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Phase3 Project

Business Objective

To help the Goverment of Tanzania monitor the condition of installed waterpumps across the country.Given a set of parameters, the model should be able to predict the status of a waterpump. Status can be as classified as:

1. Functional
2. Functional needs repair
3. non functional

Dataset

Dataset sourced from: https://www.drivendata.org/competitions/7/pump-it-up-data-mining-the-water-table/page/23/

Import libraries

In [1]:
```
import pandas as pd
import numpy as np
import geopandas as gpd
from shapely.geometry import Point, Polygon
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report
from sklearn.metrics import f1_score,accuracy_score,precision_score,recall_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import plot_confusion_matrix
import warnings
warnings.filterwarnings('ignore')
```

EDA

In [2]:
```
# importing dataset
df = pd.read_csv('waterwell.csv')
df.head()
```

Out[2]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	wpt_name
0	69572	6000.0	3/14/2011	Roman	1390	Roman	34.938093	-9.856322	none

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	wpt_name
1	8776	0.0	3/6/2013	Grumeti	1399	GRUMETI	34.698766	-2.147466	Zahanati
2	34310	25.0	2/25/2013	Lottery Club	686	World vision	37.460664	-3.821329	Kwa Mahundi
3	67743	0.0	1/28/2013	Unicef	263	UNICEF	38.486161	-11.155298	Zahanati Ya Nanyumbu
4	19728	0.0	7/13/2011	Action In A	0	Artisan	31.130847	-1.825359	Shuleni

5 rows × 41 columns

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 41 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   id                     59400 non-null  int64  
 1   amount_tsh             59400 non-null  float64
 2   date_recorded          59400 non-null  object 
 3   funder                 55765 non-null  object 
 4   gps_height             59400 non-null  int64  
 5   installer              55745 non-null  object 
 6   longitude              59400 non-null  float64
 7   latitude               59400 non-null  float64
 8   wpt_name               59400 non-null  object 
 9   num_private            59400 non-null  int64  
 10  basin                  59400 non-null  object 
 11  subvillage             59029 non-null  object 
 12  region                 59400 non-null  object 
 13  region_code            59400 non-null  int64  
 14  district_code          59400 non-null  int64  
 15  lga                    59400 non-null  object 
 16  ward                   59400 non-null  object 
 17  population             59400 non-null  int64  
 18  public_meeting         56066 non-null  object 
 19  recorded_by            59400 non-null  object 
 20  scheme_management      55523 non-null  object 
 21  scheme_name            31234 non-null  object 
 22  permit                 56344 non-null  object 
 23  construction_year      59400 non-null  int64  
 24  extraction_type        59400 non-null  object 
 25  extraction_type_group  59400 non-null  object 
 26  extraction_type_class  59400 non-null  object 
 27  management             59400 non-null  object 
 28  management_group       59400 non-null  object 
 29  payment                59400 non-null  object 
 30  payment_type           59400 non-null  object 
 31  water_quality          59400 non-null  object 
 32  quality_group          59400 non-null  object 
 33  quantity               59400 non-null  object 
 34  quantity_group         59400 non-null  object 
 35  source                 59400 non-null  object 
 36  source_type            59400 non-null  object 
```

```
 37  source_class           59400 non-null  object
 38  waterpoint_type        59400 non-null  object
 39  waterpoint_type_group  59400 non-null  object
 40  status_group           59400 non-null  object
dtypes: float64(3), int64(7), object(31)
memory usage: 18.6+ MB
```

Checking for Null values

In [4]:

```
# checking for null values and returning it as a pandas series
empty=df.isna().sum()
empty
```

Out[4]:

```
id                           0
amount_tsh                   0
date_recorded                0
funder                    3635
gps_height                   0
installer                 3655
longitude                    0
latitude                     0
wpt_name                     0
num_private                  0
basin                        0
subvillage                 371
region                       0
region_code                  0
district_code                0
lga                          0
ward                         0
population                   0
public_meeting            3334
recorded_by                  0
scheme_management         3877
scheme_name              28166
permit                    3056
construction_year            0
extraction_type              0
extraction_type_group        0
extraction_type_class        0
management                   0
management_group             0
payment                      0
payment_type                 0
water_quality                0
quality_group                0
quantity                     0
quantity_group               0
source                       0
source_type                  0
source_class                 0
waterpoint_type              0
waterpoint_type_group        0
status_group                 0
dtype: int64
```

In [5]:

```
#converting the empty series into a dictionary
empty_dict = dict(empty)

#looping thru dictionary to isolate the columns that have null values
empty_list =[]
for key,value in empty_dict.items():
    if value != 0:
```

```
        empty_list.append(key)

empty_list
# we now have the list of columns that have null values
```

Out[5]:
```
['funder',
 'installer',
 'subvillage',
 'public_meeting',
 'scheme_management',
 'scheme_name',
 'permit']
```

In [6]:
```
# examining those columns
df_empty = df[empty_list]
df_empty
```

Out[6]:

	funder	installer	subvillage	public_meeting	scheme_management	scheme_name	permit
0	Roman	Roman	Mnyusi B	True	VWC	Roman	False
1	Grumeti	GRUMETI	Nyamara	NaN	Other	NaN	True
2	Lottery Club	World vision	Majengo	True	VWC	Nyumba ya mungu pipe scheme	True
3	Unicef	UNICEF	Mahakamani	True	VWC	NaN	True
4	Action In A	Artisan	Kyanyamisa	True	NaN	NaN	True
...	...	...	...	...	...	...	...
59395	Germany Republi	CES	Kiduruni	True	Water Board	Losaa Kia water supply	True
59396	Cefa-njombe	Cefa	Igumbilo	True	VWC	Ikondo electrical water sch	True
59397	NaN	NaN	Madungulu	True	VWC	NaN	False
59398	Malec	Musa	Mwinyi	True	VWC	NaN	True
59399	World Bank	World	Kikatanyemba	True	VWC	NaN	True

59400 rows × 7 columns

In [7]:
```
df_empty.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 7 columns):
 #   Column             Non-Null Count  Dtype 
---  ------             --------------  ----- 
 0   funder             55765 non-null  object
 1   installer          55745 non-null  object
 2   subvillage         59029 non-null  object
 3   public_meeting     56066 non-null  object
 4   scheme_management  55523 non-null  object
 5   scheme_name        31234 non-null  object
```

```
 6   permit                56344 non-null  object
dtypes: object(7)
memory usage: 3.2+ MB
```

We can see that all the columns that have null values are categorical.
Also,recall from the original df that total number of rows is 59400

In [8]:
```
# Looking at scheme_name first since it has the highest number of null values
df['scheme_name'].value_counts()
```

Out[8]:
```
K                              682
None                           644
Borehole                       546
Chalinze wate                  405
M                              400
                              ... 
Shirimatunda water supply        1
Mradi wa maji  Kadas             1
REGWA COMPANY OF EGYPT           1
TWESA                            1
Mashangwi                        1
Name: scheme_name, Length: 2696, dtype: int64
```

Since 'scheme_name' has approx. 47% of the data missing, even classifying this as 'missing'
might skew the analysis. Hence it's best to remove it from the analysis.

In [9]:
```
#creating a copy of df for the analysis
df1 =df.copy()
df1.head()
```

Out[9]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	wpt_name
0	69572	6000.0	3/14/2011	Roman	1390	Roman	34.938093	-9.856322	none
1	8776	0.0	3/6/2013	Grumeti	1399	GRUMETI	34.698766	-2.147466	Zahanati
2	34310	25.0	2/25/2013	Lottery Club	686	World vision	37.460664	-3.821329	Kwa Mahundi
3	67743	0.0	1/28/2013	Unicef	263	UNICEF	38.486161	-11.155298	Zahanati Ya Nanyumbu
4	19728	0.0	7/13/2011	Action In A	0	Artisan	31.130847	-1.825359	Shuleni

5 rows × 41 columns

In [10]:
```
# removing 'scheme_name' from the df
df1.drop('scheme_name',axis=1,inplace=True)
```

Since, the rest of the columns have approx. only 6% of the data missing, we can either choose to drop it
or classify it as 'MISSING' for the analysis. Let's classify it as 'MISSING'.

In [11]:
```
#replacing the null values as 'MISSING'
df1.fillna('MISSING',inplace=True)
```

In [12]:
```
# checking the df
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 40 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   id                     59400 non-null  int64  
 1   amount_tsh             59400 non-null  float64
 2   date_recorded          59400 non-null  object 
 3   funder                 59400 non-null  object 
 4   gps_height             59400 non-null  int64  
 5   installer              59400 non-null  object 
 6   longitude              59400 non-null  float64
 7   latitude               59400 non-null  float64
 8   wpt_name               59400 non-null  object 
 9   num_private            59400 non-null  int64  
 10  basin                  59400 non-null  object 
 11  subvillage             59400 non-null  object 
 12  region                 59400 non-null  object 
 13  region_code            59400 non-null  int64  
 14  district_code          59400 non-null  int64  
 15  lga                    59400 non-null  object 
 16  ward                   59400 non-null  object 
 17  population             59400 non-null  int64  
 18  public_meeting         59400 non-null  object 
 19  recorded_by            59400 non-null  object 
 20  scheme_management      59400 non-null  object 
 21  permit                 59400 non-null  object 
 22  construction_year      59400 non-null  int64  
 23  extraction_type        59400 non-null  object 
 24  extraction_type_group  59400 non-null  object 
 25  extraction_type_class  59400 non-null  object 
 26  management             59400 non-null  object 
 27  management_group       59400 non-null  object 
 28  payment                59400 non-null  object 
 29  payment_type           59400 non-null  object 
 30  water_quality          59400 non-null  object 
 31  quality_group          59400 non-null  object 
 32  quantity               59400 non-null  object 
 33  quantity_group         59400 non-null  object 
 34  source                 59400 non-null  object 
 35  source_type            59400 non-null  object 
 36  source_class           59400 non-null  object 
 37  waterpoint_type        59400 non-null  object 
 38  waterpoint_type_group  59400 non-null  object 
 39  status_group           59400 non-null  object 
dtypes: float64(3), int64(7), object(30)
memory usage: 18.1+ MB
```

We can see that there no more missing values

Checking the datatypes

In [13]:
```
# examining the data types of the df
df1.dtypes.value_counts()
```

Out[13]:
```
object     30
int64       7
```

```
float64     3
dtype: int64
```

We can see that most of the features are categorical

Numeric data

In [14]:
```
# looking at the distributions of the numerical data
#creating a subset of the numeric data
df1_numeric = pd.DataFrame(df1.select_dtypes(include=['int64','float64']))
df1_numeric.head()
```

Out[14]:

	id	amount_tsh	gps_height	longitude	latitude	num_private	region_code	district_code	pop
0	69572	6000.0	1390	34.938093	-9.856322	0	11	5	
1	8776	0.0	1399	34.698766	-2.147466	0	20	2	
2	34310	25.0	686	37.460664	-3.821329	0	21	4	
3	67743	0.0	263	38.486161	-11.155298	0	90	63	
4	19728	0.0	0	31.130847	-1.825359	0	18	1	

Categorical data

Let's explore some of the features and see if we can glean some information:

In [15]:
```
df1[['payment','payment_type']]
```

Out[15]:

	payment	payment_type
0	pay annually	annually
1	never pay	never pay
2	pay per bucket	per bucket
3	never pay	never pay
4	never pay	never pay
...	...	...
59395	pay per bucket	per bucket
59396	pay annually	annually
59397	pay monthly	monthly
59398	never pay	never pay
59399	pay when scheme fails	on failure

59400 rows × 2 columns

Since they are the same, we can delete either 'payment' or 'payment_type'

In [16]:
```
#dropping 'payment_type' from the df
df1.drop('payment_type',axis=1,inplace=True)
```

```
In [17]: df1[['extraction_type', 'extraction_type_group', 'extraction_type_class']]
```

Out[17]:

	extraction_type	extraction_type_group	extraction_type_class
0	gravity	gravity	gravity
1	gravity	gravity	gravity
2	gravity	gravity	gravity
3	submersible	submersible	submersible
4	gravity	gravity	gravity
...	...	...	...
59395	gravity	gravity	gravity
59396	gravity	gravity	gravity
59397	swn 80	swn 80	handpump
59398	nira/tanira	nira/tanira	handpump
59399	nira/tanira	nira/tanira	handpump

59400 rows × 3 columns

Again, these are similar and we can chose to eliminate 2 of them from our analysis

```
In [18]: df1.drop(['extraction_type_group','extraction_type_class'],axis=1,inplace=True)
```

```
In [19]: df1[['management','management_group']]
```

Out[19]:

	management	management_group
0	vwc	user-group
1	wug	user-group
2	vwc	user-group
3	vwc	user-group
4	other	other
...	...	...
59395	water board	user-group
59396	vwc	user-group
59397	vwc	user-group
59398	vwc	user-group
59399	vwc	user-group

59400 rows × 2 columns

```
In [20]: df1['management'].unique()
```

```
Out[20]: array(['vwc', 'wug', 'other', 'private operator', 'water board', 'wua',
                'company', 'water authority', 'parastatal', 'unknown',
                'other - school', 'trust'], dtype=object)
```

```
In [21]: df1['management_group'].unique()
```

```
Out[21]: array(['user-group', 'other', 'commercial', 'parastatal', 'unknown'],
              dtype=object)
```

We can remove 'management_group' since 'management' provides more detail.

```
In [22]: #drop
         df1.drop('management_group',axis=1,inplace=True)
```

```
In [23]: df1[['source','source_type','source_class']]
```

Out[23]:

	source	source_type	source_class
0	spring	spring	groundwater
1	rainwater harvesting	rainwater harvesting	surface
2	dam	dam	surface
3	machine dbh	borehole	groundwater
4	rainwater harvesting	rainwater harvesting	surface
...	...	...	...
59395	spring	spring	groundwater
59396	river	river/lake	surface
59397	machine dbh	borehole	groundwater
59398	shallow well	shallow well	groundwater
59399	shallow well	shallow well	groundwater

59400 rows × 3 columns

```
In [24]: df1['source'].unique()
```

```
Out[24]: array(['spring', 'rainwater harvesting', 'dam', 'machine dbh', 'other',
                'shallow well', 'river', 'hand dtw', 'lake', 'unknown'],
              dtype=object)
```

```
In [25]: df1['source_type'].unique()
```

```
Out[25]: array(['spring', 'rainwater harvesting', 'dam', 'borehole', 'other',
                'shallow well', 'river/lake'], dtype=object)
```

```
In [26]: df1['source_class'].unique()
```

```
Out[26]: array(['groundwater', 'surface', 'unknown'], dtype=object)
```

We can choose 'source' over the other two features

```
In [27]: #drop
         df1.drop(['source_type','source_class'],axis=1,inplace=True)
```

In [28]:
```
df1[['water_quality','quality_group','quantity','quantity_group','waterpoint_type','wat
```
Out[28]:

	water_quality	quality_group	quantity	quantity_group	waterpoint_type	waterpoint_type_grou
0	soft	good	enough	enough	communal standpipe	communal standpip
1	soft	good	insufficient	insufficient	communal standpipe	communal standpip
2	soft	good	enough	enough	communal standpipe multiple	communal standpip
3	soft	good	dry	dry	communal standpipe multiple	communal standpip
4	soft	good	seasonal	seasonal	communal standpipe	communal standpip
...	...	...	...	...	...	..
59395	soft	good	enough	enough	communal standpipe	communal standpip
59396	soft	good	enough	enough	communal standpipe	communal standpip
59397	fluoride	fluoride	enough	enough	hand pump	hand pum
59398	soft	good	insufficient	insufficient	hand pump	hand pum
59399	salty	salty	enough	enough	hand pump	hand pum

59400 rows × 6 columns

In [29]:
```
df1['water_quality'].unique()
```
Out[29]:
```
array(['soft', 'salty', 'milky', 'unknown', 'fluoride', 'coloured',
       'salty abandoned', 'fluoride abandoned'], dtype=object)
```
In [30]:
```
df1['quality_group'].unique()
```
Out[30]:
```
array(['good', 'salty', 'milky', 'unknown', 'fluoride', 'colored'],
      dtype=object)
```
In [31]:
```
df1['quantity'].unique()
```
Out[31]:
```
array(['enough', 'insufficient', 'dry', 'seasonal', 'unknown'],
      dtype=object)
```
In [32]:
```
df1['quantity_group'].unique()
```
Out[32]:
```
array(['enough', 'insufficient', 'dry', 'seasonal', 'unknown'],
      dtype=object)
```
In [33]:
```
df1['waterpoint_type'].unique()
```
Out[33]:
```
array(['communal standpipe', 'communal standpipe multiple', 'hand pump',
```

```
       'other', 'improved spring', 'cattle trough', 'dam'], dtype=object)
```

In [34]:
```python
df1['waterpoint_type_group'].unique()
```

Out[34]:
```
array(['communal standpipe', 'hand pump', 'other', 'improved spring',
       'cattle trough', 'dam'], dtype=object)
```

In [35]:
```python
#dropping quality_group,quantity_group and waterpoint_type_group
df1.drop(['quality_group','waterpoint_type_group','quantity_group'],axis=1,inplace=True
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 31 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   id                 59400 non-null  int64  
 1   amount_tsh         59400 non-null  float64
 2   date_recorded      59400 non-null  object 
 3   funder             59400 non-null  object 
 4   gps_height         59400 non-null  int64  
 5   installer          59400 non-null  object 
 6   longitude          59400 non-null  float64
 7   latitude           59400 non-null  float64
 8   wpt_name           59400 non-null  object 
 9   num_private        59400 non-null  int64  
 10  basin              59400 non-null  object 
 11  subvillage         59400 non-null  object 
 12  region             59400 non-null  object 
 13  region_code        59400 non-null  int64  
 14  district_code      59400 non-null  int64  
 15  lga                59400 non-null  object 
 16  ward               59400 non-null  object 
 17  population         59400 non-null  int64  
 18  public_meeting     59400 non-null  object 
 19  recorded_by        59400 non-null  object 
 20  scheme_management  59400 non-null  object 
 21  permit             59400 non-null  object 
 22  construction_year  59400 non-null  int64  
 23  extraction_type    59400 non-null  object 
 24  management         59400 non-null  object 
 25  payment            59400 non-null  object 
 26  water_quality      59400 non-null  object 
 27  quantity           59400 non-null  object 
 28  source             59400 non-null  object 
 29  waterpoint_type    59400 non-null  object 
 30  status_group       59400 non-null  object 
dtypes: float64(3), int64(7), object(21)
memory usage: 14.0+ MB
```

In [36]:
```python
df1[['region','region_code','district_code']]
```

Out[36]:

	region	region_code	district_code
0	Iringa	11	5
1	Mara	20	2
2	Manyara	21	4
3	Mtwara	90	63
4	Kagera	18	1

	region	region_code	district_code
...	...	...	...
59395	Kilimanjaro	3	5
59396	Iringa	11	4
59397	Mbeya	12	7
59398	Dodoma	1	4
59399	Morogoro	5	2

59400 rows × 3 columns

In [37]:
```
df1['public_meeting'].unique()
```

Out[37]:
```
array([True, 'MISSING', False], dtype=object)
```

In [38]:
```
df1['recorded_by'].unique()
```

Out[38]:
```
array(['GeoData Consultants Ltd'], dtype=object)
```

In [39]:
```
df1['num_private'].unique()
```

Out[39]:
```
array([   0,   39,    5,   45,    6,    3,  698,   32,   15,    7,   25,
        102,    1,   93,   14,   34,  120,   17,  213,   47,    8,   41,
         80,  141,   20,   35,  131,    4,   22,   11,   87,   61,   65,
        136,    2,  180,   38,   62,    9,   16,   23,   42,   24,   12,
        668,  672,   58,  150,  280,  160,   50, 1776,   30,   27,   10,
         94,   26,  450,  240,  755,   60,  111,  300,   55, 1402],
      dtype=int64)
```

In [40]:
```
df1[['scheme_management','permit']]
```

Out[40]:

	scheme_management	permit
0	VWC	False
1	Other	True
2	VWC	True
3	VWC	True
4	MISSING	True
...	...	...
59395	Water Board	True
59396	VWC	True
59397	VWC	False
59398	VWC	True
59399	VWC	True

59400 rows × 2 columns

In [41]:
```
df1['scheme_management'].unique()
```

Out[41]:
```
array(['VWC', 'Other', 'MISSING', 'Private operator', 'WUG',
       'Water Board', 'WUA', 'Water authority', 'Company', 'Parastatal',
       'Trust', 'SWC', 'None'], dtype=object)
```

Looks like 'scheme_management' has the same info as 'management' and hence can be removed

In [42]:
```
#dropping scheme_management
df1.drop('scheme_management',axis=1,inplace=True)
```

In [43]:
```
#dropping id,wpt_name since they will not have a bearing on the analysis
df1.drop(['id','wpt_name'],axis=1,inplace=True)
```

In [44]:
```
df1[['funder','installer']]
```

Out[44]:

	funder	installer
0	Roman	Roman
1	Grumeti	GRUMETI
2	Lottery Club	World vision
3	Unicef	UNICEF
4	Action In A	Artisan
...	...	...
59395	Germany Republi	CES
59396	Cefa-njombe	Cefa
59397	MISSING	MISSING
59398	Malec	Musa
59399	World Bank	World

59400 rows × 2 columns

Checking for duplicate data

In [45]:
```
#checking for duplicate data based on all the columns
df[df1.duplicated()]
```

Out[45]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude
370	59310	0.0	7/18/2011	Government Of Tanzania	0	Government	0.0	-2.000000e-08
2634	26938	0.0	8/22/2011	Government Of Tanzania	0	DWE	0.0	-2.000000e-08

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude
5563	30389	0.0	8/22/2011	Government Of Tanzania	0	DWE	0.0	-2.000000e-08
6218	4377	0.0	12/11/2012	Government Of Tanzania	0	RWE	0.0	-2.000000e-08
7709	23184	0.0	2/16/2013	Dwsp	0	DWE	0.0	-2.000000e-08
...	...	...	...	...	...	...	...	...
57662	47039	0.0	10/25/2012	Dwsp	0	DWE	0.0	-2.000000e-08
57807	49622	0.0	8/26/2011	Government Of Tanzania	0	Government	0.0	-2.000000e-08
58463	1562	0.0	2/16/2013	Dwsp	0	DWE	0.0	-2.000000e-08
58859	63207	0.0	10/26/2012	Lwi	0	LWI	0.0	-2.000000e-08
59166	52986	0.0	1/22/2013	World Vision	0	World Vision	0.0	-2.000000e-08

141 rows × 41 columns

We can that there are 36 rows of duplicate data. We can remove them from the dataset

In [46]:
```
#removing duplicates
df1.drop_duplicates(inplace=True,keep='first')
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 59259 entries, 0 to 59399
Data columns (total 28 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   amount_tsh       59259 non-null  float64
 1   date_recorded    59259 non-null  object 
 2   funder           59259 non-null  object 
 3   gps_height       59259 non-null  int64  
 4   installer        59259 non-null  object 
 5   longitude        59259 non-null  float64
 6   latitude         59259 non-null  float64
 7   num_private      59259 non-null  int64  
 8   basin            59259 non-null  object 
 9   subvillage       59259 non-null  object 
 10  region           59259 non-null  object 
 11  region_code      59259 non-null  int64  
 12  district_code    59259 non-null  int64  
 13  lga              59259 non-null  object 
 14  ward             59259 non-null  object 
 15  population       59259 non-null  int64  
 16  public_meeting   59259 non-null  object 
```

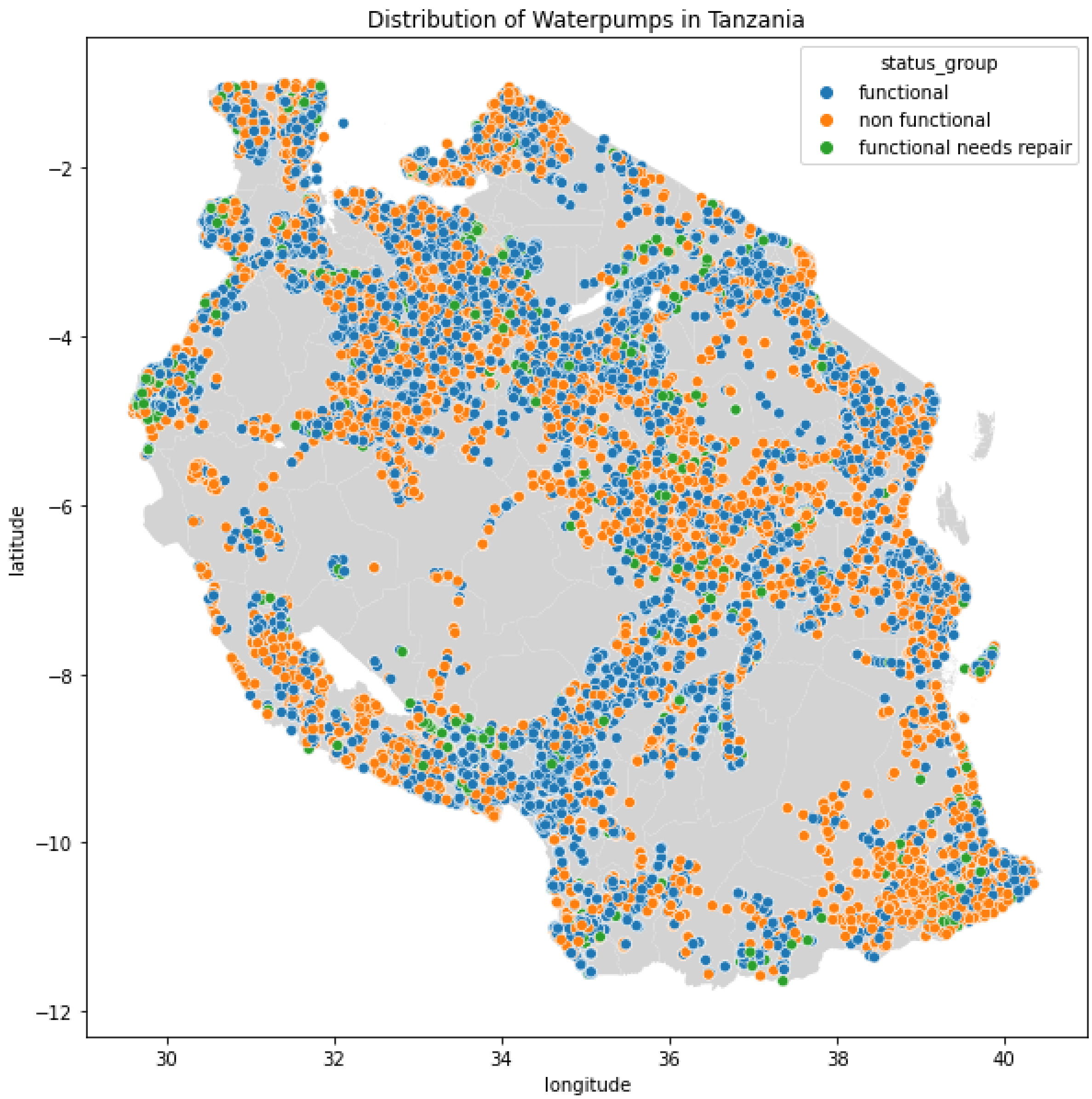
```
 17  recorded_by        59259 non-null  object
 18  permit             59259 non-null  object
 19  construction_year  59259 non-null  int64
 20  extraction_type    59259 non-null  object
 21  management         59259 non-null  object
 22  payment            59259 non-null  object
 23  water_quality      59259 non-null  object
 24  quantity           59259 non-null  object
 25  source             59259 non-null  object
 26  waterpoint_type    59259 non-null  object
 27  status_group       59259 non-null  object
dtypes: float64(3), int64(6), object(19)
memory usage: 13.1+ MB
```

We now have a dataset that in has no null and duplicate values.

Mapping waterpump distribution

In [47]:

```
#create a new df
mapdf = df1.copy()

#filter out the longitude values
mapdf = mapdf[mapdf['longitude'] > 0]

#read the shape file with geopandas
tanzania_map = gpd.read_file('Districts and TC as 2020.shp')
# tanzania_map.plot(color='lightgrey',figsize=(8,8)); just look at the map of tanzania

crs = {'init':'EPSG:4326'} #define CRS
geometry = [Point(xy) for xy in zip(mapdf['longitude'], df['latitude'])] #create Points
geo_df = gpd.GeoDataFrame(mapdf,
                          crs = crs,
                          geometry = geometry) #define the geometry df

#plot the data
fig, ax = plt.subplots(figsize = (10,10))
tanzania_map.to_crs(epsg=4326).plot(ax=ax, color='lightgrey')
sns.scatterplot(x="longitude", y="latitude",data=mapdf,hue='status_group',ax=ax);
ax.set_title('Distribution of Waterpumps in Tanzania');
```



Encoding

In [48]:

```
df1_cat = df1.select_dtypes(include=['object'])
df1_cat.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 59259 entries, 0 to 59399
Data columns (total 19 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   date_recorded   59259 non-null  object
 1   funder          59259 non-null  object
 2   installer       59259 non-null  object
 3   basin           59259 non-null  object
 4   subvillage      59259 non-null  object
 5   region          59259 non-null  object
 6   lga             59259 non-null  object
 7   ward            59259 non-null  object
 8   public_meeting  59259 non-null  object
 9   recorded_by     59259 non-null  object
 10  permit          59259 non-null  object
```

```
 11  extraction_type  59259 non-null  object
 12  management       59259 non-null  object
 13  payment          59259 non-null  object
 14  water_quality    59259 non-null  object
 15  quantity         59259 non-null  object
 16  source           59259 non-null  object
 17  waterpoint_type  59259 non-null  object
 18  status_group     59259 non-null  object
dtypes: object(19)
memory usage: 9.0+ MB
```

In [49]:

```
#Cheking for the number of unique values in each column
cols=[]
unique_number = []
for name in df1_cat.columns:
    cols.append(name)
for item in cols:
    unique_number.append(df1_cat[item].nunique())

unique_dict =dict(zip(cols,unique_number))
unique_dict
```

Out[49]:

```
{'date_recorded': 356,
 'funder': 1898,
 'installer': 2146,
 'basin': 9,
 'subvillage': 19288,
 'region': 21,
 'lga': 125,
 'ward': 2092,
 'public_meeting': 3,
 'recorded_by': 1,
 'permit': 3,
 'extraction_type': 18,
 'management': 12,
 'payment': 7,
 'water_quality': 8,
 'quantity': 5,
 'source': 10,
 'waterpoint_type': 7,
 'status_group': 3}
```

Since there are certain features with a large number of unique values, we can try encoding the categorical data by using two different methods to see which works best: label encoding and one hot encoding

Label encoding approach

In [50]:

```
#instantiate the encoder
labelencoder = LabelEncoder()

#converting df1_cat into str type
df1_cat = df1_cat.astype('str')

#fit and transform the categrical data
df1_cat_enc = df1_cat.apply(labelencoder.fit_transform)
df1_cat_enc.shape
```

Out[50]:

```
(59259, 19)
```

One-hot encoding

In [51]:
```
#using the get dummies method to one hot encode
df1_cat_ohe=pd.get_dummies(df1_cat)

#creating another copy of the df for analysis
df3 = df1.copy()
df3.drop(df1_cat.columns,axis=1,inplace=True)

#concatenating the two df's
df3 = pd.concat([df3,df1_cat_ohe],axis=1)
df3.shape
```

Out[51]:
```
(59259, 26021)
```

We can see that having such a large df would be resource-intensive to work with.

Hence, we will use the LabelEncoding approach for our analysis

In [52]:
```
#making a copy for analysis
df2 = df1.copy()

#dropping the categorical columns
df2.drop(df1_cat_enc.columns,axis=1,inplace=True)
df2.info()

#combining the encoded and numeric data
df2 = pd.concat([df2,df1_cat_enc],axis=1)
df2.head()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 59259 entries, 0 to 59399
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   amount_tsh         59259 non-null  float64
 1   gps_height         59259 non-null  int64  
 2   longitude          59259 non-null  float64
 3   latitude           59259 non-null  float64
 4   num_private        59259 non-null  int64  
 5   region_code        59259 non-null  int64  
 6   district_code      59259 non-null  int64  
 7   population         59259 non-null  int64  
 8   construction_year  59259 non-null  int64  
dtypes: float64(3), int64(6)
memory usage: 4.5 MB
```

Out[52]:

	amount_tsh	gps_height	longitude	latitude	num_private	region_code	district_code	population
0	6000.0	1390	34.938093	-9.856322	0	11	5	109
1	0.0	1399	34.698766	-2.147466	0	20	2	280
2	25.0	686	37.460664	-3.821329	0	21	4	250
3	0.0	263	38.486161	-11.155298	0	90	63	58
4	0.0	0	31.130847	-1.825359	0	18	1	0

5 rows × 28 columns

We now have df2 with encoded values that we can use for modelling.

We will build 3 different baseline models and compare their accuracies. We will then select
the one with the highest accuracy to fine tune and build upon.

Building baseline models

Logistic Regression

In [53]:

```
#creating X and y
X=df2.drop('status_group',axis=1)
y=df2[['status_group']]

#splitting the train and test sets
X_train,X_test,y_train,y_test = train_test_split(X,y,random_state=123)

#instantiate logistic regression model
logreg = LogisticRegression(random_state=123)

#fit the model onto the train sets
logreg.fit(X_train,y_train)
logreg

#predict values of the model
y_hat_train = logreg.predict(X_train)
y_hat_test = logreg.predict(X_test)

#evaluate model
names = ['functional','non functional','functional needs repair']
f1_logreg = round(f1_score(y_test,y_hat_test,average='macro'),3)
print(classification_report(y_test,y_hat_test,target_names=names))
```

```
                         precision    recall  f1-score   support

             functional       0.56      0.90      0.69      7945
         non functional       0.00      0.00      0.00      1091
functional needs repair       0.56      0.21      0.31      5779

               accuracy                           0.56     14815
              macro avg       0.38      0.37      0.33     14815
           weighted avg       0.52      0.56      0.49     14815
```

Decision Tree

In [54]:

```
#instantiate
clf = DecisionTreeClassifier(criterion='entropy',random_state=123)

#fit the model onto the train sets
clf.fit(X_train,y_train)

#predict
y_hat_train = clf.predict(X_train)
y_hat_test = clf.predict(X_test)
```

```
#evaluate model
f1_tree = round(f1_score(y_test,y_hat_test,average='macro'),3)
print(classification_report(y_test,y_hat_test,target_names=names))
```

```
                         precision    recall  f1-score   support

             functional       0.79      0.79      0.79      7945
         non functional       0.38      0.38      0.38      1091
functional needs repair       0.76      0.76      0.76      5779

               accuracy                           0.75     14815
              macro avg       0.64      0.64      0.64     14815
           weighted avg       0.75      0.75      0.75     14815
```

KNN model

In [55]:
```
#instantiate
knn_baseline_model = KNeighborsClassifier()

#fit onto the data
knn_baseline_model.fit(X_train,y_train)

#predict
y_hat_train = knn_baseline_model.predict(X_train)
y_hat_test = knn_baseline_model.predict(X_test)

#evaluate model
f1_knn = round(f1_score(y_test,y_hat_test,average='macro'),3)
print(classification_report(y_test,y_hat_test,target_names=names))
```

```
                         precision    recall  f1-score   support

             functional       0.65      0.76      0.70      7945
         non functional       0.31      0.16      0.21      1091
functional needs repair       0.61      0.52      0.56      5779

               accuracy                           0.62     14815
              macro avg       0.52      0.48      0.49     14815
           weighted avg       0.61      0.62      0.61     14815
```

Selecting a model

In [56]:
```
#import the metrics library
print(f'f1-score of baseline logistic regression is {f1_logreg}')
print(f'f1-score of baseline decision tree is {f1_tree}')
print(f'f1-score of knn model is {f1_knn}')
```

```
f1-score of baseline logistic regression is 0.333
f1-score of baseline decision tree is 0.644
f1-score of knn model is 0.492
```

Since, the decision tree baseline model has the highest performance score, we will build on that for further analysis

Decision Tree

In [57]:
```
#re-run the basline model so all variables are updated correctly
```

```
#for the train and test sets

#instantiate
clf = DecisionTreeClassifier(criterion='entropy',random_state=123)

#fit the model onto the train sets
clf.fit(X_train,y_train)
clf

#predict
y_hat_train = clf.predict(X_train)
y_hat_test = clf.predict(X_test)

#evaluate model
from sklearn.metrics import classification_report

print('TRAIN SCORES')
print(classification_report(y_train,y_hat_train,target_names=names))
print('--------------------------------------------------------------')
print('TEST SCORES')
print(classification_report(y_test,y_hat_test,target_names=names))

accuracy_baseline_train = accuracy_score(y_train,y_hat_train)
accuracy_baseline_test = accuracy_score(y_test,y_hat_test)
```

```
TRAIN SCORES
                         precision    recall  f1-score   support

             functional       1.00      1.00      1.00     24241
         non functional       1.00      1.00      1.00      3217
functional needs repair       1.00      1.00      1.00     16986

               accuracy                           1.00     44444
              macro avg       1.00      1.00      1.00     44444
           weighted avg       1.00      1.00      1.00     44444

--------------------------------------------------------------
TEST SCORES
                         precision    recall  f1-score   support

             functional       0.79      0.79      0.79      7945
         non functional       0.38      0.38      0.38      1091
functional needs repair       0.76      0.76      0.76      5779

               accuracy                           0.75     14815
              macro avg       0.64      0.64      0.64     14815
           weighted avg       0.75      0.75      0.75     14815
```

We can see that the model is clearly overfitting on the train dataset.

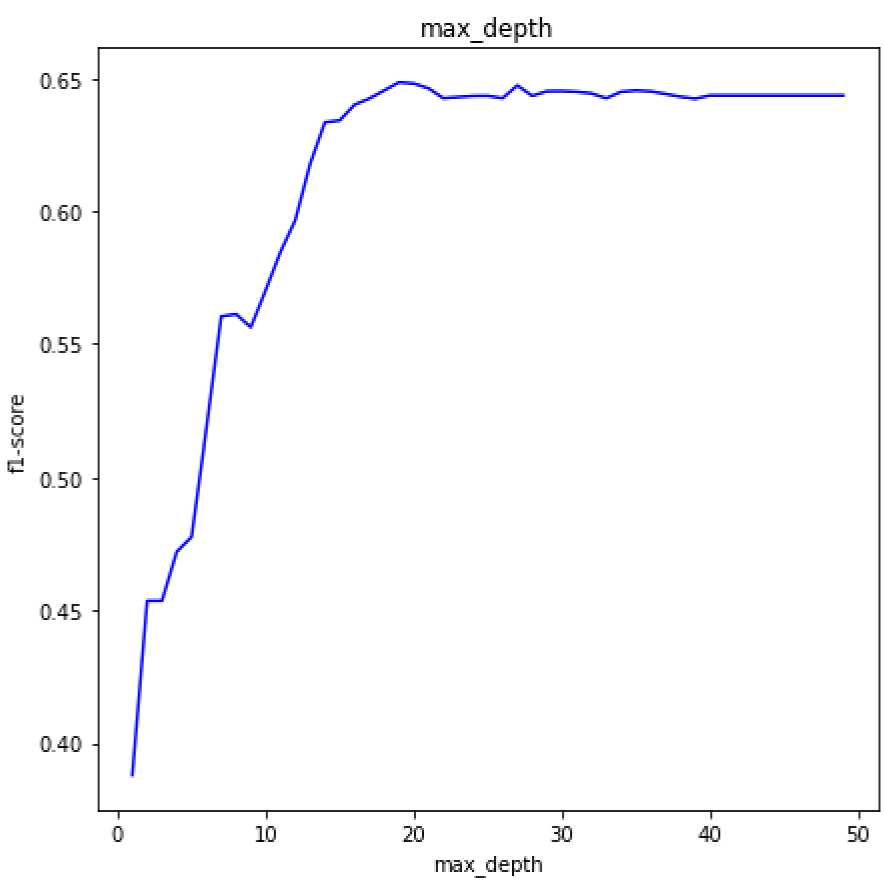
Hyperparameter Tuning

max_depth

In [58]:
```
#creating a list of depth values
max_depth = np.arange(1,50)

#creating an empty list to store scores for each depth
f1_test_scores = []
```

```python
# create a loop for the classifier to run with the different depth values
for depth in max_depth:

    #instantiate
    classifier = DecisionTreeClassifier(criterion='entropy',max_depth=depth,random_stat

    #fit the model
    classifier.fit(X_train,y_train)

    #predict values
    y_hat_test = classifier.predict(X_test)

    #calculate
    f1 = f1_score(y_test,y_hat_test,average='macro')


    #add the scores to the list
    f1_test_scores.append(f1)


#visualize the data
import matplotlib.pyplot as plt
fig,ax = plt.subplots(figsize=(7,7))
ax.plot(max_depth,f1_test_scores,c='b')
ax.set_xlabel('max_depth')
ax.set_ylabel('f1-score')
ax.set_title('max_depth')
```

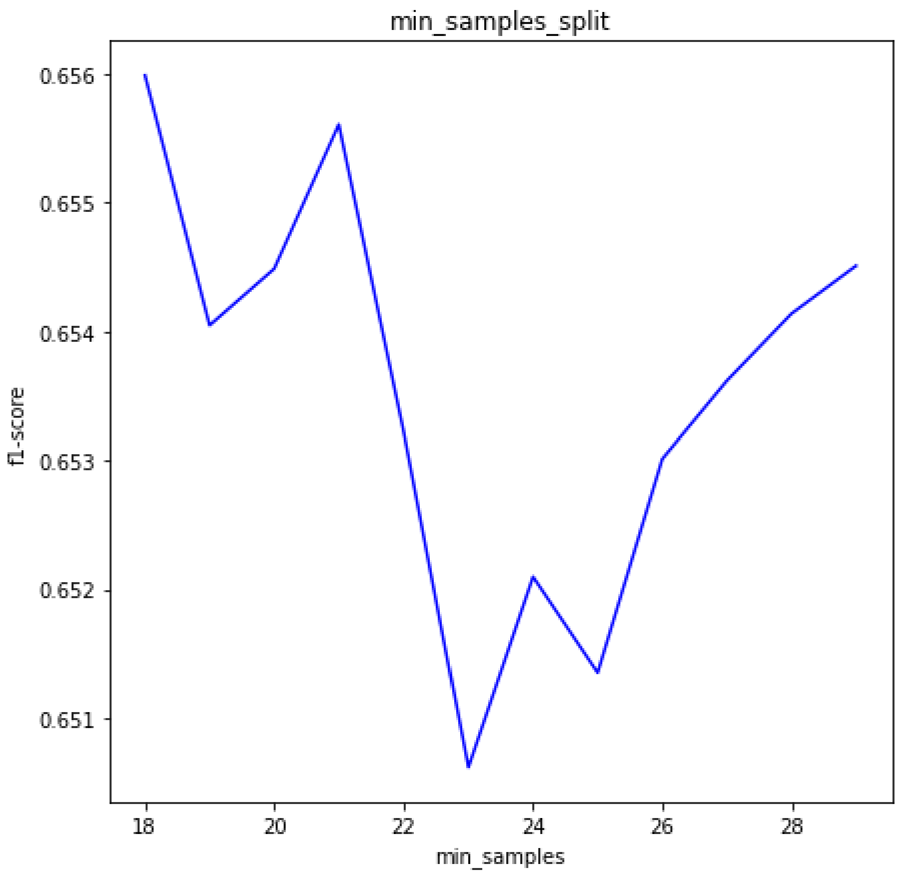
Out[58]: Text(0.5, 1.0, 'max_depth')



We can see that the accuracy for the model peaks at 20 before decreasing and levelling off

min_samples_split

In [59]:
```
#use the optimum value of depth
depth = 20

#define a range of min_samples_for each split
min_samples_range = np.arange(18,30)

#create a loop with the optimum depth and different min_samples
#creating an empty list to store scores for each depth
f1_test_scores = []
# accuracy_scores = []
# precision_scores = []
# recall_scores = []

# create a loop for the classifier to run with the different depth values
for sample in min_samples_range:

    #instantiate
    classifier = DecisionTreeClassifier(criterion='entropy',max_depth=depth,min_samples

    #fit the model
    classifier.fit(X_train,y_train)

    #predict values
    y_hat_test = classifier.predict(X_test)

    #calculate
    f1 = f1_score(y_test,y_hat_test,average='macro')

    #add the scores to the list
    f1_test_scores.append(f1)


#visualize
fig,ax = plt.subplots(figsize=(7,7))
ax.plot(min_samples_range,f1_test_scores,c='b')

ax.set_xlabel('min_samples')
ax.set_ylabel('f1-score')
ax.set_title('min_samples_split')
plt.show();
```

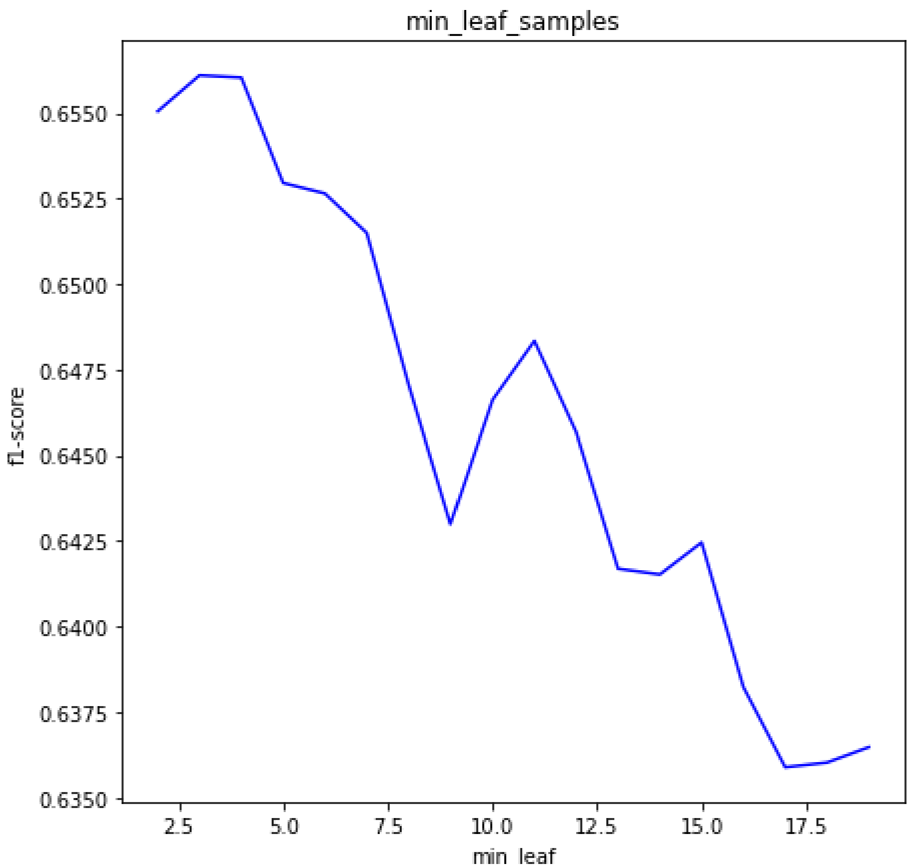


We can see that the accuracy peaks at a sample value of 30

min_samples_leaf

In [60]:
```
#use the optimum value of depth,min_samples_split
depth = 20
min_samples = 30

#define a range of min_samples_for each split
min_leaf_range = np.arange(2,20)

#create a loop with the optimum depth and different min_samples
#creating an empty list to store scores for each depth
f1_test_scores = []

# create a loop for the classifier to run with the different depth values
for sample in min_leaf_range:

    #instantiate
    classifier = DecisionTreeClassifier(criterion='entropy',max_depth=depth,min_samples_
                                        min_samples_leaf=sample, random_state=123)

    #fit the model
    classifier.fit(X_train,y_train)

    #predict values
    y_hat_test = classifier.predict(X_test)

    #calculate
    f1 = f1_score(y_test,y_hat_test,average='macro')
```

```
    #add the scores to the list
    f1_test_scores.append(f1)


#visual
fig,ax = plt.subplots(figsize=(7,7))
ax.plot(min_leaf_range,f1_test_scores,c='b')

ax.set_xlabel('min_leaf')
ax.set_ylabel('f1-score')
ax.set_title('min_leaf_samples')

plt.show();
```



We can see that the peak value is 3

model with optimized parameters

In [62]:
```
#run the model with the optimized parameters
depth=20
min_samples=30
leaf=3

#instantiate
classifier = DecisionTreeClassifier(criterion='entropy',max_depth=depth,min_samples_spl
                                    min_samples_leaf=leaf,random_state=123)

#fit the model
classifier.fit(X_train,y_train)

#predict values
```

```python
y_hat_train = classifier.predict(X_train)
y_hat_test = classifier.predict(X_test)

#scores
print('TRAIN SCORES')
print('----------------------------------------------------------')
print(classification_report(y_train,y_hat_train,target_names=names))
print('TEST SCORES')
print('-----------------------------------------------------------')
print(classification_report(y_test,y_hat_test,target_names=names))

accuracy_optimized_train = accuracy_score(y_train,y_hat_train)
accuracy_optimized_test = accuracy_score(y_test,y_hat_test)

f1_score_optimized_train = f1_score(y_train,y_hat_train,average='macro')
f1_score_optimized_test = f1_score(y_test,y_hat_test,average='macro')
```

```
TRAIN SCORES
----------------------------------------------------------
                         precision    recall  f1-score   support

             functional       0.84      0.92      0.88     24241
         non functional       0.69      0.43      0.53      3217
functional needs repair       0.87      0.82      0.85     16986

               accuracy                           0.84     44444
              macro avg       0.80      0.72      0.75     44444
           weighted avg       0.84      0.84      0.84     44444

TEST SCORES
-----------------------------------------------------------
                         precision    recall  f1-score   support

             functional       0.78      0.85      0.81      7945
         non functional       0.49      0.32      0.39      1091
functional needs repair       0.79      0.74      0.76      5779

               accuracy                           0.77     14815
              macro avg       0.69      0.64      0.66     14815
           weighted avg       0.76      0.77      0.76     14815
```

feature_importance

In [63]:

```python
#creating a df with just feature_importance data
df_importance = pd.DataFrame({'features':X_train.columns,
                             'importance':classifier.feature_importances_})


df_importance.head()
```

Out[63]:

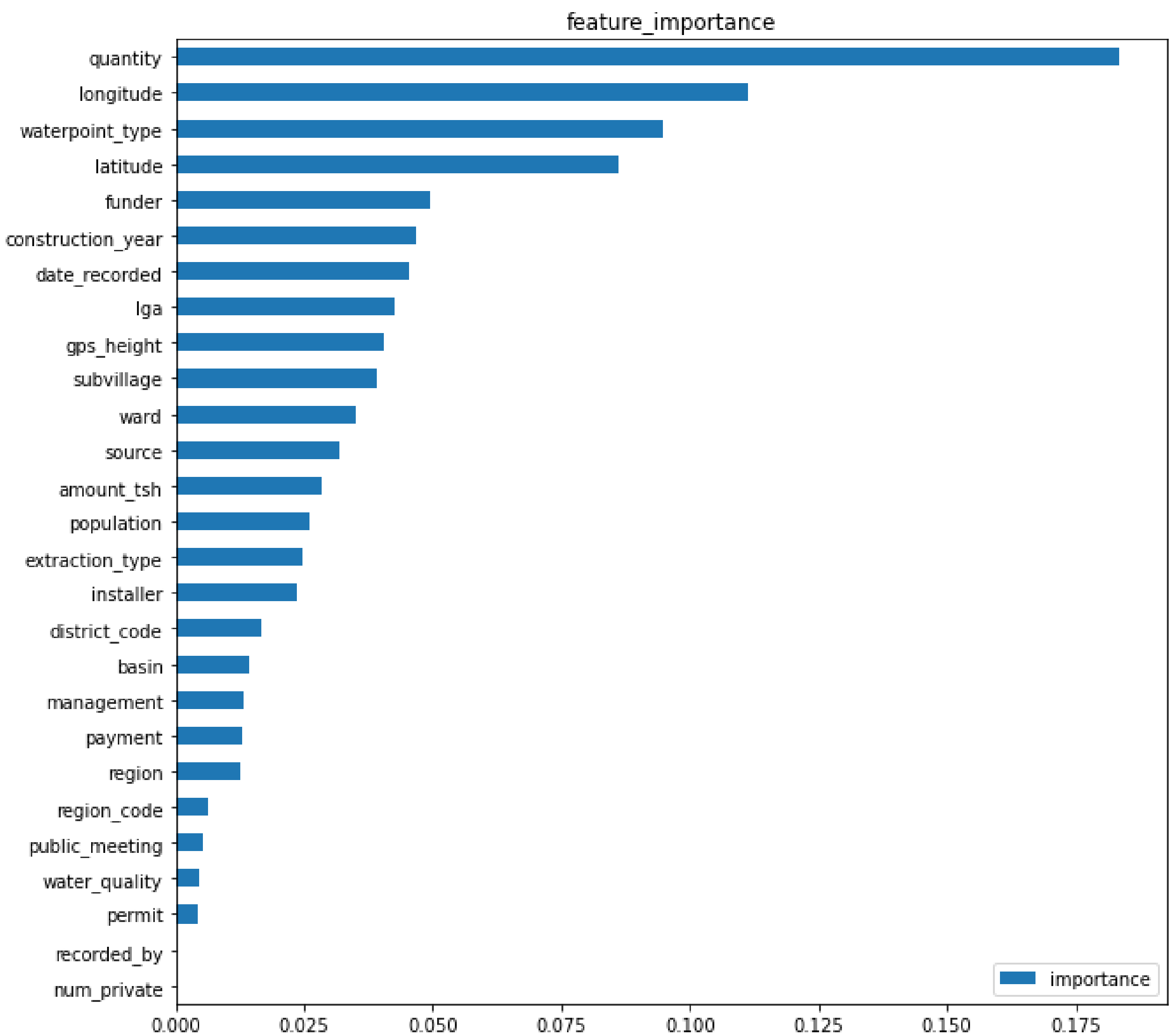
	features	importance
0	amount_tsh	0.028549
1	gps_height	0.040685
2	longitude	0.111176
3	latitude	0.086177
4	num_private	0.000000

In [64]:
```python
#sorting the importance in ascending order
df_importance_sorted = df_importance.sort_values(by=['importance'],ascending=True)
df_importance_sorted.head()
```

Out[64]:

	features	importance
4	num_private	0.000000
18	recorded_by	0.000000
19	permit	0.004375
23	water_quality	0.004708
17	public_meeting	0.005289

In [65]:
```python
#plot the data
fig,ax=plt.subplots(figsize=(10,10))
df_importance_sorted.plot(kind='barh',ax=ax);
ax.set_yticklabels(df_importance_sorted['features'])
ax.set_title('feature_importance');
ax.legend(loc=4);
```



Let's build a model based on the top_10 features to see if we can get better

```
results
```

extracting top_10 features

In [66]:
```python
#create a new df with the top_10 features alone

#get top10 features as a df
cols = df_importance_sorted['features'].tail(10)
cols=pd.DataFrame(data=cols)
cols
```

Out[66]:

	features
13	subvillage
1	gps_height
15	lga
9	date_recorded
8	construction_year
10	funder
3	latitude
26	waterpoint_type
2	longitude
24	quantity

In [67]:
```python
#df with top10 features
df_top10 =df2[list(cols['features'])]

#combine with the target variable
df_top10 = pd.concat([df_top10,df1['status_group']],axis=1)

print(df_top10.shape)
df_top10.head()
```

```
(59259, 11)
```

Out[67]:

	subvillage	gps_height	lga	date_recorded	construction_year	funder	latitude	waterpoint_type
0	11808	1390	51	171	1999	1370	-9.856322	1
1	15839	1399	103	216	2010	469	-2.147466	1
2	9075	686	108	144	2009	825	-3.821329	2
3	8983	263	87	21	1986	1742	-11.155298	2
4	7698	0	26	268	0	20	-1.825359	1

Decision Tree with the top10 features

GridSearch CV

Rather than use the earlier approach, where we built a baseline model and then tuned each hyper parameter seperately, we can combine all these steps into one using GridSearchCV

In [68]:
```
#define X & y
X = df_top10.drop('status_group',axis=1)
y=df_top10[['status_group']]

#split the data
X_top10_train,X_top10_test,y_top10_train,y_top10_test = train_test_split(X,y,random_sta

#instantiate
clf_top10 = DecisionTreeClassifier(random_state=123)

#define the parameter grid
param_grid = {'max_depth': np.arange(20,25),
              'min_samples_split': np.arange(28,33),
              'min_samples_leaf': np.arange(3,7)
             }

#instantiate
gs_tree = GridSearchCV(estimator=clf_top10,param_grid=param_grid,cv=5)

#fit
gs_tree.fit(X_top10_train,y_top10_train)

#predict
gs_tree_train = gs_tree.predict(X_top10_train)
gs_tree_test = gs_tree.predict(X_top10_test)

print('TRAIN SCORES')
print('--------------------------------------------------')
print(classification_report(y_top10_train,gs_tree_train))
print('TEST SCORES')
print('--------------------------------------------------')
print(classification_report(y_top10_test,gs_tree_test))

accuracy_grid_train = accuracy_score(y_top10_train,gs_tree_train)
accuracy_grid_test = accuracy_score(y_top10_test,gs_tree_test)

f1_score_gs_tree_train = f1_score(y_top10_train,gs_tree_train,average='macro')
f1_score_gs_tree_test = f1_score(y_top10_test,gs_tree_test,average='macro')
```

```
TRAIN SCORES
--------------------------------------------------
                         precision    recall  f1-score   support

             functional       0.82      0.91      0.86     24241
functional needs repair       0.65      0.37      0.47      3217
         non functional       0.85      0.78      0.82     16986

               accuracy                           0.82     44444
              macro avg       0.78      0.69      0.72     44444
           weighted avg       0.82      0.82      0.82     44444

TEST SCORES
--------------------------------------------------
                         precision    recall  f1-score   support
```

```
                      functional       0.77      0.86      0.81      7945
functional needs repair       0.51      0.30      0.38      1091
              non functional       0.79      0.72      0.75      5779

                    accuracy                           0.76     14815
                   macro avg       0.69      0.62      0.65     14815
                weighted avg       0.75      0.76      0.75     14815
```

In [69]:

```
#getting the best parameters
gs_tree.best_params_
```

Out[69]:

```
{'max_depth': 20, 'min_samples_leaf': 4, 'min_samples_split': 32}
```

Random Forest with top10 features

Let's use a poupular ensemble method called Random Forest on the top_10 features to and compare it to the GridSearchCV model to see if we can make imporvements. Random Forest combines Bootstrapping and Sub-Space Sampling methods to build models that are robust and immune to noise in the data.

In [70]:

```
#instantiante the classifier with the same parameters from earlier
forest=RandomForestClassifier(n_estimators=100,max_depth=depth,min_samples_split=min_sa
                              min_samples_leaf=leaf)

#fit the data
forest.fit(X_top10_train,y_top10_train)

#predict
forest_y_train = forest.predict(X_top10_train)
forest_y_test = forest.predict(X_top10_test)

#evaluate

# print('TRAIN SCORES')
# print('---------------------------------------------------')
# print(classification_report(y_top10_train,forest_y_train))
print('TEST SCORES')
print('---------------------------------------------------')
print(classification_report(y_top10_test,forest_y_test))

accuracy_forest_train = accuracy_score(y_top10_train,forest_y_train)
accuracy_forest_test = accuracy_score(y_top10_test,forest_y_test)

f1_score_rf_train = f1_score(y_top10_train,forest_y_train,average='macro')
f1_score_rf_test = f1_score(y_top10_test,forest_y_test,average='macro')
```

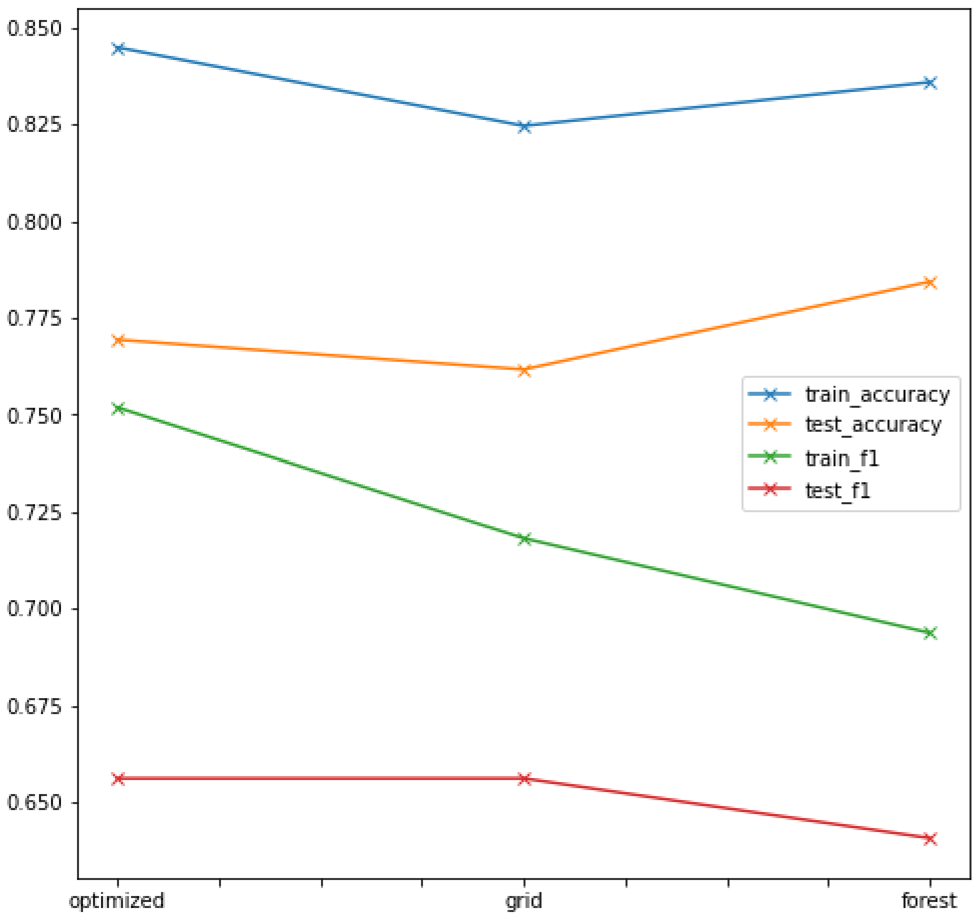
```
TEST SCORES
---------------------------------------------------
                          precision    recall  f1-score   support

                      functional       0.76      0.91      0.83      7945
functional needs repair       0.70      0.21      0.32      1091
              non functional       0.83      0.72      0.77      5779

                    accuracy                           0.78     14815
                   macro avg       0.77      0.61      0.64     14815
```

```
weighted avg       0.79      0.78      0.77     14815
```

Visualize scores

In [71]:

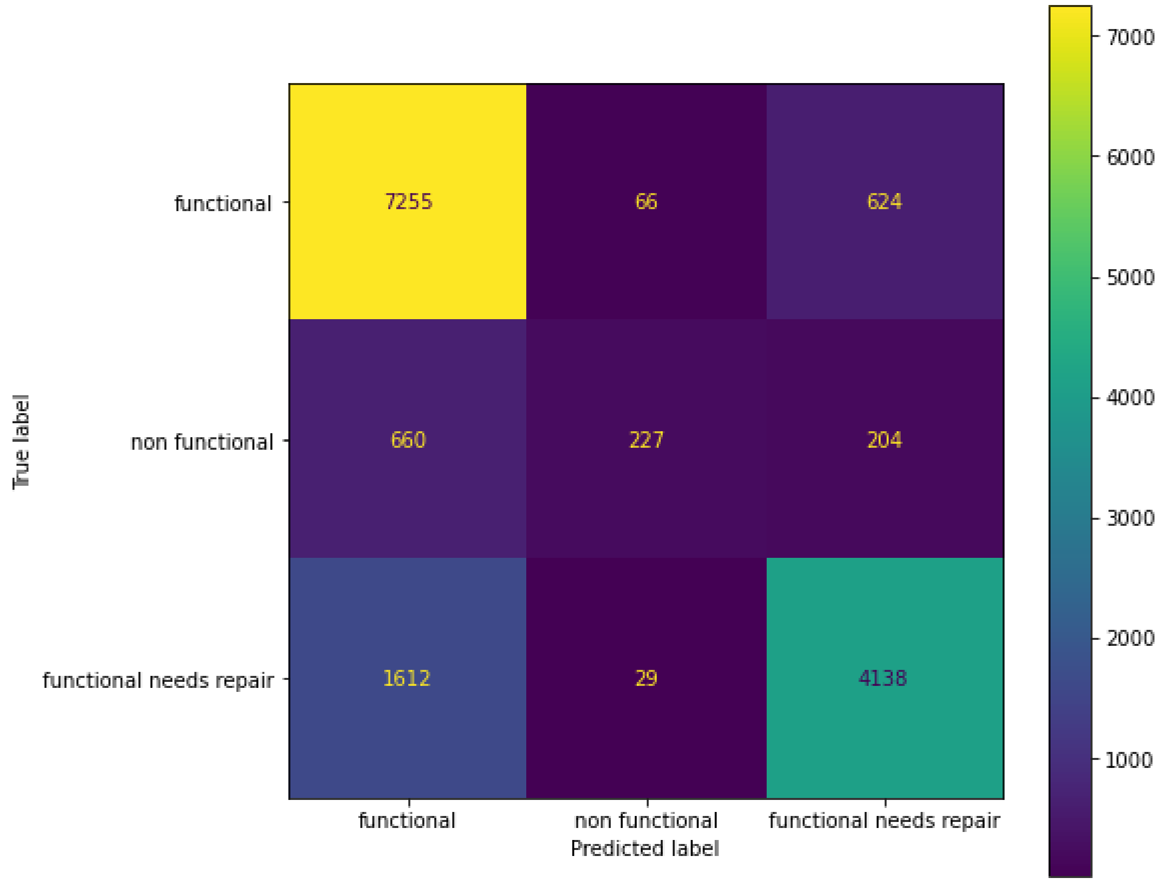
```
# create a dataframe of the scores for the different models
score_df = pd.DataFrame({'train_accuracy': [accuracy_optimized_train,accuracy_grid_trai
                        'test_accuracy': [accuracy_optimized_test,accuracy_grid_test,ac
                        'train_f1': [f1_score_optimized_train,f1_score_gs_tree_train,f1
                         'test_f1': [f1_score_optimized_test,f1_score_optimized_test,f1
                        }, index=['optimized','grid','forest'])


#plot the data
fig,ax=plt.subplots(figsize=(8,8))
score_df.plot(kind='line',ax=ax,marker='x');
```



Confusion Matrix

In [72]:

```
#Plot the confusion matrix of the random forest model
fig,ax=plt.subplots(figsize=(8,8))
plot_confusion_matrix(forest,X_top10_test,y_top10_test,ax=ax,display_labels=names);
```



We can clearly see that the 'non-functional' class is a problem for the model

Earlier, we built the model with only the top10 features based on feature importance. Let's now try and build a model with all the features and see if more data helps improve performance.

Random Forest with all the features

In [73]:

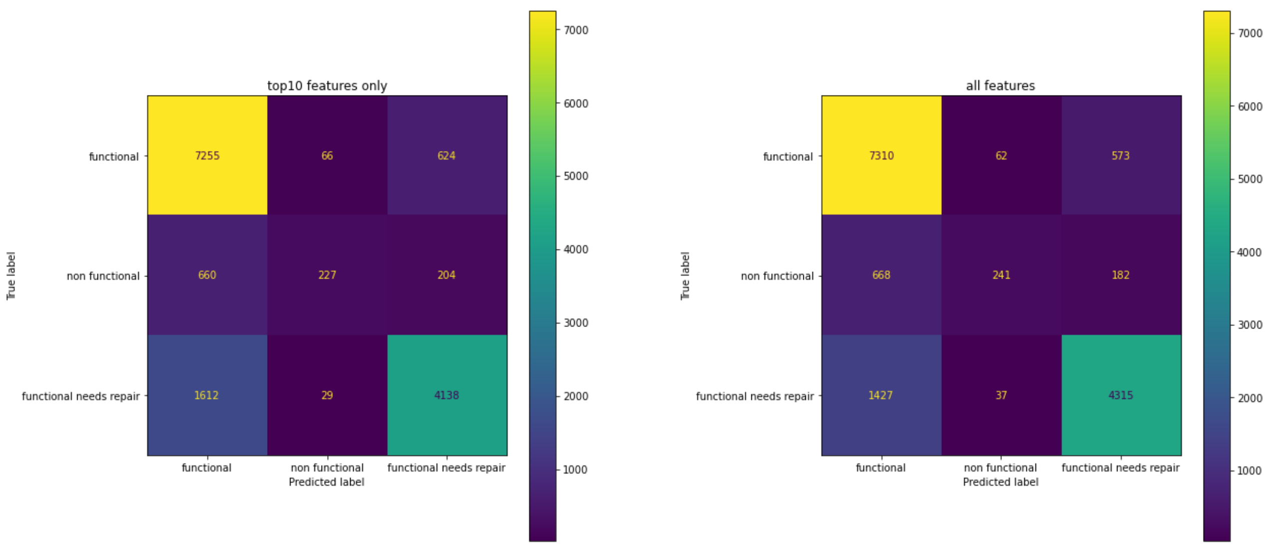
```
#define X,y
X=df2.drop('status_group',axis=1)
y=df2[['status_group']]

#using the cleaned dataset with all features
X_train,X_test,y_train,y_test = train_test_split(X,y,random_state=123)

#instantiate the classifier
new_forest =RandomForestClassifier(n_estimators=100,max_depth=depth,min_samples_split=m
                                   min_samples_leaf=leaf)

#fit the data
new_forest.fit(X_train,y_train)

#predict
y_hat_train = new_forest.predict(X_train)
y_hat_test = new_forest.predict(X_test)

#scores
# print('TRAIN SCORES')
# print('---------------------------------------------------------')
```

```
# print(classification_report(y_train,y_hat_train,target_names=names))
print('TEST SCORES')
print('----------------------------------------------------------')
print(classification_report(y_test,y_hat_test,target_names=names))
```

```
TEST SCORES
----------------------------------------------------------
                        precision    recall  f1-score   support

            functional       0.78      0.92      0.84      7945
        non functional       0.71      0.22      0.34      1091
functional needs repair       0.85      0.75      0.80      5779

              accuracy                           0.80     14815
             macro avg       0.78      0.63      0.66     14815
          weighted avg       0.80      0.80      0.79     14815
```

Confusion matrix

In [74]:
```
fig,(ax1,ax2)=plt.subplots(figsize=(20,10),nrows=1,ncols=2)
plot_confusion_matrix(forest,X_top10_test,y_top10_test,ax=ax1,display_labels=names)
plot_confusion_matrix(new_forest,X_test,y_test,ax=ax2,display_labels=names);
fig.tight_layout(pad=10.0)
ax1.set_title('top10 features only');
ax2.set_title('all features');
```



We can see that it makes a slight difference to the model.

Examining the target feature

In [75]:
```
#examining the target variable
df1['status_group'].value_counts()
```

Out[75]:
```
functional                 32186
non functional             22765
functional needs repair     4308
Name: status_group, dtype: int64
```

Clearly, we can see an imbalance between the classes. We can try to train a model with equal representation from each class and check the results.

Training a model with a balanced data set

In [76]:
```
#seperate each class into a seperate class with the same number of rows as the repair c
functional = df2[df2['status_group'] == 0]
functional = functional.iloc[0:4308,:]

non_functional = df2[df2['status_group'] == 2]
non_functional = non_functional.iloc[0:4308,:]

repair = df2[df2['status_group'] == 1]
repair['status_group'].value_counts()

#concatenate all three df's
new_df = pd.concat([functional,non_functional,repair])

#check the value counts
new_df['status_group'].value_counts()
```

Out[76]:
```
2    4308
1    4308
0    4308
Name: status_group, dtype: int64
```

In [77]:
```
#building the baseline model

#define X,y
X=new_df.drop('status_group',axis=1)
y=new_df[['status_group']]

#using the cleaned dataset with all features
X_train_new,X_test_new,y_train_new,y_test_new = train_test_split(X,y,random_state=123)

#instantiate the classifier
newdf_forest =RandomForestClassifier()

#fit the data on the new_df
forest1=newdf_forest.fit(X_train_new,y_train_new)

#predict score on the new_df
y_hat_train_new = new_forest.predict(X_train_new)
y_hat_test_new = new_forest.predict(X_test_new)

#scores
# print('TRAIN SCORES')
# print('---------------------------------------------------------')
# print(classification_report(y_train_new,y_hat_train_new,target_names=names))
print('TEST SCORES')
print('---------------------------------------------------------')
print(classification_report(y_test_new,y_hat_test_new,target_names=names))
```

```
TEST SCORES
----------------------------------------------------------
                         precision    recall  f1-score   support

             functional       0.54      0.95      0.69      1074
         non functional       0.96      0.25      0.39      1067
functional needs repair       0.80      0.80      0.80      1090

               accuracy                           0.67      3231
              macro avg       0.77      0.66      0.63      3231
```

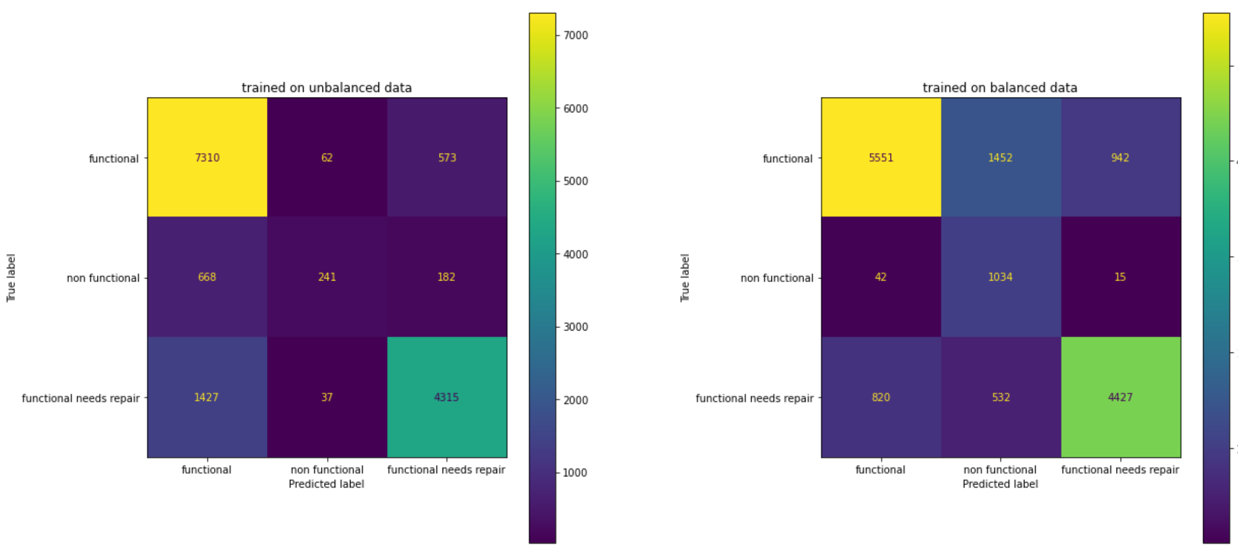
```
weighted avg       0.77      0.67      0.63      3231
```

In [78]:
```
# with the model trained on the balanced dataset, let's check for predictions on the un
y_preds_train = forest1.predict(X_train) # original df
y_preds_test = forest1.predict(X_test) #original df

print('TEST SCORES')
print('---------------------------------------------------------')
print(classification_report(y_test,y_preds_test,target_names=names))
```

```
TEST SCORES
----------------------------------------------------------
                         precision    recall  f1-score   support

             functional       0.87      0.70      0.77      7945
         non functional       0.34      0.95      0.50      1091
functional needs repair       0.82      0.77      0.79      5779

               accuracy                           0.74     14815
              macro avg       0.68      0.80      0.69     14815
           weighted avg       0.81      0.74      0.76     14815
```

Confusion Matrix

In [79]:
```
fig,(ax1,ax2)=plt.subplots(figsize=(20,10),nrows=1,ncols=2)
plot_confusion_matrix(new_forest,X_test,y_test,ax=ax1,display_labels=names)
plot_confusion_matrix(forest1,X_test,y_test,ax=ax2,display_labels=names);
fig.tight_layout(pad=10.0)
ax1.set_title('trained on unbalanced data');
ax2.set_title('trained on balanced data');
```

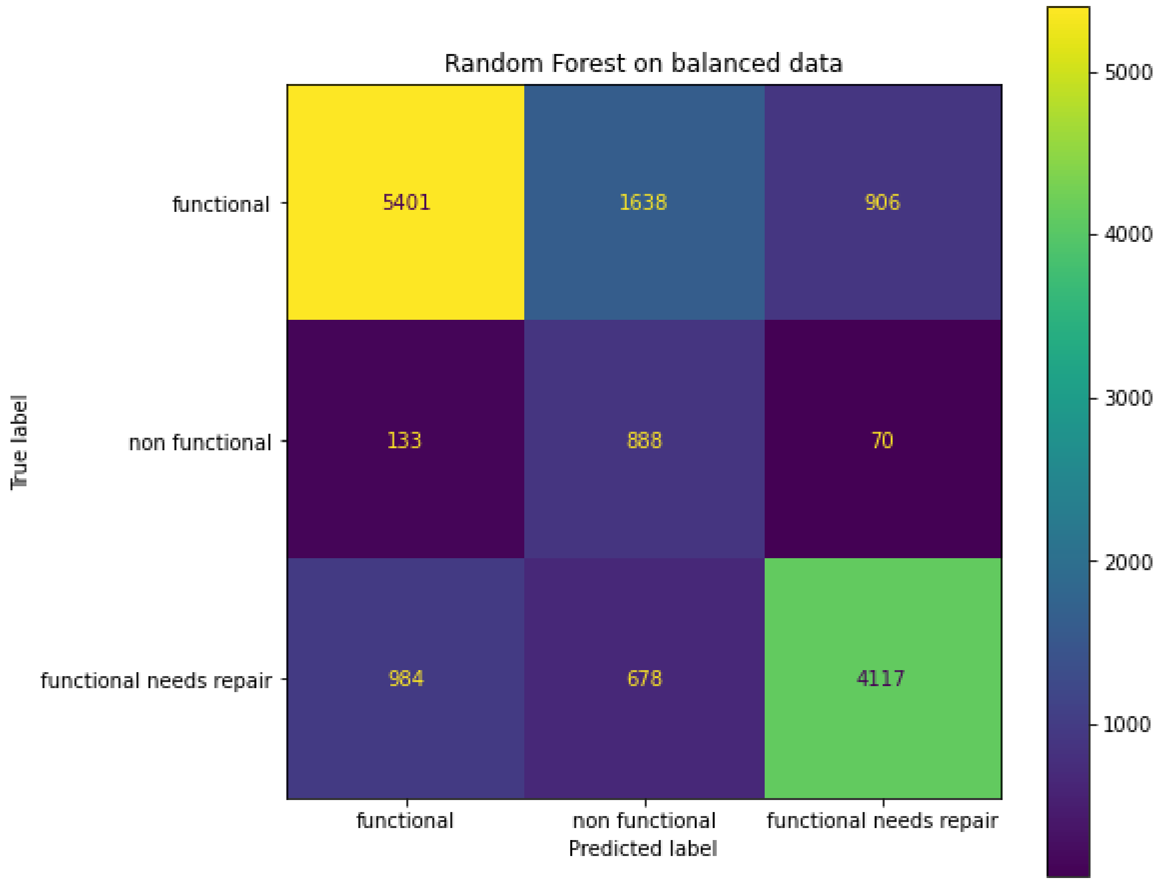


Random forest model on the balanced dataset

In [80]:
```
#instantaiate with optimized parameters from before
forest2 = RandomForestClassifier(max_depth=depth,min_samples_split=min_samples,
                                 min_samples_leaf=leaf,random_state=42)

#fit the data on the balanced dataset
forest2.fit(X_train_new,y_train_new)
```

```
# predict data on the original df
y_hat_test_preds =  forest2.predict(X_test) # original df
```

In [81]:
```
fig,ax=plt.subplots(figsize=(8,8))
plot_confusion_matrix(forest2,X_test,y_test,display_labels=names,ax=ax);
ax.set_title('Random Forest on balanced data');
```



In [82]:
```
print('TEST SCORES')
print('------------------------------------------------------------')
print(classification_report(y_test,y_hat_test_preds,target_names=names))
```

```
TEST SCORES
----------------------------------------------------------
                        precision    recall  f1-score   support

            functional       0.83      0.68      0.75      7945
        non functional       0.28      0.81      0.41      1091
functional needs repair       0.81      0.71      0.76      5779

              accuracy                           0.70     14815
             macro avg       0.64      0.74      0.64     14815
          weighted avg       0.78      0.70      0.73     14815
```

Next Steps

1. Possibly re-frame this as a binary classification problem i.e functional vs non-functional and see if we can build a better model.

2. Re-create the model with equal number of data points between functional and non-functional. Optimize parameters on this balanced dataset and test it on validation data to check for performance.