

Configuration Manual

MSc Internship Cybersecurity

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MSc Project Submission Sheet

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Module:	Internship			
Supervisor:	Prof. Christos Greco	S		
Submission-Due Date:	12/12/2019			
Project Title:	1 /	s of Machine learning matic Detection Fake		U
Word Count:	1892	Page Count	22	

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Configuration Manual

Comparative Analysis of Machine learning Algorithms using NLP Techniques in Automatic Fake News Detection on Social Media Platforms.

Manoj Kumar Murugesan X18129668

1 Introduction

Configuration manual demonstrates step by step instruction to implement the research topic "Comparative Analysis of Machine learning Algorithms using NLP Techniques in Automatic Fake News Detection on Social Media Platforms." The software and hardware requirement for the implementation are specified in the following sections. Required programming code, corresponding aim, and output results are displayed in sequence. The primary objective of the research is to design an API model that accurately classifies fake news with a low latency rate and evaluates fake rates out of the text. Machine learning algorithms such as LightGBM, XGBoost, AdaBoost, random-forest, and decision-tree were used along with NLP techniques. The following are the description of various technologies our achieve our results.

2 System Requirements

This section describes the system requirements to implement the project without hassles, and always the knowledge on the system specification is an advantage before computing experiments.

2.1 Hardware Requirements

The research was conducted both on the local system and on google cloud platform called **"Colab."** We used a local server to host API. Therefore, a part of the project was implemented using the local system.

2.1.1 Following are the specification used on the local system

1. Hard-Disk Memory – 1TB(HDD)

2.Processor – Intel® Core™ i5-6200U CPU @ 2.30GHz 2.40 GHz
3. RAM – 8GB
4.System OS – 64-bit Windows 10 OS.

2.1.2 Following are the specification cloud platform google 'Colab'

Memory Space - 358 BG
 RAM - 25GB
 Runtime Type - Python 3
 Hardware Accelerator - GPU

2.2 Software Requirements

1. Python 3 - Python was used throughout the implementation process from cleaning the dataset till deploying the final API.

2. MicrosoftOffice365 Excel – was used to import and export datasets. A few cleaning processes were performed with coding through developer option in excel sheet. Datasets were used .CSV file format.

3. Jupyter Notebook – [2] Python code was programmed and executed in the Jupyter Notebook IDE platform. It is an open-source web application that allows users to code, execute, visualize, and share documents. Jupyter Notebook version 6.0.1 was used to code with Python 3.7.2

4. Google Colab – [1] The major part of the project, which is the evaluation of the classification model, was carried out in the google cloud platform called colab. It is a collaboration of jupyter environment on the google cloud environment. The platform is exclusively designed for data researchers to code, analyze data, visualize, and evaluate machine learning models. Google account is enough to get a session allocated with colab.

3 Data Pre-Processing and Evaluation

3.1 Step-by-Step Instruction – Google Colab

- 1. Sign-in to the google account
- 2. Open <u>https://colab.research.google.com/notebooks/welcome.ipynb</u>.
- 3. Choose File -> Python 3->Connect notebook for working environment.
- 4. Choose runtime->Change runtime type->choose GPU for fast execution.
- 5. Rename the default file name and saved it in google drive.

3.2 Installing Packages and Importing raw Data

Base Dataset was acquired from <u>https://www.kaggle.com/c/fake-news/data</u>. Datasets for upsampling 1s (fake news) was obtained from <u>https://www.kaggle.com/jruvika/fake-news-detection</u> and 0s (real news) from <u>https://www.kaggle.com/snapcrack/all-the-news#articles1.csv</u>. All three datasets are downloaded from the respective sources and saved in local drive in .csv format. Packages should be installed before importing and pre-processing of data.

```
import os
import re
import sys
import numpy as np
from scipy.sparse import hstack
import time
import pandas as pd
from nltk.stem.snowball import SnowballStemmer
from sklearn.preprocessing import LabelEncoder
import wordbatch
from wordbatch.extractors import WordBag, WordHash
from nltk.corpus import stopwords
import pickle as pkl
import gzip
from wordcloud import WordCloud, STOPWORDS
```

3.3 Importing Datasets

Required datasets are uploaded in google drive and imported from there .Panda library imported as pd is used to import data.

```
train_dataset = pd.read_csv('G:/spam-thesis/Kaggle-tweetsets/fakenewstraindata1.csv',encoding='ISO-8859-1')
train_fake_dataset = pd.read_csv('G:/spam-thesis/Kaggle-tweetsets/fakedataAdd1.csv')
train_real_dataset = pd.read_csv('Documents/realnewsadd.csv')
test_dataset = pd.read_csv('G:/spam-thesis/Kaggle-tweetsets/fakenewstestdata1.csv')
```

Variable Description:

Train_dataset and test_dataset are the base dataset, train_fake_dataset is the 1s fake news dataset, and train_real_dataset is 0s real news dataset.

3.4 Data Merging and cleaning

The base dataset and other two datasets for upsampling are imported and merged as follows.



Description: First Base dataset and 1s fake dataset is filled to remove empty records, drop uncommon columns other than 'author', 'text', 'title', 'label'. Fake news dataset is added with a new column called label and filled in with 1s. Finally merged dataset is exported.

```
train_real_dataset = pa.read_csv('Documents/realnewsadd.csv')
dataset_fake = pa.read_csv('G:/spam-thesis/Kaggle-tweetsets/final_Datasetfake3.csv',encoding='ISO-8859-1')
train_real_dataset['label'] = 0
train_real_dataset['label'] = 0
train_real_dataset_final = train_real_dataset[['title', 'text', 'month'], axis=1, inplace=True)
train_real_dataset_final = train_real_dataset[['title', 'text', 'author', 'label']]
print("Filling the spaces")
# fill nans
train_real_dataset_final['author'].fillna('No author', inplace=True)
train_real_dataset_final['title'].fillna('No title', inplace=True)
train_real_dataset_final['title'].fillna('No news', inplace=True)
print("Merging with Fake and train dataset")
dataset_final = dataset_fake.append(train_real_dataset_final)
dataset_final_dotpna(inplace=True)
print("Saving final Dataset")
dataset_final.to_csv('G:/spam-thesis/Kaggle-tweetsets/final_Datasetv3.csv', index=False)
print("Done")
Filling the spaces
Merging with Fake and train dataset
```

Description: In the second step, the previously exported dataset is merged with 0s real news. The real news dataset is added with label column 0s, and the final merged dataset is exported.

3.5 Removing Noises

Unwanted symbols and characters are removed to reduce space complexity and the efficiency of the algorithm. This is done using developer option in excel and following code.

```
Function Remove(Str As String) As String
Dim xChars As String
Dim I As Long
xChars = "/."",0123456789_#$%@!()^*®Âš¯Ž&Ãf™€¢Â£Đ½D½Ñ∢еœâ€©"
For I = 1 To Len(xChars)
        Str = Replace$(Str, Mid$(xChars, I, 1), "")
Next
Remove = Str
End Function
```

Description: In the above code, special character which are to be removed are blacklisted and removed.

3.6 Data Pre-processing

3.6.1 Variable Encoding

The following code encoded the author column.

```
] print("encoded")
    train['author'].fillna('no auth', inplace=True)
    lab = LabelEncoder()
    train['author_category'] = lab.fit_transform(train['author'])
    train.head()
C→ encoded
                              author label
                                                                                                                                 title author_category
                                                                                   text
                       Daniel J. Flynn 0
     0
                                              Ever get the feeling your life circles the rou... FLYNN: Hillary Clinton Big Woman on Campus - B...
                                                                                                                                                     862
     1
                     Daniel Nussbaum 0 In these trying times Jackie Mason is the Voic... Jackie Mason: Hollywood Would Love Trump if He...
                                                                                                                                                     869
                      Alissa J. Rubin 0 PARIS 🛛 France chose an idealistic traditio... Beno®t Hamon Wins French Socialist Partys Pres...
     2
                                                                                                                                                     182
     3 Megan Twohey and Scott Shane 0 A week before Michael T Flynn resigned as nati... A Back-Channel Plan for Ukraine and Russia Cou...
                                                                                                                                                    2363
                          Aaron Klein 0 Organizing for Action the activist group that ... Obamas Organizing for Action Partners with Sor...
                                                                                                                                                      65
```

3.6.2 Stemming, Normalization, Removal of empty cells and stopwords

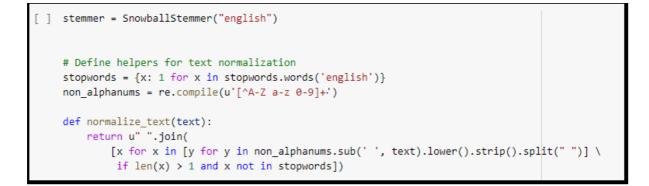
Empty cells are filled in with the code below.

```
[ ] print("Fill up")
    data_append['author'].fillna('no auth', inplace=True)
    data_append['title'].fillna('no tit', inplace=True)
    data_append['text'].fillna('no txt', inplace=True)
    Fill up
```

Texts were stemmed to extract root words from its branches using the following code.

```
[ ] print("stemming starts")
    data_append['title_stemmed'] = data_append['title'].map(lambda x: ' '.join([stemmer.stem(y) for y in x.split(' ')]))
    print("stemming_text")
    data_append['text_stemmed'] = data_append['text'].map(lambda x: ' '.join([stemmer.stem(y) for y in x.split(' ')]))
    C> stemming starts
    stemming_text
```

Texts were normalized, and stopwords were removed with the following code.



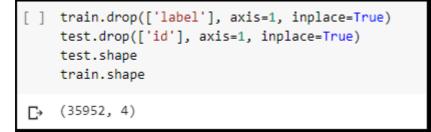
3.7 Evaluation of LightGBM and XGBoost Classification Models.

3.7.1 Bag of Words – Document-Term Matrix

Train Dataset size is calculated and stored in train_size variable and label column that has 0s and 1s are stored in variable 'y' as shown below.

```
[ ] train_size = train.shape[0]
y = train['label']
test_ids = test['id']
test_size = test.shape[0]
print(train.shape)
```

Description: Once labels are stored in variable 'y', column label is dropped to reduce space complexity.



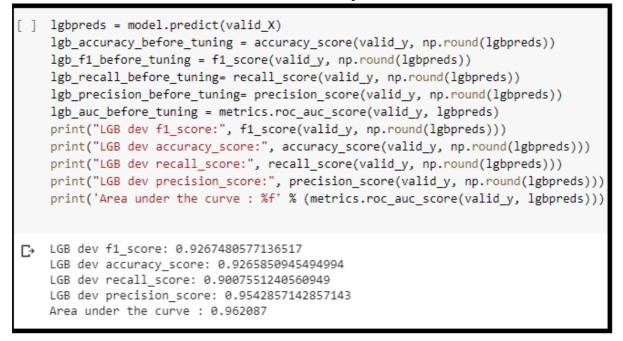
Description: Data is transformed using WordBatch library and from which WordBag function is imported to assign a weight to each word and generate features. The dataset is then normalized using Normalize_text function, which calls above mentioned function and does the pre-processing process. Finally, the transformed dataset is sparsed horizontally using hstack.



3.7.2 LightGBM

Dataset split is done to train and validated with the remaining portion of the dataset, as shown below. Earl stopping round is given to stop when validation results go too weak.

The Classification model is evaluated with metric imported from sklearn, as shown below.



The randomized search function is used to find the best combination of parameters for tuning, as shown below.



The best parameters, as chosen by a randomized search, is displayed below.

Parallel(n_jobs=1)]: Done 20 out of 20 | elapsed: 40.1min finished 'subsample': 0.85, 'reg_alpha': 0.01, 'num_leaves': 60, 'n_estimators': 2000, 'min_split_gain': 0.3, 'min_samples_split': 10, 'min_samples_leaf': 4, 'max_depth': 20, 'learning_rate': 0.03, 'colsample_byt

The model was executed with given best parameters from the hyper-tuning technique.



3.7.3 XGBoost

XGBoost model was built with bag of words data transformation technique, and data splits were did as shown below.

```
X = sparse_data[:train_size]
X_test = sparse_data[train_size:]
train_X, valid_X, train_y, valid_y = train_test_split(X, y, test_size=0.3, random_state=5)
print('train_X')
print(train_X.shape)
print(X_test)
print(valid_X.shape)
```

XGBoost built with default parameters.



XGBoost algorithm was tuned using a randomized search technique, and the best combination can be found with code given below.

```
] from sklearn.model_selection import RandomizedSearchCV, GridSearchCV
  import xgboost
  classifier=xgboost.XGBClassifier()
  params={
    "learning_rate" : [0.05, 0.10, 0.15, 0.20, 0.25, 0.30],
   "max depth"
                     : [ 3, 4, 5, 6],
   "min_child_weight" : [ 1, 3, 5, 7 ],
   "gamma"
                     : [ 0.0, 0.1, 0.2 , 0.3, 0.4 ],
   "colsample_bytree" : [ 0.3, 0.4, 0.5 , 0.7 ]
  }
  random_search=RandomizedSearchCV(classifier,param_distributions=params,n_iter=3,scoring='roc_auc',n_jobs=-1,cv=2,verbose=3)
  from datetime import datetime
  # Here we go
  random_search.fit(train_X,train_y)
```

Hyper-parameter tuning gave the best parameters, as shown below.

```
[ ] random_search.best_params_
[ ] random_search.best_params_
[ ] {'colsample_bytree': 0.7,
    'gamma': 0.2,
    'learning_rate': 0.1,
    'max_depth': 5,
    'min_child_weight': 5}
```

XGBoost model with tuning parameters.

```
from xgboost.sklearn import XGBClassifier
xgbmodel= XGBClassifier(colsample_bytree= 0.7,
    gamma=0.2,
    learning_rate= 0.1,
    max_depth= 5,
    min_child_weight= 5)
print(xgbmodel.get_xgb_params())

f ('base_score': 0.5, 'booster': 'gbtree', 'colsample_bylevel': 1, 'colsample_bynode': 1, 'colsample_bytree': 0.7, 'gamma': 0.2, 'learning_rate':
```

3.8 Evaluation Decision tree, Random-forest and AdaBoost Algorithms

3.8.1 TF-IDF – Document-Term Matrix

Ensemble-based machine learning algorithms are efficient with the TF-IDF transformation technique than Bag of words. Texts are vectorized and given n_gram of range from 1 to 3. Algorithms choose the best feature for the best accuracy rate.

```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
test=test_en.fillna(' ')
train=train_en.fillna(' ')
test_en['total']=test_en['title_stemmed']+' '+test_en['author']+test_en['text_stemmed']
train_en['total']=train_en['title_stemmed']+' '+train_en['author']+train_en['text_stemmed']
#tfidf
transformer = TfidfTransformer(smooth_idf=False)
count_vectorizer = CountVectorizer(ngram_range=(1, 3))
counts = count_vectorizer.fit_transform(train_en['total'].values)
tfidf = transformer.fit_transform(counts)
```

Test and Train data is split into 30% and 70%. Label values are stored in the target variable for validation.

```
[ ] targets =train_en['label'].values
test_counts = count_vectorizer.transform(test_en['total'].values)
test_tfidf = transformer.fit_transform(test_counts)
#split in samples
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(tfidf, targets,test_size=0.3, random_state=4)
```

3.8.2 AdaBoost

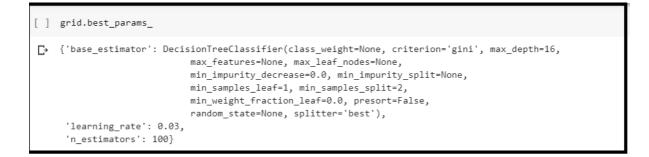
The AdaBoost algorithm was fed with the dataset and ran with default parameters. The code is given below.

```
[ ] from sklearn.ensemble import AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier
Adab= AdaBoostClassifier(DecisionTreeClassifier())
Adab.fit(X_train, y_train)
#
adpred = Adab.predict(X_test)
print('confusion matrix')
print(metrics.confusion_matrix(y_test, adpred))
print('classification_report(y_test, adpred))
ad_accuracy_before_tuning = (metrics.accuracy_score(y_test, adpred))
ad_flscore_before_tuning = metrics.fl_score(y_test, adpred)
ad_recall_before_tuning = metrics.recall_score(y_test, adpred)
ad_roc_before_tuning = metrics.roc_auc_score(y_test, adpred)
print('Accuracy : %f' % (metrics.accuracy_score(y_test, adpred)))
print('Area under the curve : %f' % (metrics.roc_auc_score(y_test, adpred))))
```

AdaBoost was fine-tuned with the hyper-parameter tuning technique. Randomized search technique was used to find the best combination of parameters, and code is as given below.

```
m sklearn.ensemble import AdaBoostClassifier
    t time
  om sklearn.metrics import accuracy_score
from sklearn.metrics import roc auc score
from sklearn.metrics import confusion_matrix
from scipy.stats import randint as sp_randint
from scipy.stats import uniform as sp_uniform
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy score, classification report, confusion matrix
From sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint
base_est = [DecisionTreeClassifier(max_depth = i) for i in [10,13,16,19]]
, 'learning_rate': [0.01, 0.03, 0.1, 0.3, 1]
       }
adac = AdaBoostClassifier()
grid = RandomizedSearchCV(estimator = adac, param_distributions = params, n_iter =2, n_jobs = -1, cv = 2, scoring = 'accuracy', verbose = 2)
grid.fit(X_train, y_train)
```

The best parameters chosen for better results.



The AdaBoost algorithm was optimized with the best parameters given by the hyperparameter tuning technique, as shown below.

```
from sklearn.tree import DecisionTreeClassifier
Adabt= AdaBoostClassifier(DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=16,
                                                max_features=None, max_leaf_nodes=None,
                                                min_impurity_decrease=0.0, min_impurity_split=None,
                                                min samples leaf=1, min samples split=2,
                                                min_weight_fraction_leaf=0.0, presort=False,
                                                random_state=None, splitter='best'),
                                                learning_rate = 0.03,
                                                n_estimators = 100)
Adabt.fit(X_train, y_train)
adtpred = Adabt.predict(X_test)
ad_accuracy_after_tuning = (metrics.accuracy_score(y_test, adtpred))
ad_f1score_after_tuning = metrics.f1_score(y_test, adtpred)
ad_recall_after_tuning = metrics.recall_score(y_test, adtpred)
ad_roc_after_tuning = metrics.roc_auc_score(y_test, adtpred)
print('confusion matrix')
print(metrics.confusion_matrix(y_test, adtpred))
print('classification report')
print(metrics.classification_report(y_test, adtpred))
```

3.8.3 Random-Forest Algorithm

The random-forest algorithm with default parameters is as given below. The performance was not good without tuning and hence tuned later.

```
[ ] from sklearn.ensemble import RandomForestClassifier
    from sklearn import metrics
    from sklearn.metrics import f1_score, accuracy_score, recall_score, precision_score
    Rand= RandomForestClassifier()
    Rand.fit(X_train, y_train)
    #
    rfpred = Rand.predict(X_test)
    print('confusion matrix without tuning')
    print(metrics.confusion_matrix(y_test, rfpred))
    print('classification report')
    rf accuracy before tuning = metrics.accuracy score(y test, rfpred)
    rf_flscore_before_tuning = metrics.fl_score(y_test, rfpred)
    rf_precison_before_tuning = metrics.precision_score(y_test, rfpred)
    rf_recall_before_tuning = metrics.recall_score(y_test, rfpred)
    rf_auc_before_tuning = metrics.roc_auc_score(y_test, rfpred)
    print(metrics.classification_report(y_test, rfpred))
    print('Accuracy : %f' % (metrics.accuracy_score(y_test, rfpred)))
    print('Area under the curve : %f' % (metrics.roc_auc_score(y_test, rfpred)))
```

Hyper-parameter tuning with a randomized search technique is used to find the best combination of parameters to boost up a random forest algorithm from the impoverished state. The code is as given below



The best combination of parameters given by the hyper-parameters technique is as given below.

```
[ ] rf_random.best_params_
[ ] rf_random.best_params_
[ * {'bootstrap': False,
    'max_depth': 110,
    'max_features': 'auto',
    'min_samples_leaf': 1,
    'min_samples_split': 10,
    'n_estimators': 400}
```

The random-forest algorithm reacted very well with tuning parameters and got boosted up to 10%. The code is as follows.

```
from sklearn.ensemble import RandomForestClassifier
from sklearn import metrics
from sklearn.metrics import f1_score, accuracy_score , recall_score , precision_sc
Rand= RandomForestClassifier(bootstrap = False,
max_depth= 110,
max_features = 'auto',
min_samples_leaf = 1,
min_samples_split = 10,
n_estimators = 400)
Rand.fit(X_train, y_train)
#
predrf = Rand.predict(X_test)
rf_accuracy_after_tuning = metrics.accuracy_score(y_test, predrf)
rf_f1score_after_tuning = metrics.f1_score(y_test, predrf)
rf_precison_after_tuning = metrics.precision_score(y_test, predrf)
rf_recall_after_tuning = metrics.recall_score(y_test, predrf)
rf_auc_after_tuning = metrics.roc_auc_score(y_test, predrf)
print('confusion matrix with tuning')
print(metrics.confusion_matrix(y_test, predrf))
print('classification report')
print(metrics.classification_report(y_test, predrf))
print('Accuracy : %f' % (metrics.accuracy_score(y_test, predrf)))
print('Area under the curve : %f' % (metrics.roc_auc_score(y_test, predrf)))
```

3.8.4 Decision Tree Algorithm

The decision tree algorithm with default parameters has given excellent performance, and code is as given below.

```
1 from sklearn.tree import DecisionTreeClassifier
   from sklearn import metrics
   from sklearn.metrics import f1_score, accuracy_score , recall_score , precision_score
  clf = DecisionTreeClassifier()
   # Train Decision Tree Classifer
  clf = clf.fit(X_train,y_train)
  #Predict the response for test dataset
   #
  dpred = clf.predict(X_test)
  print('confusion matrix')
  print(metrics.confusion_matrix(y_test, dtpred))
  print('classification report')
  print(metrics.classification_report(y_test, dpred))
  dcc_accuracy_before_tuning = metrics.accuracy_score(y_test, dpred)
  dcc_f1score_before_tuning = metrics.f1_score(y_test, dpred)
  dcc_recall_before_tuning = metrics.recall_score(y_test, dpred)
  dcc_roc_before_tuning = metrics.roc_auc_score(y_test, dpred)
  print('Accuracy : %f' % (metrics.accuracy_score(y_test, dpred)))
  print('Area under the curve : %f' % (metrics.roc_auc_score(y_test, dpred)))
```

Hyper-Parameter tuning was used to find the best combination of parameters. The result and the code is as shown below.

```
[ ] from sklearn.model_selection import RandomizedSearchCV
from sklearn.tree import DecisionTreeClassifier
from scipy.stats import randint
param_dist = {"max_depth" : [3, None],
        "min_samples_leaf": randint(1,9),
        "criterion": ["gini", "entropy"]}
tree = DecisionTreeClassifier()
tree_cv = RandomizedSearchCV(tree, param_dist, cv=3)
tree_cv.fit(X_train, y_train)
print("Tuned Decision Tree parameters: {}".format(tree_cv.best_params_))
print("Best SCore is {}".format(tree_cv.best_score_))
```

Decision Tree with tuning parameters has shown a small improvement, and the code is as given below.



4 Evaluation metrics

Finally, all the classification model is evaluated based on a few metrics imported from sklearn library like accuracy, precision, f1-score, recall rate, and AUC. The code for the evaluation and results of all the models together tabulated as follows.

0	from tabulate import tabulate table = [["Decision Tree without Hyper-parameter Tuning",dcc_accuracy_before_tuning, dcc_fiscore_before_tuning, dcc_recall_before_tuning, dcc_precision_before_ ["Decision Tree with Hyper-parameter Tuning",dcc_accuracy_after_tuning, dcc_fiscore_after_tuning, dcc_recall_after_tuning, dcc_precision_after_tuning,
	["Random forest without Hyper-parameter Tuning",rf_accuracy_before_tuning,
	rf_flscore_before_tuning, rf_recall_before_tuning, rf_precision before_tuning,
	rf_auc_before_tuning], ["Random forest with Hyper-parameter Tuning",rf_accuracy_after_tuning,
	rf_fiscore_after_tuning, rf_recall_after_tuning, rf_precison_after_tuning,
	<pre>rf_auc_after_tuning],</pre>
	["AdaBoost without Hyper-parameter Tuning",ad_accuracy_before_tuning , ad_fiscore_before_tuning, ad_recall_before_tuning, ad_precision_before_tuning , ["AdaBoost Tree with Hyper-parameter Tuning",ad_accuracy_after_tuning, ad_fiscore_after_tuning,ad_recall_after_tuning,ad_precision_after_tuning,ad_re
	["XGBoost without Hyper-parameter Tuning",xg_accuracy_before_tuning, xg_fiscore_before_tuning, xg_recall_before_tuning, xg_precison_before_tuning,xg_e ["XGBoost with Hyper-parameter Tuning",xg_accuracy_after_tuning,xg_fiscore_after_tuning ,xg_recall_after_tuning,xg_precison_after_tuning,xg_auc_after_
	["LightGBM without Hyper-parameter Tuning",1gb_accuracy_before_tuning, 1gb_fi_before_tuning, 1gb_recall_before_tuning, 1gb_precision_before_tuning,1gb_ ["LightGBM with Hyper-parameter Tuning",1gb_accuracy_after_tuning,1gb_fi_after_tuning ,1gb_recall_after_tuning,1gb_precision_after_tuning,1gb_auc_afte
	<pre>print (tabulate(table, headers=["Algorithm", "Accuracy", "f1-score", "Recall", "Precision", "AUC"])) table_cd_DataForeme(table)</pre>

[Algorithm	Accuracy	f1-score	Recall	Precision	AUC
	Decision Tree without Hyper-parameter Tuning	0.886241	0.892113	0.894394	0.889844	0.885797
	Decision Tree with Hyper-parameter Tuning	0.891619	0.896098	0.888752	0.903567	0.891775
	Random forest without Hyper-parameter Tuning	0.797144	0.793857	0.742772	0.852489	0.800111
	Random forest with Hyper-parameter Tuning	0.908214	0.90944	0.87641	0.945057	0.909949
	AdaBoost without Hyper-parameter Tuning	0.877897	0.88424	0.886812	0.881683	0.877411
	AdaBoosst Tree with Hyper-parameter Tuning	0.903486	0.906612	0.890867	0.922922	0.904174
	XGBoost without Hyper-parameter Tuning	0.905989	0.910138	0.914189	0.906123	0.905634
	XGBoost with Hyper-parameter Tuning	0.917486	0.919978	0.910806	0.929337	0.917775
	LightGBM without Hyper-parameter Tuning	0.926585	0.926748	0.900755	0.954286	0.962087
	LightGBM with Hyper-parameter Tuning	0.931591	0.931931	0.908306	0.956818	0.963168

Interpretation: LightGBM has given outstanding performance with the highest AUC and Accuracy rates. Hence, an API model is designed with the LightGBM mechanism of classification and predicted fake news with high accuracy and efficiency.

4 API Model

4.1 Saving Models

LightGBM classification model with the best iteration is saved and exported as a text file that is to be used for the classification model. The code is as given below.

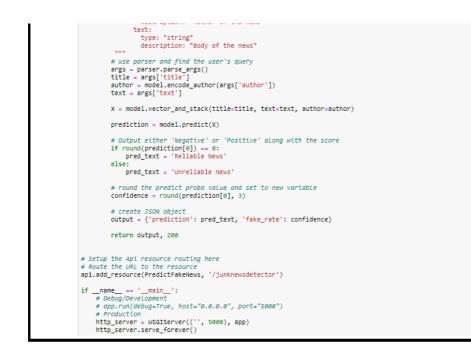
```
] model.save_model('/content/drive/My Drive/model_copy.txt', num_iteration=model.best_itertaion)
with open('/content/drive/My Drive/wb_transform.pkl', 'wb') as model file:
    pkl.dump(wb, model_file, protocol=2)
```

4.2 API Interface Design

The API is developed with the swagger tool, and data-preprocessing such as normalization, word bags are carried out before the classification model makes the prediction.

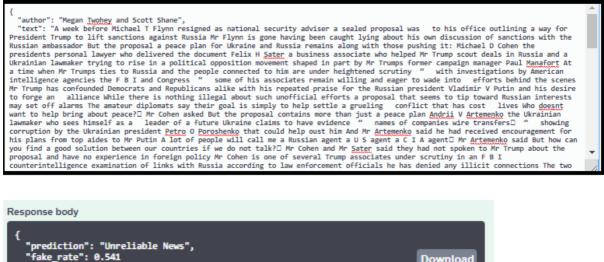
In []:	<pre>import re from flask import Flask from flask_cors import CQRS from gevent.pywsgi import WSGIServer from scipy.sparse import hstack from flasgger import Swagger import pickle as pkl import numpy as np import lightgbm as lgb from nltk.stem.snowball import SnowballStemmer from nltk.corpus import stopwords import pandas as pd</pre>
	<pre>app = Flask(name) #api = Api(app) cors = CORS(app, resources={r"/*": {"origins": "*"}}) api = Api(app) swagger = Swagger(app) stemmer = SnowballStemmer("english") # Define helpers for text normalization stopwords = {x: 1 for x in stopwords.words('english')} non_alphanums = re.compile(u'[^A-Za-z0-9]+') #app = Flask(name) #api = Api(app) def normalize_text(text): return u" ".join(</pre>

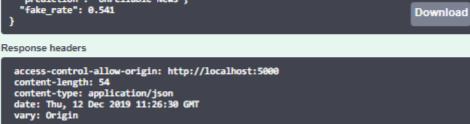
This examples uses FlaskRestFul Resource	
tags:	
- "is fake news?"	
summary: "Check if news is fake"	
description: ""	
operationId: "isfakenews"	
consumes:	
- "application/json"	
produces:	
- "application/json"	
parameters:	
- in: "body"	
name: "body"	
description: "Check if News is fake"	
required: true	
schema :	
<pre>\$ref: "#/definitions/News"</pre>	
responses:	
200':	
description: 'news checked'	
'400':	
description: 'invalid input, object invalid'	
definitions:	
News:	
type: object	
required:	
- "title"	
- "author"	
- "text"	
properties:	
title:	
type: "string"	
description: "Title of the news"	
author:	
type: "string"	
description: "Author of the news"	
text:	
type: "string"	
description: "Body of the news"	



4.3 Installing Packages

Before running the previous code, application file path must be created with package file 'npm'. Therefore 'npm' is installed using 'pip install 'npm' and use code 'npm i -g junknewsdetector' to create directory where all the necessary software packages to host swaggerAPI is imported.





Description: Above screenshots depicts correct prediction of fake news text which is an actual fake news data.

5 Conclusion

Hence, step by step implementation, which is given in this report, works 100%, if any interested third-party people repeat it. Therefore, the research is successful that attained the objectives framed.

References

[1] Medium. (2019). *Google Colab Free GPU Tutorial*. [online] Available at: https://medium.com/deep-learning-turkey/google-colab-free-gpu-tutorial-e113627b9f5d [Accessed 12 Dec. 2019].

[2] Jupyter.org. (2019). *Project Jupyter*. [online] Available at: https://jupyter.org/ [Accessed 12 Dec. 2019].