

AUTOMATED CLASSIFICATION OF TWEETS INTO SMART CITIES DIMENSIONS USING MACHINE LEARNING ALGORITHMS

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Department of Computer Science and Engineering

CERTIFICATE

This is to certify that the thesis entitled AUTOMATED CLASSIFICATION OF TWEETS INTO SMART CITIES DIMENSIONS USING MACHINE LEARNING ALGORITHMS submitted by P.V.N.MAHESH(17341A05E5), S.CHANDRA SEKHAR(17341A05F5), M.ROHINI(16341A05B4), A.SUNIL KUMAR(16341A0516) has been carried out in partial fulfilment of the requirement for the award of degree of Bachelor of Technology in Computer Science and Engineering of GMRIT, Rajam affiliated to JNTUK, KAKINADA is a record of bonafide work carried out by them under my guidance & supervision. The results embodied in this report have not been submitted to any other University or Institute for the award of any degree.

Signature of Supervisor Mrs. N. Lakshmi Devi Assistant Professor Department of CSE GMRIT, Rajam. Signature of HOD Dr. A. V. Ramana Professor & Head Department of CSE GMRIT, Rajam.

| The report is submitted for the viva-voce exa | mination held on |
|---|--------------------------------|
| Signature of Internal Examiner | Signature of External Examiner |

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ABSTRACT

Smart cities work mutually with data and technology for efficient results and make better decisions to improve the standard of life. Real-time data give the unfold picture from the citizen's perspective, understand the area of concern, and respond faster. Various city models are proposed with various dimensions and indicators to follow for the evolution of a city into a smart city. Now a days citizens are rising complaints and problems about the services by interacting directly with the respective social network profiles(water, transportation, energy etc) of the government entities using social networks as a gateway. In this paper we applied machine learning algorithms over the preprocessed data collected from Twitter to create classifiers that categorize citizens messages into smart cities services dimension. The classifiers generated here can be integrated into various city services and systems like Government Support decision systems, customer complaint systems, police offices, transportation companies, environmental agencies. The extracted tweets are vectorized using countVectorizer and TF_IDF vectorizer. The various supervised machine learning algorithms used in this project are Random Forest, Decision Tree Classifier, K Nearest Neighbor Classifier. Supervised machine learning models are trained and tested using the vectorizers.

Keywords:

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LIST OF SYMBOLS & ABBREVIATIONS

ISO International organization for standardization

SML Supervised Machine Learning

LR Logistic Regression

RF Random Forest

LSVC Linear Support Vector Classifier

SVC Support Vector Classifier

MNF Maximum Number of Features

TF Term Frequency

IDF Inverse Document Frequency

INTRODUCTION

1.1 INTRODUCTION

People are using social media networks to raise complaints in their locality on issues related to different kinds of problems like no water supply, electricity, telecommunication, environment, economy, solid wastes, education, fire emergency, sanitation, health emergency, transport, criminal cases, etc. Hence in this project, all the complaints posted on Twitter are examined to classify the new tweets into these dimensions which helps an organization dealing with that particular issue to get to know about the issue and resolve it at the earliest. This model also helps to get to know about the opinion of the citizens and also to monitor and manage various government bodies in an effective way. In this project, the data was extracted using different keywords, the extracted data were filtered by removing the hyperlinks, emoticons, converting the texts into the lower case for easy processing, the extracted data was labeled according to the dimensions mentioned above. The data extracted is the complaints made by the citizens of a particular city, which need not be the same on all the abovementioned labels hence the dataset is biased.

1.2 OBJECTIVE

Smart City models have been proposed looking for standard metrics to follow cities development and compare their performance into the various domains. ISO 37120 establishes a set of themes/dimensions related to city services and quality of life, and each theme has a set of indicators. Some examples can be verified on Fig. 1. In this work each dimension of ISO corresponds to a topic in the classification approach that will be discussed in next sessions. The International Organization for Standardization (ISO) developed this standard to provide a recommendation of what to measure and how [21]. The main objective of ISO with this model is to help cities to measure the management of municipal services performance and quality of life over time, facilitate the learning of one city with the other, allowing comparison in a wide range of measures and share best practices.

1.3 PROPOSED WORK

There is a good volume of published research applying OSN data to cities context. Regarding this paper scope and purposes it is important to understand:

- (a) how social media has been used to deal with urban issues
- (b) if there are cases integrating OSN data into city services
- (c) classifying OSN data into Smart City indicators models.

In the three scenarios the main interest is for the kind of classification performed in those researches, looking specially for those approaches using machine learning techniques.

LITERATURE SURVEY

1. Wang, Q., Bhandal, J., Huang, S., &Luo, B.(2017), IEEE explore "classification of private tweets using tweet content".

This project deals with the detailed information on the four different levels of text classification and the optimization of machine learning classifiers for text analysis prediction. One is Naive Bayes, which needs small dataset for training on text classification and is quite fast in learning. Others are tree based classifiers which are J48, BF Tree and One R. When compared to other classifiers J48 can work with larger training datasets. Here both unigrams and bigrams are considered with J48 algorithm.

2. Moschen, S. A, Macke, J., Bebber, S., &da Silva, M.B.C (2019).

"Sustainable development of communities".

In this project, calculated text score at which opinion lexicons are considered, proposed combination of dictionary based technique with Machine Learning approach, worked on six different products reviews taken from amazon and used SVM and concluded that machine learning techniques gives the best results on product reviews, considered performance metrics here are accuracy, precision and F1 score.

3. De Oliveira, M., de Souza Baptista, C., Campelo, C. E., & Bertolotto(2017)

"A gold-standard social media corpus for urban issues. In proceedings of the Symposium on Applied computing"

This project is focused on the effect of gender and age in text classification, because it can make process easy for retailers of e-commerce to marketing their goods based on different age groups. Demographics play a prominent part while determining the retailing techniques for various goods. BOW, Word2Vec feature extraction techniques was used. Dictionary based technique was also discussed. For determining text accuracy Naive Bayes, Maximum Entropy, SVM and Long Short Term Memory algorithms are used. Finally showed the experimental results of Machine Learning approaches and their result analysis on a dataset created based on a questionnaire. Here, among gender, female data got good accuracy and among different age groups, age group above 50 got predictions more correctly.

SYSTEM ANALYSIS

3.1 FUNCTIONAL REQUIREMENTS

The functional requirement of the system defines a function of software

system or its components. A function is described as set of inputs,

behavior of a system and output.

• Fast and efficient

• Simple Computation

3.2 NON FUNTIONAL REQUIREMENTS

In systems engineering and requirements engineering, a non-functional

requirement (NFR) is a requirement that specifies criteria that can be

used to judge the operation of a system, rather than specific behaviors.

They are contrasted with functional requirements that define specific

behavior or functions.

3.3 SOFTWARE REQUIREMENTS

• IDE : Jupyter notebook. (Google colab)

• Programming Language: Python

3.4 HARDWARE REQUIREMENTS

• RAM : 4 GB

METHODOLOGY

4.1 MODULES AND LIBRARIES

Matplotlib: Matplotlib is one of the most popular Python packages used for data visualization. It is a cross-platform library for making 2D plots from data in arrays. It provides an objectoriented API that helps in embedding plots in applications using Python GUI toolkits such as PyQt, WxPythonotTkinter. It can be used in Python and IPython shells, Jupyter notebook and web application servers also.

Pyplot : Matplotlib.pyplot is a collection of functions that make matplotlib work like MATLAB. Each pyplot function makes some change to a figure: e.g., creates a figure, creates a plotting area in a figure, plots some lines in a plotting area, decorates the plot with labels, etc.

Numpy: Numpy is a python library used for working with arrays. It also has functions for working in domain of linear algebra, fourier transform and matrices. Numpy Stands for numerical Python. In python there are lists to use but they are slow to process where as numpy provides an object of array which is almost 50 times faster than the traditional python lists because numpy arrays are stored at one continuous place in memory unlike lists, so processes can access and manipulate them very efficiently.

Import os : The OS module in Python provides a way of using operating system dependent functionality. The functions that the OS module provides allows you to interface with the underlying operating system that Python is running on – be that Windows, Mac or Linux. You can find important information about your location or about the process. In this post I will show some of these functions.

Import random: The random module is a built-in module to generate the pseudorandom variables. It can be used perform some action randomly such as to get a random number, selecting a random elements from a list, shuffle elements randomly, etc.

4.2 FLOWCHART

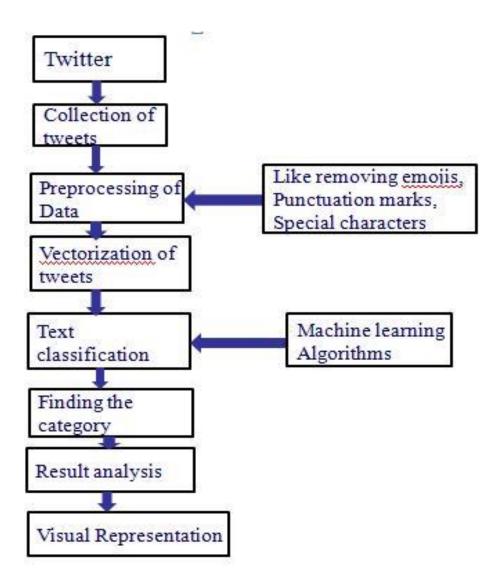


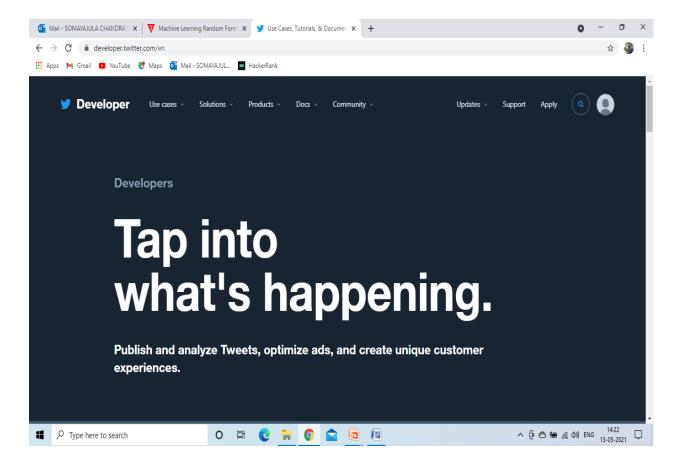
Fig 4.2.1 Flowchart

4.3 DATA SET DESCRIPTION

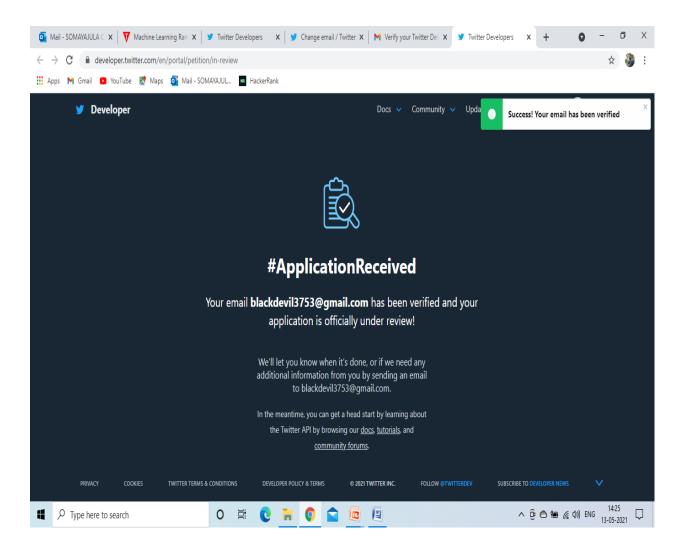
We have collected data from twitter by using API key. So, in order to retrieve data from twitter using API keys we need a developer account in twitter.

Here are the following steps to create a developer account

- 1) Open Chrome browser and login to your twitter account using the given URL developer.twitter.com
- 2) Then you find a screen like this. Then click on Apply



- 3) Give all the credentials which are required to create a developer account in Twitter.
- 4) After completing all the steps, you will get a screen like this.



Data Extraction:

```
def Extract_data(label,qu,n):
 df = pd.DataFrame()
 q = qu + '-filter:retweets'
 for status in tweepy. Cursor (api. search, q=q, lang='en',
tweet_mode='extended').items(n):
   df = df.append({'createdTime' : status.created_at, 'Tweet' :
status.full_text.replace('\n',''), 'User': status.user.screen_name.encode('utf-8'),
'label': label}, ignore_index=True)
 fname = qu + '.csv'
 df.to_csv(fname)
 return df
Different keys of Twitter:
consumer_key="¡EEWinIsUKeoiUH0a4I8MKkUp"
consumer_secret="2eDqARYiYaPn7ewcAOs1oKHPOVyrOaSwuGhOSWU96ZSvOyGBpi"
access_token="1394502294490607617i6pyYLrmZsoQtM17BD78uFKmd6jZyX"
access_token_secret="xYdmZh7nkXqlDCln3fHCVEYUlTwI8TP7BcTkE8p0WUAwI"
```

Sample dataset:

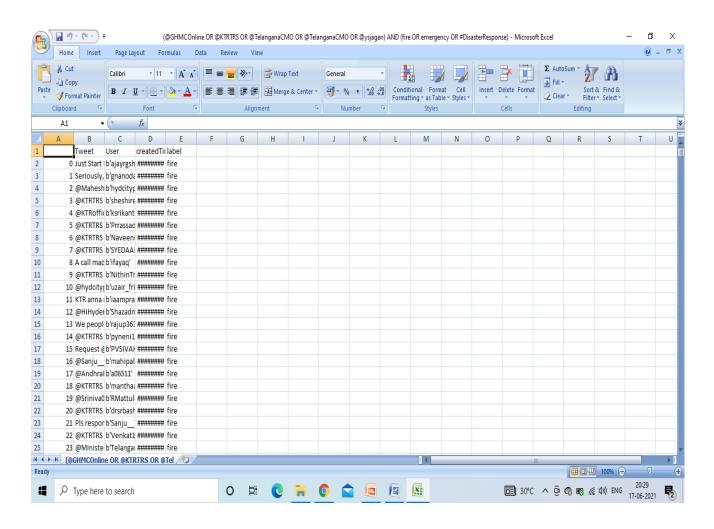


Fig 4.3.1 Fire department dataset

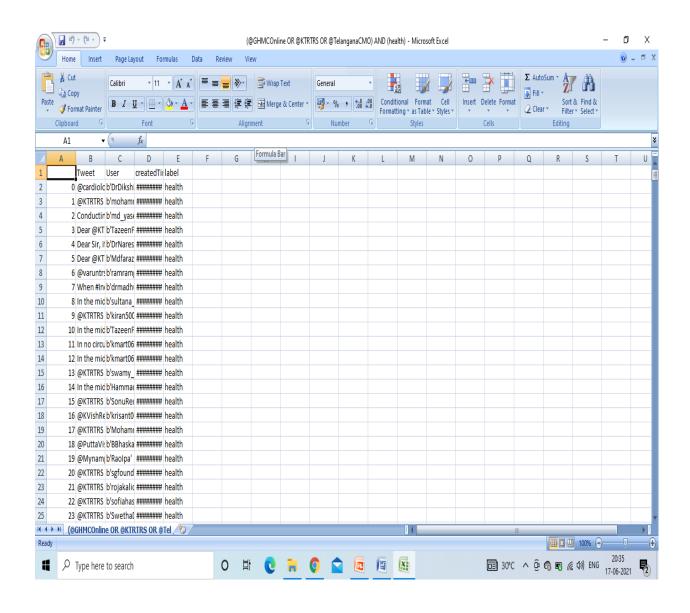


Fig 4.3.2 Health department dataset

4.4 PROPOSED MODELS AND METHODS

Here, we have used 8 supervised learning models(SLM) to classify our data. They are

- > Decision Tree classifier
- ➤ Random Forest classifier
- ➤ K Nearest Neighbor classifier
- ➤ Compliment Naïve Bayes
- ➤ Logistic regression
- ➤ Multinomial regression
- > Support Vector classifier
- ➤ Linear SVC

Decision Tree classifier:

- Decision Tree is a supervised learning technique that can be used for both classification and regression problems but mostly it is preferred for solving classification problems.
- It is tree-structured classifier, where internal nodes represent the features of a dataset, branches represent the decision rules and each leaf node represents the outcome.
- In a decision tree, for prediction the class of the given dataset the algorithm starts from the root node of the tree. This algorithm compares the values of

root attribute with the record attribute and based on the comparison, follows the branch and jumps to the next node.

- For the next node, the algorithm again compares the attribute value with the other sub-nodes and move further. It continues the process until it reaches the leaf node of the tree.
- Decision tree usually mimic human thinking ability while making a decision,
 so it is easy to understand.

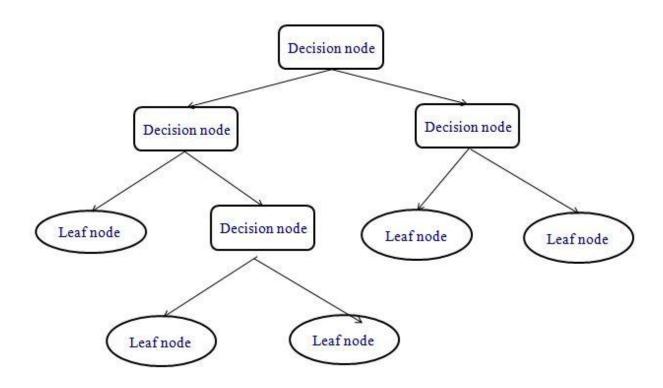


Fig 4.4.1 Decision tree classifier

Random Forest Classifier:

- Random Forest is a classifier that contains a number of decision tress on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset.
- Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output.
- Random Forest works in two-phase. first is to create the random forest by combining N decision tree, and second is to make predictions for each tree created in the first phase.
- Random Forest combines multiple trees to predict the class of the data set it
 is possible that some decision trees may predict the correct output while
 others may not but together all the trees predict the correct output.
- It takes less training time as compared to other algorithms.
- Although random forest can be used for both classification and regression tasks it is not more suitable for regression tasks.

K- Nearest Neighbor Classifier:

- K-NN algorithm assumes the similarity between new case and available cases and put the new case in the category that is most similar to the available categories.
- K-NN algorithm stores all the available data and classifies a new data point based on the similarity .This means when new data appears than it can be easily classified into a well suite category by using KNN algorithm .
- It is also called a lazy learner algorithm because it does not learn from the training set immediately instead it stores the data set and at the time of classification it performs an action on the dataset.
- Firstly, we will choose the number of neighbors next we will calculate the Euclidean distance between the data points. By calculating the Euclidean distance we will get the nearest neighbors by finding nearest neighbors new data point will form.

Complement Naïve Bayes:

- Complement Naïve Bayes is somewhat an adaptation of the multinomial Naïve bayes algorithm.
- Multinomial Naïve Bayes does not perform well on imbalanced datasets.

 Imbalanced datasets are datasets where the number of examples of some classes is higher than the number of examples belonging to their classes.
 This means that the Distribution of examples is not uniform.

Logistic Regression:

- The logistic model (or logit model) is used to model the probability of a certain class or event existing such as pass/fail, win/lose, alive/dead or healthy/sick.
- This can be extended to model several classes of events such as determining whether an image contains a cat, dog, lion, etc.
- Each object being detected in the image would be assigned a probability between 0 and 1, with a sum of one.

Multinomial Naïve Bayes:

- The multinomial Naive Bayes classifier is suitable for classification with discrete features
- The multinomial distribution normally requires integer feature counts.

 However, in practice, fractional counts such as tf-idf may also work.
- The algorithm is based on the Bayes Theorem and predicts the tag of a text such as piece of email or newspaper article.

Support vector Classifier:

- Support vector classifier is to fit to the data you provide, returning a "best fit" hyperplane that divides or categorize our data.
- The fit time scales at least quadratically with the number of samples and may be impractical beyond tens of thousands of samples.
- The multiclass support is handled according to a one-vs-one scheme.

Linear SVC:

- Similar to SVC with parameter kernel = "linear".
- but implemented in terms of liblinear rather than libsym, so it has more flexibility in the choice of penalties and loss functions and should scale better to large numbers of samples.
- This class supports both dense and sparse input and the multiclass support is handled according to a one-vs-the-rest scheme.

PROPOSED METHODS:

Here we have used two vectorizer methods to vectorize the data.

The vectorized methods proposed in this project are

- Count vectorizer
- Tf-Idf vectorizer

Count Vectorizer:

• The count vectorizer assigns a unique value for each unique word in the whole data set and all the unique words are the features.

doc=["One Cent, Two Cents, Old Cent, New Cent: All About Money"]

| doc | about | about all | all cent 1 3 | cents | money 1 | new old | old | one 1 | two 1 | In theory (a) |
|-------|-------|-----------|--------------|-------|------------|---------|-----|----------|----------|-----------------|
| | 1 1 | 1 | | | | | 1 | | | |
| | | | | | ı | | | | | |
| | | | | | | | | | | <u> </u> |
| Index | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | In practice (b) |
| doc | 1 | | 3 | | 4 | 4 | 4 | 4 | 1 | |

Fig 4.4.2 Count vectorizer

TF-IDF vectorizer:

- Stands for Term Frequency Inverse Document Frequency.
- In the TF-IDF vectorizer, we calculate the Term Frequency, the Inverse
 Document Frequency, and the TF-IDF score using the below formulae.
 Words with a higher TF-IDF score are more important, and those with a
 lower score are less important.
- Term frequency can be calculated by dividing the no of times a particular word appears in a document to the total no of words in a document.

$$TF_{t,d} = n_{t,d} / No.of terms in the document$$

• Inverse document Frequency can be calculated by performing the logarithm of ratio of no of documents to the total no of documents with the term "t".

$$IDF_t = log\{No. of documents / No. of documents with term 't'\}$$

• The TFIDF is calculated by performing multiplication of TF and IDF.

$$TF$$
- $IDF_{t,d} = TF_{t,d} * IDF_t$

IMPLEMENTATION

5.1 STEPS FOR IMPLEMENTATION

- 1. Load the data from Twitter.
- 2. Preprocessing of data like removing punctuation marks, emojis and any other hyperlinks.
- 3. Vectorization of data using count and Tf-idf vectorizer.
- 4. Text classification using given supervised learning models.
- 5. Finding the category.
- 6. Result analysis
- 7. Visual representation.

5.2 SOURCE CODE

import csv import re import tweepy import nltk import pandas as pd import numpy as np import sklearn import matplotlib.pyplot as plt import seaborn as sns from sklearn.feature_extraction.text import TfidfVectorizer from sklearn.feature_extraction.text import CountVectorizer from sklearn.feature_selection import chi2 from sklearn.model_selection import train_test_split from sklearn.naive_bayes import MultinomialNB from sklearn.linear_model import LogisticRegression from sklearn.ensemble import RandomForestClassifier from sklearn.svm import LinearSVC from sklearn.neighbors import KNeighborsClassifier from sklearn.naive_bayes import ComplementNB

```
from sklearn.tree import DecisionTreeClassifier
```

from sklearn.svm import SVC

from sklearn.model_selection import cross_val_score

import matplotlib.pyplot as plt

from sklearn.metrics import f1_score

from sklearn.metrics import confusion_matrix

from sklearn import metrics

from sklearn.metrics import make_scorer, accuracy_score, precision_score,

recall_score, f1_score

import sklearn.model_selection as model_selection

from sklearn.model_selection import cross_validate

#Different keys of Twitter developer account

```
consumer_key = "CONSUMER KEY"
```

consumer secret = 'CONSUMER SECRET"

access_token = "ACCESS TOKEN"

access_token_secret = "ACCESS TOKEN SECRET"

auth = tweepy.OAuthHandler(consumer_key, consumer_secret)

```
auth.set_access_token(access_token, access_token_secret)
api = tweepy.API(auth, wait_on_rate_limit = True)
#Data Extraction
            def Extract_data(label,qu,n):
             df = pd.DataFrame()
             q = qu + '-filter:retweets'
             for status in tweepy. Cursor (api.search, q=q, lang='en',
      tweet_mode='extended').items(n):
                df = df.append({'createdTime' : status.created_at, 'Tweet' :
      status.full_text.replace('\n',' '), 'User': status.user.screen_name.encode('utf-
      8'), 'label': label}, ignore_index=True)
             fname = qu + '.csv'
              df.to_csv(fname)
              return df
d2 = Extract_data('water', '@GHMCOnline AND water', 1000)
d3 = Extract_data('electricity', '@GHMCOnline AND (electricity OR electric)',
1000)
d4 = Extract_data('electricity', '@TsspdclCorporat AND power', 1000)
```

```
d5 = Extract_data('police', '(@HYDTP OR @TelanganaCOPs)', 1000)
d6 = Extract_data('solid waste', '(@GHMCOnline OR @KTRTRS) AND (garbage
OR waste)', 1000)
d7 = Extract_data('sanitation', '(@GHMCOnline OR @KTRTRS) AND sanitation',
1000)
d8 = Extract_data('education', '(@GHMCOnline OR @KTRTRS) AND education',
1000)
d9 = Extract_data('environment', '(@GHMCOnline OR @KTRTRS) AND
(environment OR trees OR plant OR tree OR pollution)', 1000)
d10 = Extract_data('economy', '(@GHMCOnline OR @KTRTRS OR
@TelanganaCMO OR @trsharish) AND (economy OR finance OR financial OR
gdp)', 1000)
d11 = Extract_data('fire', '(@GHMCOnline OR @KTRTRS OR @TelanganaCMO
OR @TelanganaCMO OR @ysjagan) AND (fire OR emergency OR
#DisasterResponse)', 1000)
d12 = Extract_data('health', '(@GHMCOnline OR @KTRTRS OR
@TelanganaCMO) AND (health)', 1000)
d13 = Extract_data('health', '(@TelanganaHealth OR @Eatala_Rajender) AND
(hospital OR medical OR health OR suffering)', 1000)
```

```
d14 = Extract_data('transport', '(@GHMCOnline OR @KTRTRS) AND (road OR
bus OR transport OR train OR metro)', 1000)
d15 = Extract_data('telecommunication', '(@GHMCOnline OR @KTRTRS) AND
(bsnl OR network OR communications OR 5G OR 4G OR fibre OR fiber OR
broadband )', 1000)
df = pd.concat([d2,d3,d4,d5,d6,d7,d8,d9,d10,d11,d12,d13,d14,d15])
#Data Preprocessing
from nltk.stem import PorterStemmer
from nltk.tokenize import word_tokenize as wt
nltk.download('stopwords')
nltk.download('punkt')
from nltk.corpus import stopwords
def preProcessing(tweets):
 tweets = tweets.tolist()
 ps = PorterStemmer()
 processedTweets = []
```

```
punct = ['.',',','?','!',';',':','-
','_','(',')','{','}','[',']','&','*','+','=','''','''','<','>','|',\\','/',\`','~','@','#']
 sWords = set(stopwords.words('english'))
 for tweet in tweets:
  tweet = tweet.encode().decode()
  tweet = tweet.encode('ascii', 'ignore').decode('ascii') #removing the emojis
  tweet = tweet.encode('latin-1', 'ignore').decode('latin-1')
  tweet = re.sub(r'http\S+', ", tweet) #removing the urls
  tweet = tweet.lower() #converting the text into lower cases
  words = wt(tweet) #tokenization
  processedWords = []
  for word in words:
   if word in punct or word in sWords:
     continue
   if words[words.index(word) - 1]!='@' and words[words.index(word) - 1]!=
'#':
    processedWords.append(word)
  processedWords.remove(processedWords[0])
  processedTweets.append(' '.join(processedWords))
return processedTweets
```

```
df.Tweet = preProcessing(df.Tweet)
df1=df[['Tweet','label']].copy()
df1.columns=['tweet','label']
df1['category_id'] = df1['label'].factorize()[0]
category_id_df = df1[['label', 'category_id']].drop_duplicates()
# Dictionaries for future use
category_to_id = dict(category_id_df.values)
id_to_category = dict(category_id_df[['category_id', 'label']].values)
fig = plt.figure(figsize=(8,6))
colors = ['grey','grey','grey','grey','grey','grey','grey','grey',
  'grey', 'darkblue', 'darkblue', 'darkblue']
df1.groupby('label').tweet.count().sort_values().plot.barh(
  ylim=0, color=colors, title= 'NUMBER OF TWEETS IN EACH
CATEGORY\n')
plt.xlabel('Number of occurrences', fontsize = 10);
```

#CountVectorizer Feature Selection

```
vectorizer = CountVectorizer(ngram_range=(1, 3),
            stop_words='english')
features = vectorizer.fit_transform(df1.tweet).toarray()
labels = df1.category_id
print("Each of the %d tweets is represented by %d features" %(features.shape))
#Training the models
X = df1['tweet']
y = df1['label']
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                test_size=0.2,
                               random_state = 0
models = [ RandomForestClassifier(n_estimators=100, max_depth=5,
random_state=0),
  LinearSVC(),
  MultinomialNB(),
```

```
LogisticRegression(random_state=0),
  KNeighborsClassifier(n_neighbors=1),
  ComplementNB(),
  DecisionTreeClassifier(random_state=0),
  SVC(),
]
CV = 5
cv_df = pd.DataFrame(index=range(CV * len(models)))
entries = []
score=['f1_macro','f1_micro']
for model in models:
  model_name = model.__class__._name__
  accuracies = cross_validate(model, features, labels, scoring=score, cv=CV)
  for f1_macro,f1_micro in
zip(accuracies['test_f1_macro'],accuracies['test_f1_micro']):
    entries.append((model_name,f1_macro,f1_micro))
cv_df = pd.DataFrame(entries, columns=['model_name','f1_macro','f1_micro'])
fl_macro = cv_df.groupby('model_name').fl_macro.mean()
f1_micro = cv_df.groupby('model_name').f1_micro.mean()
```

```
acc = pd.concat([f1_macro,f1_micro], axis= 1,
      ignore_index=True)
acc.columns = ['f1-macro_mean','f1-micro_mean']
acc=acc.sort_values(by=['f1-macro_mean'], ascending=False)
print(acc) #Accuracy scores
#Plotting the metrics of 8 algorithms
plt.figure(figsize=(20,5))
sns.boxplot(x='model_name', y='f1_macro',
      data=cv_df,
      showmeans=True)
plt.title("f1-macro (cv = 5)\n", size=14);
plt.figure(figsize=(20,5))
sns.boxplot(x='model_name', y='f1_micro',
      data=cv_df,
      showmeans=True)
plt.title("f1-micro (cv = 5)\n", size=14);
X_train, X_test, y_train, y_test, indices_train, indices_test =
train_test_split(features,labels,df1.index,test_size=0.2,random_state=1)
```

#Minimum Document Frequency method

```
X = df1['tweet'] \# Collection of documents
  y = df1['label'] # Target or the labels we want to predict (i.e., the 13 different
complaints of products)
  X_train, X_test, y_train, y_test = train_test_split(X, y,
                               test_size=0.2,
                               random_state = 0
  models = [
  LinearSVC(max_iter=100000),
  LogisticRegression(random_state=0,max_iter=10000),
  DecisionTreeClassifier(random_state=0),
  ]
  # 5 Cross-validation
  CV = 5
  cv_df = pd.DataFrame(index=range(CV * len(models)))
  entries = []
  score=['f1_macro','f1_micro']
  for model in models:
```

```
model_name = model.__class__.__name__
    accuracies = cross_validate(model, features, labels, scoring=score, cv=CV)
    i=0
    for f1_macro,f1_micro in
zip(accuracies['test_f1_macro'],accuracies['test_f1_micro']):
      entries.append((i,model_name,f1_macro,f1_micro))
      i+=1
  cv_df = pd.DataFrame(entries,
columns=['index','model_name','f1_macro','f1_micro'])
  f1_macro = cv_df.groupby('model_name').f1_macro.mean()
  f1 micro = cv df.groupby('model name').f1 micro.mean()
  demo_acc = pd.concat([f1_macro,f1_micro], axis= 1, ignore_index=True)
  demo_acc.columns = ['f1-macro_mean','f1-micro_mean']
  print("Scores for min-df=",x," are given below:\n")
  print(demo_acc)
  11=demo_acc['f1-macro_mean'].tolist()
  12=demo_acc['f1-micro_mean'].tolist()
  13=[]
  13=[x]+11+12
  final2.append(13)
```

```
x+=1
```

```
temp=pd.DataFrame(final2,columns=['mnf','DTC_f1-macro','LSVC_f1-macro','LR_f1-macro','DTC_f1-micro','LSVC_f1-micro','LR_f1-micro'])
temp.to_csv('scores from countvectorizer(mnf).csv')
print(temp)
```

#Plotting the results

```
temp.plot(x='min_df',y=['DTC_f1-macro','LSVC_f1-macro','LR_f1-macro'],marker='^',figsize=(10,5),ylim=(0.7,0.8));
```

#Maximum number of Features method

```
# We transform each complaint into a vector
  demo_features = vectorizer.fit_transform(df1.tweet).toarray()
  labels = df1.category_id
  print("\nFor max-features=",w,", each of the %d tweets is represented by %d
features\n" %(demo_features.shape))
  X = df1['tweet'] \# Collection of documents
  y = df1['label'] # Target or the labels we want to predict (i.e., the 13 different
complaints of products)
  X_train, X_test, y_train, y_test = train_test_split(X, y,
                               test_size=0.2,
                               random_state = 0
  models = [
  LinearSVC(max_iter=100000),
  LogisticRegression(random_state=0,max_iter=10000),
  DecisionTreeClassifier(random_state=0),
  ]
  # 5 Cross-validation
  CV = 5
```

```
cv_df = pd.DataFrame(index=range(CV * len(models)))
  entries = []
  score=['f1_macro','f1_micro']
  for model in models:
    model_name = model.__class__.__name__
    accuracies = cross_validate(model, demo_features, labels, scoring=score,
cv=CV)
    i=0
    for f1_macro,f1_micro in
zip(accuracies['test_f1_macro'],accuracies['test_f1_micro']):
      entries.append((i,model_name,f1_macro,f1_micro))
     i+=1
  cv_df = pd.DataFrame(entries,
columns=['index','model_name','f1_macro','f1_micro'])
  f1_macro = cv_df.groupby('model_name').f1_macro.mean()
  f1_micro = cv_df.groupby('model_name').f1_micro.mean()
  demo_acc = pd.concat([f1_macro,f1_micro], axis= 1, ignore_index=True)
  demo_acc.columns = ['f1-macro_mean','f1-micro_mean']
  print("Scores for max features=",w," are given below:\n")
```

```
print(demo_acc)
  11=demo_acc['f1-macro_mean'].tolist()
  12=demo_acc['f1-micro_mean'].tolist()
  13=[]
  13=[w]+11+12
  final1.append(13)
  w + = 500
temp1=pd.DataFrame(final1,columns=['mnf','DTC_f1-macro','LSVC_f1-
macro', 'LR_f1-macro', 'DTC_f1-micro', 'LSVC_f1-micro', 'LR_f1-micro'])
temp1.to_csv('scores from countvectorizer(mnf).csv')
print(temp1)
#Plotting the results
temp1.plot(x='mnf',y=['DTC_f1-macro','LSVC_f1-macro','LR_f1-
macro'],marker='^',figsize=(10,5),ylim=(0.7,0.8));
#TF-IDF Feature Selection
tfidf = TfidfVectorizer(sublinear_tf=True,
```

```
ngram_range=(1, 3),
            stop_words='english')
features1 = tfidf.fit_transform(df1.tweet).toarray()
labels = df1.category_id
print("Each of the %d tweets is represented by %d features (TF-IDF score of
unigrams and bigrams)" %(features1.shape))
X = df1['tweet']
y = df1['label']
X_train, X_test, y_train, y_test = train_test_split(X, y,
                               test_size=0.2,
                               random_state = 0
models = [
  RandomForestClassifier(n_estimators=100, max_depth=5, random_state=0),
  LinearSVC(),
  MultinomialNB(),
  LogisticRegression(random_state=0),
```

```
KNeighborsClassifier(n_neighbors=1),
  ComplementNB(),
  DecisionTreeClassifier(random_state=0),
  SVC(),
]
CV = 5
cv_df = pd.DataFrame(index=range(CV * len(models)))
entries = []
score=['f1_macro','f1_micro']
for model in models:
  model_name = model.__class__._name__
  accuracies = cross_validate(model, features1, labels, scoring=score, cv=CV)
  for f1_macro,f1_micro in
zip(accuracies['test_f1_macro'],accuracies['test_f1_micro']):
    entries.append((model_name,f1_macro,f1_micro))
cv_df = pd.DataFrame(entries, columns=['model_name','f1_macro','f1_micro'])
f1_macro = cv_df.groupby('model_name').f1_macro.mean()
f1_micro = cv_df.groupby('model_name').f1_micro.mean()
```

```
plt.figure(figsize=(20,5))

sns.boxplot(x='model_name', y='f1_macro',

data=cv_df,

showmeans=True)

plt.title("F1-MACRO MEAN (cv = 5)\n", size=14);

plt.figure(figsize=(20,5))

sns.boxplot(x='model_name', y='f1_micro',

data=cv_df,

showmeans=True)

plt.title("F1-MICRO MEAN (cv = 5)\n", size=14);
```

#Minimum number of features method

```
final3=[]
x=1
while(x <= 30):
  vectorizer = TfidfVectorizer(sublinear_tf=True,
                   min_df=x,
                    ngram_range=(1, 3),
                    stop_words='english',
                   )
  demo_features1 = vectorizer.fit_transform(df1.tweet).toarray()
  labels = df1.category_id
  print("\nFor min-df=",x,", each of the %d tweets is represented by %d
features\n" %(demo_features1.shape))
  X = df1['tweet']
  y = df1['label']
  X_train, X_test, y_train, y_test = train_test_split(X, y,
                                test_size=0.2,
                                random_state = 0
```

```
models = [
  LinearSVC(max_iter=100000),
  LogisticRegression(random_state=0,max_iter=10000),
  DecisionTreeClassifier(random_state=0),
  ]
  # 5 Cross-validation
  CV = 5
  cv_df = pd.DataFrame(index=range(CV * len(models)))
  entries = []
  score=['f1_macro','f1_micro']
  for model in models:
    model_name = model.__class__._name__
    accuracies = cross_validate(model, demo_features1, labels, scoring=score,
cv=CV)
    i=0
    for f1_macro,f1_micro in
zip(accuracies['test_f1_macro'],accuracies['test_f1_micro']):
      entries.append((i,model_name,f1_macro,f1_micro))
```

```
i+=1
  cv_df = pd.DataFrame(entries,
columns=['index','model_name','f1_macro','f1_micro'])
  f1_macro = cv_df.groupby('model_name').f1_macro.mean()
  f1_micro = cv_df.groupby('model_name').f1_micro.mean()
  demo_acc = pd.concat([f1_macro,f1_micro], axis= 1, ignore_index=True)
  demo_acc.columns = ['f1-macro_mean','f1-micro_mean']
  print("Scores for min-df=",x," are given below:\n")
  print(demo_acc)
  11=demo_acc['f1-macro_mean'].tolist()
  12=demo acc['f1-micro mean'].tolist()
  13=[]
  13=[x]+11+12
  final3.append(13)
  x+=1
temp3=pd.DataFrame(final1,columns=['min_df','DTC_f1-macro','LSVC_f1-
macro', 'LR_f1-macro', 'DTC_f1-micro', 'LSVC_f1-micro', 'LR_f1-micro'])
temp3.to_csv('scores from tf-idf.csv')
print(temp3)
```

#Plotting the results

```
temp3.plot(x='min\_df',y=['DTC\_f1-macro','LSVC\_f1-macro','LR\_f1-macro'], marker='^', figsize=(10.5), ylim=(0.7,0.8));
```

#Maximum number of features method

```
X = df1['tweet']
y = df1['label']
X_train, X_test, y_train, y_test = train_test_split(X, y,
                            test_size=0.2,
                            random_state = 0
models = [
LinearSVC(max_iter=100000),
LogisticRegression(random_state=0,max_iter=10000),
DecisionTreeClassifier(random_state=0),
1
# 5 Cross-validation
CV = 5
cv_df = pd.DataFrame(index=range(CV * len(models)))
entries = []
score=['f1_macro','f1_micro']
for model in models:
  model_name = model.__class__._name__
```

```
accuracies = cross_validate(model, demo_features2, labels, scoring=score,
cv=CV)
    i=0
    for f1_macro,f1_micro in
zip(accuracies['test_f1_macro'],accuracies['test_f1_micro']):
      entries.append((i,model_name,f1_macro,f1_micro))
      i+=1
  cv_df = pd.DataFrame(entries,
columns=['index','model_name','f1_macro','f1_micro'])
  f1_macro = cv_df.groupby('model_name').f1_macro.mean()
  f1 micro = cv df.groupby('model name').f1 micro.mean()
  demo_acc = pd.concat([f1_macro,f1_micro], axis= 1, ignore_index=True)
  demo_acc.columns = ['f1-macro_mean','f1-micro_mean']
  print("Scores for max features=",w," are given below:\n")
  print(demo_acc)
  11=demo_acc['f1-macro_mean'].tolist()
  12=demo_acc['f1-micro_mean'].tolist()
  13=[]
  13=[w]+11+12
  final4.append(13)
```

```
w + = 500
```

```
temp4=pd.DataFrame(final1,columns=['mnf','DTC_f1-macro','LSVC_f1-macro','LR_f1-macro','DTC_f1-micro','LSVC_f1-micro','LR_f1-micro'])
temp4.to_csv('scores from tf-idf(mnf).csv')
print(temp4)
```

#Plotting the results

```
temp4.plot(x='mnf',y=['DTC_f1-macro','LSVC_f1-macro','LR_f1-macro'],marker='^',figsize=(10,5));
```

#Classification of new texts

$$X_{train}, X_{test}, y_{train}, y_{test} = train_{test_split}(X, y, \\ test_{size} = 0.2, \\ random_{state} = 0)$$

```
fitted\_vectorizer = tfidf.fit(X\_train) \\ tfidf\_vectorizer\_vectors = fitted\_vectorizer.transform(X\_train) \\ model = DecisionTreeClassifier(random\_state=0).fit(tfidf\_vectorizer\_vectors, y\_train) \\
```

stop_words='english')

new_tweet = input('Enter any text to classify:')

print(model.predict(fitted_vectorizer.transform([new_tweet])))

RESULTS AND DISCUSSION

Here we have used a new metric called F1 score. Accuracy is used when True positives and True negatives are important while F1 score is used when False positives and False Negatives are crucial. Here we are using Biased data. So there's a high possibility that we might get more then 4 categories. So, Accuracy mightnot be better metric for this data. That's why we are using F1 score.

Calculating F1 score for the models with count vectorizer:

| Model | F1 score |
|--------------------------|----------|
| Decision tree classifier | 0.785344 |
| Linear SVC | 0.719764 |
| Logistic regression | 0.680612 |
| Complement NB | 0.625890 |
| Multinomial NB | 0.548618 |
| SVC | 0.481840 |
| K Neighbors classifier | 0.284201 |
| Random Forest classifier | 0.123618 |

Calculating F1 score for the models with TF-IDF vectorizer:

| Model | F1 score |
|--------------------------|----------|
| Decision tree classifier | 0.866512 |
| Linear SVC | 0.852839 |
| Logistic regression | 0.840093 |
| Complement NB | 0.746002 |
| Multinomial NB | 0.734878 |
| SVC | 0.732793 |
| K Neighbors classifier | 0.541136 |
| Random Forest classifier | 0.466280 |

Table

Plotting Graph for Supervised Learning Models with TF-IDF vectorizer

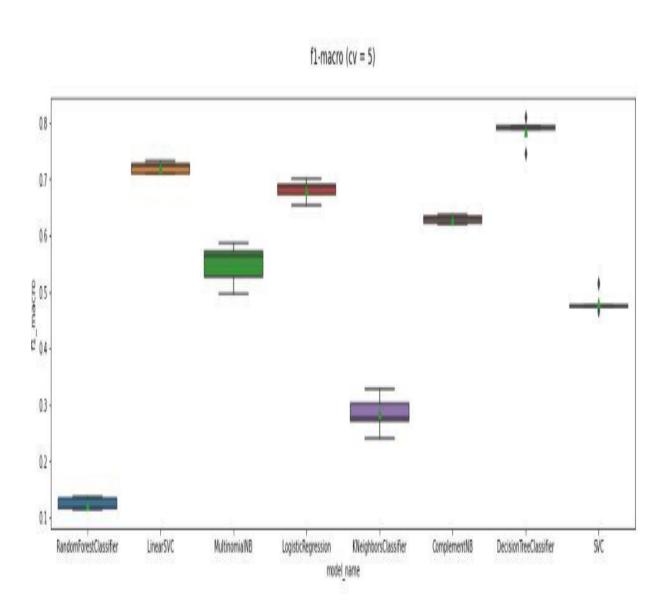


Fig F1 scores of SLM on TF-IDF vectorizers

Plotting Graph for Supervised Learning Models with count vectorizer

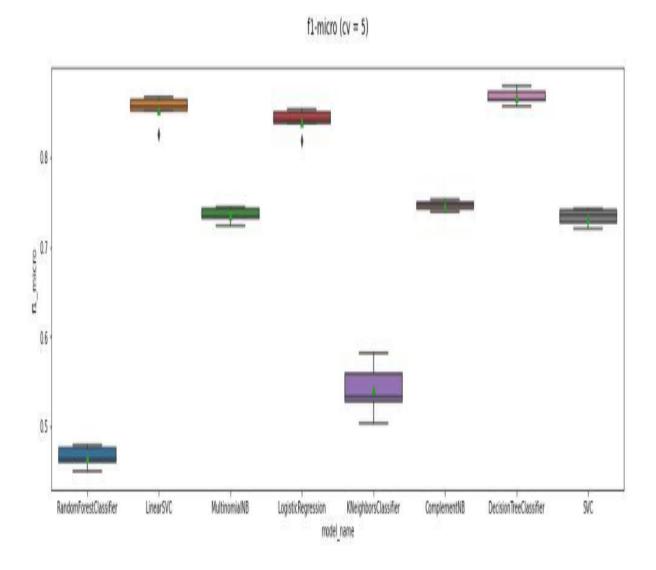


Fig F1 scores of all SLM with count vectorizer

By applying Supervised learning models on both the vectorizers, Decision Tree Classifier performed better among all the other Supervised Learning Models.

Confusion Matrix for the best learning model

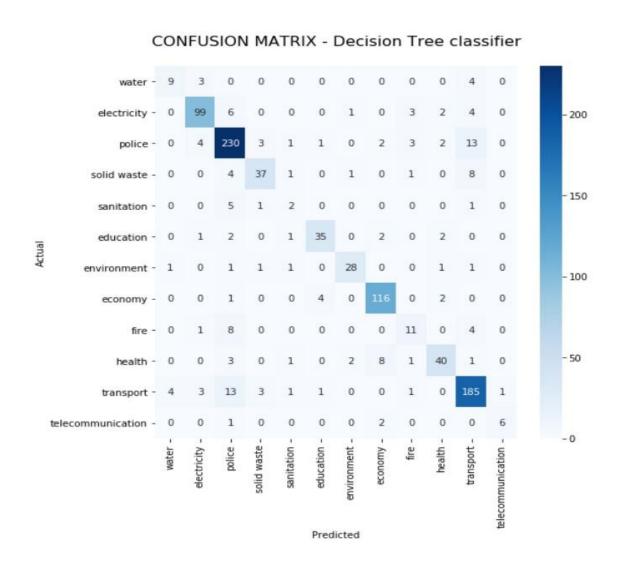


Fig Confusion matrix for decision tree classifier

The classification

The code snippet of Classification of the new tweets into the dimensions mentioned above is shown below

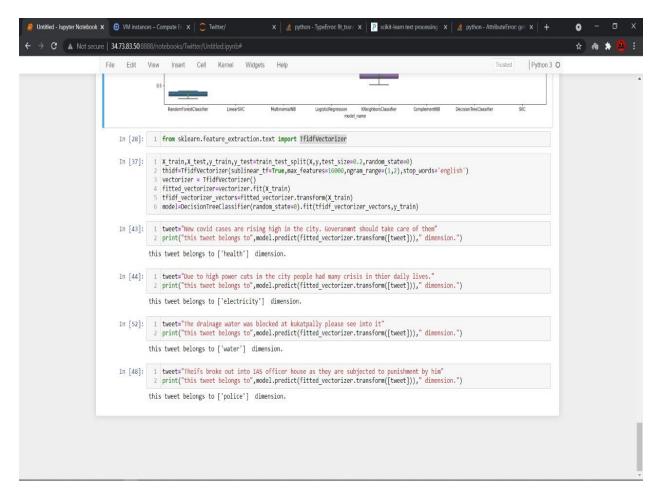


Fig Classification of code snippet

CONCLUSION AND FUTURE SCOPE

This study approached Topic Classification in social networks datasets collected from Twitter. The main question was how to determine a SLM to classify messages into Smart City dimensions using ISO 37120 as the standard model. The feature selection process method was defined in a way to optimize the classifiers

selected, which is the essence of the wrapper approach. Due to the fact the datasets were extremely imbalanced, the classifier's evaluation was done using firstly F1 macro global averages in the features selection process. Considering that the top models were not statistically different from the others following approach was used to determine the best SLM.

REFERENCES

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