Set Up

Importing needed packages and loading the original data file

In [1]:
```
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import plot_confusion_matrix
from sklearn.neighbors import KNeighborsClassifier
from sklearn import tree
from sklearn.metrics import precision_score, recall_score, accuracy_score
from imblearn.over_sampling import SMOTE
from imblearn.combine import SMOTETomek
import graphviz
from sklearn.model_selection import KFold, cross_val_score, RandomizedSearchC
V, GridSearchCV, train_test_split
from scipy import stats
```

In [2]:
```
df = pd.read_sas('C:\\Users\\Ben\\OneDrive\\Documents\\Study\\CIND820\\Data\\L
LCP2021.XPT')
```

```
C:\Users\Ben\anaconda3\envs\coursera\lib\site-packages\pandas\io\sas\sas_xpor
t.py:475: PerformanceWarning: DataFrame is highly fragmented.  This is usuall
y the result of calling `frame.insert` many times, which has poor performanc
e.  Consider joining all columns at once using pd.concat(axis=1) instead.  To
get a de-fragmented frame, use `newframe = frame.copy()`
  df[x] = v
```

Column Removal

Removing columns and rows from the data below. Please see literature review document for reasoning on individual columns/rows

In [3]:
```
df = df[df.DISPCODE != 1200] #drop rows where DISPCODE = 1200 (Partially Compl
ete Interview)
df.drop(['DISPCODE', '_STATE','FMONTH', 'IDATE', 'IMONTH', 'IDAY', 'IYEAR', 'S
EQNO', '_PSU', 'CTELENM1', 'PVTRESD1',
         'COLGHOUS', 'STATERE1', 'CELPHON1', 'LADULT1', 'NUMADULT', 'NUMMEN',
'NUMWOMEN', 'RESPSLCT', 'SAFETIME',
         'CTELNUM1', 'CELLFON5', 'CADULT1', 'PVTRESD3', 'CCLGHOUS', 'CSTATE1',
'LANDLINE', 'HHADULT', 'DIABAGE3',
         'ARTHEXER', 'ARTHEDU', 'ARTHDIS2', 'RENTHOM1', 'NUMHHOL3', 'NUMPHON
3', 'CPDEMO1B', 'VETERAN3', 'EMPLOY1',
         'CHILDREN', 'PREGNANT','DIFFWALK', 'DIFFDRES', 'DIFFALON', 'FLSHTMY
3', 'IMFVPLA2', 'HIVTST7', 'HIVTSTD3', 'PDIABTST',
        'BLDSUGAR', 'FEETCHK3', 'DOCTDIAB', 'CVDCRHD4', 'CVDSTRK3', 'ASTHMA3',
'ASTHNOW', 'CHCSCNCR', 'CHCOCNCR', 'CHCCOPD3',
        'ADDEPEV3', 'CHCKDNY2', 'DIABETE4', 'HAVARTH5', 'LMTJOIN3', 'JOINPAI
2', 'DEAF', 'BLIND', 'DECIDE', 'PREDIAB1', 'INSULIN1',
        'FEETCHK', 'EYEEXAM1', 'DIABEYE', 'DIABEDU', 'TOLDCFS', 'HAVECFS', 'WO
RKCFS', 'TOLDHEPC', 'TRETHEPC', 'PRIRHEPC',
        'HAVEHEPC', 'HAVEHEPB', 'MEDSHEPB', 'HPVADVC4', 'HPVADSHT', 'TETANUS
1', 'SHINGLE2', 'LCSCTSCN', 'HADMAM', 'HOWLONG',
        'CERVSCRN', 'CRVCLCNC', 'CRVCLPAP', 'CRVCLHPV', 'HADHYST2', 'PSATEST
1', 'PSATIME1', 'PCPSARS2', 'PCSTALK', 'HADSIGM4',
        'COLNSIGM', 'COLNTES1', 'SIGMTES1', 'LASTSIG4', 'COLNCNCR', 'VIRCOLO
1', 'VCLNTES1', 'SMALSTOL', 'STOLTEST', 'STOOLDN1',
        'BLDSTFIT', 'SDNATES1', 'CNCRDIFF', 'CNCRAGE', 'CNCRTYP1', 'CSRVTRT3',
'CSRVDOC1', 'CSRVSUM', 'CSRVRTRN', 'CSRVINST',
        'CSRVINSR', 'CSRVDEIN', 'CSRVCLIN', 'CSRVPAIN', 'CSRVCTL2', 'HOMRGCH
K', 'HOMBPCHK', 'WHEREBP', 'SHAREBP', 'WTCHSALT',
        'DRADVISE', 'CIMEMLOS', 'CDHOUSE', 'CDASSIST', 'CDHELP', 'CDSOCIAL',
'CDDISCUS', 'CAREGIV1', 'CRGVREL4', 'CRGVLNG1'
        , 'CRGVHRS1', 'CRGVPRB3', 'CRGVALZD', 'CRGVPER1', 'CRGVHOU1', 'CRGVEXP
T', 'ACEDEPRS', 'ACEDRINK', 'ACEDRUGS', 'ACEPRISN',
        'ACEDIVRC', 'ACEPUNCH', 'ACEHURT1', 'ACESWEAR', 'ACETOUCH', 'ACETTHE
M', 'ACEHVSEX', 'ACEADSAF', 'ACEADNED',
        'GUNLOAD', 'LOADULK2', 'RCSRLTN2', 'RCSGENDR', 'CASTHDX2', 'CASTHNO2',
'BIRTHSEX', 'SOMALE', 'SOFEMALE', 'TRNSGNDR',
        'QSTVER', 'QSTLANG', '_METSTAT', '_URBSTAT', 'MSCODE', '_STSTR', '_STR
WT', '_RAWRAKE', '_WT2RAKE', '_CHISPNC', '_CRACE1',
        '_CPRACE1', 'CAGEG', '_CLLCPWT', '_DUALUSE', '_DUALCOR', '_LLCPWT2',
'_LLCPWT', '_RFHLTH', '_PHYS14D', '_MENT14D',
        '_HLTHPLN', '_HCVU652', '_TOTINDA', '_RFHYPE6', '_CHOLCH3', '_RFCHOL
3', '_MICHD', '_LTASTH1', '_CASTHM1', '_ASTHMS1',
        '_DRDXAR3', '_DRDXAR3', '_LMTWRK3', '_PRACE1', '_MRACE1', '_HISPANC',
'_RACE', '_RACEG21', '_RACEGR3', '_RACEPRV', '_SEX',
        '_AGEG5YR', '_AGE65YR', '_AGE80', '_AGE_G', 'HEIGHT3', 'HTM4', 'WEIGHT
2', '_BMI5', '_RFBMI5', '_CHLDCNT', '_EDUCAG',
        'INCOME3', '_RFSMOK3', '_CURECI1', 'DRNKANY5', 'DROCDY3_', '_RFBING5',
'_DRNKWK1', '_RFDRHV7', '_FLSHOT7', '_PNEUMO3',
        '_AIDTST4', '_MISFRT1', '_FRTRES1', '_VEGRES1',
        '_FRUTSU1', '_VEGESU1', '_FRTLT1A', '_VEGLT1A', '_FRT16A', '_VEGETE1',
'_FRUITE1', '_VEG23A', 'FIREARM5', 'COLGSEX',
        'LANDSEX', 'CELLSEX', 'PERSDOC3', 'PNEUVAC4', 'FLUSHOT7', 'CHKHEMO3',
'_LMTACT3', 'HTIN4', 'SMOKE100','SMOKDAY2', '_MISVEG1'
        ,'FRUIT2', 'FRUITJU2', 'FVGREEN1', 'FRENCHF1', 'POTATOE1', 'VEGETAB2',
'FTJUDA2_', 'FRUTDA2_', 'GRENDA1_', 'FRNCHDA_', 'POTADA1_', 'VEGEDA2_', '_SMOK
```

```
ER3', 'PRIMINSR'
        , 'MARITAL', 'DRNK3GE5', 'LASTSMK2', 'STOPSMK2', 'USEMRJN3', 'WTKG3'],
axis=1, inplace=True)

df.set_axis(range(len(df)), inplace=True)
```

Imputing Values

In each of the variables there are common scenarioes where values are either blank or have an assigned value such as 777, 888, 999, 77,88,99 etc. that indicate the respondent is unsure, refused to answer or was not asked the question. Below is the process of imputing values (either mode, median or mean) depending on the variables distribution and type. There are certain scenarios where I have chosen not to impute a value until a later stage into null values as this question may have been non applicable to the particular respondent and further logic is required.

In [4]:
```
#pd.crosstab(index=df['LCSLAST'], columns='count')
#sns.displot(df, x="LCSLAST")
df['LCSLASTMEDIAN'] = df['LCSLAST'].replace({777:np.nan, 999:np.nan})
LCSLASTMEDIAN=int(df['LCSLASTMEDIAN'].median())
df['LCSLAST']=df['LCSLAST'].replace({777:LCSLASTMEDIAN, 999:LCSLASTMEDIAN})
df.drop(['LCSLASTMEDIAN'], axis=1, inplace=True)

#Due to distribution being relatively uniform I have chosen to use the median
value to impute for 777 and 999. I have
#complete this in above manner as I do not want them to be mixed with the true
null answers which are valid null answers and
#should not be imputed for
```

In [5]:
```
i=1
for i in range(len(df.ALCDAY5)):
    if df['ALCDAY5'][i] > 100 and df['ALCDAY5'][i] < 108:
        df['ALCDAY5'][i]=round(((df['ALCDAY5'][i] - 100)*4.34524))
    elif df['ALCDAY5'][i] > 200 and df['ALCDAY5'][i] < 231:
        df['ALCDAY5'][i]=df['ALCDAY5'][i] - 200
    elif df['ALCDAY5'][i] == 777:
        df['ALCDAY5'][i]=df['ALCDAY5'][i] = 0
    elif df['ALCDAY5'][i] == 888:
        df['ALCDAY5'][i]=df['ALCDAY5'][i] = 0
    elif df['ALCDAY5'][i] == 999:
        df['ALCDAY5'][i]=df['ALCDAY5'][i] = 0
    else:
        df['ALCDAY5'][i] = df['ALCDAY5'][i]
#This variable required transformation in order to convert to a consistent num
ber for analysis (e.g. respondents could answer
#in number of days they drank per week or per month). Where value represents r
efused to answer etc. imputing mode (0) as not
#a normal distribution
```

In [6]:
```
df['AVEDRNK3']=df['AVEDRNK3'].replace({88:0, 77:np.nan, 99:np.nan})
#pd.crosstab(index=df['AVEDRNK3'], columns='count') - This was used to establi
sh mode was best value - not normal dist.
AVEDRNK3MODE=int(df['AVEDRNK3'].mode())
df['AVEDRNK3']=df['AVEDRNK3'].replace({np.nan:AVEDRNK3MODE})
```

In [7]:
```
#sns.displot(df, x="WTKG3")
#sns.displot(df, x="_BMI5")

#Reviewing for normal distribution as continuous variable, approximately norma
l distribution confirmed for both.
#Will use the mean value for imputation below if required
```

In [8]:
```
df['GENHLTH']=df['GENHLTH'].replace({7:np.nan,9:np.nan})
GENHLTHMEAN = round(df['GENHLTH'].mean())
df['GENHLTH']=df['GENHLTH'].replace({np.nan:GENHLTHMEAN})

df['_INCOMG1']=df['_INCOMG1'].replace({9:np.nan})
_INCOMG1MEAN = round(df['_INCOMG1'].mean())
df['_INCOMG1']=df['_INCOMG1'].replace({np.nan:_INCOMG1MEAN})


#This is an ordinal categorical variabl. 7 and 9 are both values used to indic
ate a lack of answer. 7 and 9 were removed
#first to avoid skewing the average response.
```

In [9]:
```
df['PHYSHLTH']=df['PHYSHLTH'].replace({77:np.nan, 99:np.nan, 88:0})
PHYSHLTHMODE=int(df['PHYSHLTH'].mode())
df['PHYSHLTH']=df['PHYSHLTH'].replace({np.nan:PHYSHLTHMODE})

df['MENTHLTH']=df['MENTHLTH'].replace({77:np.nan, 99:np.nan, 88:0})
MENTHLTHMODE=int(df['MENTHLTH'].mode())
df['MENTHLTH']=df['MENTHLTH'].replace({np.nan:MENTHLTHMODE})

df['POORHLTH']=df['POORHLTH'].replace({77:np.nan, 99:np.nan, 88:0})
POORHLTHMODE=int(df['POORHLTH'].mode())
df['POORHLTH']=df['POORHLTH'].replace({np.nan:POORHLTHMODE})

df['MEDCOST1']=df['MEDCOST1'].replace({7:np.nan,9:np.nan})
MEDCOST1MODE=int(df['MEDCOST1'].mode())
df['MEDCOST1']=df['MEDCOST1'].replace({np.nan:MEDCOST1MODE})

df['CHECKUP1']=df['CHECKUP1'].replace({7:np.nan,9:np.nan})
CHECKUP1MODE=int(df['CHECKUP1'].mode())
df['CHECKUP1']=df['CHECKUP1'].replace({np.nan:CHECKUP1MODE})

df['EXERANY2']=df['EXERANY2'].replace({7:np.nan,9:np.nan})
EXERANY2MODE=int(df['EXERANY2'].mode())
df['EXERANY2']=df['EXERANY2'].replace({np.nan:EXERANY2MODE})

df['BPHIGH6']=df['BPHIGH6'].replace({7:np.nan,9:np.nan})
BPHIGH6MODE=int(df['BPHIGH6'].mode())
df['BPHIGH6']=df['BPHIGH6'].replace({np.nan:BPHIGH6MODE})

df['CHOLCHK3']=df['CHOLCHK3'].replace({7:np.nan,9:np.nan})
CHOLCHK3MODE=int(df['CHOLCHK3'].mode())
df['CHOLCHK3']=df['CHOLCHK3'].replace({np.nan:CHOLCHK3MODE})

df['EDUCA']=df['EDUCA'].replace({9:np.nan})
EDUCAMODE=int(df['EDUCA'].mode())
df['EDUCA']=df['EDUCA'].replace({np.nan:EDUCAMODE})

df['USENOW3']=df['USENOW3'].replace({7:np.nan,9:np.nan})
USENOW3MODE=int(df['USENOW3'].mode())
df['USENOW3']=df['USENOW3'].replace({np.nan:USENOW3MODE})

df['ECIGNOW1']=df['ECIGNOW1'].replace({7:np.nan,9:np.nan})
ECIGNOW1MODE=int(df['ECIGNOW1'].mode())
df['ECIGNOW1']=df['ECIGNOW1'].replace({np.nan:ECIGNOW1MODE})


_BMI5CATMODE=int(df['_BMI5CAT'].mode())
df['_BMI5CAT']=df['_BMI5CAT'].replace({np.nan:_BMI5CATMODE})


#Similiar to above imputation, however mode was used to calculate the above as this was the strong majority of responses in these
#cases after reviewing distribution plots (non normal dist) or in some cases due to it being a non-ordinal categorical
#variable.
```

In [10]:
```
df['BPMEDS']=df['BPMEDS'].replace({7:1,9:1})

df['TOLDHI3']=df['TOLDHI3'].replace({7:2,9:2})

df['CHOLMED3']=df['CHOLMED3'].replace({7:2,9:2})

df['MAXDRNKS']=df['MAXDRNKS'].replace({77:1,99:1})

df['LCSFIRST']=df['LCSFIRST'].replace({777:18,999:18,888:18})

df['LCSNUMCG']=df['LCSNUMCG'].replace({777:20,999:20})

df['MARIJAN1']=df['MARIJAN1'].replace({88:0,77:0,99:0})

df['RSNMRJN2']=df['RSNMRJN2'].replace({7:3,9:3})

#blanks in this situation is acceptable as question only asked based on previo
us responses. Certain values are being imputed
#because these imply an answer in a previous question that means they should b
e answered, however the respondent refused
#or wasnt sure.
```

In [11]:
```
df['CVDINFR4']=df['CVDINFR4'].replace({7:np.nan,9:np.nan})
df = df.dropna(axis=0, subset=['CVDINFR4'])
df.set_axis(range(len(df)), inplace=True)
#Removing rows where the value is 7 (Don't Know/Not Sure) or 9 (Refused) or Bl
ank (Not asked or Missing). Since this is my
#target variable I did not see a benefit in keeping a record where the outcome
was not clear and did not want to introduce
#any bias.
```

Bucketing Variables

For variables where the values were continuous numerical values, I have elected to bucket these into groups to assist with categorical machine learning in later steps. These groups were decided based on evenly dividing the variables range, or in a manner which was related to the variable itself (e.g. smoking age - 0-18 Y/O as a starting point, with larger ranges as age increases since number of people starting smoking at an older age reduces)

In [12]:
```
i=1
for i in range(len(df.PHYSHLTH)):
    if df['PHYSHLTH'][i] <= 6:
        df['PHYSHLTH'][i]= 1
    elif df['PHYSHLTH'][i] > 6 and df['PHYSHLTH'][i] <= 12:
        df['PHYSHLTH'][i]=2
    elif df['PHYSHLTH'][i] > 12 and df['PHYSHLTH'][i] <= 18:
        df['PHYSHLTH'][i]=3
    elif df['PHYSHLTH'][i] > 18 and df['PHYSHLTH'][i] <= 24:
        df['PHYSHLTH'][i]=4
    elif df['PHYSHLTH'][i] > 24 and df['PHYSHLTH'][i] <= 30:
        df['PHYSHLTH'][i]=5
```

In [13]:
```
i=1
for i in range(len(df.MENTHLTH)):
    if df['MENTHLTH'][i] <= 6:
        df['MENTHLTH'][i]= 1
    elif df['MENTHLTH'][i] > 6 and df['MENTHLTH'][i] <= 12:
        df['MENTHLTH'][i]=2
    elif df['MENTHLTH'][i] > 12 and df['MENTHLTH'][i] <= 18:
        df['MENTHLTH'][i]=3
    elif df['MENTHLTH'][i] > 18 and df['MENTHLTH'][i] <= 24:
        df['MENTHLTH'][i]=4
    elif df['MENTHLTH'][i] > 24 and df['MENTHLTH'][i] <= 30:
        df['MENTHLTH'][i]=5
```

In [14]:
```
i=1
for i in range(len(df.POORHLTH)):
    if df['POORHLTH'][i] <= 6:
        df['POORHLTH'][i]= 1
    elif df['POORHLTH'][i] > 6 and df['POORHLTH'][i] <= 12:
        df['POORHLTH'][i]=2
    elif df['POORHLTH'][i] > 12 and df['POORHLTH'][i] <= 18:
        df['POORHLTH'][i]=3
    elif df['POORHLTH'][i] > 18 and df['POORHLTH'][i] <= 24:
        df['POORHLTH'][i]=4
    elif df['POORHLTH'][i] > 24 and df['POORHLTH'][i] <= 30:
        df['POORHLTH'][i]=5
```

In [15]:
```
i=1
for i in range(len(df.ALCDAY5)):
    if df['ALCDAY5'][i] == 0:
        df['ALCDAY5'][i]= 0
    elif df['ALCDAY5'][i] > 0 and df['ALCDAY5'][i] <= 6:
        df['ALCDAY5'][i]=1
    elif df['ALCDAY5'][i] > 6 and df['ALCDAY5'][i] <= 12:
        df['ALCDAY5'][i]=2
    elif df['ALCDAY5'][i] > 12 and df['ALCDAY5'][i] <= 18:
        df['ALCDAY5'][i]=3
    elif df['ALCDAY5'][i] > 18 and df['ALCDAY5'][i] <= 24:
        df['ALCDAY5'][i]=4
    elif df['ALCDAY5'][i] > 24 and df['ALCDAY5'][i] <= 30:
        df['ALCDAY5'][i]=5
```

In [16]:
```
i=1
for i in range(len(df.MAXDRNKS)):
    if df['MAXDRNKS'][i] == 0:
        df['MAXDRNKS'][i]= 0
    elif df['MAXDRNKS'][i] > 0 and df['MAXDRNKS'][i] <= 6:
        df['MAXDRNKS'][i]=1
    elif df['MAXDRNKS'][i] > 6 and df['MAXDRNKS'][i] <= 12:
        df['MAXDRNKS'][i]=2
    elif df['MAXDRNKS'][i] > 12 and df['MAXDRNKS'][i] <= 18:
        df['MAXDRNKS'][i]=3
    elif df['MAXDRNKS'][i] > 18 and df['MAXDRNKS'][i] <= 24:
        df['MAXDRNKS'][i]=4
    elif df['MAXDRNKS'][i] > 24:
        df['MAXDRNKS'][i]=5
```

In [17]:
```
i=1
for i in range(len(df.LCSFIRST)):
    if df['LCSFIRST'][i] <= 18:
        df['LCSFIRST'][i]= 1
    elif df['LCSFIRST'][i] > 18 and df['LCSFIRST'][i] <= 25:
        df['LCSFIRST'][i]=2
    elif df['LCSFIRST'][i] > 25 and df['LCSFIRST'][i] <= 35:
        df['LCSFIRST'][i]=3
    elif df['LCSFIRST'][i] > 35 and df['LCSFIRST'][i] <= 45:
        df['LCSFIRST'][i]=4
    elif df['LCSFIRST'][i] > 45:
        df['LCSFIRST'][i]=5
```

In [18]:
```
i=1
for i in range(len(df.LCSLAST)):
    if df['LCSLAST'][i] <= 18:
        df['LCSLAST'][i]= 1
    elif df['LCSLAST'][i] > 18 and df['LCSLAST'][i] <= 25:
        df['LCSLAST'][i]=2
    elif df['LCSLAST'][i] > 25 and df['LCSLAST'][i] <= 35:
        df['LCSLAST'][i]=3
    elif df['LCSLAST'][i] > 35 and df['LCSLAST'][i] <= 45:
        df['LCSLAST'][i]=4
    elif df['LCSLAST'][i] > 45:
        df['LCSLAST'][i]=5
```

In [19]:
```
i=1
for i in range(len(df.LCSNUMCG)):
    if df['LCSNUMCG'][i] <= 10:
        df['LCSNUMCG'][i]= 1
    elif df['LCSNUMCG'][i] > 10 and df['LCSNUMCG'][i] <= 20:
        df['LCSNUMCG'][i]=2
    elif df['LCSNUMCG'][i] > 20 and df['LCSNUMCG'][i] <= 40:
        df['LCSNUMCG'][i]=3
    elif df['LCSNUMCG'][i] > 40 and df['LCSNUMCG'][i] <= 50:
        df['LCSNUMCG'][i]=4
    elif df['LCSNUMCG'][i] > 50:
        df['LCSNUMCG'][i]=5
```

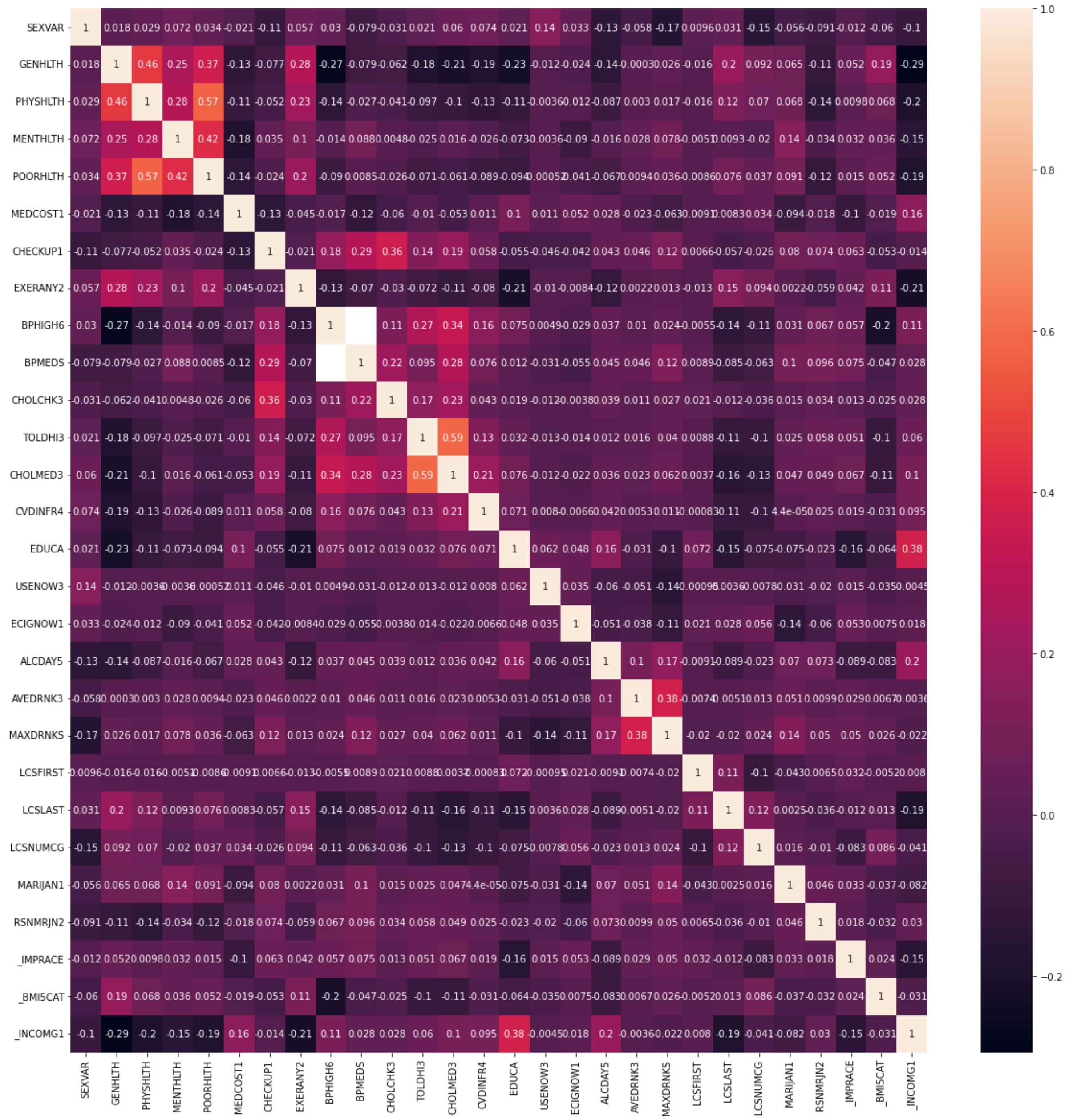
In [20]:
```
i=1
for i in range(len(df.MARIJAN1)):
    if df['MARIJAN1'][i] <= 6:
        df['MARIJAN1'][i]= 1
    elif df['MARIJAN1'][i] > 6 and df['MARIJAN1'][i] <= 12:
        df['MARIJAN1'][i]=2
    elif df['MARIJAN1'][i] > 12 and df['MARIJAN1'][i] <= 18:
        df['MARIJAN1'][i]=3
    elif df['MARIJAN1'][i] > 18 and df['MARIJAN1'][i] <= 24:
        df['MARIJAN1'][i]=4
    elif df['MARIJAN1'][i] > 24 and df['MARIJAN1'][i] <= 30:
        df['MARIJAN1'][i]=5
```

In [21]:
```
i=1
for i in range(len(df.AVEDRNK3)):
    if df['AVEDRNK3'][i] == 0:
        df['AVEDRNK3'][i]= 0
    elif df['AVEDRNK3'][i] > 0 and df['AVEDRNK3'][i] <= 6:
        df['AVEDRNK3'][i]=1
    elif df['AVEDRNK3'][i] > 6 and df['AVEDRNK3'][i] <= 12:
        df['AVEDRNK3'][i]=2
    elif df['AVEDRNK3'][i] > 12 and df['AVEDRNK3'][i] <= 18:
        df['AVEDRNK3'][i]=3
    elif df['AVEDRNK3'][i] > 18 and df['AVEDRNK3'][i] <= 24:
        df['AVEDRNK3'][i]=4
    elif df['AVEDRNK3'][i] > 24:
        df['AVEDRNK3'][i]=5
```

Correlation Analysis

Reviewing variables for potential correlation as a method to reduce the number of variables in the analysis post the initial grooming of variables

In [22]:
```
plt.rcParams["figure.figsize"] = (20,20)
corr_matrix = df.corr()
sns.heatmap(corr_matrix, annot=True)
plt.show()
#There are currently variables with a moderately strong correlation (Poor Heal
th vs Physical Health, Chol Medication vs High Chol etc.)
#however at this stage I am opting to keep these variables as is but will keep
in mind and potentially remove when
#implementing learning models
```



Further Data Processing

In order to prepare for further analysis, need to either consolidate columns or further impute values to remove any nulls with values that make sense so that the algorithms can run successfully

In [23]:
```
df['MAXDRNKS']=df['MAXDRNKS'].replace({np.nan:0})
#These are respondents who do not drink, imputing 0 as a method to add a categ
ory representing those who does not drink
```

In [24]:
```
df['TOLDHI3']=df['TOLDHI3'].replace({np.nan:2})
#These are respondents who have not had a cholesterol check. Imputing 'no' as
to whether they have been told they have high
#blood pressure
```

In [25]:
```
df['LCSFIRST']=df['LCSFIRST'].replace({np.nan:0})
df['LCSLAST']=df['LCSLAST'].replace({np.nan:0})
df['LCSNUMCG']=df['LCSNUMCG'].replace({np.nan:0})
#These are respondents who do not smoke, imputing 0 as a method to add a categ
ory representing those who does not smoke
```

In [26]:
```
df['MARIJAN1']=df['MARIJAN1'].replace({np.nan:0})
df['RSNMRJN2']=df['RSNMRJN2'].replace({np.nan:0})
#These are respondents who do not use marijuana, imputing 0 as a method to add
a category representing those who does not use marijuana
```

In [27]:
```
df.drop(['BPMEDS', 'CHOLMED3' ], axis=1, inplace=True)
#Dropping due to correlation with BPHIGH6 and TOLDHI3
```

Balancing Data & Splitting Test/Train

In this section I have split the data into a training set and a test set. This is a method I am using in order to avoid overtraining the algorithms. In my future 'refining' of the algorithm I also intend to implement cross validation to ensure I do not have an outlier situation with this split of data.

As a secondary method of mitigating bias I have also used a technique called SMOTE in order to balance my data set. SMOTE is synthetically increasing the number of 'positive' heart attack cases within the data set as these were a minority before.

In [28]:
```
smt = SMOTETomek(random_state=25)
feature_cols1 = ['EXERANY2', 'USENOW3', 'ECIGNOW1', 'ALCDAY5', 'AVEDRNK3', 'MA
XDRNKS', 'LCSFIRST','LCSLAST', 'LCSNUMCG', 'MARIJAN1', '_BMI5CAT']
x1=df[feature_cols1]
y1=df['CVDINFR4']
X_smt_CVT, y_smt_CVT = smt.fit_resample(x1,y1)
df = pd.concat([X_smt_CVT, y_smt_CVT])
```

In [29]:
```
X_train, X_test, y_train, y_test = train_test_split(X_smt_CVT,y_smt_CVT,random
_state=25, test_size=0.2)
```

Modeling Attempt 1 - All variables

Utilizing lifestyle variables and ignoring any demographic related variables or general health variables. As I refine the process and analyze further for significance, for more accurate results in the next stage I may choose to reduce the number of variables

Logistic Regression

In [30]:
```
model = LogisticRegression(solver='liblinear', random_state=25).fit(X_train,y_
train)
```

K Nearest Neighbours

In [31]:
```
classifier = KNeighborsClassifier(n_neighbors=5)
classifier=classifier.fit(X_train,y_train)
```

Decision Tree

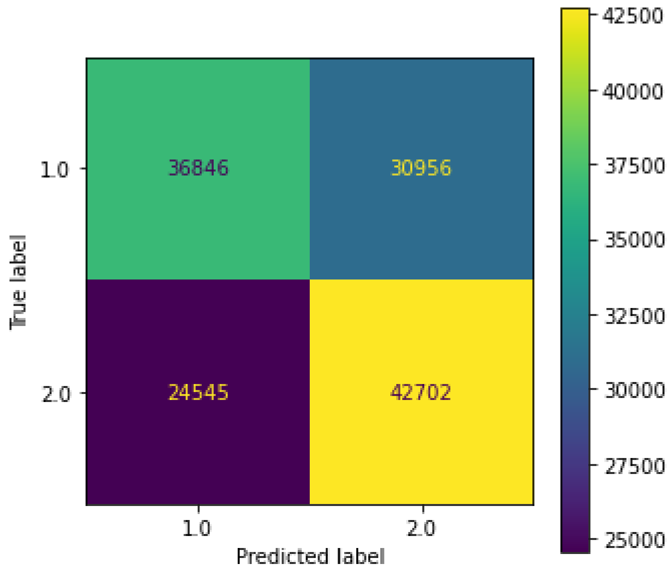
In [30]:
```
clf = tree.DecisionTreeClassifier(random_state=25)
clf = clf.fit(X_train,y_train)
```

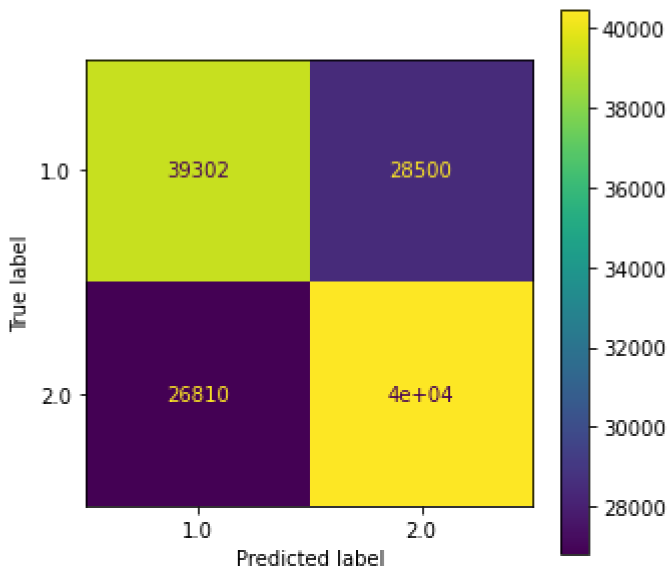
Results from Logistic Regression, KNN and Decision Tree

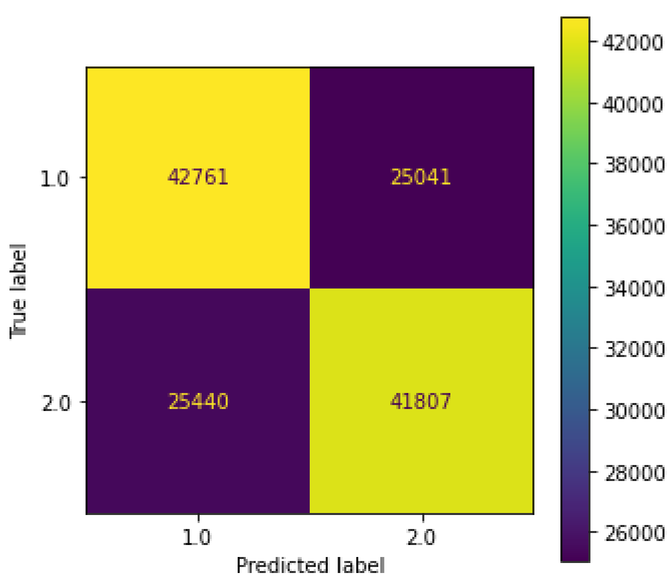
Overall my interest in assessing the initial 'success' of the algorithms is based on accuracy. I do not have any reason to consider recall or precision at a higher priority as I consider the consequence of a false positive or false negative to be equally consequential in the interpretation of these results.

In [33]:
```
plt.rcParams["figure.figsize"] = (5,5)
plot_confusion_matrix(model, X_test, y_test)
plot_confusion_matrix(classifier, X_test, y_test)
plot_confusion_matrix(clf, X_test, y_test)
```

Out[33]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x204e069b640>







In [34]:
```
X1_Estimate_Log = model.predict(X_test)
X1_Estimate_KNN = classifier.predict(X_test)
X1_Estimate_CLF = clf.predict(X_test)

Accuracy_Log= accuracy_score(y_test, X1_Estimate_Log)
Recall_Log=recall_score(y_test, X1_Estimate_Log, pos_label=1)
Precision_Log= precision_score(y_test, X1_Estimate_Log, pos_label=1.0)

Accuracy_KNN= accuracy_score(y_test, X1_Estimate_KNN)
Recall_KNN=recall_score(y_test, X1_Estimate_KNN, pos_label=1)
Precision_KNN= precision_score(y_test, X1_Estimate_KNN, pos_label=1.0)

Accuracy_CLF= accuracy_score(y_test, X1_Estimate_CLF)
Recall_CLF=recall_score(y_test, X1_Estimate_CLF, pos_label=1)
Precision_CLF= precision_score(y_test, X1_Estimate_CLF, pos_label=1.0)


print("Accuracy Log Model: ", Accuracy_Log,"\n",
    "Recall Log Model: ",Recall_Log,"\n",
    "Precision Log Model: ",Precision_Log, "\n",
    "Accuracy KNN Model: ",Accuracy_KNN,"\n",
    "Recall KNN Model: ",Recall_KNN,"\n",
    "Precision KNN Model: ",Precision_KNN,"\n",
    "Accuracy Decision Tree Model: ",Accuracy_CLF,"\n",
    "Recall Decision Tree Model: ",Recall_CLF,"\n",
    "Precision Decision Tree Model: ",Precision_CLF)
```

```
Accuracy Log Model:  0.5890306481351213
 Recall Log Model:  0.5434352968938969
 Precision Log Model:  0.6001856949715756
 Accuracy KNN Model:  0.590444949610882
 Recall KNN Model:  0.5796584171558361
 Precision KNN Model:  0.5944760406582769
 Accuracy Decision Tree Model:  0.6262023413723907
 Recall Decision Tree Model:  0.6306746113683962
 Precision Decision Tree Model:  0.6269849415697717
```

Next steps

As I now have a base level of 'clean' data for the purposes of analysis and a base measure of accuracy regarding some machine learning algorithms I intend to explore:

```
 - Can I build an improved model to a statistically significant measure
 - Utilize cross validation in order to ensure I am correctly/accurately assessing
the accuracy of predictions against the test data set
 - Although not directly related to my machine learning goal, I will explore utiliz
ing data mining techniques to help provide context to my reasearch questions around
health/lifestyle choices and their relation to the likelihood of a heart attack.
 - Summarize my machine learning findings as well as comment on the potential stati
stics significance of any improvement in the above models
```

Enhancing initial model

Cross Validation

In order to ensure I am enhancing based on accurate values, Going forward I am changing my method of algorithm evalutation to Cross Validation. This will help to minimize the chance of outliers being involved in a one off 80 / 20 training split like I utilized above and reduce variability in the 'accuracy' reported of each model.

In [56]:
```
k_folds = KFold(n_splits = 10, shuffle = True, random_state=25)
scoresCLF = cross_val_score(clf, X_train,y_train, cv = k_folds)
scoresLRM = cross_val_score(model, X_train,y_train, cv = k_folds)
scoresKNN = cross_val_score(classifier, X_train,y_train, cv = k_folds)


print("CLF Cross Validation Score: ", scoresCLF.mean(), "\n",
     "LRM Cross Validation Score: ", scoresLRM.mean(), "\n",
     "KNN Cross Validation Score: ", scoresKNN.mean())
```

```
CLF Cross Validation Score:  0.6265218922896156
 LRM Cross Validation Score:  0.5885152493652408
 KNN Cross Validation Score:  0.5750367805302561
```

Improve KNN Accuracy Attempt

In [36]:
```
Misclassified_KNN = []
```

In [37]:
```
for i in range(20,30):
    classifier2= KNeighborsClassifier(n_neighbors=i)
    classifier2.fit(X_train,y_train)
    pred_i=classifier2.predict(X_test)
    Misclassified_KNN.append((y_test != pred_i).sum())
```

In [38]:
```
Misclassified_KNN
```

Out[38]:
```
[55449, 55399, 55452, 55432, 55176, 55225, 55341, 54871, 54642, 54844]
```

The smallest number of misclassified items from this range is where i=28, so I will use this in the improved model (I did also check where i is from 1 to 20. Although it appears it may be plausible that an even larger number of n would decrease the error, I have chosen not to go any higher due to performance concerns.

In [39]:
```
classifier_v2 = KNeighborsClassifier(n_neighbors=28)
classifier2=classifier_v2.fit(X_train,y_train)
```

Improve Decision Tree Accuracy Attempt

In [40]:
```
parameters = {'max_depth': (70, 90, 100, 120, 150),
              'criterion' : ('gini', 'entropy'),
              'max_features': ('auto', 'sqrt', 'log2'),
              'min_samples_split': (1,3,5,10,15)
              }
```

In [41]:
```
DT_grid = RandomizedSearchCV(tree.DecisionTreeClassifier(), param_distribution
s= parameters, cv=5, verbose = True, random_state=25, n_jobs=-1)
DT_grid.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

C:\Users\Ben\anaconda3\envs\coursera\lib\site-packages\sklearn\model_selectio
n\_search.py:922: UserWarning: One or more of the test scores are non-finite:
[0.62595544 0.62623312        nan        nan 0.62588325        nan
 0.62627755 0.62615537 0.62620905 0.62593878]
  warnings.warn(
```

Out[41]:
```
RandomizedSearchCV(cv=5, estimator=DecisionTreeClassifier(), n_jobs=-1,
                   param_distributions={'criterion': ('gini', 'entropy'),
                                        'max_depth': (70, 90, 100, 120, 150),
                                        'max_features': ('auto', 'sqrt',
                                                         'log2'),
                                        'min_samples_split': (1, 3, 5, 10, 1
5)},
                   random_state=25, verbose=True)
```

In [42]:
```
DT_grid.best_estimator_
```

Out[42]:
```
DecisionTreeClassifier(criterion='entropy', max_depth=120, max_features='sqr
t',
                       min_samples_split=5)
```

In [31]:
```
clf_v2 = tree.DecisionTreeClassifier(criterion='entropy', max_depth=120, max_f
eatures='sqrt',
                       min_samples_split=5, random_state=25)
clf2 = clf_v2.fit(X_train,y_train)
```

Improve log model

In [44]:
```
logmodel =LogisticRegression(random_state=25)
```

In [45]:
```
param_grid = [
    {'penalty' : ['l1', 'l2', 'elasticnet', 'none'],
    'C': np.logspace(-4,4,20),
    'solver': ['lbfgs', 'newton-cg', 'liblinear', 'sag', 'saga'],
    'max_iter': [100, 1000, 2500, 5000]
    }
]
```

In [47]:
```
model2=GridSearchCV(logmodel, param_grid = param_grid, cv=3, verbose=True, n_j
obs=-1)
```

In [48]:
```
best_model= model2.fit(X_train,y_train)
```

```
Fitting 3 folds for each of 1600 candidates, totalling 4800 fits

C:\Users\Ben\anaconda3\envs\coursera\lib\site-packages\sklearn\model_selectio
n\_search.py:922: UserWarning: One or more of the test scores are non-finite:
[       nan        nan 0.57876878 ...        nan 0.58887254 0.58887069]
  warnings.warn(
```

In [49]:
```
best_model.best_estimator_
```

Out[49]:
```
LogisticRegression(C=0.0018329807108324356, random_state=25, solver='liblinea
r')
```

In [55]:
```
model2 = LogisticRegression(C=0.0018329807108324356, solver='liblinear', rando
m_state=25).fit(X_train,y_train)
```

Evaluating improvements

Based on the above tweaks I am now comparing accuracy against the above CV results to get an idea of whether there is any improvement in the models based on training data

In [57]:
```
k_folds = KFold(n_splits = 10, shuffle = True, random_state=25)
scoresCLF2 = cross_val_score(clf2, X_train,y_train, cv = k_folds)
scoresLRM2 = cross_val_score(model2, X_train,y_train, cv = k_folds)
scoresKNN2 = cross_val_score(classifier2, X_train,y_train, cv = k_folds)


print("CLF Cross Validation Score: ", scoresCLF2.mean(), "\n",
     "LRM Cross Validation Score: ", scoresLRM2.mean(), "\n",
     "KNN Cross Validation Score: ", scoresKNN2.mean())
```

```
CLF Cross Validation Score:  0.6265496599887493
 LRM Cross Validation Score:  0.5935134370940924
 KNN Cross Validation Score:  0.5992539732221825
```

Comment on whether accuracy has improved

CLF Cross Validation Score: 0.6265 to 0.6265 (No change at 4DP) LRM Cross Validation Score: 0.5885 to 0.5935 (.005 change at 4DP OR .8% increase) KNN Cross Validation Score: 0.5750 to 0.5992 (.0242 change at 4 DP OR 4.2% increase)

Overall the optimization of some of the parameters within the algorithms has resulted in a small increase in accuracy when compared against the training set of data.

Using a statistical test to confirm which model is best

Comparing the 3 different algorithms to understand which perform at the highest accuracy to statistically significant level (95% confidence level):

In [67]:
```
stats.ttest_rel(scoresCLF2, scoresLRM2, alternative= 'greater')
```

Out[67]:
```
Ttest_relResult(statistic=40.53840692835603, pvalue=8.42048100637809e-12)
```

Since P is less than alpha (.05) I can reject the null hypothosis in favour of the alternate which is that the CLF is more accurate than LRM

In [68]:
```
stats.ttest_rel(scoresCLF2, scoresKNN2, alternative= 'greater')
```

Out[68]:
```
Ttest_relResult(statistic=19.42160991959141, pvalue=5.879947409412096e-09)
```

Since P is less than alpha (.05) I can reject the null hypothosis in favour of the alternate which is that the CLF is more accurate than KNN

In [72]:
```
stats.ttest_rel(scoresKNN2, scoresLRM2, alternative= 'greater')
```

Out[72]:
```
Ttest_relResult(statistic=3.0355220746436564, pvalue=0.007059940723171199)
```

Since P is less than alpha (.05) I can reject the null hypothosis in favour of the alternate which is that the KNN is more accurate than LRM

Comparing accuracy against test data

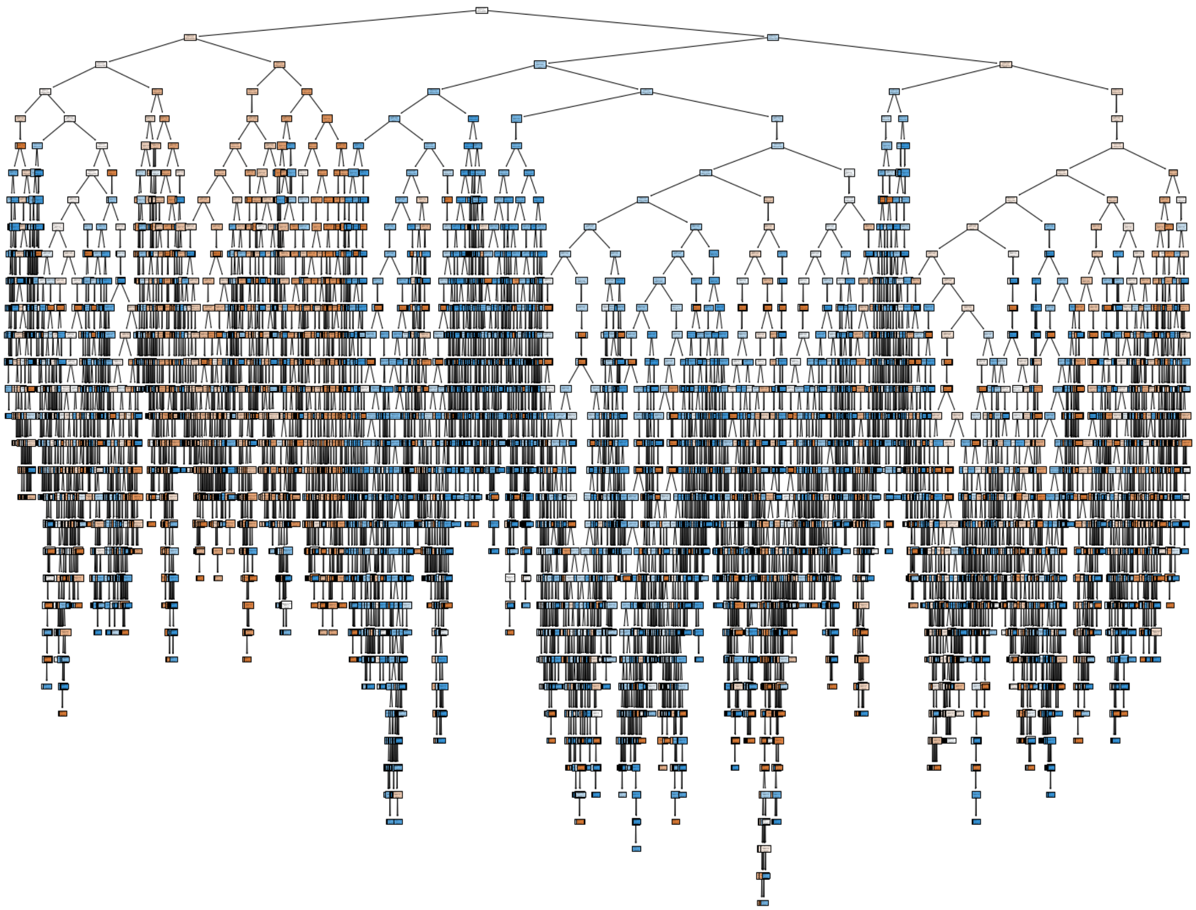
In [42]:
```
scoresCLF2Test = cross_val_score(clf2, X_test,y_test, cv = k_folds)
scoresCLF2Test.mean()
```

Out[42]:
```
0.6189901800456562
```

In [41]:
```
stats.ttest_rel(scoresCLF2, scoresCLF2Test, alternative= 'greater')
```

Out[41]:
```
Ttest_relResult(statistic=4.529595264254881, pvalue=0.0007135122795511 96)
```

In [46]:
```
fig = plt.figure(figsize=(25,20))
_ = tree.plot_tree(clf2,
                   feature_names=feature_cols1,
                   class_names='CVDINFR4',
                   filled=True)
```



Above is a visual representation of the decision tree model, this would of course need to be magnified multiple times in order to provide any visual insight but it does help to reflect some of the complexity in the decision tree.

Conclusion

The most accurate model based on my testing is the CLF model (Decision Tree) followed by the K Nearest Neighbour model and finally my least accurate model which is the logistic regression model. For full conclusion notes, next steps and what I would do differently please see 'Literature Review_Final'

In [ ]: