Applied Machine Learning :Homework 2

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Dataset: The Alphabet dataset used below consists of images of alphabets represented by a total of 785 columns, where the first column represents the alphabet numbering from 0-25 as A-Z.

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import VotingClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score,f1_score
from sklearn.linear_model import LogisticRegression, SGDClassifier
import warnings
warnings.filterwarnings("ignore")
```

Download and load the dataset. Split into train and test sets. Create a validation set . Display a few images.

In [2]:
```
#load the dataset
data=pd.read_csv("Alphabet_Data.csv")
data.head(10)
```

Out[2]:

	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	...	0.639	0.640	0.641	0.642	0.643	0.644	0.645	0.646
0	3	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
1	20	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
2	17	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
3	19	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
4	14	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
5	10	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
6	14	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
7	25	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0
9	14	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0

10 rows × 785 columns

The first column in the dataset, represented as '0', corresponds to the alphabetical characters from A-Z and is numbered from 0-25

In [3]:
```
data.shape
```

Out[3]:
```
(93121, 785)
```

There are 93121 rows and 785 columns

In [4]:
```
#splitting data into training and testing sets.
#The stratify parameter ensures that the label distribution is maintained between t
train,test = train_test_split(data, test_size=0.20, stratify=data['0'])
train.shape,test.shape
```

Out[4]:
```
((74496, 785), (18625, 785))
```

In [5]:
```
#count the number of occurrences of each label in the train DataFrame
label_counts = train['0'].value_counts()
label_counts
```

Out[5]:
```
14    11565
18     9684
20     5802
2      4682
19     4499
15     3869
13     3802
0      2774
12     2467
11     2318
17     2314
4      2288
24     2172
22     2157
3      2027
1      1734
9      1699
7      1444
23     1254
25     1215
16     1162
6      1153
10     1121
21      837
5       233
8       224
Name: 0, dtype: int64
```

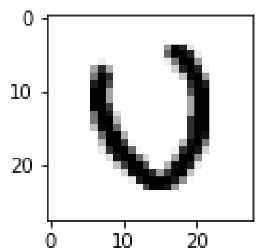
In [6]:
```
#dropping the first column ('0') from the train
x = train.drop('0', axis=1)
#extracting the label data from the train
y = train['0']

#splitting the training data into a new training set and a validation set.
x_train, x_val, y_train, y_val = train_test_split(x, y, test_size=0.16666, random_s

x_test = test.drop('0', axis=1)
y_test = test['0']

```

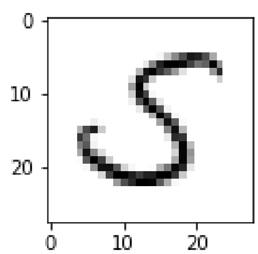
In [7]:
```
x_train.shape,x_val.shape,y_train.shape,y_val.shape
```

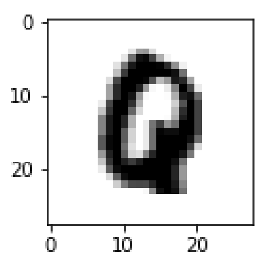
Out[7]:
```
((62080, 784), (12416, 784), (62080,), (12416,))
```

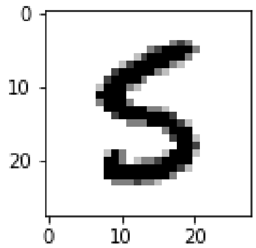
In [33]:

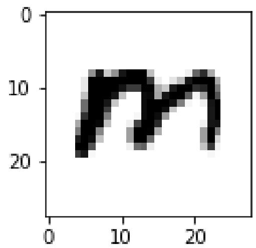
```python
'''
Displaying a few more images. We are padding the pixel data into a 28x28 array and
plot the image. We are displaying 10 random images from the train dataset.
'''

disp_index = [1,141,100,811,512,3003,1111,807,3166,2294]

for m in disp_index:
    img_data = []
    k = []
    cnt = 1
    for z in x_train.loc[m]:
        if(int(cnt)%28 == 0):
            k.append(z)
            img_data.append(k)
            cnt+=1
            k=[]
        else:
            k.append(z)
            cnt+=1
    plt.figure(figsize=(2, 2))
    plt.imshow(img_data, cmap=plt.cm.binary)
    plt.show()

```

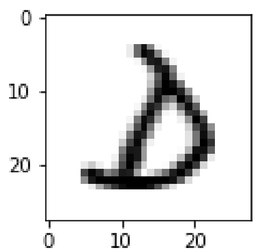


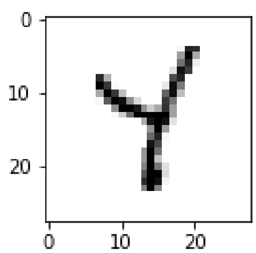


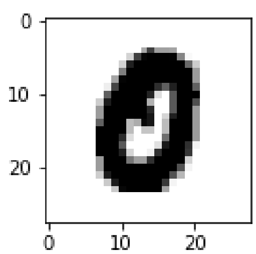


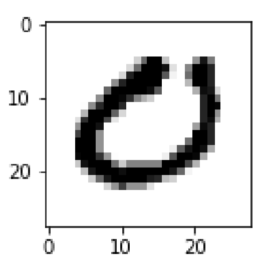


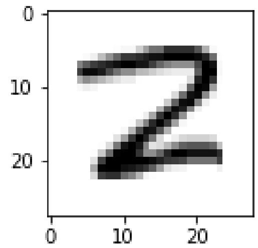











0
10
20
0
10
20

Multinomial Logistic Regression (softmax regression)

In [122]:

```
'''
We will be changing the values of 3 hyper-parameters:- penalty, max_iter and C, to
The solver parameter specifies the algorithm to use in the optimization problem.
The penalty parameter specifies the type of regularization to be used.
The max_iter parameter specifies the maximum number of iterations for the solver to
The C parameter specifies the inverse of the regularization strength.
'''

penalty = ['none', 'l2']
max_iter = [100, 500, 1000]
C = [0.001, 1.0, 100.0]

for a in penalty:
    for b in max_iter:
        for c in C:
            model_1 = LogisticRegression(multi_class='multinomial', solver='lbfgs',
            model_1.fit(x_train, y_train)
            y_pred_train = model_1.predict(x_train)
            accuracy_train = accuracy_score(y_train, y_pred_train)
            f1_train=f1_score(y_train, y_pred_train, average='weighted')
            y_pred_val = model_1.predict(x_val)
            accuracy_val = accuracy_score(y_val, y_pred_val)
            f1_val = f1_score(y_val, y_pred_val, average='weighted')
            y_pred_test = model_1.predict(x_test)
            accuracy_test = accuracy_score(y_test, y_pred_test)
            f1_test = f1_score(y_test, y_pred_test, average='weighted')
            print("Model with penalty =",a,"max_iter =",b,"C =",c)
            print("Train Accuracy:", accuracy_train, "Validation Accuracy:", accura
            print("Train F1 score:", f1_train, "Validation F1 score:", f1_val, "Te
            print("\n")
```

```
Model with penalty = none max_iter = 100 C = 0.001
Train Accuracy: 0.892284149484536 Validation Accuracy: 0.8663820876288659 Test Accura
cy: 0.8686174496644296
Train F1 score: 0.891647500222681 Validation F1 score: 0.8651989850299983 Test f1 sco
re: 0.8677401775515268


Model with penalty = none max_iter = 100 C = 1.0
Train Accuracy: 0.892284149484536 Validation Accuracy: 0.8663820876288659 Test Accura
cy: 0.8686174496644296
Train F1 score: 0.891647500222681 Validation F1 score: 0.8651989850299983 Test f1 sco
re: 0.8677401775515268


Model with penalty = none max_iter = 100 C = 100.0
Train Accuracy: 0.892284149484536 Validation Accuracy: 0.8663820876288659 Test Accura
cy: 0.8686174496644296
Train F1 score: 0.891647500222681 Validation F1 score: 0.8651989850299983 Test f1 sco
re: 0.8677401775515268


Model with penalty = none max_iter = 500 C = 0.001
Train Accuracy: 0.9029961340206185 Validation Accuracy: 0.8563949742268041 Test Accur
acy: 0.8589530201342281
Train F1 score: 0.9025757203615234 Validation F1 score: 0.8552185074120079 Test f1 sc
ore: 0.8581371423107979


Model with penalty = none max_iter = 500 C = 1.0
Train Accuracy: 0.9029961340206185 Validation Accuracy: 0.8563949742268041 Test Accur
acy: 0.8589530201342281
Train F1 score: 0.9025757203615234 Validation F1 score: 0.8552185074120079 Test f1 sc
ore: 0.8581371423107979


Model with penalty = none max_iter = 500 C = 100.0
Train Accuracy: 0.9029961340206185 Validation Accuracy: 0.8563949742268041 Test Accur
acy: 0.8589530201342281
Train F1 score: 0.9025757203615234 Validation F1 score: 0.8552185074120079 Test f1 sc
ore: 0.8581371423107979


Model with penalty = none max_iter = 1000 C = 0.001
Train Accuracy: 0.9040753865979382 Validation Accuracy: 0.8564755154639175 Test Accur
acy: 0.8577181208053691
Train F1 score: 0.9036727198096002 Validation F1 score: 0.8553038059290389 Test f1 sc
ore: 0.8568789033267602


Model with penalty = none max_iter = 1000 C = 1.0
Train Accuracy: 0.9040753865979382 Validation Accuracy: 0.8564755154639175 Test Accur
acy: 0.8577181208053691
Train F1 score: 0.9036727198096002 Validation F1 score: 0.8553038059290389 Test f1 sc
ore: 0.8568789033267602


Model with penalty = none max_iter = 1000 C = 100.0
Train Accuracy: 0.9040753865979382 Validation Accuracy: 0.8564755154639175 Test Accur
acy: 0.8577181208053691
Train F1 score: 0.9036727198096002 Validation F1 score: 0.8553038059290389 Test f1 sc
```

```
ore: 0.8568789033267602


Model with penalty = l2 max_iter = 100 C = 0.001
Train Accuracy: 0.8929284793814433 Validation Accuracy: 0.8682345360824743 Test Accur
acy: 0.8694228187919463
Train F1 score: 0.8924003626502173 Validation F1 score: 0.8671584528559252 Test f1 sc
ore: 0.8686607434404423


Model with penalty = l2 max_iter = 100 C = 1.0
Train Accuracy: 0.8917525773195877 Validation Accuracy: 0.8675096649484536 Test Accur
acy: 0.8686711409395973
Train F1 score: 0.8911845070194099 Validation F1 score: 0.8663975061525153 Test f1 sc
ore: 0.8679463086828001


Model with penalty = l2 max_iter = 100 C = 100.0
Train Accuracy: 0.8919942010309279 Validation Accuracy: 0.8663820876288659 Test Accur
acy: 0.8679731543624161
Train F1 score: 0.8913908258754442 Validation F1 score: 0.8652234984330588 Test f1 sc
ore: 0.8671435139756593


Model with penalty = l2 max_iter = 500 C = 0.001
Train Accuracy: 0.9032538659793814 Validation Accuracy: 0.8571198453608248 Test Accur
acy: 0.8610469798657718
Train F1 score: 0.9028353032399865 Validation F1 score: 0.8560013192151189 Test f1 sc
ore: 0.8602397770722425


Model with penalty = l2 max_iter = 500 C = 1.0
Train Accuracy: 0.9029317010309278 Validation Accuracy: 0.8572003865979382 Test Accur
acy: 0.859489932885906
Train F1 score: 0.9025047919685264 Validation F1 score: 0.8560037496028221 Test f1 sc
ore: 0.8586540573011576


Model with penalty = l2 max_iter = 500 C = 100.0
Train Accuracy: 0.9032216494845361 Validation Accuracy: 0.8569587628865979 Test Accur
acy: 0.8597046979865772
Train F1 score: 0.9027724217156703 Validation F1 score: 0.8557489475135232 Test f1 sc
ore: 0.8588944089479061


Model with penalty = l2 max_iter = 1000 C = 0.001
Train Accuracy: 0.90402706185567 Validation Accuracy: 0.8574420103092784 Test Accurac
y: 0.8588993288590604
Train F1 score: 0.9036204765152476 Validation F1 score: 0.8562521326806717 Test f1 sc
ore: 0.8580541457801041


Model with penalty = l2 max_iter = 1000 C = 1.0
Train Accuracy: 0.9041398195876289 Validation Accuracy: 0.8556701030927835 Test Accur
acy: 0.8581476510067114
Train F1 score: 0.9037383504921748 Validation F1 score: 0.8544409275325945 Test f1 sc
ore: 0.8573709508617379


Model with penalty = l2 max_iter = 1000 C = 100.0
Train Accuracy: 0.9043009020618556 Validation Accuracy: 0.8556701030927835 Test Accur
```

```
acy: 0.8572348993288591
Train F1 score: 0.9038944094755548 Validation F1 score: 0.8544561984338221 Test f1 sc
ore: 0.8564640963192844
```

The logistic regression model with penalty=l2, max_iter=100, and C=0.001 was found to be the best-performing model based on the results obtained. It achieved higher test accuracy (0.869) and test F1 score (0.8686) than all other models. The use of regularization through penalty=l2 generally led to better performance across the models. Although logistic regression achieved an accuracy of about 85-86% on the test set, there may be other models that could potentially outperform it and produce better results.

Support Vector Machines

SGD as LinearSVC

In [11]:

```
C = [0.001, 1.0, 100.0]
for c in C:
    sgd = SGDClassifier(loss='hinge', alpha=1/(len(x_train)*c), fit_intercept=True
    sgd.fit(x_train, y_train)
    y_pred_train = sgd.predict(x_train)
    accuracy_train = accuracy_score(y_train, y_pred_train)
    f1_train=f1_score(y_train, y_pred_train, average='weighted')
    y_pred_val = sgd.predict(x_val)
    accuracy_val = accuracy_score(y_val, y_pred_val)
    f1_val = f1_score(y_val, y_pred_val, average='weighted')
    y_pred_test = sgd.predict(x_test)
    accuracy_test = accuracy_score(y_test, y_pred_test)
    f1_test = f1_score(y_test, y_pred_test, average='weighted')
    print("Model with C =",c)
    print("Train Accuracy:", accuracy_train, "Validation Accuracy:", accuracy_val,
    print("Train F1 score:", f1_train, "Validation F1 score:", f1_val, "Test f1 sco
    print("\n")
```

```
Model with C = 0.001
Train Accuracy: 0.7882087628865979 Validation Accuracy: 0.7629671391752577 Test Accur
acy: 0.7706308724832215
Train F1 score: 0.7892802458571851 Validation F1 score: 0.7616655877082997 Test f1 sc
ore: 0.7711497492937867


Model with C = 1.0
Train Accuracy: 0.7020779639175257 Validation Accuracy: 0.6805734536082474 Test Accur
acy: 0.6904161073825503
Train F1 score: 0.6966198646842083 Validation F1 score: 0.6721897550830878 Test f1 sc
ore: 0.6833812781515608


Model with C = 100.0
Train Accuracy: 0.7655605670103093 Validation Accuracy: 0.7417042525773195 Test Accur
acy: 0.7481342281879194
Train F1 score: 0.7668890017104963 Validation F1 score: 0.7420549745762961 Test f1 sc
ore: 0.7485420978720004
```

The value of the regularization parameter C determines the trade-off between the model's ability to fit the training data closely and its ability to generalize well to new data. When C is set to a very small value like 0.001, the model is highly regularized and may not fit the training data well, but it may generalize better to new data. However, if C is set too high, the model may overfit to the training data and not generalize well. Therefore, finding the optimal value of C requires careful experimentation and evaluation on multiple datasets.In the above scenario, model with c=0.001 performs better with test accuracy as 0.77

Using different Kernels

In [13]:
```

kernel = ['linear','rbf','poly']
C = [0.001, 1.0, 100.0]
gamma = ['scale','auto']

batch_size = 10000
num_batches = int(x_train.shape[0] / batch_size)

for a in kernel:
    for b in C:
        for c in gamma:
            model_2 = SVC(kernel=a,gamma=c,C=b)
            for i in range(num_batches):
                batch_x = x_train[i*batch_size:(i+1)*batch_size]
                batch_y = y_train[i*batch_size:(i+1)*batch_size]
                model_2.fit(batch_x, batch_y)
            y_pred_train = model_2.predict(x_train)
            accuracy_train = accuracy_score(y_train, y_pred_train)
            f1_train = f1_score(y_train, y_pred_train,average='weighted')
            y_pred_val = model_2.predict(x_val)
            accuracy_val = accuracy_score(y_val, y_pred_val)
            f1_val = f1_score(y_val, y_pred_val,average='weighted')
            y_pred_test = model_2.predict(x_test)
            accuracy_test = accuracy_score(y_test, y_pred_test)
            f1_test = f1_score(y_test, y_pred_test,average='weighted')
            print("Model with kernel =",a," C=",b," gamma=",c)
            print("Train Accuracy:", accuracy_train, "Validation Accuracy:", accur
            print("Train f1 score:", f1_train, "Validation f1 score:", f1_val, "Te
            print("\n")
```

```
Model with kernel = linear  C= 0.001  gamma= scale
Train Accuracy: 0.8890302835051547 Validation Accuracy: 0.8658182989690721 Test Accur
acy: 0.8653959731543625
Train f1 score: 0.889267013426636 Validation f1 score: 0.865771021155259 Test f1 scor
e: 0.8655351371142919


Model with kernel = linear  C= 0.001  gamma= auto
Train Accuracy: 0.8890302835051547 Validation Accuracy: 0.8658182989690721 Test Accur
acy: 0.8653959731543625
Train f1 score: 0.889267013426636 Validation f1 score: 0.865771021155259 Test f1 scor
e: 0.8655351371142919


Model with kernel = linear  C= 1.0  gamma= scale
Train Accuracy: 0.8890302835051547 Validation Accuracy: 0.8658182989690721 Test Accur
acy: 0.8653959731543625
Train f1 score: 0.889267013426636 Validation f1 score: 0.865771021155259 Test f1 scor
e: 0.8655351371142919


Model with kernel = linear  C= 1.0  gamma= auto
Train Accuracy: 0.8890302835051547 Validation Accuracy: 0.8658182989690721 Test Accur
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Train f1 score: 0.889267013426636 Validation f1 score: 0.865771021155259 Test f1 scor
e: 0.8655351371142919


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Train Accuracy: 0.8890302835051547 Validation Accuracy: 0.8658182989690721 Test Accur
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Train f1 score: 0.889267013426636 Validation f1 score: 0.865771021155259 Test f1 scor
e: 0.8655351371142919


Model with kernel = linear  C= 100.0  gamma= auto
Train Accuracy: 0.8890302835051547 Validation Accuracy: 0.8658182989690721 Test Accur
acy: 0.8653959731543625
Train f1 score: 0.889267013426636 Validation f1 score: 0.865771021155259 Test f1 scor
e: 0.8655351371142919


Model with kernel = rbf  C= 0.001  gamma= scale
Train Accuracy: 0.1552673969072165 Validation Accuracy: 0.15512242268041238 Test Accu
racy: 0.1552751677852349
Train f1 score: 0.04173573080463085 Validation f1 score: 0.04166305760458433 Test f1
score: 0.041739627758042415


Model with kernel = rbf  C= 0.001  gamma= auto
Train Accuracy: 0.1552673969072165 Validation Accuracy: 0.15512242268041238 Test Accu
racy: 0.1552751677852349
Train f1 score: 0.04173573080463085 Validation f1 score: 0.04166305760458433 Test f1
score: 0.041739627758042415


Model with kernel = rbf  C= 1.0  gamma= scale
Train Accuracy: 0.9306056701030928 Validation Accuracy: 0.9186533505154639 Test Accur
acy: 0.9254765100671141
Train f1 score: 0.9299107157880034 Validation f1 score: 0.917618645244788 Test f1 sco
```

```
re: 0.9246227986391252


Model with kernel = rbf  C= 1.0  gamma= auto
Train Accuracy: 0.30908505154639176 Validation Accuracy: 0.17694909793814434 Test Acc
uracy: 0.17540939597315436
Train f1 score: 0.3082936584989006 Validation f1 score: 0.08488258897942177 Test f1 s
core: 0.08174153251994004


Model with kernel = rbf  C= 100.0  gamma= scale
Train Accuracy: 0.9477931701030928 Validation Accuracy: 0.9358086340206185 Test Accur
acy: 0.9385234899328859
Train f1 score: 0.9475220171112791 Validation f1 score: 0.9353216091484924 Test f1 sc
ore: 0.9381063875868415


Model with kernel = rbf  C= 100.0  gamma= auto
Train Accuracy: 0.30908505154639176 Validation Accuracy: 0.17694909793814434 Test Acc
uracy: 0.17540939597315436
Train f1 score: 0.3082936584989006 Validation f1 score: 0.08488258897942177 Test f1 s
core: 0.08174153251994004


Model with kernel = poly  C= 0.001  gamma= scale
Train Accuracy: 0.24370167525773195 Validation Accuracy: 0.2506443298969072 Test Accu
racy: 0.24515436241610739
Train f1 score: 0.15088529091655406 Validation f1 score: 0.1542103195833361 Test f1 s
core: 0.15112744449369034


Model with kernel = poly  C= 0.001  gamma= auto
Train Accuracy: 0.9256926546391753 Validation Accuracy: 0.9088273195876289 Test Accur
acy: 0.9128053691275168
Train f1 score: 0.9254142864550521 Validation f1 score: 0.9084467673485823 Test f1 sc
ore: 0.9125670014327856


Model with kernel = poly  C= 1.0  gamma= scale
Train Accuracy: 0.8939432989690722 Validation Accuracy: 0.8805573453608248 Test Accur
acy: 0.8838120805369127
Train f1 score: 0.8947350879540427 Validation f1 score: 0.8807599846558871 Test f1 sc
ore: 0.8845162296370496


Model with kernel = poly  C= 1.0  gamma= auto
Train Accuracy: 0.9256926546391753 Validation Accuracy: 0.9088273195876289 Test Accur
acy: 0.9128053691275168
Train f1 score: 0.9254142864550521 Validation f1 score: 0.9084467673485823 Test f1 sc
ore: 0.9125670014327856


Model with kernel = poly  C= 100.0  gamma= scale
Train Accuracy: 0.9257731958762887 Validation Accuracy: 0.909068943298969 Test Accura
cy: 0.913020134228188
Train f1 score: 0.925484797501365 Validation f1 score: 0.9086807176284423 Test f1 sco
re: 0.9127686168427475


Model with kernel = poly  C= 100.0  gamma= auto
Train Accuracy: 0.9256926546391753 Validation Accuracy: 0.9088273195876289 Test Accur
```

```
acy: 0.9128053691275168
Train f1 score: 0.9254142864550521 Validation f1 score: 0.9084467673485823 Test f1 sc
ore: 0.9125670014327856
```

From the results above, it appears that the linear kernel with different combinations of C and gamma values produce similar accuracy and f1 score results for all three datasets, whereas the rbf kernel yielded better results, particularly with higher C values. The most optimal model was identified as the rbf kernel with C=100 and gamma=scale. It is worth noting that the rbf kernel with gamma=auto performed poorly, potentially due to the default calculation of 1 / (n_features * X.var()) not being the most appropriate for this dataset. Overall, the rbf kernel with C=100 and gamma=scale emerged as the most effective model out of all the models examined with an accuracy of 0.9385.

Polynomial Kernel

In [9]:

```
degrees = [1, 2, 3, 5, 7, 9]

batch_size = 10000
num_batches = int(x_train.shape[0] / batch_size)
for degree_value in degrees:
            model_2 = SVC(kernel='poly',degree=degree_value)
            for i in range(num_batches):
                batch_x = x_train[i*batch_size:(i+1)*batch_size]
                batch_y = y_train[i*batch_size:(i+1)*batch_size]
                model_2.fit(batch_x, batch_y)
            y_pred_train = model_2.predict(x_train)
            accuracy_train = accuracy_score(y_train, y_pred_train)
            f1_train = f1_score(y_train, y_pred_train,average='weighted')
            y_pred_val = model_2.predict(x_val)
            accuracy_val = accuracy_score(y_val, y_pred_val)
            f1_val = f1_score(y_val, y_pred_val,average='weighted')
            y_pred_test = model_2.predict(x_test)
            accuracy_test = accuracy_score(y_test, y_pred_test)
            f1_test = f1_score(y_test, y_pred_test,average='weighted')
            print("Model with degree =",degree_value)
            print("Train Accuracy:", accuracy_train, "Validation Accuracy:", accur
            print("Train f1 score:", f1_train, "Validation f1 score:", f1_val, "Te
            print("\n")
```

```
Model with degree = 1
Train Accuracy: 0.8852770618556701 Validation Accuracy: 0.8770135309278351 Test Accur
acy: 0.88048322147651
Train f1 score: 0.8841154669943685 Validation f1 score: 0.8753495745400449 Test f1 sc
ore: 0.8789631799001123


Model with degree = 2
Train Accuracy: 0.9165431701030928 Validation Accuracy: 0.9060083762886598 Test Accur
acy: 0.9111946308724832
Train f1 score: 0.9157512542693804 Validation f1 score: 0.9048787243771336 Test f1 sc
ore: 0.9102608282787787


Model with degree = 3
Train Accuracy: 0.8939432989690722 Validation Accuracy: 0.8805573453608248 Test Accur
acy: 0.8838120805369127
Train f1 score: 0.8947350879540427 Validation f1 score: 0.8807599846558871 Test f1 sc
ore: 0.8845162296370496


Model with degree = 5
Train Accuracy: 0.7978898195876288 Validation Accuracy: 0.7771423969072165 Test Accur
acy: 0.7822281879194631
Train f1 score: 0.8181555529923229 Validation f1 score: 0.7967383096408899 Test f1 sc
ore: 0.8017207081000921


Model with degree = 7
Train Accuracy: 0.7019813144329897 Validation Accuracy: 0.6777545103092784 Test Accur
acy: 0.6812885906040268
Train f1 score: 0.743294641947625 Validation f1 score: 0.7184499351498191 Test f1 sco
re: 0.7215492091921462


Model with degree = 9
Train Accuracy: 0.6267557989690722 Validation Accuracy: 0.5932667525773195 Test Accur
acy: 0.593503355704698
Train f1 score: 0.6810959867662455 Validation f1 score: 0.6454973531595835 Test f1 sc
ore: 0.6466184503337715
```

The results indicate that the polynomial model with degree=2 performs the best on both the validation and test sets, with the highest accuracy and F1 score. The models with degree=1 and 3 also perform well, but not as well as the degree=2 model. On the other hand, the models with degree=5 , 7 and 9 perform worse than the models with degree=1, 2, and 3. Therefore, it appears that a polynomial model with degree=2 is the most suitable choice for this particular classification task with an accuracy of 0.91

Random Forest Classifier

In [12]:

```
'''
We will be changing the values of 3 hyper-parameters:- n_estimators, max_depth and
'''

n_estimators = [10, 50, 100]
max_depth = [5, 10, 20]
min_samples_split = [2, 5, 10]

for a in n_estimators:
    for b in max_depth:
        for c in min_samples_split:
            model_3 = RandomForestClassifier(n_estimators=a, max_depth=b, min_samp
            model_3.fit(x_train, y_train)
            y_pred_train = model_3.predict(x_train)
            accuracy_train = accuracy_score(y_train, y_pred_train)
            y_pred_val = model_3.predict(x_val)
            accuracy_val = accuracy_score(y_val, y_pred_val)
            y_pred_test = model_3.predict(x_test)
            accuracy_test = accuracy_score(y_test, y_pred_test)
            print("Model with n_estimators =",a,"max_depth =",b,"min_samples_split
            print("Train Accuracy:", accuracy_train, "Validation Accuracy:", accura
            print("\n")
```

```
Train Accuracy: 0.6402867268041237 Validation Accuracy: 0.6315238402061856 Test Acc
uracy: 0.6374228187919463


Model with n_estimators = 50 max_depth = 10 min_samples_split = 2
Train Accuracy: 0.921520618556701 Validation Accuracy: 0.8817654639175257 Test Accu
racy: 0.8878389261744967


Model with n_estimators = 50 max_depth = 10 min_samples_split = 5
Train Accuracy: 0.9209729381443299 Validation Accuracy: 0.8848260309278351 Test Acc
uracy: 0.8897718120805369


Model with n_estimators = 50 max_depth = 10 min_samples_split = 10
Train Accuracy: 0.918347293814433 Validation Accuracy: 0.8784632731958762 Test Accu
racy: 0.8896107382550336


Model with n_estimators = 50 max_depth = 20 min_samples_split = 2
```

Based on the above results, it was observed that the model with n_estimators = 100, max_depth = 20, and min_samples_split = 2 had the best accuracy with value of 0.944 on both the validation and test sets. While increasing the number and depth of decision trees tends to increase accuracy, excessive depth may result in overfitting. Additionally, an increase in the minimum number of samples required to split an internal node can prevent overfitting.

In [16]:

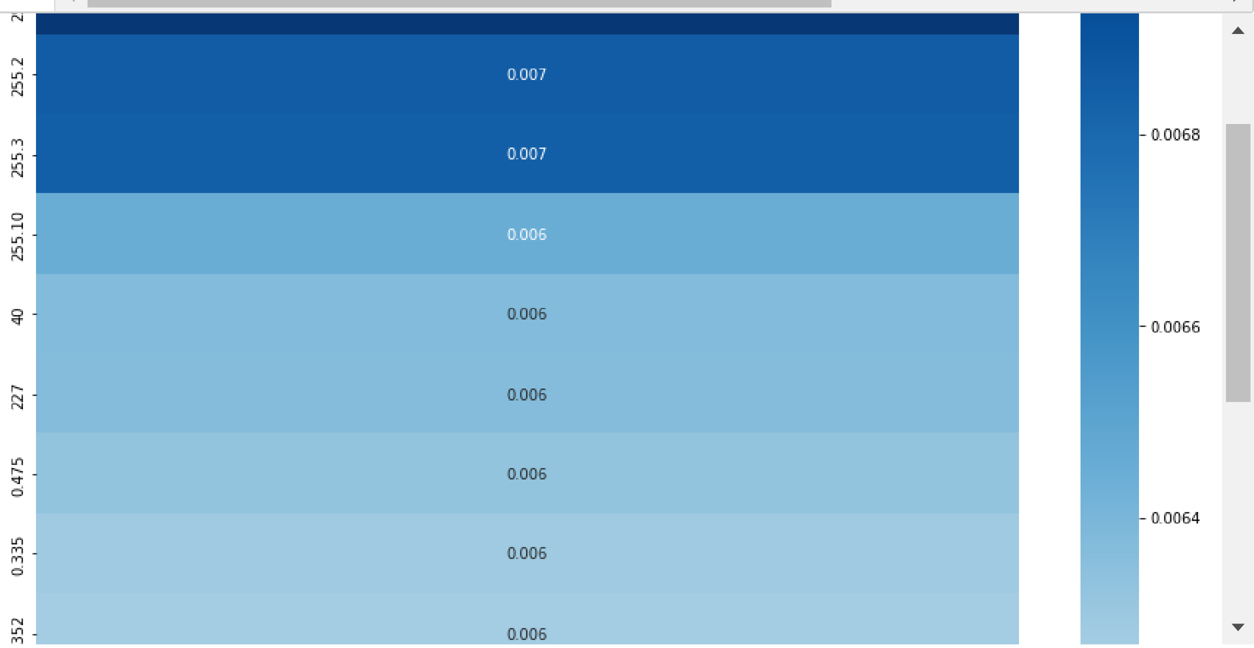
```
'''
Feature importance analysis using in-built function for random forest. From this, w
impacting and features which have the least influence on the model.
'''
import seaborn as sns
clf_rf = RandomForestClassifier(n_estimators=100, max_depth=20, min_samples_split=
clf_rf.fit(x_train, y_train)
feature_importance = dict(zip(x_train.columns, clf_rf.feature_importances_))
indices = np.argsort(feature_importance)[::-1]

feature_importance = dict(zip(x_train.columns, clf_rf.feature_importances_))

df_feature_importance = pd.DataFrame.from_dict(feature_importance, orient='index',
df_feature_importance = df_feature_importance.sort_values('Importance', ascending=

# Selecting top 15 features
top_features = df_feature_importance[:15]


fig, ax = plt.subplots(figsize=(15,15))
sns.heatmap(top_features, cmap='Blues', annot=True, fmt='.3f', ax=ax)
plt.title('Feature Importance (Top 15)')
plt.show()
```



The above plot shows top 15 features which are selected based on their importance scores, and a heatmap is plotted .The heatmap exhibits the top 15 features with their respective importance scores, where a higher score implies a greater importance in predicting the target variable.The column '0.372' has the highest feature importance with a value of 0.007.

Ensemble

In [17]:
```
'''
We will now create an ensemble model out of the 3 best performing models which are
Multinomial Logistic Regression (Softmax Regression) with penalty = 'l2' | max_ite
SVM with kernel as 'rbf'
Random Forest Classifier with n_estimators = 100 | max_depth = 20 | min_samples_sp
'''

clf_lr = LogisticRegression(multi_class='multinomial', solver='lbfgs', penalty='l2
clf_svm = SVC(kernel='rbf',probability=True)
clf_rf = RandomForestClassifier(n_estimators=100, max_depth=20, min_samples_split=
```

In [18]:
```
voting_clf = VotingClassifier(
 estimators=[('lr', clf_lr), ('svm', clf_svm), ('rf', clf_rf)],
 voting='soft')
voting_clf.fit(x_train, y_train)
```

Out[18]:
```
VotingClassifier(estimators=[('lr',
                              LogisticRegression(C=0.001,
                                                 multi_class='multinomial')),
                             ('svm', SVC(probability=True)),
                             ('rf',
                              RandomForestClassifier(max_depth=20,
                                                     min_samples_split=10))],
                 voting='soft')
```

In [19]:
```
y_pred = voting_clf.predict(x_test)
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.9495838926174497
```

The above voting classifier utilizes three models, namely logistic regression, support vector machine, and random forest, to combine their predictions using soft voting. In soft voting, the predicted class is selected based on the highest probability of a class across all models. TThe accuracy of the voting classifier is reported to be almost 0.95. This accuracy is better than all the individual accuracies achieved by the three models used in the ensemble, suggesting that the combination of models and the voting method helped to improve the overall accuracy of the predictions.