss: 0.0831 -
accuracy: 0.9724 - val_loss: 0.1270 - val_accuracy: 0.9570

Epoch 4/25

746/746 [=====] - 4s 5ms/step - loss: 0.0650 -
accuracy: 0.9780 - val_loss: 0.1325 - val_accuracy: 0.9620

Epoch 5/25

746/746 [=====] - 4s 5ms/step - loss: 0.0449 -
accuracy: 0.9844 - val_loss: 0.1571 - val_accuracy: 0.9593

Epoch 6/25

746/746 [=====] - 4s 5ms/step - loss: 0.0308 -
accuracy: 0.9881 - val_loss: 0.1732 - val_accuracy: 0.9573

249/249 - 0s - loss: 0.1252 - accuracy: 0.9556 - 344ms/epoch - 1ms/step

Validation accuracy for layer sizes of 500 and 100with dropout 0.4 :

0.9556254148483276

Epoch 1/25

746/746 [=====] - 4s 5ms/step - loss: 0.2131 -
accuracy: 0.9294 - val_loss: 0.1299 - val_accuracy: 0.9549

Epoch 2/25

746/746 [=====] - 4s 5ms/step - loss: 0.1119 -
accuracy: 0.9623 - val_loss: 0.1218 - val_accuracy: 0.9588

Epoch 3/25

746/746 [=====] - 4s 5ms/step - loss: 0.0922 -
accuracy: 0.9689 - val_loss: 0.1210 - val_accuracy: 0.9593

Epoch 4/25

746/746 [=====] - 4s 5ms/step - loss: 0.0741 -
accuracy: 0.9745 - val_loss: 0.1293 - val_accuracy: 0.9583

Epoch 5/25

746/746 [=====] - 4s 5ms/step - loss: 0.0608 -
accuracy: 0.9795 - val_loss: 0.1379 - val_accuracy: 0.9607

Epoch 6/25

746/746 [=====] - 3s 5ms/step - loss: 0.0445 -
accuracy: 0.9841 - val_loss: 0.1546 - val_accuracy: 0.9594

Epoch 7/25

746/746 [=====] - 4s 5ms/step - loss: 0.0370 -
accuracy: 0.9870 - val_loss: 0.1645 - val_accuracy: 0.9591

Epoch 8/25

746/746 [=====] - 3s 4ms/step - loss: 0.0280 -
accuracy: 0.9902 - val_loss: 0.1881 - val_accuracy: 0.9613
249/249 - 0s - loss: 0.1210 - accuracy: 0.9593 - 342ms/epoch - 1ms/step

Validation accuracy for layer sizes of 500 and 100with dropout 0.5 :
0.9592708945274353

Epoch 1/25

746/746 [=====] - 5s 6ms/step - loss: 0.1669 -
accuracy: 0.9450 - val_loss: 0.1285 - val_accuracy: 0.9540

Epoch 2/25

746/746 [=====] - 4s 6ms/step - loss: 0.0914 -
accuracy: 0.9692 - val_loss: 0.1308 - val_accuracy: 0.9559

Epoch 3/25

746/746 [=====] - 4s 6ms/step - loss: 0.0641 -
accuracy: 0.9780 - val_loss: 0.1399 - val_accuracy: 0.9588

Epoch 4/25

746/746 [=====] - 4s 6ms/step - loss: 0.0384 -
accuracy: 0.9860 - val_loss: 0.1481 - val_accuracy: 0.9551

Epoch 5/25

746/746 [=====] - 4s 6ms/step - loss: 0.0211 -
accuracy: 0.9922 - val_loss: 0.1961 - val_accuracy: 0.9581

Epoch 6/25

746/746 [=====] - 4s 6ms/step - loss: 0.0143 -
accuracy: 0.9946 - val_loss: 0.2287 - val_accuracy: 0.9564
249/249 - 0s - loss: 0.1285 - accuracy: 0.9540 - 380ms/epoch - 2ms/step

Validation accuracy for layer sizes of 500 and 500with dropout 0.2 :
0.953991174697876

Epoch 1/25

746/746 [=====] - 5s 6ms/step - loss: 0.1751 -
accuracy: 0.9405 - val_loss: 0.1345 - val_accuracy: 0.9526

Epoch 2/25

746/746 [=====] - 4s 6ms/step - loss: 0.1004 -
accuracy: 0.9660 - val_loss: 0.1373 - val_accuracy: 0.9565

Epoch 3/25

746/746 [=====] - 4s 6ms/step - loss: 0.0757 -
accuracy: 0.9749 - val_loss: 0.1214 - val_accuracy: 0.9573

Epoch 4/25

746/746 [=====] - 5s 6ms/step - loss: 0.0548 -
accuracy: 0.9814 - val_loss: 0.1380 - val_accuracy: 0.9559

Epoch 5/25

746/746 [=====] - 5s 6ms/step - loss: 0.0376 -
accuracy: 0.9865 - val_loss: 0.1644 - val_accuracy: 0.9596

Epoch 6/25

746/746 [=====] - 5s 6ms/step - loss: 0.0250 -
accuracy: 0.9904 - val_loss: 0.2119 - val_accuracy: 0.9586

Epoch 7/25

746/746 [=====] - 5s 6ms/step - loss: 0.0195 -

```
accuracy: 0.9925 - val_loss: 0.2300 - val_accuracy: 0.9590
Epoch 8/25
746/746 [=====] - 4s 6ms/step - loss: 0.0146 -
accuracy: 0.9952 - val_loss: 0.2575 - val_accuracy: 0.9576
249/249 - 0s - loss: 0.1214 - accuracy: 0.9573 - 378ms/epoch - 2ms/step
```

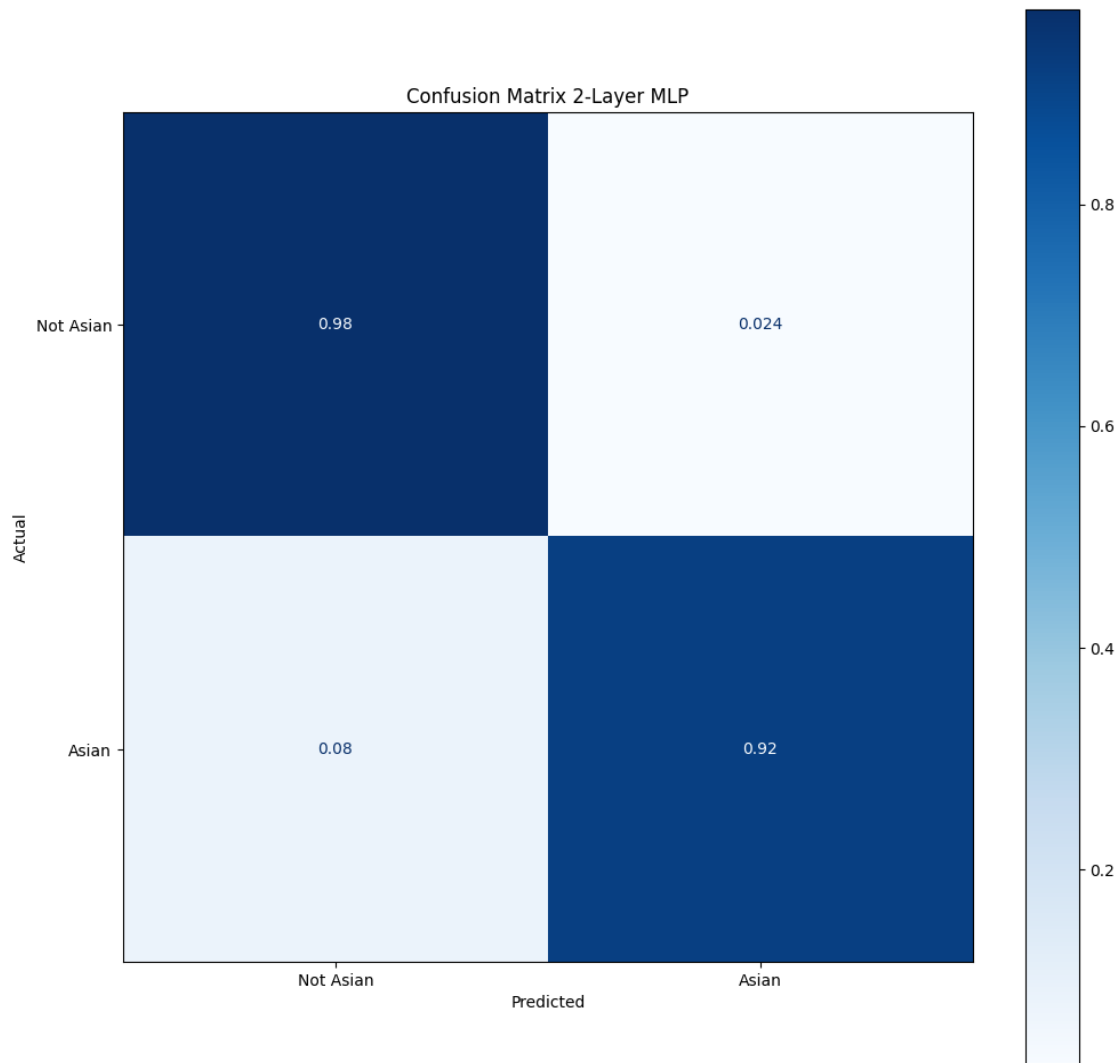
Validation accuracy for layer sizes of 500 and 500with dropout 0.4 :
0.9572595953941345

```
Epoch 1/25
746/746 [=====] - 5s 6ms/step - loss: 0.1880 -
accuracy: 0.9376 - val_loss: 0.1265 - val_accuracy: 0.9554
Epoch 2/25
746/746 [=====] - 4s 6ms/step - loss: 0.1060 -
accuracy: 0.9630 - val_loss: 0.1484 - val_accuracy: 0.9530
Epoch 3/25
746/746 [=====] - 4s 6ms/step - loss: 0.0831 -
accuracy: 0.9703 - val_loss: 0.1294 - val_accuracy: 0.9589
Epoch 4/25
746/746 [=====] - 4s 6ms/step - loss: 0.0649 -
accuracy: 0.9786 - val_loss: 0.1384 - val_accuracy: 0.9599
Epoch 5/25
746/746 [=====] - 4s 5ms/step - loss: 0.0480 -
accuracy: 0.9832 - val_loss: 0.1491 - val_accuracy: 0.9579
Epoch 6/25
746/746 [=====] - 4s 6ms/step - loss: 0.0343 -
accuracy: 0.9880 - val_loss: 0.1683 - val_accuracy: 0.9593
249/249 - 0s - loss: 0.1265 - accuracy: 0.9554 - 370ms/epoch - 1ms/step
```

Validation accuracy for layer sizes of 500 and 500with dropout 0.5 :
0.955374002456665

```
249/249 [=====] - 1s 2ms/step
```

```
[35]: [Text(0.5, 0, 'Predicted'),
      Text(0, 0.5, 'Actual'),
      Text(0.5, 1.0, 'Confusion Matrix 2-Layer MLP')]
```



```
[36]: test_loss, test_acc = best_mlp.evaluate(X_test, y_test, verbose=2)

print(best_params_mlp)
print(test_acc)
```

```
249/249 - 0s - loss: 0.1247 - accuracy: 0.9599 - 364ms/epoch - 1ms/step
[500, 20, 0.2]
0.9598994255065918
```

Validate results using best practices

For Logistic Regression and Gradient Boosting, 5-fold cross validation was used to tune hyperparameters. For each model, a grid search was performed over a space of potential hyperparameters, and the model with the highest cross validation score was selected. For Random Forests, a grid search was also performed over a space of hyperparameters, and the model was tuned using the

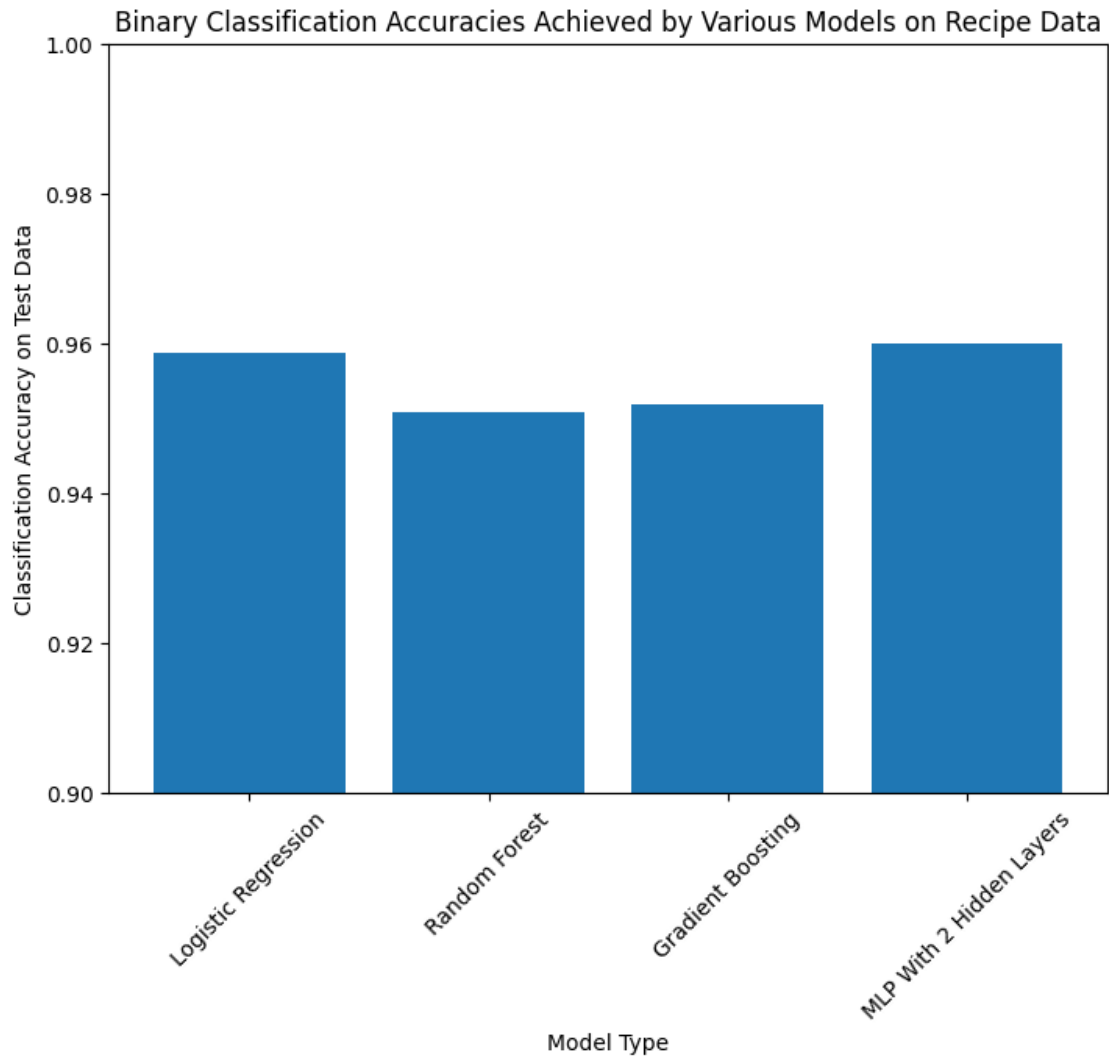
best out of bag error. This was used instead of cross validation because the out of bag error provides a built-in method for evaluating models without polluting the data with information from the test set. Finally, MLPs were tuned using a 60/20/20 train/validation/test split, as 5-fold cross validation would have been computationally expensive to perform. I argue this is acceptable, as there are over 10,000 observations per class.

Finally, each model's performance was evaluated on the reserved test set, which is 20% of the original dataset. The classification accuracy for each model is reported below.

```
[39]: # Models and accuracies
models = ['Logistic Regression', 'Random Forest', 'Gradient Boosting', 'MLP_
↳With 2 Hidden Layers']
scores = [0.9587680703959773, 0.9508485229415462, 0.9518541797611565, 0.
↳9598994255065918]

# Plot results
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(models,scores)

plt.title("Binary Classification Accuracies Achieved by Various Models on_
↳Recipe Data")
plt.xlabel("Model Type")
plt.ylabel("Classification Accuracy on Test Data")
plt.ylim(0.90, 1.00)
plt.xticks(rotation = 45) # Rotates X-Axis Ticks by 45-degrees
plt.show()
```



```
[43]: # Analyze best models
best_rfc = best_fit
best_gdb = fit_gdb

best_models = [fit_logistic_regression, best_rfc, best_gdb, best_mlp]
```

```
[60]: # Interpretation for Logistic Regression
ingredients = fit_logistic_regression.feature_names_in_
coefficients = fit_logistic_regression.coef_
ingredients_with_coefficients = sorted([(coefficients[0][i], ingredients[i])]
    ↪for i in range(len(ingredients)))
print("100 INGREDIENTS WITH LOWEST COEFFICIENTS")
for elem in ingredients_with_coefficients[:100]:
    print(elem)
```

```

print("\n100 INGREDIENTS WITH HIGHEST COEFFICIENTS")
for elem in ingredients_with_coefficients[-100:]:
    print(elem)

```

```

100 INGREDIENTS WITH LOWEST COEFFICIENTS
(-7.566190933591636, 'collard greens')
(-5.373888178463512, 'yellow peppers')
(-5.075871224236179, 'tomatillos')
(-4.93253542321623, 'fresh mozzarella')
(-4.887891897681399, 'jack cheese')
(-4.878882429634259, 'green tomatoes')
(-4.789368750663951, 'spanish chorizo')
(-4.780051239170036, 'quickcooking grits')
(-4.7503953403439905, 'flour tortillas')
(-4.519947583828841, 'fish stock')
(-4.514706434616924, 'andouille sausage')
(-4.462997264258147, 'corn tortillas')
(-4.396566361202337, 'cajun seasoning')
(-4.189479497994981, 'bourbon whiskey')
(-4.183943805424018, 'taco seasoning mix')
(-4.169471164663107, 'black-eyed peas')
(-4.162236424930194, 'oregano')
(-4.107967670033046, 'bacon slices')
(-3.864868334754141, 'thyme')
(-3.811475049261159, 'celery seed')
(-3.781368435753405, 'clam juice')
(-3.737255506306593, 'ancho chile pepper')
(-3.7181393209497435, 'creole seasoning')
(-3.715128304978399, 'cachaca')
(-3.6973129494786763, 'fresh rosemary')
(-3.6494579555343023, 'anise seed')
(-3.621944545059715, 'capers')
(-3.6193660741220666, 'dark rum')
(-3.5715012123379064, 'pearl onions')
(-3.5671403105379853, 'masa harina')
(-3.565695459177761, 'monterey jack')
(-3.54682428705684, 'lemon rind')
(-3.5212514393922296, 'preserved lemon')
(-3.4926444498945357, 'dried rosemary')
(-3.480287754647485, 'polenta')
(-3.437849793971542, 'mozzarella cheese')
(-3.4367173567408633, 'salsa')
(-3.3931179242317424, 'artichok heart marin')
(-3.381673943372155, 'tequila')
(-3.353194473410984, 'fresh dill')
(-3.3525564483783126, 'roasted red peppers')

```

(-3.3353100295623768, 'parmigiano reggiano cheese')
(-3.3139208552486505, 'pinto beans')
(-3.31020906272445, 'smoked sausage')
(-3.2846142469152215, 'canned black beans')
(-3.282337370879731, 'rum')
(-3.2485996748175268, 'fresh thyme')
(-3.236557151378241, 'salsa verde')
(-3.22985035243606, 'fresh raspberries')
(-3.2264025616530856, 'blackberries')
(-3.225836616357485, 'pasta')
(-3.185212739865023, 'peaches')
(-3.099783152056866, 'chipotle chile')
(-3.084762764480891, 'fresh tarragon')
(-3.0795114503491763, 'italian sausage')
(-3.055556762896701, 'chunky salsa')
(-3.043772234767549, 'pecans')
(-3.028239950953402, 'sausage casings')
(-3.022047552445567, 'hot pepper sauce')
(-2.9965286149813957, 'creole mustard')
(-2.95239451970565, 'dried oregano')
(-2.9376629839870785, 'crawfish')
(-2.9333848224918504, 'gruyere cheese')
(-2.925753151936104, 'ground almonds')
(-2.9222668103827356, 'pesto')
(-2.900675252516386, 'dill')
(-2.893508388064122, 'shredded cheese')
(-2.882144104629409, 'marinara sauce')
(-2.876848567957566, 'tortilla chips')
(-2.8507682099705556, 'non-fat sour cream')
(-2.8182241810754545, 'bacon drippings')
(-2.81035888800712, 'chopped fresh thyme')
(-2.7909947609817736, 'pancetta')
(-2.7693735278316027, 'grits')
(-2.762906841018936, 'biscuits')
(-2.7612289575639024, 'cream of chicken soup')
(-2.7456774590572404, 'poblano peppers')
(-2.740754660891333, 'ground allspice')
(-2.7400244606576525, 'hazelnuts')
(-2.734893563157257, 'Mexican cheese blend')
(-2.7347704359912237, 'white cornmeal')
(-2.730597533462434, 'dried parsley')
(-2.6845781862844316, 'shredded Monterey Jack cheese')
(-2.6733470147187353, 'dried thyme')
(-2.647085076595256, 'black beans')
(-2.605992798572479, 'bread slices')
(-2.598455587907825, 'chopped fresh chives')
(-2.5790839254736957, 'roasted tomatoes')
(-2.5746111124917475, 'smoked ham hocks')

(-2.5425247503502315, 'enchilada sauce')
(-2.541846543287635, 'chees fresh mozzarella')
(-2.5396792821206002, 'grated parmesan cheese')
(-2.5375583454574815, 'cornmeal')
(-2.533012685549646, 'guajillo chiles')
(-2.51851352095994, 'italian salad dressing')
(-2.5128084448452697, 'yellow bell pepper')
(-2.499999746646481, 'olives')
(-2.4992047536107784, 'fresh marjoram')
(-2.498148784404995, 'navel oranges')
(-2.481581910915738, 'serrano chilies')

100 INGREDIENTS WITH HIGHEST COEFFICIENTS

(2.278684394517401, 'rice vinegar')
(2.2830056326043007, 'low sodium soy sauce')
(2.2878690710651117, 'peeled fresh ginger')
(2.2885209291523654, 'curry leaves')
(2.3195579889725817, 'oyster sauce')
(2.3262973931641002, 'brown mustard seeds')
(2.3895174947367486, 'grated coconut')
(2.3971478529563974, 'garlic chili sauce')
(2.443396988674866, 'fresh ginger root')
(2.45120065278883, 'roasted peanuts')
(2.4647115976829115, 'beef rib short')
(2.476209452784622, 'tamarind paste')
(2.4778663601915594, 'tofu')
(2.52670521548098, 'star anise')
(2.529273568155629, 'curds')
(2.533547571217842, 'ground cardamom')
(2.5353789383659873, 'fat free yogurt')
(2.537080166679546, 'mung bean sprouts')
(2.5523617831740415, 'kaffir lime leaves')
(2.5792150020448505, 'toasted sesame oil')
(2.59638936379394, 'lemongrass')
(2.6079462734646888, 'sweet chili sauce')
(2.629339588871879, 'peppercorns')
(2.6472302297997636, 'cornflour')
(2.649711915302233, 'yoghurt')
(2.674777392017576, 'chutney')
(2.6817811015067257, 'green cardamom')
(2.6865684572760067, 'ginger root')
(2.700588782151752, 'shredded carrots')
(2.7268974895882696, 'unsalted dry roast peanuts')
(2.7587009817308603, 'toasted sesame seeds')
(2.8357521942789523, 'plain low-fat yogurt')
(2.8481324298815944, 'sesame oil')
(2.941928428208029, 'jasmine rice')
(2.9535196348814385, 'chili oil')

(2.9748658715263456, 'seaweed')
(2.975201257704513, 'mango chutney')
(2.9762541306313057, 'ghee')
(2.9769724658762615, 'paneer')
(2.9826756990750427, 'dark soy sauce')
(3.05776860474543, 'cardamom')
(3.102804932049275, 'mirin')
(3.145416953698943, 'dipping sauces')
(3.1877408839258705, 'minced ginger')
(3.2812280959012563, 'curry')
(3.3095407330672337, 'curry paste')
(3.3166377262648665, 'tamari soy sauce')
(3.3226120982476033, 'soy sauce')
(3.347386546876785, 'dashi')
(3.349365530424029, 'rice flour')
(3.3720029180124946, 'baby bok choy')
(3.3728265438967457, 'reduced sodium soy sauce')
(3.3940612151799603, 'light soy sauce')
(3.396632457353441, 'curry powder')
(3.4109572823558234, 'firm tofu')
(3.411603349722296, 'pork belly')
(3.5079935904028168, 'lemon grass')
(3.5526737837426294, 'rice wine')
(3.5704649970403604, 'extra firm tofu')
(3.5858115402658344, 'beansprouts')
(3.7388686464173064, 'sake')
(3.7669242412873567, 'dark sesame oil')
(3.7899847584344486, 'garam masala')
(3.8345332576524283, 'soba noodles')
(3.8752657339199765, 'lower sodium soy sauce')
(3.9003734257800806, 'white miso')
(3.910717848418795, 'Gochujang base')
(4.0736276357796095, 'fenugreek leaves')
(4.0837860078828045, 'green cardamom pods')
(4.119722035098293, 'rice noodles')
(4.120546551837827, 'cardamom pods')
(4.143166214557933, 'szechwan peppercorns')
(4.16279401865162, 'ginger paste')
(4.216386981471767, 'nori')
(4.26316419728593, 'miso paste')
(4.288851678533675, 'snow peas')
(4.311603966016466, 'palm sugar')
(4.356054415582322, 'fresh curry leaves')
(4.364330965610741, 'thai basil')
(4.3993907882561, 'chinese five-spice powder')
(4.563167722395101, 'urad dal')
(4.723478725418322, 'hoisin sauce')
(4.783910593367832, 'Shaoxing wine')

```
(4.873324733787246, 'egg roll wrappers')
(5.005643860489858, 'white sesame seeds')
(5.03444001771963, 'bok choy')
(5.2161005538424865, 'edamame')
(5.233323979433468, 'rice paper')
(5.24839559484324, 'konbu')
(5.366157026689697, 'kimchi')
(5.4758163970621965, 'thai chile')
(5.581132174465842, 'Thai fish sauce')
(5.636237979129408, 'masala')
(5.7447067471376885, 'daikon')
(5.7694017117803735, 'sushi rice')
(5.816820018128965, 'fish sauce')
(5.966638197631045, 'spring roll wrappers')
(6.198418698065396, 'asian fish sauce')
(6.272364008123512, 'red curry paste')
(7.408197742452477, 'Thai red curry paste')
```

```
[68]: # Interpretation for Random Forests and Gradient Boosting
def get_feature_importance_names(f):
    x = list(zip(f, X_train.columns))
    x.sort(reverse = True, key = lambda e: e[0])
    return [e[1] for e in x]

def get_feature_importances(f):
    x = list(zip(f, X_train.columns))
    x.sort(reverse = True, key = lambda e: e[0])
    return [e[0] for e in x]

print("TOP 100 MOST IMPORTANT FEATURES")
print(f"{'GRADIENT BOOSTING':<40}{'RANDOM FOREST':<40}")
print("\n".join(map(lambda e: f"{e[0]:<40}{e[1]:<40}",
    zip(get_feature_importance_names(best_gdb.best_estimator_.
↪feature_importances_)[:100],
        get_feature_importance_names(best_rfc.feature_importances_)[:100]))))

print("\nFEATURE IMPORTANCE SCORES OF 100 MOST IMPORTANT FEATURES")
print(f"{'GRADIENT BOOSTING':<40}{'RANDOM FOREST':<40}")
print("\n".join(map(lambda e: f"{e[0]:<40}{e[1]:<40}",
    zip(get_feature_importances(best_gdb.best_estimator_.feature_importances_[:
↪100],
        get_feature_importances(best_rfc.feature_importances_)[:100]))))
```

TOP 100 MOST IMPORTANT FEATURES

GRADIENT BOOSTING

soy sauce

fish sauce

garam masala

RANDOM FOREST

soy sauce

fish sauce

sesame oil

ginger
fresh ginger
low sodium soy sauce
olive oil
ground turmeric
curry powder
sesame oil
light soy sauce
rice vinegar
ghee
oil
coconut milk
asian fish sauce
cumin seed
Thai fish sauce
ground allspice
extra-virgin olive oil
mirin
ground cardamom
peeled fresh ginger
butter
dried oregano
unsalted butter
corn tortillas
rice flour
fresh ginger root
evaporated milk
basmati rice
tofu
dried thyme
plain yogurt
toasted sesame oil
sesame seeds
oyster sauce
sweetened condensed milk
water
yoghurt
ground cinnamon
fresh parsley
sour cream
thyme
konbu
beansprouts
chinese five-spice powder
ground black pepper
coconut
corn starch
nori

ginger
fresh ginger
rice vinegar
garam masala
oil
ground turmeric
coconut milk
curry powder
cumin seed
olive oil
mirin
peeled fresh ginger
scallions
corn starch
oyster sauce
ghee
beansprouts
low sodium soy sauce
sesame seeds
hoisin sauce
tumeric
sake
vegetable oil
light soy sauce
lemongrass
water
sugar
toasted sesame oil
butter
salt
extra-virgin olive oil
all-purpose flour
red chili peppers
fresh ginger root
dark soy sauce
green chilies
unsalted butter
green onions
ground cardamom
asian fish sauce
basmati rice
garlic
spring onions
garlic paste
thai chile
cilantro leaves
chinese five-spice powder
carrots

cornflour
Thai red curry paste
cardamom pods
vegetable oil
cooking oil
urad dal
rice paper
curry paste
dijon mustard
lemongrass
all-purpose flour
brown mustard seeds
flour tortillas
chutney
instant yeast
allspice
teriyaki sauce
miso paste
garlic cloves
collard greens
green chilies
diced tomatoes
black-eyed peas
cinnamon
jasmine rice
red beans
pork belly
cream cheese
tomatoes
lower sodium soy sauce
daikon
cooking spray
reduced sodium soy sauce
light coconut milk
edamame
fillets
scallions
granny smith apples
preserved lemon
vanilla beans
star anise
milk
cashew nuts
grated parmesan cheese
salsa
fresh thyme
navel oranges
peanut oil

onions
toasted sesame seeds
rice noodles
peanut oil
Thai fish sauce
brown sugar
pepper
mustard seeds
dark sesame oil
eggs
cooking oil
garlic cloves
ground black pepper
plain yogurt
milk
dried oregano
yoghurt
sour cream
reduced sodium soy sauce
daikon
Thai red curry paste
rice flour
Sriracha
corn tortillas
dashi
peanuts
nori
ground cumin
cashew nuts
fresh parsley
grated parmesan cheese
curry leaves
curry paste
black pepper
large eggs
ground cinnamon
tofu
Shaoxing wine
kosher salt
minced ginger
coriander powder
konbu
dried thyme
coriander
tomatoes
cardamom pods
vanilla extract
ground coriander

unsweetened coconut milk

star anise

FEATURE IMPORTANCE SCORES OF 100 MOST IMPORTANT FEATURES

GRADIENT BOOSTING

0.33489520872693046
0.12124791050292826
0.11596783907667019
0.050800557320154545
0.04200467190104259
0.029904169963800176
0.018674079067289757
0.01589043023901329
0.013755103712579894
0.01359535039791967
0.013196466582343212
0.012315791391651808
0.010005754402754065
0.008741784980861369
0.008017945931537264
0.00778781437030113
0.007707592758777167
0.007680431194913628
0.005763756958521427
0.00478296804636419
0.004087132124933287
0.003799267480841038
0.0037885176416351894
0.0032553768227224352
0.0030862298396988077
0.0029751540187466555
0.002942181369383457
0.0023480307034471886
0.002229076484813301
0.0021202916412102805
0.0019541599601066895
0.0019144614388850309
0.0018611359294811356
0.0018315886926732149
0.0017737048643245012
0.0017543258632139668
0.0016613660723779364
0.0015633288745284715
0.0015336366386161154
0.0015121386822045599
0.001476808683323516
0.0014552551005967396
0.0014483391610878502
0.001366970695428436

RANDOM FOREST

0.08626081254014471
0.0441355097676913
0.04175992443818465
0.03606159108264598
0.03577213694357911
0.02746497907723055
0.023483134381061095
0.01609747123664968
0.01545411987297334
0.014104880181548004
0.013532484323020356
0.012942375014364337
0.012045750695274996
0.011499768550861881
0.011047579318892876
0.010743742662714788
0.009907310943285298
0.008943643824625917
0.008218045108894496
0.007920019149255534
0.007854846297017585
0.007469400693783545
0.007071844786774658
0.0066993497020486304
0.006596062536784725
0.006579644295507667
0.006504724729482513
0.006455467977925394
0.006100291603628865
0.006091147182145832
0.006079373935114571
0.0056545780224967175
0.005456006312625609
0.0053567460121228495
0.005282864888218221
0.005030085441748848
0.00485058246224077
0.004843250952020643
0.004349010142048322
0.004255787723873462
0.004209234504540599
0.004128605936040275
0.004038416024470797
0.004020560156025173

0.0013348657062072738	0.0038742999050975038
0.0012967327415996392	0.0037600480262122817
0.0011552266746294227	0.003710399244014207
0.0010838737711296727	0.003705521821609146
0.0010666911949296833	0.003689604794005473
0.001061967655176322	0.0035991559366408887
0.0010492216838738338	0.003259839668767381
0.0010439166951849669	0.0031218737654693904
0.0010296422581953693	0.003081176841752381
0.0009839860925810143	0.0030379891363947055
0.0009643702565602893	0.0028807905721508374
0.0009192947764686666	0.002873898831641295
0.0008854394698137187	0.0027845365782462874
0.0008841707191886425	0.002768224375176178
0.0008821501715055387	0.0027455924186580924
0.0008761427980226651	0.0027146908614822892
0.0008740279282776524	0.002667703992947159
0.0008688545568760178	0.0025902223195047526
0.0008361864790670023	0.0025681678555451643
0.0008126759026615669	0.0025580888103624226
0.0008046857647988115	0.0025294003235711146
0.0008027983920660044	0.0024675213918583946
0.0008023519856297784	0.002440172788200702
0.0007843036869626343	0.002424361554616519
0.000757456826346421	0.002404150516436126
0.000745061035590042	0.002403171992234693
0.0007351745281239062	0.002306959640177074
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0.0006126621623131103	0.0019338052386565921
0.0005995489670141169	0.0019008607133676923
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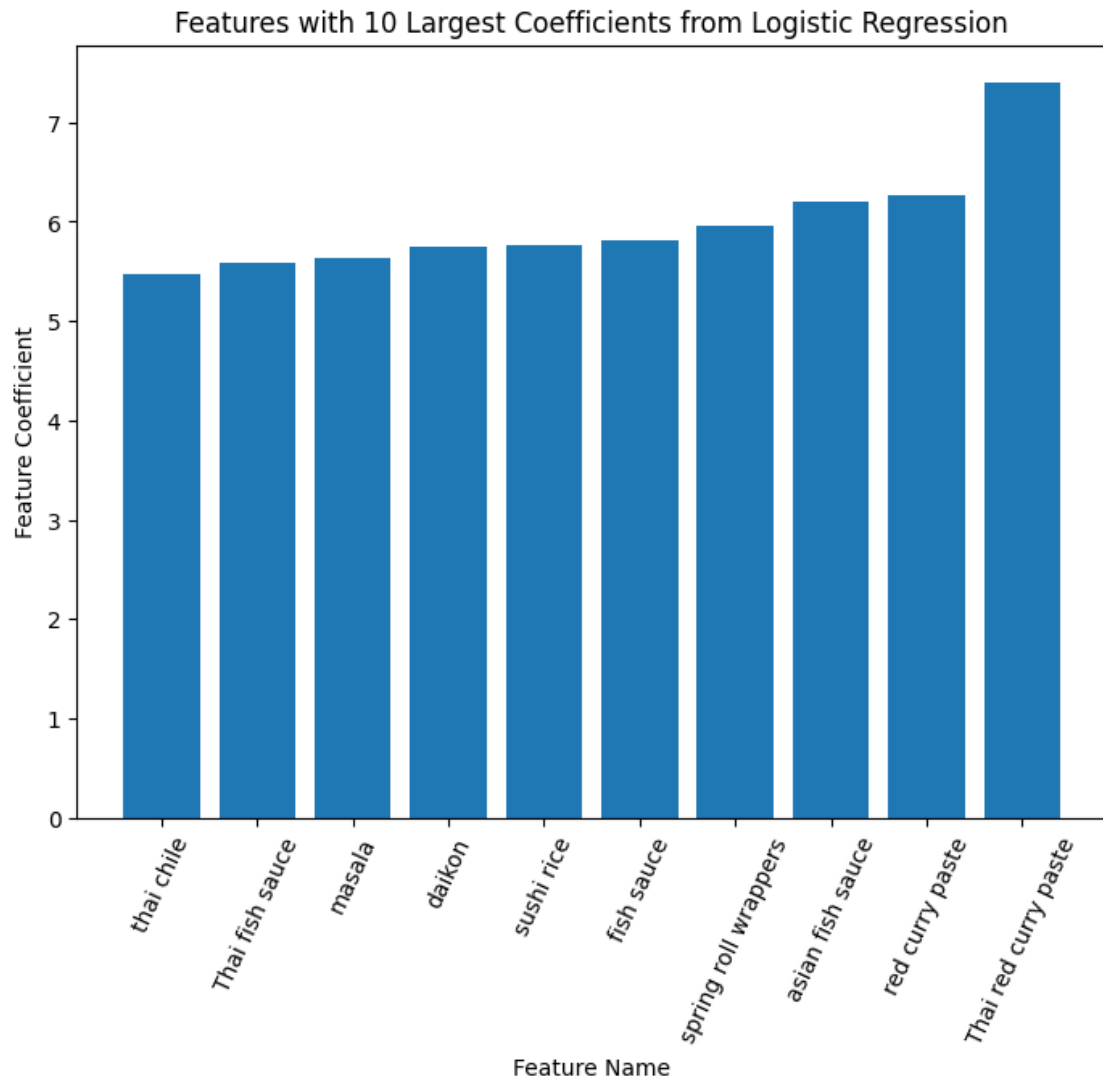
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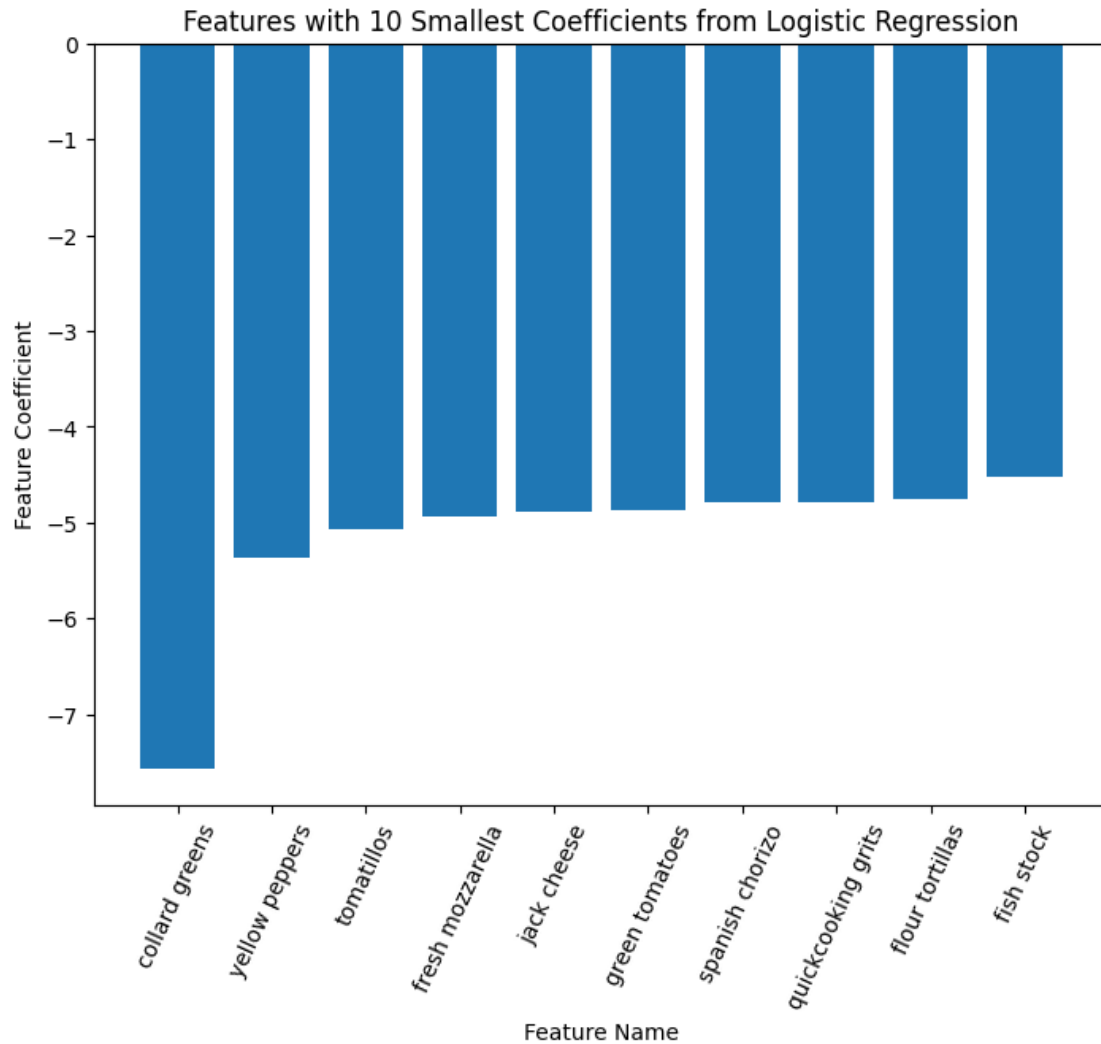
```
[95]: # Visualize feature importances for all models
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar([i[1] for i in ingredients_with_coefficients[-10:]], [i[0] for i in
    ingredients_with_coefficients[-10:]])

plt.title("Features with 10 Largest Coefficients from Logistic Regression")
plt.xlabel("Feature Name")
plt.ylabel("Feature Coefficient")
plt.xticks(rotation = 65) # Rotates X-Axis Ticks by 45-degrees
plt.show()

fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar([i[1] for i in ingredients_with_coefficients[:10]], [i[0] for i in
    ingredients_with_coefficients[:10]])

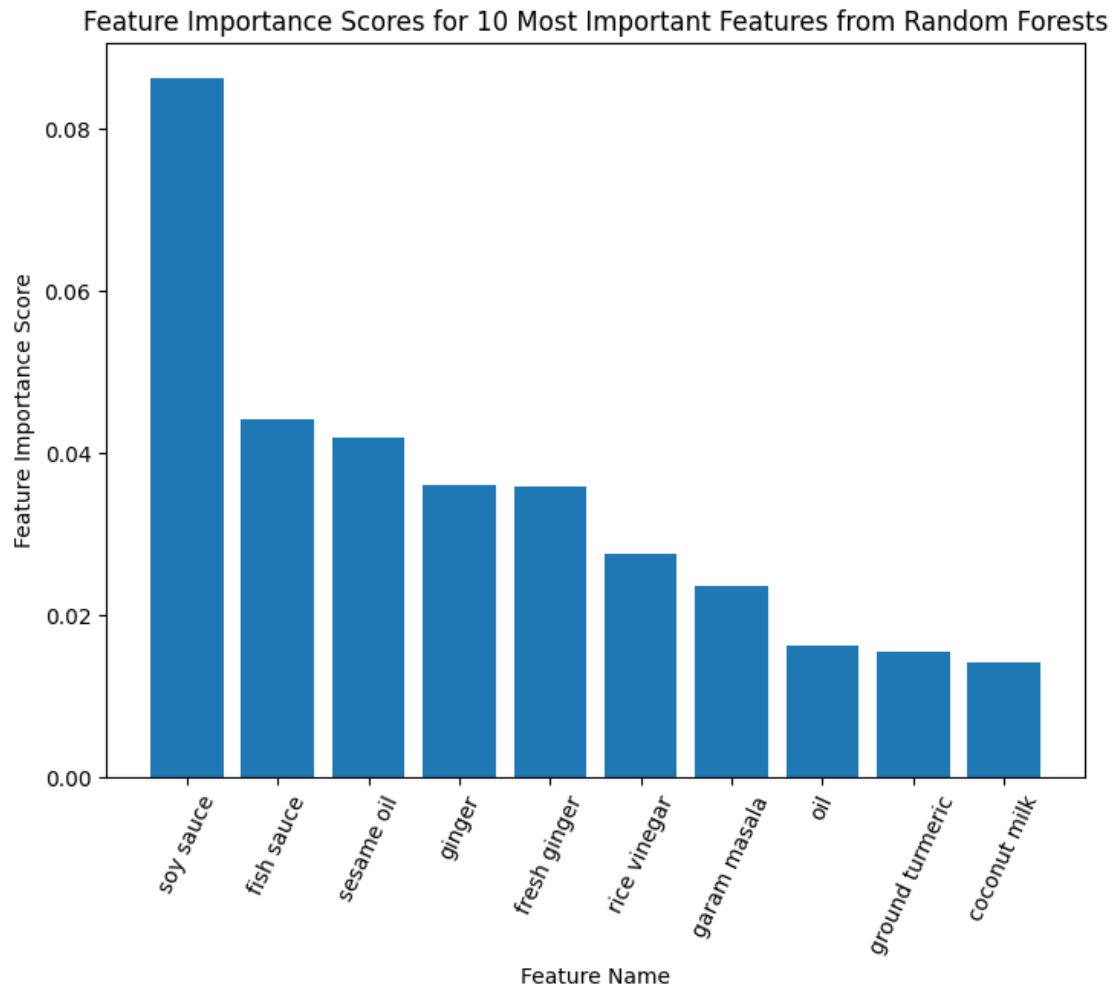
plt.title("Features with 10 Smallest Coefficients from Logistic Regression")
plt.xlabel("Feature Name")
plt.ylabel("Feature Coefficient")
plt.xticks(rotation = 65) # Rotates X-Axis Ticks by 45-degrees
plt.show()
```





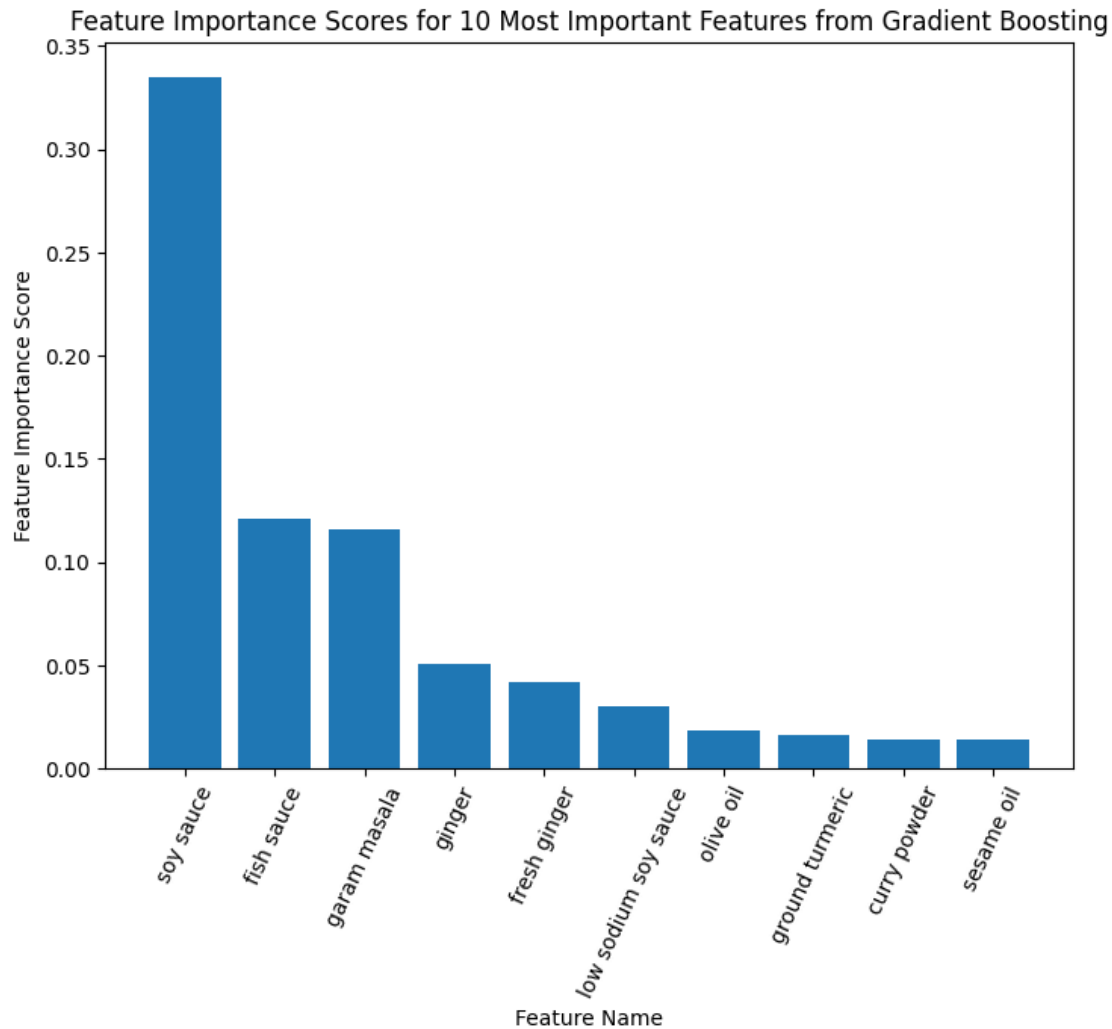
```
[94]: fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(get_feature_importance_names(best_rfc.feature_importances_)[:
↪10],get_feature_importances(best_rfc.feature_importances_)[:10])

plt.title("Feature Importance Scores for 10 Most Important Features from Random_
↪Forests")
plt.xlabel("Feature Name")
plt.ylabel("Feature Importance Score")
plt.xticks(rotation = 65) # Rotates X-Axis Ticks by 45-degrees
plt.show()
```



```
[93]: fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.bar(get_feature_importance_names(best_gdb.best_estimator_.
    ↳feature_importances_)[:10],get_feature_importances(best_gdb.best_estimator_.
    ↳feature_importances_)[:10])

plt.title("Feature Importance Scores for 10 Most Important Features from_
    ↳Gradient Boosting")
plt.xlabel("Feature Name")
plt.ylabel("Feature Importance Score")
plt.xticks(rotation = 65) # Rotates X-Axis Ticks by 45-degrees
plt.show()
```



Interpret results and draw conclusions

Above, the features with the highest coefficient magnitudes from logistic regression are displayed. The features with the highest importance scores for random forests and gradient boosting are also listed. As expected, there are ingredients that are distinctly Asian, and not all ingredients are equally useful for determining whether a recipe is from an Asian cuisine or not.

However, it is interesting that each of the models selected different ingredients as the most important features. For example, the ingredient with the largest coefficient for logistic regression is thai chili. However, for both random forests and gradient boosting, thai red chilis do not even appear in the list of features with the top 10 feature importance scores. Conversely, ginger and fresh ginger appear in the top 10 most important ingredients for both tree based models, yet they do not appear in the top 10 most important ingredients for logsitic regression. Notably, different types of fish sauce are selected among the top 10 most important features across all 3 models.

Significant differences exist between the feature importance scores for gradient boosting and random forests as well. Although soy sauce and fish sauce were the two ingredients with the highest

importance scores for both models, soy sauce has a feature importance of 0.34 for gradient boosting, and 0.11 for random forests. Fish sauce has a feature importance score of around 0.13 for gradient boosting and a score of around 0.045 for random forests. Beyond the top 5 most important features for each model, there seems to be little correlation between the best features and their corresponding importance scores.

In addition to identifying ingredients that are distinctly asian, the logistic regression also helps interpret which ingredients are explicitly not Asian. For example, collared greens, yellow peppers, and mozzarella cheese are among the features with the most negative coefficients. This can be interpreted to mean that the presence of these ingredients (along with other ingredients with large negative coefficients) decreases the odds that a recipe is predicted to be from an Asian cuisine.

In conclusion, it appears that recipe ingredients are useful features for predicting whether a recipe is from an asian cuisine or not. Specifically, the presence of soy sauce and fish sauce in a recipe are strong indicators that a recipe may be from an Asian cuisine. Additionally, there are ingredients that can be identified as distinctly not Asian. For example, we would expect tomatillos and masa to be part of Mexican recipes, but not part of Asian recipes, and the classifiers confirm this concept. Additionally, some ingredients may be shared among Asian and non-Asian cuisines. These ingredients may be identified by examining features whose coefficients have a very small magnitude in the logistic regression model and the features that have low feature importance scores in the tree based models.