In [7]:

```
#import libraries

#sklearn library
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.decomposition import PCA
from sklearn import preprocessing
from sklearn.model_selection import KFold
from sklearn.metrics import classification_report
from sklearn.metrics import plot_confusion_matrix
from sklearn.model_selection import train_test_split

#os library
from os import listdir
from os.path import isdir,join

#other libraries
import numpy as np
import h5py
import cv2 as cv
import statistics
import pandas as pd
import datetime
import matplotlib.pyplot as plt

# input/output paths
# this ipynb file MUST be placed in 'English' folder to work properly
path_find_images =  './Hnd/Img'
#path_output_grid = './grid_output.csv' #only used to output results
```

In [4]:

```
#load data, preprocess (normalise,invert,resize,add average pixel data(optional))
def load_data(file_path, pixels_ld, extra_feature_ld):
    """
    This function converts raw image data into numpy arrays. It takes in as arguments the path dir
ectory of the dataset [file_path],
    the image size in pixels [pixels_ld x pixels_ld] and a boolean [extra_feature_ld] for optional
feature extraction of mean value of the pixel
    data.
    After reading in the raw image files, each image is converted to grayscale, inverted, bounded,
flattened and finally normalised to ensure each
    image is universally defined. If the extra feature option is True, an additional feature of th
e mean pixel value is calculated and appended to
    the image.
    The function returns the images and corresponding labels as a numpy array.
    """
    target = [] # labels array (integer format items)
    target_names = [] # labels array(string format items)
    filenames = [] # path to each image(string format items)

    container_path = file_path
    folders = [f for f in sorted(listdir(container_path)) if isdir(join(container_path, f))]

    # initialize target, target_names and filenames
    for label, folder in enumerate(folders):
        target_names.append(folder)
        folder_path = join(container_path, folder)
        documents = [join(folder_path, d) for d in sorted(listdir(folder_path))]
        target.extend(len(documents) * [label])
        filenames.extend(documents)

    # convert to nparray
    filenames = np.array(filenames) # full paths for each img
    target = np.array(target) # label for each img (corresponding to "filenames" array)

    #load and preprocess images
    img_array = [] # to store all flatten images
    # resize shape
    rows,cols = pixels_ld, pixels_ld
```

```
    for filename in filenames:
        read_img = cv.imread(filename)
        gray = cv.cvtColor(read_img,cv.COLOR_BGR2GRAY)
        ret,thresh = cv.threshold(gray,127,255,cv.THRESH_BINARY_INV)
        contours, hierarchy = cv.findContours(thresh,cv.RETR_EXTERNAL,cv.CHAIN_APPROX_SIMPLE)
        cnt = contours[0]
        x,y,w,h = cv.boundingRect(cnt) # get the rectangle
        thresh = thresh[y:y+h,x:x+w] # cut the image
        thresh = cv.resize(thresh,(rows,cols)).flatten() # resize to same size
        img_array.append(thresh/255)
    image = np.array(img_array)
    #add column containing average pixel data for each object
    if extra_feature_ld:
        image = np.append(image,np.zeros((image.shape[0],1)),axis=1)
        for i in range(image.shape[0]):
            image[i, image.shape[1]-1] = sum(image[i,:rows*cols])/(rows*cols)
    return image,target


# option to write and read hdf5 files to avoid having to load each image from a file each time
def write_hdf5(filename, h5dataset_name, dataset):
    """Function to write data to a hdf5 file. The h5 filename, dataset name and the dataset must b
e passed as arguments."""
    with h5py.File(filename, 'w') as H:
        H.create_dataset(h5dataset_name, data = dataset)
def read_hdf5(filename, h5dataset_name):
    """
    Function to load data from a hdf5 file. The h5 filename and dataset name must be passed as arg
uments. This function returns
    the dataset as a numpy array.
    """
    with h5py.File(filename,'r') as H:
        data = np.copy(H[h5dataset_name])
    return data

# algorithm
def classifier(X_train,y_train,X_test, cp1_cl, cp2_cl, cp3_cl):
    """
    This function defines the Random Forest classifier from sklearn library. It takes in arguments
for training data and labels, test data,
    max_depth and min_leaf_samples, and returns the predicted labels.
    """
    clf = RandomForestClassifier(max_depth = cp1_cl, criterion = cp2_cl, min_samples_leaf = cp3_cl,
random_state = 0).fit(X_train, y_train)
    predictions = clf.predict(X_test)
    return predictions
```

In [12]:

```
# principal components analysis application
def pca_reduction(X_train, X_test,components):
    """
    This function is used to reduce the dimensionality of the training and test data. It takes in
as arguments training data, test data and
    the number of PCA components the user wants to retain after PCA transformation.
    This function returns the transformed training and test data.
    """
    X_t_scaled = preprocessing.scale(X_train)
    X_v_scaled = preprocessing.scale(X_test)
    pca = PCA(n_components=components, random_state=1).fit(X_t_scaled)
    X_t_PCA = pca.transform(X_t_scaled)
    X_v_PCA = pca.transform(X_v_scaled)
    #print(pca.explained_variance_ratio_.sum())
    return X_t_PCA,X_v_PCA

# split the dataset into training and testing subsets
def tr_te_split(data_ts, labels_ts):
    """This function splits dataset and labels into training set and test set in a 4:1 ratio. It r
eturns the split data."""
    return train_test_split(data_ts, labels_ts, test_size = 0.2, shuffle=False)

#plot confusion matrix
def plot_matrix(X_t,y_t,X_v,y_v,cp1_cl, cp2_cl, cp3_cl):
    """
    This function is used to plot the confusion matrix generated by the model with the best parame
ters. It takes in as arguments
```

```
    the training set, test set and other parameters for the Random Tree classifier. It returs the
plot of the confusion matrix.
    NOTE: the command to save the plot as a .png file has been commented out to avoid unwanted ove
rwriting of files. Please uncomment
    this command if you wish to save the plot as a .png file. Keep in mind that any file named 'co
nfusion_matrix.png' in the working
    directory will be overwritten if this command is executed.
    """
    clf = RandomForestClassifier(max_depth = cp1_cl, criterion = cp2_cl, min_samples_leaf = cp3_cl,
random_state = 0).fit(X_t, y_t)
    char_ticks = [0,9,10,37,38,61] #indices for 0,9,A,Z,a,z
    char_labels = ['0','9','A','Z','a','z']
    plot_confusion_matrix(clf,X_v,y_v, cmap='hot',include_values=False,normalize='true')
    plt.title("Confusion Matrix - Random Forest Classifier",fontsize=16)
    plt.xlabel("Predicted characters 0-9, A-Z, a-z",fontsize=12)
    plt.ylabel("Actual characters 0-9, A-Z, a-z",fontsize=12)
    plt.xticks(char_ticks, char_labels)
    plt.yticks(char_ticks, char_labels)
    plt.gcf().set_size_inches(20, 10)
    plt.savefig('confusion_matrix.png',dpi=100)


def kfold_cv(folds,data,labels,pca_option,components, cp1_kf, cp2_kf, cp3_kf):
    """
    This function implements a k-fold cross validation technique using sklearn. It splits data int
o training and test data k times
    in a random order. It takes in user-defined number of folds [folds], the dataset, a boolean to
check if user wants to apply
    PCA [pca_option], number of PCA components to retain [components] and parameters for the Rando
m Tree classifier.
    This function makes use of all functions defined above and is a crucial part of this model.
    This function returns a list which contains the mean values of scoring metrics for the model.
    """
    kf = KFold(n_splits=folds, shuffle=True, random_state=0)
    kf.get_n_splits(data)
    result_scores = np.zeros((folds,10))
    fold_num = 0
    for train_index, test_index in kf.split(data):
        #print('{}-fold CV: Fold = {}'.format(folds, fold_num+1))
        X_t = data[train_index,:]
        X_v = data[test_index,:]
        y_t = labels[train_index]
        y_v = labels[test_index]

        #PCA
        if pca_option:
            X_t, X_v = pca_reduction(X_t, X_v,components)

        #algorithm
        labels_p = classifier(X_t,y_t,X_v, cp1_kf, cp2_kf, cp3_kf)

        #model evaluation
        #note that zero division warnings have been suppressed in following code
        fold_result = classification_report(y_v,labels_p, output_dict=True, zero_division = 0)
        result_scores[fold_num,0] = fold_result['accuracy']
        result_scores[fold_num,1] = fold_result['macro avg']['precision']
        result_scores[fold_num,2] = fold_result['macro avg']['recall']
        result_scores[fold_num,3] = fold_result['macro avg']['f1-score']
        fold_num += 1

        #printing confusion matrix for one random train-validation set
        if fold_num == 1:
            plot_matrix(X_t,y_t,X_v,y_v, cp1_kf, cp2_kf, cp3_kf)
    return result_scores

def print_stats(results):
    """This function is used to print the scoring metrics of the model obtained using k-fold cross
validation."""
    print('Final test sample result - accuracy: ', statistics.mean(results[:,0]))
    print('Final test sample result - precision: ', statistics.mean(results[:,1]))
    print('Final test sample result - recall: ', statistics.mean(results[:,2]))
    print('Final test sample result - f1-score: ', statistics.mean(results[:,3]))

def preloaded(data_pl, labels_pl, pc_pl, cp1_pl, cp2_pl, cp3_pl):
    """
    This function carries out 10 fold cross validation on the model with the best parameters. It t
akes in
```

```
    data and labels, number of PCA components and parameters needed for the Random Tree classifier
.
    """
    X_tr, X_te, y_tr, y_te = tr_te_split(data_pl, labels_pl)
    results = kfold_cv(10,data,labels,True,pc_pl,cp1_pl, cp2_pl, cp3_pl)
    print_stats(results)
    return statistics.mean(results[:,0])
```

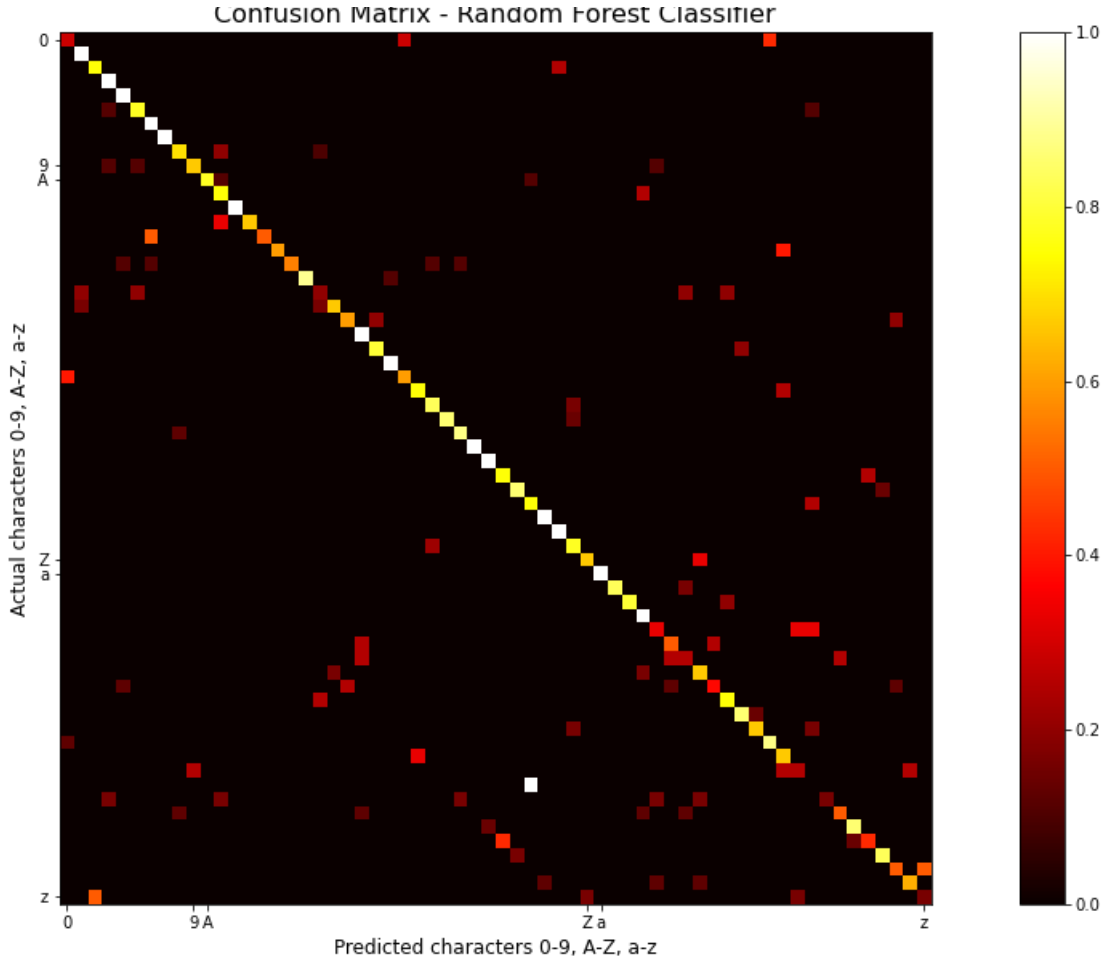
Notes on running the following cell

- After all the above functions have been defined, the next cell runs the model and prints scoring metrics and plots a confusion matrix.
- Please note that the cell below can be used for grid search for hyperparameter tuning and/or to evaluate the model. For convenience, we have commented out the grid search section for hyperparameter tuning of the model. Instead, we have predetermined the best paramers for the model and applied it to the cell already.
- If grid search does need to be performed please uncomment the parameters as shown below. Please refer to Appendix A1 on the report for more details on running the grid search.
- Thank you :)

In [11]:

```
"""
Parameters for grid search
To run grid search, please replace each parameter and hyperparameter with the following lists.
pixel size (i.e px x px = image size): px = [6, 20, 45, 80]
pca_component: pc = [8,16,32,64]
extra features: ef = [True,False]
max_depth: cp1 = [13,22,35]
decisions: cp2 = ['gini','entropy']
min no. of samples per leaf: cp3 = [1,2,5]
"""
grid_results = []
#initialisation
px, ef, pc, cp1, cp2, cp3 = 0,False,0,0,0,0

#best params for random forest: px = 17, ef = False, pc = 34, max_depth (cp1) = 35, criterion (cp2
) = 'gini', min_samples_leaf = 1
#see Table in 'Best Performance' subsection of 'Results' in report for more information

# perform the combinations of all grid search parameters in loops
for px in [17]: #data pixels
    for ef in [False]: #extra features
        print('Loading data with',px**2, 'pixels: ', datetime.datetime.now())
        data, labels = load_data(path_find_images,px,ef)
        print('Load complete, ', datetime.datetime.now())
        for pc in [34]: #pca number
            if pc < px**2:

                #INSERT YOUR CLASSIFIER PARAMETERS TO TRY
                for cp1 in [35]: #max_depth
                    for cp2 in ['gini']: # gini or entropy decisions
                        for cp3 in [1]: #min number of samples per leaf
                            print('Start run with settings: ', px, ef, pc, cp1, cp2, cp3, datetime.
atetime.now())
                            a = datetime.datetime.now()
                            grid_results.append([px, ef, pc, cp1, cp2, cp3, preloaded(data, labels,
pc, cp1, cp2, cp3), a, datetime.datetime.now()])
                            #pd.DataFrame(np.array(grid_results)).to_csv(path_output_grid)

                            print('Completed run with settings: ', px, ef, pc, cp1, cp2, cp3, datet
me.datetime.now())
```

```
Loading data with 289 pixels:  2020-11-18 13:46:56.657557
Load complete,  2020-11-18 13:47:38.904026
Start run with settings:  17 False 34 35 gini 1 2020-11-18 13:47:38.905026
Final test sample result - accuracy:  0.7343108504398828
Final test sample result - precision:  0.7361685178620662
Final test sample result - recall:  0.7372390960294186
Final test sample result - f1-score:  0.7134275110176871
Completed run with settings:  17 False 34 35 gini 1 2020-11-18 13:48:03.604534
```


Confusion Matrix - Random Forest Classifier
Actual characters 0-9, A-Z, a-z
Predicted characters 0-9, A-Z, a-z
0
9
A
Z
a
z
0
9A
Za
z
1.0
0.8
0.6
0.4
0.2
0.0

In [ ]:

In [ ]: