3_model_building_tuning_F13

November 18, 2022

$0.1 \# 3_model_building_LSTM_F13$

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Description: Applying 7 Algorithms on the daily data.

- 1. Dummy Predictor
- 2. Logistics Regression
- 3. Random Forest
- 4. XGBoost
- 5. LGBM
- 6. FNN
- 7. Tabnet
- We are builing a basic model using the columns and the target provided in the intial dataset.
- Used Feature Set 13 which are basic features and we have calculated the Lag, Ta metrics

0.1.1 Pre requisites:

1. And add the shortcut of the drive link: https://drive.google.com/drive/folders/1F8P3UlqSE6lFpHyBidVArd to your personal drive.

Files: crypto_data_hour_cleaned_v2.csv - Hourly Data

0.1.2 Output files:

Files:model files

• Observation : Overall we have build 6 models and optimised 3 models to see if we can get best results. Amoung all the models we see best results with Xgboost and LGBM

1 Load and transform data

```
[2]: ## Packages to be installed
  !pip install ta
  !pip install bayesian-optimization
  !pip install pytorch-tabnet
  !pip install tensorflow-addons
  !pip install verstack
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Collecting ta
  Downloading ta-0.10.2.tar.gz (25 kB)
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages
(from ta) (1.21.6)
Requirement already satisfied: pandas in /usr/local/lib/python3.7/dist-packages
(from ta) (1.3.5)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-
packages (from pandas->ta) (2022.6)
Requirement already satisfied: python-dateutil>=2.7.3 in
/usr/local/lib/python3.7/dist-packages (from pandas->ta) (2.8.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-
packages (from python-dateutil>=2.7.3->pandas->ta) (1.15.0)
Building wheels for collected packages: ta
  Building wheel for ta (setup.py) ... done
  Created wheel for ta: filename=ta-0.10.2-py3-none-any.whl size=29104
\verb|sha| 256 = 1f34b0 = af75b52 = a36763f4041 = e531a95013a545a86ce62c0fc790f6c157dba| \\
  Stored in directory: /root/.cache/pip/wheels/31/31/f1/f2ff471bbc5b84a4b973698c
eecdd453ae043971791adc3431
Successfully built ta
Installing collected packages: ta
Successfully installed ta-0.10.2
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Collecting bayesian-optimization
  Downloading bayesian optimization-1.3.1-py3-none-any.whl (16 kB)
Requirement already satisfied: numpy>=1.9.0 in /usr/local/lib/python3.7/dist-
packages (from bayesian-optimization) (1.21.6)
Requirement already satisfied: scikit-learn>=0.18.0 in
/usr/local/lib/python3.7/dist-packages (from bayesian-optimization) (1.0.2)
Requirement already satisfied: scipy>=1.0.0 in /usr/local/lib/python3.7/dist-
packages (from bayesian-optimization) (1.7.3)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-
packages (from scikit-learn>=0.18.0->bayesian-optimization) (1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.7/dist-packages (from scikit-learn>=0.18.0->bayesian-
optimization) (3.1.0)
Installing collected packages: bayesian-optimization
Successfully installed bayesian-optimization-1.3.1
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Collecting pytorch-tabnet
  Downloading pytorch_tabnet-4.0-py3-none-any.whl (41 kB)
                       | 41 kB 537 kB/s
Requirement already satisfied: scipy>1.4 in /usr/local/lib/python3.7/dist-
packages (from pytorch-tabnet) (1.7.3)
Requirement already satisfied: numpy<2.0,>=1.17 in
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/usr/local/lib/python3.7/dist-packages (from pytorch-tabnet) (1.21.6)
Requirement already satisfied: tqdm<5.0,>=4.36 in /usr/local/lib/python3.7/dist-
packages (from pytorch-tabnet) (4.64.1)
Requirement already satisfied: torch<2.0,>=1.2 in /usr/local/lib/python3.7/dist-
packages (from pytorch-tabnet) (1.12.1+cu113)
Requirement already satisfied: scikit_learn>0.21 in
/usr/local/lib/python3.7/dist-packages (from pytorch-tabnet) (1.0.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.7/dist-packages (from scikit_learn>0.21->pytorch-tabnet)
(3.1.0)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-
packages (from scikit_learn>0.21->pytorch-tabnet) (1.2.0)
Requirement already satisfied: typing-extensions in
/usr/local/lib/python3.7/dist-packages (from torch<2.0,>=1.2->pytorch-tabnet)
Installing collected packages: pytorch-tabnet
Successfully installed pytorch-tabnet-4.0
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Collecting tensorflow-addons
  Downloading tensorflow_addons-0.18.0-cp37-cp37m-manylinux_2_17_x86_64.manylinu
x2014 x86 64.whl (1.1 MB)
                       | 1.1 MB 4.8 MB/s
Requirement already satisfied: typeguard>=2.7 in
/usr/local/lib/python3.7/dist-packages (from tensorflow-addons) (2.7.1)
Requirement already satisfied: packaging in /usr/local/lib/python3.7/dist-
packages (from tensorflow-addons) (21.3)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in
/usr/local/lib/python3.7/dist-packages (from packaging->tensorflow-addons)
(3.0.9)
Installing collected packages: tensorflow-addons
Successfully installed tensorflow-addons-0.18.0
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Collecting verstack
 Downloading verstack-3.2.5.tar.gz (9.6 MB)
                      | 9.6 MB 5.0 MB/s
Requirement already satisfied: pandas in /usr/local/lib/python3.7/dist-
packages (from verstack) (1.3.5)
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-packages
(from verstack) (1.21.6)
Requirement already satisfied: xgboost in /usr/local/lib/python3.7/dist-packages
(from verstack) (0.90)
Collecting scikit-learn==1.0.1
 Downloading
scikit_learn-1.0.1-cp37-cp37m-manylinux_2_12_x86_64.manylinux2010_x86_64.whl
(23.2 MB)
     Ι
                       | 23.2 MB 1.4 MB/s
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Collecting lightgbm==3.3.0
  Downloading lightgbm-3.3.0-py3-none-manylinux1_x86_64.whl (2.0 MB)
                       | 2.0 MB 47.3 MB/s
Collecting optuna == 2.10.0
  Downloading optuna-2.10.0-py3-none-any.whl (308 kB)
                       | 308 kB 69.4 MB/s
Collecting plotly==5.3.1
 Downloading plotly-5.3.1-py2.py3-none-any.whl (23.9 MB)
                       | 23.9 MB 1.3 MB/s
Requirement already satisfied: matplotlib in
/usr/local/lib/python3.7/dist-packages (from verstack) (3.2.2)
Collecting python-dateutil==2.8.1
  Downloading python_dateutil-2.8.1-py2.py3-none-any.whl (227 kB)
                       | 227 kB 36.6 MB/s
Collecting holidays==0.11.3.1
  Downloading holidays-0.11.3.1-py3-none-any.whl (155 kB)
                       | 155 kB 66.7 MB/s
Requirement already satisfied: mlxtend in /usr/local/lib/python3.7/dist-
packages (from verstack) (0.14.0)
Collecting tensorflow==2.7.0
  Downloading https://us-python.pkg.dev/colab-wheels/public/tensorflow/tensorflo
w-2.7.0%2Bzzzcolab20220506150900-cp37-cp37m-linux x86 64.whl (665.5 MB)
                       | 665.5 MB 19 kB/s
Collecting keras==2.7.0
 Downloading keras-2.7.0-py2.py3-none-any.whl (1.3 MB)
                       | 1.3 MB 63.6 MB/s
Collecting category_encoders==2.4.0
  Downloading category_encoders-2.4.0-py2.py3-none-any.whl (86 kB)
                       | 86 kB 5.5 MB/s
Requirement already satisfied: scipy>=1.0.0 in
/usr/local/lib/python3.7/dist-packages (from category_encoders==2.4.0->verstack)
Requirement already satisfied: patsy>=0.5.1 in /usr/local/lib/python3.7/dist-
packages (from category_encoders==2.4.0->verstack) (0.5.3)
Requirement already satisfied: statsmodels>=0.9.0 in
/usr/local/lib/python3.7/dist-packages (from category_encoders==2.4.0->verstack)
Requirement already satisfied: convertdate>=2.3.0 in
/usr/local/lib/python3.7/dist-packages (from holidays==0.11.3.1->verstack)
Requirement already satisfied: hijri-converter in /usr/local/lib/python3.7/dist-
packages (from holidays==0.11.3.1->verstack) (2.2.4)
Requirement already satisfied: korean-lunar-calendar in
/usr/local/lib/python3.7/dist-packages (from holidays==0.11.3.1->verstack)
(0.3.1)
Requirement already satisfied: wheel in /usr/local/lib/python3.7/dist-packages
(from lightgbm==3.3.0->verstack) (0.38.3)
Collecting cmaes>=0.8.2
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Downloading cmaes-0.9.0-py3-none-any.whl (23 kB)
Requirement already satisfied: tqdm in /usr/local/lib/python3.7/dist-packages
(from optuna==2.10.0->verstack) (4.64.1)
Collecting alembic
  Downloading alembic-1.8.1-py3-none-any.whl (209 kB)
                       | 209 kB 50.9 MB/s
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.7/dist-packages (from optuna==2.10.0->verstack) (21.3)
Collecting colorlog
 Downloading colorlog-6.7.0-py2.py3-none-any.whl (11 kB)
Requirement already satisfied: sqlalchemy>=1.1.0 in
/usr/local/lib/python3.7/dist-packages (from optuna==2.10.0->verstack) (1.4.43)
Requirement already satisfied: PyYAML in /usr/local/lib/python3.7/dist-packages
(from optuna==2.10.0->verstack) (6.0)
Collecting cliff
  Downloading cliff-3.10.1-py3-none-any.whl (81 kB)
                       | 81 kB 9.6 MB/s
Requirement already satisfied: tenacity>=6.2.0 in
/usr/local/lib/python3.7/dist-packages (from plotly==5.3.1->verstack) (8.1.0)
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages
(from plotly==5.3.1->verstack) (1.15.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.7/dist-packages (from scikit-learn==1.0.1->verstack)
(3.1.0)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-
packages (from scikit-learn==1.0.1->verstack) (1.2.0)
Requirement already satisfied: astunparse>=1.6.0 in
/usr/local/lib/python3.7/dist-packages (from tensorflow==2.7.0->verstack)
Requirement already satisfied: termcolor>=1.1.0 in
/usr/local/lib/python3.7/dist-packages (from tensorflow==2.7.0->verstack)
Requirement already satisfied: wrapt>=1.11.0 in /usr/local/lib/python3.7/dist-
packages (from tensorflow==2.7.0->verstack) (1.14.1)
Requirement already satisfied: h5py>=2.9.0 in /usr/local/lib/python3.7/dist-
packages (from tensorflow==2.7.0->verstack) (3.1.0)
Requirement already satisfied: keras-preprocessing>=1.1.1 in
/usr/local/lib/python3.7/dist-packages (from tensorflow==2.7.0->verstack)
(1.1.2)
Requirement already satisfied: gast<0.5.0,>=0.2.1 in
/usr/local/lib/python3.7/dist-packages (from tensorflow==2.7.0->verstack)
(0.4.0)
Requirement already satisfied: typing-extensions>=3.6.6 in
/usr/local/lib/python3.7/dist-packages (from tensorflow==2.7.0->verstack)
(4.1.1)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in
/usr/local/lib/python3.7/dist-packages (from tensorflow==2.7.0->verstack)
(1.50.0)
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Requirement already satisfied: google-pasta>=0.1.1 in
/usr/local/lib/python3.7/dist-packages (from tensorflow==2.7.0->verstack)
(0.2.0)
Requirement already satisfied: opt-einsum>=2.3.2 in
/usr/local/lib/python3.7/dist-packages (from tensorflow==2.7.0->verstack)
Requirement already satisfied: protobuf>=3.9.2 in /usr/local/lib/python3.7/dist-
packages (from tensorflow==2.7.0->verstack) (3.19.6)
Requirement already satisfied: flatbuffers<3.0,>=1.12 in
/usr/local/lib/python3.7/dist-packages (from tensorflow==2.7.0->verstack) (1.12)
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.21.0 in
/usr/local/lib/python3.7/dist-packages (from tensorflow==2.7.0->verstack)
(0.27.0)
Requirement already satisfied: libclang>=9.0.1 in /usr/local/lib/python3.7/dist-
packages (from tensorflow==2.7.0->verstack) (14.0.6)
Requirement already satisfied: absl-py>=0.4.0 in /usr/local/lib/python3.7/dist-
packages (from tensorflow==2.7.0->verstack) (1.3.0)
Collecting tensorflow-estimator<2.8,~=2.7.0rc0
 Downloading tensorflow_estimator-2.7.0-py2.py3-none-any.whl (463 kB)
                       | 463 kB 69.4 MB/s
Requirement already satisfied: tensorboard~=2.6 in
/usr/local/lib/python3.7/dist-packages (from tensorflow==2.7.0->verstack)
Requirement already satisfied: pymeeus<=1,>=0.3.13 in
/usr/local/lib/python3.7/dist-packages (from
convertdate>=2.3.0->holidays==0.11.3.1->verstack) (0.5.11)
Requirement already satisfied: cached-property in /usr/local/lib/python3.7/dist-
packages (from h5py>=2.9.0->tensorflow==2.7.0->verstack) (1.5.2)
Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in
/usr/local/lib/python3.7/dist-packages (from
packaging>=20.0->optuna==2.10.0->verstack) (3.0.9)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-
packages (from pandas->verstack) (2022.6)
Requirement already satisfied: importlib-metadata in
/usr/local/lib/python3.7/dist-packages (from
sqlalchemy>=1.1.0->optuna==2.10.0->verstack) (4.13.0)
Requirement already satisfied: greenlet!=0.4.17 in
/usr/local/lib/python3.7/dist-packages (from
sqlalchemy>=1.1.0->optuna==2.10.0->verstack) (2.0.1)
Requirement already satisfied: setuptools>=41.0.0 in
/usr/local/lib/python3.7/dist-packages (from
tensorboard~=2.6->tensorflow==2.7.0->verstack) (57.4.0)
Requirement already satisfied: google-auth-oauthlib<0.5,>=0.4.1 in
/usr/local/lib/python3.7/dist-packages (from
tensorboard~=2.6->tensorflow==2.7.0->verstack) (0.4.6)
Requirement already satisfied: werkzeug>=1.0.1 in /usr/local/lib/python3.7/dist-
packages (from tensorboard~=2.6->tensorflow==2.7.0->verstack) (1.0.1)
Requirement already satisfied: tensorboard-plugin-wit>=1.6.0 in
```

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/usr/local/lib/python3.7/dist-packages (from
tensorboard~=2.6->tensorflow==2.7.0->verstack) (1.8.1)
Requirement already satisfied: google-auth<3,>=1.6.3 in
/usr/local/lib/python3.7/dist-packages (from
tensorboard~=2.6->tensorflow==2.7.0->verstack) (2.14.1)
Requirement already satisfied: tensorboard-data-server<0.7.0,>=0.6.0 in
/usr/local/lib/python3.7/dist-packages (from
tensorboard~=2.6->tensorflow==2.7.0->verstack) (0.6.1)
Requirement already satisfied: requests<3,>=2.21.0 in
/usr/local/lib/python3.7/dist-packages (from
tensorboard~=2.6->tensorflow==2.7.0->verstack) (2.23.0)
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.7/dist-
packages (from tensorboard~=2.6->tensorflow==2.7.0->verstack) (3.4.1)
Requirement already satisfied: cachetools<6.0,>=2.0.0 in
/usr/local/lib/python3.7/dist-packages (from google-
auth<3,>=1.6.3->tensorboard~=2.6->tensorflow==2.7.0->verstack) (5.2.0)
Requirement already satisfied: pyasn1-modules>=0.2.1 in
/usr/local/lib/python3.7/dist-packages (from google-
auth<3,>=1.6.3->tensorboard~=2.6->tensorflow==2.7.0->verstack) (0.2.8)
Requirement already satisfied: rsa<5,>=3.1.4 in /usr/local/lib/python3.7/dist-
packages (from google-
auth<3,>=1.6.3->tensorboard~=2.6->tensorflow==2.7.0->verstack) (4.9)
Requirement already satisfied: requests-oauthlib>=0.7.0 in
/usr/local/lib/python3.7/dist-packages (from google-auth-
oauthlib<0.5,>=0.4.1->tensorboard~=2.6->tensorflow==2.7.0->verstack) (1.3.1)
Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.7/dist-
packages (from importlib-metadata->sqlalchemy>=1.1.0->optuna==2.10.0->verstack)
(3.10.0)
Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in
/usr/local/lib/python3.7/dist-packages (from pyasn1-modules>=0.2.1->google-
auth<3,>=1.6.3->tensorboard~=2.6->tensorflow==2.7.0->verstack) (0.4.8)
Requirement already satisfied: chardet<4,>=3.0.2 in
/usr/local/lib/python3.7/dist-packages (from
requests<3,>=2.21.0->tensorboard~=2.6->tensorflow==2.7.0->verstack) (3.0.4)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in
/usr/local/lib/python3.7/dist-packages (from
requests<3,>=2.21.0->tensorboard~=2.6->tensorflow==2.7.0->verstack) (1.24.3)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-
packages (from
requests<3,>=2.21.0->tensorboard~=2.6->tensorflow==2.7.0->verstack) (2.10)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.7/dist-packages (from
requests<3,>=2.21.0->tensorboard~=2.6->tensorflow==2.7.0->verstack) (2022.9.24)
Requirement already satisfied: oauthlib>=3.0.0 in /usr/local/lib/python3.7/dist-
packages (from requests-oauthlib>=0.7.0->google-auth-
oauthlib<0.5,>=0.4.1->tensorboard~=2.6->tensorflow==2.7.0->verstack) (3.2.2)
Collecting Mako
  Downloading Mako-1.2.4-py3-none-any.whl (78 kB)
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| 78 kB 6.7 MB/s
Requirement already satisfied: importlib-resources in
/usr/local/lib/python3.7/dist-packages (from alembic->optuna==2.10.0->verstack)
(5.10.0)
Collecting pbr!=2.1.0,>=2.0.0
 Downloading pbr-5.11.0-py2.py3-none-any.whl (112 kB)
                      | 112 kB 67.0 MB/s
Collecting stevedore>=2.0.1
 Downloading stevedore-3.5.2-py3-none-any.whl (50 kB)
                      | 50 kB 6.1 MB/s
Collecting autopage>=0.4.0
  Downloading autopage-0.5.1-py3-none-any.whl (29 kB)
Requirement already satisfied: PrettyTable>=0.7.2 in
/usr/local/lib/python3.7/dist-packages (from cliff->optuna==2.10.0->verstack)
(3.5.0)
Collecting cmd2>=1.0.0
 Downloading cmd2-2.4.2-py3-none-any.whl (147 kB)
                      | 147 kB 54.3 MB/s
Requirement already satisfied: wcwidth>=0.1.7 in
/usr/local/lib/python3.7/dist-packages (from
cmd2 >= 1.0.0 - cliff - optuna == 2.10.0 - verstack) (0.2.5)
Collecting pyperclip>=1.6
 Downloading pyperclip-1.8.2.tar.gz (20 kB)
Requirement already satisfied: attrs>=16.3.0 in /usr/local/lib/python3.7/dist-
packages (from cmd2>=1.0.0->cliff->optuna==2.10.0->verstack) (22.1.0)
Requirement already satisfied: MarkupSafe>=0.9.2 in
/usr/local/lib/python3.7/dist-packages (from
Mako->alembic->optuna==2.10.0->verstack) (2.0.1)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.7/dist-packages (from matplotlib->verstack) (1.4.4)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-
packages (from matplotlib->verstack) (0.11.0)
Building wheels for collected packages: verstack, pyperclip
 Building wheel for verstack (setup.py) ... done
  Created wheel for verstack: filename=verstack-3.2.5-py3-none-any.whl
size=83395
sha256=82621d4069ca53242eff4410dceadb0d423a11515c68281b233991c6fb701704
  Stored in directory: /root/.cache/pip/wheels/43/4a/43/a38229cce0db60c2f7f124f2
9d15e4b6cbd5f28cdb7441d3ff
 Building wheel for pyperclip (setup.py) ... done
  Created wheel for pyperclip: filename=pyperclip-1.8.2-py3-none-any.whl
size=11137
Stored in directory: /root/.cache/pip/wheels/9f/18/84/8f69f8b08169c7bae2dde6bd
7daf0c19fca8c8e500ee620a28
Successfully built verstack pyperclip
Installing collected packages: python-dateutil, pyperclip, pbr, stevedore, Mako,
cmd2, autopage, tensorflow-estimator, scikit-learn, keras, colorlog, cmaes,
```

```
cliff, alembic, tensorflow, plotly, optuna, lightgbm, holidays, category-
encoders, verstack
  Attempting uninstall: python-dateutil
   Found existing installation: python-dateutil 2.8.2
   Uninstalling python-dateutil-2.8.2:
      Successfully uninstalled python-dateutil-2.8.2
  Attempting uninstall: tensorflow-estimator
   Found existing installation: tensorflow-estimator 2.9.0
   Uninstalling tensorflow-estimator-2.9.0:
      Successfully uninstalled tensorflow-estimator-2.9.0
  Attempting uninstall: scikit-learn
    Found existing installation: scikit-learn 1.0.2
    Uninstalling scikit-learn-1.0.2:
      Successfully uninstalled scikit-learn-1.0.2
 Attempting uninstall: keras
    Found existing installation: keras 2.9.0
   Uninstalling keras-2.9.0:
      Successfully uninstalled keras-2.9.0
 Attempting uninstall: tensorflow
   Found existing installation: tensorflow 2.9.2
   Uninstalling tensorflow-2.9.2:
      Successfully uninstalled tensorflow-2.9.2
  Attempting uninstall: plotly
   Found existing installation: plotly 5.5.0
   Uninstalling plotly-5.5.0:
      Successfully uninstalled plotly-5.5.0
  Attempting uninstall: lightgbm
   Found existing installation: lightgbm 2.2.3
   Uninstalling lightgbm-2.2.3:
      Successfully uninstalled lightgbm-2.2.3
 Attempting uninstall: holidays
   Found existing installation: holidays 0.16
   Uninstalling holidays-0.16:
      Successfully uninstalled holidays-0.16
ERROR: pip's dependency resolver does not currently take into account all
the packages that are installed. This behaviour is the source of the following
dependency conflicts.
prophet 1.1.1 requires holidays>=0.14.2, but you have holidays 0.11.3.1 which is
incompatible.
Successfully installed Mako-1.2.4 alembic-1.8.1 autopage-0.5.1 category-
encoders-2.4.0 cliff-3.10.1 cmaes-0.9.0 cmd2-2.4.2 colorlog-6.7.0
holidays-0.11.3.1 keras-2.7.0 lightgbm-3.3.0 optuna-2.10.0 pbr-5.11.0
plotly-5.3.1 pyperclip-1.8.2 python-dateutil-2.8.1 scikit-learn-1.0.1
stevedore-3.5.2 tensorflow-2.7.0+zzzcolab20220506150900 tensorflow-
estimator-2.7.0 verstack-3.2.5
```

```
[6]: ## Import the packages
     import pandas as pd
     import warnings
     warnings.filterwarnings("ignore")
     import matplotlib.pyplot as plt
     import seaborn as sns
     import numpy as np
     import xgboost
     import pickle
     import tensorflow
     # import tensorflow_addons as tfa
     import torch
     from pytorch_tabnet.tab_model import TabNetClassifier
     from tensorflow.keras.layers import Input, Dense, Dropout
     from tensorflow.keras.models import Model
     # from tensorflow.keras.optimizers import SGD, Adam
     from sklearn.dummy import DummyClassifier
     from ta import add_all_ta_features
     from sklearn.model_selection import RandomizedSearchCV
     from sklearn.linear_model import LogisticRegression
     from xgboost.sklearn import XGBClassifier
     from bayes opt import BayesianOptimization
     from sklearn.model_selection import cross_val_score
     #picking models for prediction.
     from sklearn.svm import SVC
     from sklearn.metrics import classification_report
     from sklearn.metrics import accuracy_score, precision_score, recall_score,

¬f1_score
     from sklearn.model_selection import RandomizedSearchCV
     from sklearn.metrics import confusion matrix
     from sklearn.ensemble import RandomForestClassifier
[7]: from pip._internal.utils.misc import get_installed_distributions
     import sys
```

```
[7]: from pip._internal.utils.misc import get_installed_distributions
import sys
#import numpy as np # imported to test whether numpy shows up, which it does!

def get_imported_packages():
    p = get_installed_distributions()
    p = {package.key:package.version for package in p}

imported_modules = set(sys.modules.keys())

imported_modules.remove('pip')

modules = [(m, p[m]) for m in imported_modules if p.get(m, False)]
```

```
return modules
    def generate_requirements(filepath:str, modules):
        with open(filepath, 'w') as f:
            for module, version in modules:
                f.write(f"{module}=={version}")
    generate_requirements('requirements.txt', get_imported_packages())
[]: # file path
    folder_path = '/content/drive/MyDrive/MADS_23_DL_final_project'
    daily = pd.read_csv('crypto_data_daily_cleaned_v1.csv')
[]: daily.head()
[]:
        Open Time
                      Open
                              High
                                        Low
                                               Close
                                                         Volume train_test Crypto
    0 2013-04-01
                    93.155 105.90
                                     93.155
                                             104.750 11008.524
                                                                     Train
                                                                              BTC
    1 2013-04-02 104.720 127.00
                                     99.000
                                             123.016
                                                      24187.398
                                                                     Train
                                                                              BTC
    2 2013-04-03 123.001 146.88 101.511
                                             125.500
                                                      31681.780
                                                                     Train
                                                                              BTC
    3 2013-04-04 125.500 143.00 125.500
                                             135.632
                                                      15035.206
                                                                     Train
                                                                              BTC
    4 2013-04-05 136.000 145.00 135.119
                                             142.990 11697.741
                                                                     Train
                                                                              BTC
        Train / Test Split
[]: # checking the Count of the records
    daily['train test'].value counts(normalize=True)
[]: Train
             0.82546
             0.17454
    Test
    Name: train_test, dtype: float64
[]: df = daily.copy()
[]: # train test split
    train_df = df[df['train_test'] == 'Train']
    test_df = df[df['train_test']=='Test']
[]: train df.head()
[]:
        Open Time
                      Open
                              High
                                        Low
                                               Close
                                                         Volume train_test Crypto
    0 2013-04-01
                    93.155
                           105.90
                                     93.155
                                             104.750
                                                                     Train
                                                      11008.524
                                                                              BTC
    1 2013-04-02
                   104.720
                            127.00
                                     99.000
                                             123.016
                                                      24187.398
                                                                     Train
                                                                              BTC
    2 2013-04-03 123.001
                            146.88
                                    101.511
                                             125.500
                                                      31681.780
                                                                     Train
                                                                              BTC
    3 2013-04-04 125.500
                           143.00 125.500
                                             135.632
                                                     15035.206
                                                                     Train
                                                                              BTC
```

```
4 2013-04-05 136.000 145.00 135.119 142.990 11697.741
                                                                    BTC
                                                            Train
```

```
[]: train_df.columns
[]: Index(['Open Time', 'Open', 'High', 'Low', 'Close', 'Volume', 'train_test',
            'Crypto'],
          dtype='object')
```

Calculate percentage change

```
[]: def calculate_pct_change(df):
         The funnction calculate the pct Change for the all the records for one \sqcup
      \hookrightarrow period.
         input:
         df: The input dataFrame
         output:
         df_pct_change : The dataframe with percentage Calculated.
         coins = df.Crypto.unique()
         df_pct_change = pd.DataFrame()
         for coin in coins:
             x = df[df['Crypto'] == coin]
             x['pct_change_1day'] = x['Close'].pct_change(1)
             df_pct_change = pd.concat([df_pct_change,x])
         return df_pct_change
     test_df = calculate_pct_change(test_df)
```

```
[]: train_df = calculate_pct_change(train_df)
```

```
[]: test_df.head()
```

[]:		Open Time	Open	High	Low	Close	Volume	\
3	8098	2021-10-01	43828.89	48500.00	43287.44	48165.76	38375.517	
3	8099	2021-10-02	48185.61	48361.83	47438.00	47657.69	12310.011	
3	100	2021-10-03	47649.00	49300.00	47119.87	48233.99	14411.104	
3	3101	2021-10-04	48233.99	49530.53	46895.80	49245.54	25695.213	
3	3102	2021-10-05	49244.13	51922.00	49057.18	51493.99	30764.491	

	train_test	Crypto	pct_change_1day
3098	Test	BTC	NaN
3099	Test	BTC	-0.010548
3100	Test	BTC	0.012092
3101	Test	BTC	0.020972
3102	Test	BTC	0 045658

3.1 Generate new features

3.1.1 Lag features, moving average, exponential moving average and market cap

```
[]: def create_shift_features(df, col = 'pct_change_1day',lags=10, freq='daily'):
         Creating the lag volatitlity for the data.
         input:
         df: the input dataframe
         col: the column on which the calculation should be made.
         lags: The periods for which the calculations should be made
         freq: Teh frequencey or time period
         output:
         df: the final dataframe withe lag columns added
       if freq=='daily':
        mul_fact = 1
         symbol = 'd'
       elif freq=='weekly':
         mul_fact = 7
         symbol = 'W'
       elif freq=='monthly':
         mul_fact = 31
         symbol = 'mon'
      else:
         # setting default to daily
         mul_fact = 1
         symbol = 'd'
       for iterator in range(1,lags+1):
```

```
df['{}_{}_lag'.format(iterator, symbol)] = df[col].
shift(periods=iterator*mul_fact)
# df.loc[:,"Volatility_{}_{}".format(iterator, symbol)] = df[col].
rolling(iterator*mul_fact).std().shift(1)

return df
```

[]:

```
[]: #list to collect all relevant lags
    def create_analysis_colums(df):
        Create the additional features for the model building
        input:
        df: the input dataframe
        output:
        master_df: the final dataframe withe lag, ta columns added
      master_df = pd.DataFrame()
      crypto_coins = df['Crypto'].unique()
      for coin in crypto_coins:
        temp_df = df[df['Crypto'] == coin]
        temp_df['pct_change_1day'] = temp_df['Close'].pct_change()
        # temp df = create shift features(temp df.copy(),col =
      → 'pct_change_1day', lags=5, freq='weekly')
        temp_df = create_shift_features(temp_df.copy(),col =__
      temp df = create shift features(temp df.copy(),col = ___

¬'pct_change_1day',lags=4, freq='weekly')
        temp_df = create_shift_features(temp_df.copy(),col =__

¬'pct_change_1day',lags=8, freq='daily')
        temp_df = add_all_ta_features(temp_df.copy(), open="Open", high="High", u
      ⇔low="Low", close="Close", volume="Volume", fillna=True)
        if master_df.empty :
          master_df = temp_df
        else:
          master_df = pd.concat([master_df, temp_df])
      return master_df
```

```
[]: # Creating the additional columns for the model building
    train_df =create_analysis_colums(train_df)
    test_df =create_analysis_colums(test_df)
[]: train_df.columns
[]: Index(['Open Time', 'Open', 'High', 'Low', 'Close', 'Volume', 'train_test',
            'Crypto', 'pct_change_1day', '1_mon_lag',
            'momentum_ppo', 'momentum_ppo_signal', 'momentum_ppo_hist',
           'momentum_pvo', 'momentum_pvo_signal', 'momentum_pvo_hist',
            'momentum_kama', 'others_dr', 'others_dlr', 'others_cr'],
          dtype='object', length=109)
[]: # adding the total value ratio and market value columns
    train_df =create_market_volumn_features(train_df.copy())
    test_df =create_market_volumn_features(test_df.copy())
[]: # printing the 50 columns
    train_df.columns[:50]
[]: Index(['Open Time', 'Open', 'High', 'Low', 'Close', 'Volume', 'train_test',
            'Crypto', 'pct_change_1day', '1_mon_lag', '2_mon_lag', '1_W_lag',
           '2_W_lag', '3_W_lag', '4_W_lag', '1_d_lag', '2_d_lag', '3_d_lag',
            '4_d_lag', '5_d_lag', '6_d_lag', '7_d_lag', '8_d_lag', 'volume_adi',
            'volume_obv', 'volume cmf', 'volume_fi', 'volume em', 'volume_sma_em',
            'volume_vpt', 'volume_vwap', 'volume_mfi', 'volume_nvi',
            'volatility_bbm', 'volatility_bbh', 'volatility_bbl', 'volatility_bbw',
           'volatility_bbp', 'volatility_bbhi', 'volatility_bbli',
            'volatility_kcc', 'volatility_kch', 'volatility_kcl', 'volatility_kcw',
            'volatility_kcp', 'volatility_kchi', 'volatility_kcli',
            'volatility_dcl', 'volatility_dch', 'volatility_dcm'],
          dtype='object')
[]: # Based on our previous model building activities we have selected specific,
      ⇔columns
    feat_to_keep = ['Open Time', 'Open', 'High', 'Low', 'Close', 'Volume', |
      'Crypto',
      -- 'pct_change_1day', 'volatility_kcw', 'trend_cci', 'volume_adi', 'momentum_ppo_hist|, 'momentum_s
                  'volatility_dcw','volume_vpt','volatility_bbw','Total_Value',_
     lag cols = [col for col in train df.columns if 'lag' in col]
    #volatility_cols = [col for col in train_df.columns if 'Volatility' in col]
    feat_to_keep.extend(lag_cols)
     #feat_to_keep.extend(volatility_cols)
```

```
[]: # length of the columns selected
     len(feat_to_keep)
[]: 36
[]: # slicing the tain and test columns
     train_df = train_df[feat_to_keep]
     test_df = test_df[feat_to_keep]
[]: # length of the columns selected
     len(train_df.columns)
[]: 36
[]: # extracting the importatant features
     impo_feat =_
     →['volatility_kcw','trend_cci','volume_adi','momentum_ppo_hist','momentum_stoch|,'volatility
                  'volatility_dcw','volume_vpt','volatility_bbw']
     for feat in impo_feat:
      train_df[feat] = train_df[feat].shift(1)
      test_df[feat] = test_df[feat].shift(1)
```

3.2 Extract year, month, day, hour and weekday from time stamp

3.2.1 Encoding of ordinals

```
[]: def encode_cyclicals(df_x):
         The function converts the date features encoded in the Sine and cosines.
         Input:
         df_x: Input data frame to be processed
         Output :
         df_x: processed dataframe.
         df_x['month_sin'] = np.sin(2*np.pi*df_x.month/12)
         df_x['month_cos'] = np.cos(2*np.pi*df_x.month/12)
         df_x.drop('month', axis=1, inplace=True)
         df_x['day_sin'] = np.sin(2*np.pi*df_x.day/31)
         df_x['day_cos'] = np.cos(2*np.pi*df_x.day/31)
         df_x.drop('day', axis=1, inplace=True)
         df_x['dayofweek_sin'] = np.sin(2*np.pi*df_x.weekday/7)
         df_x['dayofweek_cos'] = np.cos(2*np.pi*df_x.weekday/7)
         df_x.drop('weekday', axis=1, inplace=True)
         df_x['hour_sin'] = np.sin(2*np.pi*df_x.hour/24)
         df_x['hour_cos'] = np.cos(2*np.pi*df_x.hour/24)
```

```
df_x.drop('hour', axis=1, inplace=True)

df_x['hour_sin'] = np.sin(2*np.pi*df_x.minute/60)

df_x['hour_cos'] = np.cos(2*np.pi*df_x.minute/60)

df_x.drop('minute', axis=1, inplace=True)
return df_x
```

```
[]: def date values extraction(new df):
       The function to split the date columns.
       Input:
       new_df : Input data frame to be processed
       Output :
       df: processed dataframe.
       I \cap I
       df = new_df.copy()
       df['year'] = pd.DatetimeIndex(df['Open Time']).year
       df['month'] = pd.DatetimeIndex(df['Open Time']).month
       df['day'] = pd.DatetimeIndex(df['Open Time']).day
       df['weekday'] = pd.DatetimeIndex(df['Open Time']).dayofweek
       df['Open Time'] = pd.to datetime(df['Open Time'])
       df['minute'] = df['Open Time'].dt.minute
       df['hour'] = df['Open Time'].dt.hour
       df = encode_cyclicals(df.copy())
       return df
```

```
[]: # Extract the date featues
train_df = date_values_extraction(train_df)
test_df = date_values_extraction(test_df)
```

3.3 One hot coding the coins

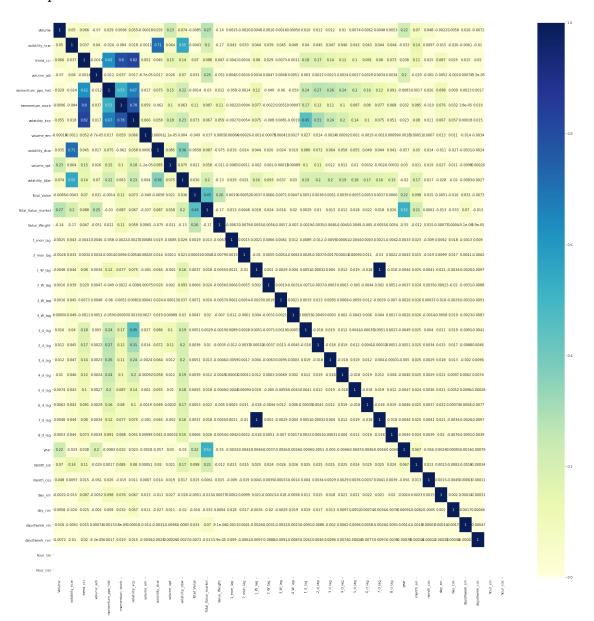
```
df = pd.concat([df, y_dummies], axis=1)
       df.drop(['Crypto'], axis=1, inplace=True)
       # creating a additional column if the model is used for new coin.
       df['other_crypto'] =0
       return df
[]: # The train and test where one hot encoded
     train_df = crypto_one_hot_encoding(train_df)
     test_df = crypto_one_hot_encoding(test_df)
[]: train_df['pct_change_1day'].describe()
[]: count
              17115.000000
    mean
                  0.005533
     std
                  0.162083
    min
                 -0.564847
     25%
                 -0.025641
    50%
                  0.000000
    75%
                  0.028824
                 19.058824
    max
    Name: pct_change_1day, dtype: float64
[]: test_df['pct_change_1day'].describe()
[]: count
              3611.000000
                -0.001452
    mean
                 0.046840
     std
    min
                -0.204696
     25%
                -0.026274
     50%
                 0.000000
    75%
                 0.024091
                 0.344702
    max
    Name: pct_change_1day, dtype: float64
```

4 Defining the Target Variable.

We devide the data into 3 classes, one is with return below 0, one is above 0 but below market rate of return, one is above market rate of return. The market rate of return we use here is annual return of S&P 500 index in 2021.

```
market RoR = 26.89
       market_RoR_1d = market_RoR/365
       df['Target'] = np.where(df['pct_change_1day']>0, 1,0)
       df['Target'] = np.where(df['pct_change_1day']>market_RoR_1d, 2,1)
       df['Target'][df['Target']==1] = np.
      ⇔where(df['pct_change_1day'][df['Target']==1]>=0, 1,0)
       return df
[]: # Applying the target columns
     train_df = create_target(train_df)
     test_df = create_target(test_df)
[]: train_df['Target'].value_counts(normalize=True)
[]: 0
         0.460088
     1
          0.449343
          0.090569
     2
     Name: Target, dtype: float64
[]: test_df['Target'].value_counts(normalize=True)
[]: 0
          0.491025
          0.464513
     1
          0.044463
     2
     Name: Target, dtype: float64
[]: test_df.drop(['pct_change_1day'], axis=1, inplace=True) # droppping the columnu
     →as we already extracted the target
     train_df.drop(['pct_change_1day'], axis=1, inplace=True) # droppping the column_
      →as we already extracted the target
[]: train_df.shape
[]: (17125, 55)
[]: test_df.shape
[]: (3621, 55)
[]: target = train_df['Target']
     test_target = test_df['Target']
    4.0.1 Drop columns
[]: train_df.drop(['Target','Open Time','train_test',],axis=1,inplace=True)
[]: test_df.drop(['Target', 'Open Time', 'train_test',],axis=1,inplace=True)
```

[]: <AxesSubplot:>



• The correlation matrix shows that columns are not much correlated each other.

```
[]: # dropping the listof the columns
     # drop_columns = []
    drop_columns = ['Open','Close']
    if drop_columns:
      norm_train_df = train_df.drop(drop_columns,axis=1)
      norm_test_df = test_df.drop(drop_columns,axis=1)
    else:
      norm_train_df = train_df
      norm_test_df = test_df
[]: norm_train_df.columns
[]: Index(['High', 'Low', 'Volume', 'volatility_kcw', 'trend_cci', 'volume_adi',
            'momentum ppo hist', 'momentum stoch', 'volatility kcp', 'volume em',
            'volatility_dcw', 'volume_vpt', 'volatility_bbw', 'Total_Value',
            'Total_Value_market', 'Value_Weight', '1_mon_lag', '2_mon_lag',
            '1_W_lag', '2_W_lag', '3_W_lag', '4_W_lag', '1_d_lag', '2_d_lag',
            '3_d_lag', '4_d_lag', '5_d_lag', '6_d_lag', '7_d_lag', '8_d_lag',
            'year', 'month_sin', 'month_cos', 'day_sin', 'day_cos', 'dayofweek_sin',
            'dayofweek_cos', 'hour_sin', 'hour_cos', 'Crypto_ADA', 'Crypto_BTC',
            'Crypto_ETC', 'Crypto_ETH', 'Crypto_LINK', 'Crypto_LTC', 'Crypto TRX',
            'Crypto_XLM', 'Crypto_XMR', 'Crypto_XRP', 'other_crypto'],
          dtype='object')
[]: norm_train_df.shape
[]: (17125, 50)
[]: target.shape
[]: (17125,)
[]: def generate_model_report(y_actual, y_predicted, metric_type):
         This function we are calculating the main metrics
         input:
         y_actual: the actual values
         y_predicted : The predicted values
        metric_type : which type of metric
        print("=======Printing the {} metrics=======".
      →format(metric_type))
         if metric type=='micro':
          print("Accuracy = " , round(accuracy_score(y_actual, y_predicted),3))
```

5 Model Building

5.1 Dummy classifier

The baseline Model which others model should be beating.

```
[]: # Fitting the Dummt classifier

dummy_model = DummyClassifier(strategy='prior')

dummy_model.fit(train_df.fillna(0), target)
```

[]: DummyClassifier()

```
[]:  # predicting the values
dummy_pred = dummy_model.predict(test_df)
```

```
[]: # Evaluation metrics
generate_model_report(test_target, dummy_pred, 'micro')
generate_model_report(test_target, dummy_pred, 'macro')
generate_model_report(test_target, dummy_pred, 'weighted')

print('\nClassification Report\n')
print(classification_report(test_target, dummy_pred))
```

```
F1 Score = 0.323
```

Classification Report

	precision	recall	f1-score	support
0	0.49	1.00	0.66	1778
1	0.00	0.00	0.00	1682
2	0.00	0.00	0.00	161
accuracy			0.49	3621
macro avg	0.16	0.33	0.22	3621
weighted avg	0.24	0.49	0.32	3621

5.2 Logistic Regression

```
[]: # Building the Logistic Regression Model

logreg = LogisticRegression(multi_class='multinomial', solver='lbfgs')

# Set Large C value for low regularization to preventure overfitting
logreg.fit(train_df.fillna(0), target)
```

[]: LogisticRegression(multi_class='multinomial')

```
[]: # Predicting teh
logreg_pred = logreg.predict(test_df.fillna(0))
```

```
[]: generate_model_report(test_target, logreg_pred, 'micro')
   generate_model_report(test_target, logreg_pred, 'macro')
   generate_model_report(test_target, logreg_pred, 'weighted')

from sklearn.metrics import classification_report
   print('\nClassification Report\n')
   print(classification_report(test_target, logreg_pred))
```

======Printing the micro metrics=======

Accuracy = 0.493 Precision = 0.493

Classification Report

	precision	recall	f1-score	support
0	0.49 0.56	0.98	0.66 0.04	1778 1682
2	0.00	0.00	0.00	161
accuracy			0.49	3621
macro avg	0.35	0.33	0.23	3621
weighted avg	0.50	0.49	0.34	3621

5.3 XGBoost - Untuned

[]: XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1, enable_categorical=False, eval_metric='mlogloss', gamma=0, gpu_id=-1, importance_type=None, interaction_constraints='', learning_rate=0.300000012, max_delta_step=0, max_depth=30, min_child_weight=1, missing=nan, monotone_constraints='()', n_estimators=1000, n_jobs=-1, num_class=2, num_parallel_tree=1, objective='multi:softprob', predictor='auto', random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=None, subsample=1, tree_method='exact',

validate_parameters=1, ...)

```
[]: xgb_clf
[]: XGBClassifier(base score=0.5, booster='gbtree', colsample_bylevel=1,
                 colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
                 eval_metric='mlogloss', gamma=0, gpu_id=-1, importance_type=None,
                 interaction_constraints='', learning_rate=0.300000012,
                 max_delta_step=0, max_depth=30, min_child_weight=1, missing=nan,
                 monotone_constraints='()', n_estimators=1000, n_jobs=-1,
                 num_class=2, num_parallel_tree=1, objective='multi:softprob',
                 predictor='auto', random_state=0, reg_alpha=0, reg_lambda=1,
                 scale_pos_weight=None, subsample=1, tree_method='exact',
                 validate_parameters=1, ...)
[]: # Predicting the values
    predicted_values = xgb_clf.predict(norm_test_df)
[]: # Evaluation metrics
    generate_model_report(test_target, predicted_values, 'micro')
    generate_model_report(test_target, predicted_values, 'macro')
    generate_model_report(test_target, predicted_values, 'weighted')
    =========Printing the micro metrics===========
   Accuracy = 0.5
   Precision = 0.5
   Recall = 0.5
   F1 Score = 0.5
   _____
   ======Printing the macro metrics=========
   Precision = 0.396
   Recall = 0.399
   F1 Score = 0.393
   =======Printing the weighted metrics=========
   Precision = 0.506
   Recall = 0.5
   F1 Score = 0.497
    ______
[]: print('\nClassification Report\n')
    print(classification_report(test_target, predicted_values))
   Classification Report
                precision recall f1-score
                                              support
```

```
0.54
                               0.42
                                                     1778
           0
                                          0.48
                    0.50
                               0.61
                                          0.55
                                                     1682
           1
           2
                    0.14
                               0.16
                                          0.15
                                                     161
                                          0.50
                                                     3621
    accuracy
   macro avg
                               0.40
                                          0.39
                                                     3621
                    0.40
weighted avg
                    0.51
                               0.50
                                          0.50
                                                     3621
```

5.4 XGBoost tuning with Bayesian optimization

```
[]: def xgbc_cv( max_depth,
                     n_estimators,
                     gamma,
                     learning_rate,
                     min_child_weight,
                      subsample):
         estimator_function = XGBClassifier(max_depth=int(max_depth),
                                                 learning_rate= learning_rate,
                                                 n_estimators= int(n_estimators),
                                                min_child_weight =
      →int(min_child_weight),
                                                nthread = -1,
                                                 subsample = max(subsample, 0),
                                                 objective="multi:softprob",
                                                 eval_metric = 'mlogloss',
                                                num_class = 2,
                                                 scoring='f1',
                                                seed = 32)
         # Fit the estimator
         estimator_function.fit(norm_train_df.fillna(0), target)
         # calculate out-of-the-box roc_score using validation set 1
```

```
predicted_values = estimator_function.predict(norm_test_df.fillna(0))
    score = f1_score(test_target, predicted_values, average='weighted')
    # return the mean validation score to be maximized
    return score
def bayesOpt(train_x, train_y):
    lgbB0 = BayesianOptimization(xgbc_cv, {
                                                "max_depth": (25,30),
                                               "n_estimators": (600,1000),
                                               "gamma": (0.03,0.05),
                                                "learning_rate": (0.04,0.09),
                                               "min_child_weight": (5,20),
                                                # "colsample_bytree":(0.4,0.8),
                                               "subsample": (0.50,0.85)
                                  )
    lgbBO.maximize(init_points=5, n_iter=30)
     print(lqbBO.res['max'])
    print(lgbB0.max)
bayesOpt(norm_train_df.fillna(0), target)
    iter
            | target
                                    | learni... | max_depth | min_ch... |
                            gamma
n_esti... | subsample |
```

[16:22:10] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.5.0/src/learner.cc:576:
Parameters: { "scoring" } might not be used.

This could be a false alarm, with some parameters getting used by language bindings but

then being mistakenly passed down to XGBoost core, or some parameter actually being used

```
[16:24:16] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.5.0/src/learner.cc:576:
Parameters: { "scoring" } might not be used.
```

then being mistakenly passed down to XGBoost core, or some parameter actually being used

but getting flagged wrongly here. Please open an issue if you find any such cases.

This could be a false alarm, with some parameters getting used by language bindings but

then being mistakenly passed down to XGBoost core, or some parameter actually being used

but getting flagged wrongly here. Please open an issue if you find any such cases.

This could be a false alarm, with some parameters getting used by language bindings but

then being mistakenly passed down to ${\tt XGBoost}$ core, or some parameter actually being used

```
win64_release_1.5.0/src/learner.cc:576:
Parameters: { "scoring" } might not be used.
```

then being mistakenly passed down to XGBoost core, or some parameter actually being used

but getting flagged wrongly here. Please open an issue if you find any such cases.

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but getting flagged wrongly here. Please open an issue if you find any such cases.

This could be a false alarm, with some parameters getting used by language bindings but

then being mistakenly passed down to XGBoost core, or some parameter actually being used

```
| 17 | 0.4888 | 0.03528 | 0.0715
```

```
| 29.38 | 13.8 | 937.7 | 0.8089
|
[17:08:40] WARNING: C:/Users/Administrator/workspace/xgboost-
win64_release_1.5.0/src/learner.cc:576:
Parameters: { "scoring" } might not be used.
```

then being mistakenly passed down to XGBoost core, or some parameter actually being used

but getting flagged wrongly here. Please open an issue if you find any such cases.

This could be a false alarm, with some parameters getting used by language bindings but

then being mistakenly passed down to XGBoost core, or some parameter actually being used

but getting flagged wrongly here. Please open an issue if you find any such cases.

This could be a false alarm, with some parameters getting used by language bindings but

then being mistakenly passed down to XGBoost core, or some parameter actually being used

```
win64_release_1.5.0/src/learner.cc:576:
Parameters: { "scoring" } might not be used.
```

then being mistakenly passed down to XGBoost core, or some parameter actually being used

but getting flagged wrongly here. Please open an issue if you find any such cases.

This could be a false alarm, with some parameters getting used by language bindings but

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but getting flagged wrongly here. Please open an issue if you find any such cases.

This could be a false alarm, with some parameters getting used by language bindings but

then being mistakenly passed down to XGBoost core, or some parameter actually being used

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being used

but getting flagged wrongly here. Please open an issue if you find any such cases.

Parameters: { "scoring" } might not be used.

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then being mistakenly passed down to XGBoost core, or some parameter actually being used

but getting flagged wrongly here. Please open an issue if you find any such cases.

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then being mistakenly passed down to ${\tt XGBoost}$ core, or some parameter actually being used

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but getting flagged wrongly here. Please open an issue if you find any such cases.

This could be a false alarm, with some parameters getting used by language bindings but

then being mistakenly passed down to XGBoost core, or some parameter actually being used

but getting flagged wrongly here. Please open an issue if you find any such cases.

```
33 | 0.4801 | 0.04962 | 0.08702
```

```
| 25.51 | 19.42 | 819.3 | 0.6651
|
[17:43:03] WARNING: C:/Users/Administrator/workspace/xgboost-
win64_release_1.5.0/src/learner.cc:576:
Parameters: { "scoring" } might not be used.
```

This could be a false alarm, with some parameters getting used by language bindings but

then being mistakenly passed down to XGBoost core, or some parameter actually being used

but getting flagged wrongly here. Please open an issue if you find any such cases.

This could be a false alarm, with some parameters getting used by language bindings but

then being mistakenly passed down to XGBoost core, or some parameter actually being used

but getting flagged wrongly here. Please open an issue if you find any such cases.

```
{'target': 0.49717263911048104, 'params': {'gamma': 0.03127013296857564,
'learning_rate': 0.04498314951689869, 'max_depth': 29.401153112346318,
'min_child_weight': 11.719617320022135, 'n_estimators': 686.8341805804602,
'subsample': 0.7094565386859188}}
```

5.5 RandomizedSearchCV - XGBoost

```
[]: # Importing RandomizedSearchCV
[]: # EG Fitting 3 folds for each of 100 candidates, totalling 300 fits
```

```
cv = 3,
                                    verbose=1 ,
                                    scoring='f1',
                                    n_jobs=-1,
                                    random_state=42)
[]: xg_random.fit(norm_train_df, target)
    Fitting 3 folds for each of 10 candidates, totalling 30 fits
[]: RandomizedSearchCV(cv=3,
                        estimator=XGBClassifier(eval_metric='mlogloss', max_depth=30,
                                                n_jobs=-1, num_class=2,
                                                objective='multi:softprob'),
                        n_jobs=-1,
                        param_distributions={'colsample_bytree': [0.4, 0.8],
                                             'gamma': [0.03, 0.05],
                                             'learning_rate': [0.02, 0.09],
                                             'min_child_weight': [5, 10],
                                             'n_estimators': [300, 400, 500],
                                             'subsample': [0.5, 0.85]},
                        random_state=42, scoring='f1', verbose=1)
[]: xg_random.cv_results_
[]: {'mean fit time': array([284.74294734, 533.94794067, 324.38395802, 273.51564415,
             217.38379757, 293.17546924, 320.41527597, 107.98551663,
             143.0566748 , 188.16923523]),
      'std_fit_time': array([16.54543366, 39.83647681, 22.32838181, 19.46776648,
     15.59290301,
             21.21693124, 28.53303815, 7.15326628, 9.65456451, 14.22315131]),
      'mean_score_time': array([ 4.39842884, 17.06368883, 5.13770858, 2.45175536,
     8.86828566,
              3.52253485, 2.5757939, 1.60393675, 3.2699577, 7.45017727]),
      'std_score_time': array([0.29605027, 1.46149761, 0.1760782 , 0.10329311,
     1.60875665,
             0.98636956, 0.13675698, 0.13713717, 0.52527974, 0.8564662]),
      'param_subsample': masked_array(data=[0.5, 0.85, 0.85, 0.5, 0.85, 0.85, 0.85,
     0.5, 0.5, 0.5],
                   mask=[False, False, False, False, False, False, False, False,
                         False, False],
             fill_value='?',
                  dtype=object),
      'param_n_estimators': masked_array(data=[400, 500, 300, 500, 400, 300, 400,
     300, 300, 500],
                   mask=[False, False, False, False, False, False, False, False,
                         False, False],
             fill_value='?',
```

```
dtype=object),
 'param min child weight': masked array(data=[10, 5, 5, 10, 10, 10, 10, 10, 5,
10],
              mask=[False, False, False, False, False, False, False, False,
                    False, False],
        fill_value='?',
             dtype=object),
 'param_learning_rate': masked_array(data=[0.02, 0.02, 0.02, 0.09, 0.02, 0.02,
0.09, 0.09, 0.02,
                    0.02],
              mask=[False, False, False, False, False, False, False, False,
                    False, False],
        fill_value='?',
             dtype=object),
 'param_gamma': masked_array(data=[0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.03,
0.05, 0.03,
                    0.03],
              mask=[False, False, False, False, False, False, False, False,
                    False, False],
        fill_value='?',
             dtype=object),
 'param_colsample_bytree': masked_array(data=[0.8, 0.8, 0.8, 0.8, 0.4, 0.8, 0.8,
0.4, 0.4, 0.4],
              mask=[False, False, False, False, False, False, False, False,
                    False, False],
        fill value='?',
             dtype=object),
 'params': [{'subsample': 0.5,
   'n_estimators': 400,
   'min_child_weight': 10,
   'learning_rate': 0.02,
   'gamma': 0.05,
   'colsample_bytree': 0.8},
  {'subsample': 0.85,
   'n_estimators': 500,
   'min_child_weight': 5,
   'learning_rate': 0.02,
   'gamma': 0.05,
   'colsample bytree': 0.8},
  {'subsample': 0.85,
   'n_estimators': 300,
   'min_child_weight': 5,
   'learning_rate': 0.02,
   'gamma': 0.05,
   'colsample_bytree': 0.8},
  {'subsample': 0.5,
   'n_estimators': 500,
```

```
'min_child_weight': 10,
  'learning_rate': 0.09,
  'gamma': 0.05,
  'colsample_bytree': 0.8},
 {'subsample': 0.85,
  'n_estimators': 400,
  'min_child_weight': 10,
  'learning_rate': 0.02,
  'gamma': 0.05,
  'colsample_bytree': 0.4},
 {'subsample': 0.85,
  'n_estimators': 300,
  'min_child_weight': 10,
  'learning_rate': 0.02,
  'gamma': 0.05,
  'colsample_bytree': 0.8},
 {'subsample': 0.85,
  'n_estimators': 400,
  'min_child_weight': 10,
  'learning_rate': 0.09,
  'gamma': 0.03,
  'colsample_bytree': 0.8},
 {'subsample': 0.5,
  'n estimators': 300,
  'min_child_weight': 10,
  'learning rate': 0.09,
  'gamma': 0.05,
  'colsample_bytree': 0.4},
 {'subsample': 0.5,
  'n_estimators': 300,
  'min_child_weight': 5,
  'learning_rate': 0.02,
  'gamma': 0.03,
  'colsample_bytree': 0.4},
 {'subsample': 0.5,
  'n_estimators': 500,
  'min_child_weight': 10,
  'learning_rate': 0.02,
  'gamma': 0.03,
  'colsample_bytree': 0.4}],
'rank_test_score': array([ 1, 2, 3, 4, 5, 6, 7, 8, 9, 10],
dtype=int32)}
```

```
[]: xg_random
[]: RandomizedSearchCV(cv=3,
                      estimator=XGBClassifier(eval_metric='mlogloss', max_depth=30,
                                             n jobs=-1, num class=2,
                                             objective='multi:softprob'),
                      n_{jobs}=-1,
                      param_distributions={'colsample_bytree': [0.4, 0.8],
                                           'gamma': [0.03, 0.05],
                                           'learning_rate': [0.02, 0.09],
                                           'min_child_weight': [5, 10],
                                          'n_estimators': [300, 400, 500],
                                           'subsample': [0.5, 0.85]},
                      random_state=42, scoring='f1', verbose=1)
[]: # Picking teh best estimator
    final_model = xg_random.best_estimator_
[]: # Saving the file
    temp_file_path = '/content/drive/MyDrive/MADS_23_DL_final_project/data/
     →model_files/svc_hourly'
    with open(temp_file_path + '/xgb_clf_f13.pkl', 'wb') as f: # Python 3: open(...
     →, 'wb')
        pickle.dump(final_model, f)
[]: # Predicting the values
    predicted_values = final_model.predict(norm_test_df)
[]: # calculating the metrics
    generate_model_report(test_target, predicted_values, 'micro')
    generate_model_report(test_target, predicted_values, 'macro')
    generate_model_report(test_target, predicted_values, 'weighted')
    =========Printing the micro metrics=========
    Accuracy = 0.511
    Precision = 0.511
    Recall = 0.511
    F1 Score = 0.511
    _____
    =========Printing the macro metrics=========
    Precision = 0.394
    Recall = 0.373
    F1 Score = 0.373
    =========Printing the weighted metrics=============
    Precision = 0.503
    Recall = 0.511
```

```
F1 Score = 0.501
```

```
[]: # Best params
     param_grid = {'gamma': 0.03127013296857564, 'learning rate': 0.
      →04498314951689869, 'max_depth': 29.401153112346318, 'min_child_weight': 11.
      4719617320022135, 'n estimators': 686.8341805804602, 'subsample': 0.
      →7094565386859188}
[]: param_grid
[]: {'gamma': 0.03127013296857564,
      'learning_rate': 0.04498314951689869,
      'max_depth': 29.401153112346318,
      'min_child_weight': 11.719617320022135,
      'n_estimators': 686.8341805804602,
      'subsample': 0.7094565386859188}
[]: %timeit
     xgb_clf = XGBClassifier(num_class = 2,
                             learning_rate =param_grid['learning_rate'],
                             n_estimators = int(param_grid['n_estimators']),
                             gamma= param_grid['gamma'],
                             max_depth = int(param_grid['max_depth']),
                             subsample= param_grid['subsample'],
                             objective="multi:softprob",
                             eval_metric = 'mlogloss',
                             n_jobs=-1,num_boost_round=15)
     xgb_clf.fit(norm_train_df.fillna(0), target)
```

[20:06:53] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.5.0/src/learner.cc:576:
Parameters: { "num_boost_round" } might not be used.

This could be a false alarm, with some parameters getting used by language bindings but

then being mistakenly passed down to XGBoost core, or some parameter actually being used

but getting flagged wrongly here. Please open an issue if you find any such cases.

```
[]: XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
                 colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
                 eval_metric='mlogloss', gamma=0.03127013296857564, gpu_id=-1,
                 importance_type=None, interaction_constraints='',
                 learning rate=0.04498314951689869, max delta step=0, max depth=29,
                 min_child_weight=1, missing=nan, monotone_constraints='()',
                 n estimators=686, n jobs=-1, num boost round=15, num class=2,
                 num_parallel_tree=1, objective='multi:softprob', predictor='auto',
                 random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=None,
                 subsample=0.7094565386859188, tree_method='exact', ...)
[]: xgb_clf
[]: XGBClassifier(base score=0.5, booster='gbtree', colsample_bylevel=1,
                 colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
                 eval_metric='mlogloss', gamma=0.03127013296857564, gpu_id=-1,
                 importance_type=None, interaction_constraints='',
                 learning_rate=0.04498314951689869, max_delta_step=0, max_depth=29,
                 min_child_weight=1, missing=nan, monotone_constraints='()',
                 n_estimators=686, n_jobs=-1, num_boost_round=15, num_class=2,
                 num_parallel_tree=1, objective='multi:softprob', predictor='auto',
                 random_state=0, reg_alpha=0, reg_lambda=1, scale_pos_weight=None,
                 subsample=0.7094565386859188, tree_method='exact', ...)
[]: predicted_values = xgb_clf.predict(norm_test_df)
[]: generate_model_report(test_target, predicted_values, 'micro')
    generate_model_report(test_target, predicted_values, 'macro')
    generate_model_report(test_target, predicted_values, 'weighted')
    ========Printing the micro metrics=========
   Accuracy = 0.502
   Precision = 0.502
   Recall = 0.502
   F1 Score = 0.502
    _____
    =======Printing the macro metrics=========
   Precision = 0.381
   Recall = 0.379
   F1 Score = 0.374
    ______
    Precision = 0.507
   Recall = 0.502
   F1 Score = 0.496
```

```
FileNotFoundError Traceback (most recent call last)

~\AppData\Local\Temp/ipykernel_33188/2713381438.py in <module>
2 import pickle
3 temp_file_path = '/content/drive/MyDrive/MADS_23_DL_final_project/data/

~model_files/svc_hourly'
----> 4 with open(temp_file_path + '/xgb_clf_f13_tuned.pkl', 'wb') as f: #__

~Python 3: open(..., 'wb')
5 pickle.dump(final_model, f)

FileNotFoundError: [Errno 2] No such file or directory: '/content/drive/MyDrive_MADS_23_DL_final_project/data/model_files/svc_hourly/xgb_clf_f13_tuned.pkl'
```

```
[]: print('\nClassification Report\n')
print(classification_report(test_target, predicted_values))
```

Classification Report

support	f1-score	recall	precision	
1770	0.40	0.40	0.54	0
1778	0.48	0.42	0.54	0
1682	0.55	0.61	0.50	1
161	0.15	0.16	0.14	2
3621	0.50			accuracy
3621	0.39	0.40	0.40	macro avg
3621	0.50	0.50	0.51	weighted avg

```
[]: xgb_clf
```

5.6 Fully Connected Neural Network

```
hidden_size_1 = 1024
hidden_size_2 = 2048
hidden_size_3 = 1024
number_of_classes =3
# Model.
#######
inputs = Input(shape=(norm_train_df.fillna(0).shape[1]))
# Hidden layer
##############
hidden_output = Dense(hidden_size_1, activation='relu')(inputs)
hidden_output = Dropout(0.5)(hidden_output)
hidden_output_2 = Dense(hidden_size_2, activation='relu')(hidden_output)
hidden_output_2 = Dropout(0.3)(hidden_output_2)
hidden_output_3 = Dense(hidden_size_3, activation='relu')(hidden_output_2)
# Softmax
########
predictions = Dense(3, activation='softmax')(hidden_output_3)
# Whole model
##############
# Nothing more is left, than to instantiate the model
# Please ensure input and output is right!
model = Model(inputs=inputs, outputs=predictions)
# Optimization
##############
# For now, we stick to this.
optimizer = Adam(lr=0.01)
# Compilation and teaching
###########################
model.compile(optimizer=optimizer,
              loss='sparse_categorical_crossentropy', # use this cross entropy_
 \rightarrow variant
                                                       # since the input is not_
 ⇔one-hot encoded
```

$\label{eq:metrics} \begin{tabular}{ll} metrics=[\ 'accuracy']) \textit{ \#We measure and print accuracy during} \\ \hookrightarrow training \end{tabular}$

[]: model.summary()

Model: "model_2"

Layer (type)	Output Shape	Param #
input_3 (InputLayer)	[(None, 54)]	0
dense_8 (Dense)	(None, 1024)	56320
dropout_4 (Dropout)	(None, 1024)	0
dense_9 (Dense)	(None, 2048)	2099200
dropout_5 (Dropout)	(None, 2048)	0
dense_10 (Dense)	(None, 1024)	2098176
dense_11 (Dense)	(None, 3)	3075

Total params: 4,256,771 Trainable params: 4,256,771 Non-trainable params: 0

```
Epoch 5/30
accuracy: 0.4604 - val_loss: 0.8577 - val_accuracy: 0.4910
536/536 [============ ] - 19s 35ms/step - loss: 459.7038 -
accuracy: 0.4575 - val_loss: 0.8591 - val_accuracy: 0.4645
536/536 [============= ] - 19s 35ms/step - loss: 219.5765 -
accuracy: 0.4569 - val_loss: 0.8639 - val_accuracy: 0.4645
Epoch 8/30
536/536 [=========== ] - 18s 34ms/step - loss: 0.9347 -
accuracy: 0.4566 - val_loss: 0.8572 - val_accuracy: 0.4645
Epoch 9/30
accuracy: 0.4517 - val_loss: 0.8625 - val_accuracy: 0.4645
Epoch 10/30
536/536 [=========== ] - 18s 34ms/step - loss: 0.9346 -
accuracy: 0.4546 - val_loss: 0.8597 - val_accuracy: 0.4645
Epoch 11/30
536/536 [============ ] - 19s 35ms/step - loss: 66.3475 -
accuracy: 0.4558 - val_loss: 0.8637 - val_accuracy: 0.4910
Epoch 12/30
accuracy: 0.4525 - val_loss: 0.8586 - val_accuracy: 0.4910
Epoch 13/30
accuracy: 0.4464 - val_loss: 0.8577 - val_accuracy: 0.4910
Epoch 14/30
536/536 [============= ] - 18s 34ms/step - loss: 13979.8789 -
accuracy: 0.4554 - val_loss: 0.8612 - val_accuracy: 0.4910
Epoch 15/30
536/536 [============= ] - 19s 35ms/step - loss: 100.4182 -
accuracy: 0.4586 - val_loss: 0.8556 - val_accuracy: 0.4910
Epoch 16/30
536/536 [============ ] - 18s 34ms/step - loss: 619.7780 -
accuracy: 0.4547 - val_loss: 0.8619 - val_accuracy: 0.4910
Epoch 17/30
536/536 [============= ] - 18s 33ms/step - loss: 0.9349 -
accuracy: 0.4497 - val_loss: 0.8563 - val_accuracy: 0.4645
Epoch 18/30
536/536 [============ ] - 18s 34ms/step - loss: 0.9347 -
accuracy: 0.4566 - val_loss: 0.8587 - val_accuracy: 0.4645
536/536 [=========== ] - 18s 33ms/step - loss: 0.9346 -
accuracy: 0.4629 - val_loss: 0.8637 - val_accuracy: 0.4645
Epoch 20/30
536/536 [============= ] - 19s 35ms/step - loss: 0.9351 -
accuracy: 0.4508 - val_loss: 0.8597 - val_accuracy: 0.4910
```

```
accuracy: 0.4603 - val_loss: 0.8609 - val_accuracy: 0.4645
   536/536 [============ ] - 19s 35ms/step - loss: 0.9348 -
   accuracy: 0.4535 - val_loss: 0.8626 - val_accuracy: 0.4910
   536/536 [============= ] - 18s 33ms/step - loss: 60779.2734 -
   accuracy: 0.4591 - val_loss: 0.8596 - val_accuracy: 0.4645
   Epoch 24/30
   536/536 [============ ] - 19s 35ms/step - loss: 398.0602 -
   accuracy: 0.4549 - val_loss: 0.8583 - val_accuracy: 0.4645
   Epoch 25/30
   536/536 [=========== ] - 18s 34ms/step - loss: 22489.8516 -
   accuracy: 0.4555 - val_loss: 0.8607 - val_accuracy: 0.4645
   Epoch 26/30
   536/536 [============= ] - 18s 33ms/step - loss: 20542.8906 -
   accuracy: 0.4533 - val_loss: 0.8591 - val_accuracy: 0.4910
   Epoch 27/30
   accuracy: 0.4500 - val_loss: 0.8550 - val_accuracy: 0.4910
   Epoch 28/30
   accuracy: 0.4562 - val_loss: 0.8562 - val_accuracy: 0.4645
   Epoch 29/30
   accuracy: 0.4564 - val_loss: 0.8589 - val_accuracy: 0.4645
   Epoch 30/30
   536/536 [============ ] - 18s 33ms/step - loss: 0.9348 -
   accuracy: 0.4572 - val_loss: 0.8617 - val_accuracy: 0.4910
[]: <keras.callbacks.History at 0x7fdcb7d34450>
[]: # Predicting the test data
   nn_pred=model.predict(norm_test_df.fillna(0))
   114/114 [=========== ] - 8s 68ms/step
[]: # Extracting the argmax
   df = pd.DataFrame(nn_pred)
   nn_pred = df.idxmax(axis=1)
[]: # Evaluation metrics
   generate_model_report(test_target, nn_pred, 'micro')
   generate_model_report(test_target, nn_pred, 'macro')
   generate_model_report(test_target, nn_pred, 'weighted')
   Accuracy = 0.4645
```

Epoch 21/30

```
Precision = 0.4645
   Recall = 0.4645
   F1 Score = 0.4645
   _____
   ========Printing the macro metrics========
   Precision = 0.1548
   Recall = 0.3333
   F1 Score = 0.2115
   _____
   ========Printing the weighted metrics============
   Precision = 0.2158
   Recall = 0.4645
   F1 Score = 0.2947
   _____
[]: print('\nClassification Report\n')
   print(classification_report(test_target, nn_pred))
```

5.7 Tabnet

```
[]: # define the model and fit
     clf1_nopreproc = TabNetClassifier(optimizer_fn=torch.optim.Adam,
                            optimizer_params=dict(lr=2e-2),
                            scheduler_params={"step_size":10, # how to use learning_
      ⇔rate scheduler
                                              "gamma":0.9},
                            scheduler_fn=torch.optim.lr_scheduler.StepLR,
                            mask_type='entmax' # "sparsemax"
     # fit the model
     clf1_nopreproc.fit(
         norm_train_df.fillna(0).values, target.values,
         eval_set=[(norm_train_df.fillna(0).values, target.values), (norm_test_df.
      →fillna(0).values, test_target.values)],
         eval name=['train', 'valid'],
         eval_metric=['balanced_accuracy'],
         max_epochs=150 , patience=120,
         batch_size=64, virtual_batch_size=128,
         num_workers=0,
         weights=1,
         drop_last=False
     )
```

```
epoch 0 | loss: 1.08729 | train_balanced_accuracy: 0.42932 |
valid_balanced_accuracy: 0.39624 | 0:00:06s
epoch 1 | loss: 1.03804 | train_balanced_accuracy: 0.45699 |
valid_balanced_accuracy: 0.41154 | 0:00:15s
```

```
epoch 2 | loss: 1.03205 | train_balanced_accuracy: 0.44434 |
valid_balanced_accuracy: 0.37765 | 0:00:23s
epoch 3 | loss: 1.0262 | train_balanced_accuracy: 0.46195 |
valid_balanced_accuracy: 0.38644 | 0:00:29s
epoch 4 | loss: 1.0118 | train balanced accuracy: 0.44718 |
valid balanced accuracy: 0.35146 | 0:00:36s
epoch 5 | loss: 1.00969 | train balanced accuracy: 0.46104 |
valid_balanced_accuracy: 0.38105 | 0:00:43s
epoch 6 | loss: 1.00283 | train balanced accuracy: 0.47166 |
valid_balanced_accuracy: 0.4123 | 0:00:50s
epoch 7 | loss: 1.00314 | train_balanced_accuracy: 0.48128 |
valid_balanced_accuracy: 0.40423 | 0:00:56s
epoch 8 | loss: 0.99158 | train_balanced_accuracy: 0.47601 |
valid_balanced_accuracy: 0.39889 | 0:01:02s
epoch 9 | loss: 0.99393 | train_balanced_accuracy: 0.47143 |
valid_balanced_accuracy: 0.35349 | 0:01:09s
epoch 10 | loss: 0.98888 | train_balanced_accuracy: 0.50008 |
valid_balanced_accuracy: 0.36751 | 0:01:16s
epoch 11 | loss: 0.96833 | train_balanced_accuracy: 0.49872 |
valid balanced accuracy: 0.37467 | 0:01:23s
epoch 12 | loss: 0.9655 | train balanced accuracy: 0.50002 |
valid balanced accuracy: 0.3877 | 0:01:29s
epoch 13 | loss: 0.95158 | train_balanced_accuracy: 0.49681 |
valid_balanced_accuracy: 0.37479 | 0:01:35s
epoch 14 | loss: 0.95198 | train_balanced_accuracy: 0.50588 |
valid_balanced_accuracy: 0.35936 | 0:01:42s
epoch 15 | loss: 0.94276 | train_balanced_accuracy: 0.51632 |
valid_balanced_accuracy: 0.37477 | 0:01:48s
epoch 16 | loss: 0.91723 | train_balanced_accuracy: 0.49726 |
valid_balanced_accuracy: 0.35505 | 0:01:55s
epoch 17 | loss: 0.92767 | train_balanced_accuracy: 0.52077 |
valid_balanced_accuracy: 0.39867 | 0:02:01s
epoch 18 | loss: 0.91834 | train_balanced_accuracy: 0.52945 |
valid_balanced_accuracy: 0.37378 | 0:02:08s
epoch 19 | loss: 0.90961 | train balanced accuracy: 0.53995 |
valid_balanced_accuracy: 0.35771 | 0:02:14s
epoch 20 | loss: 0.90027 | train balanced accuracy: 0.52485 |
valid_balanced_accuracy: 0.37378 | 0:02:21s
epoch 21 | loss: 0.89831 | train_balanced_accuracy: 0.54238 |
valid_balanced_accuracy: 0.37217 | 0:02:27s
epoch 22 | loss: 0.88976 | train_balanced_accuracy: 0.54312 |
valid_balanced_accuracy: 0.36684 | 0:02:34s
epoch 23 | loss: 0.8859 | train_balanced_accuracy: 0.53463 |
valid_balanced_accuracy: 0.37275 | 0:02:40s
epoch 24 | loss: 0.88835 | train_balanced_accuracy: 0.56075 |
valid_balanced_accuracy: 0.3878 | 0:02:47s
epoch 25 | loss: 0.87744 | train_balanced_accuracy: 0.55285 |
valid_balanced_accuracy: 0.37537 | 0:02:53s
```

```
epoch 26 | loss: 0.87619 | train_balanced_accuracy: 0.55923 |
valid_balanced_accuracy: 0.35302 | 0:02:59s
epoch 27 | loss: 0.8626 | train_balanced_accuracy: 0.55779 |
valid_balanced_accuracy: 0.36577 | 0:03:06s
epoch 28 | loss: 0.85214 | train balanced accuracy: 0.55575 |
valid balanced accuracy: 0.37775 | 0:03:12s
epoch 29 | loss: 0.85189 | train balanced accuracy: 0.56313 |
valid_balanced_accuracy: 0.36688 | 0:03:19s
epoch 30 | loss: 0.85508 | train balanced accuracy: 0.54049 |
valid_balanced_accuracy: 0.36918 | 0:03:25s
epoch 31 | loss: 0.85084 | train_balanced_accuracy: 0.58154 |
valid_balanced_accuracy: 0.37334 | 0:03:32s
epoch 32 | loss: 0.84567 | train_balanced_accuracy: 0.55808 |
valid_balanced_accuracy: 0.36088 | 0:03:38s
epoch 33 | loss: 0.84306 | train_balanced_accuracy: 0.55913 |
valid_balanced_accuracy: 0.35683 | 0:03:44s
epoch 34 | loss: 0.83348 | train_balanced_accuracy: 0.57997 |
valid_balanced_accuracy: 0.35898 | 0:03:51s
epoch 35 | loss: 0.83438 | train_balanced_accuracy: 0.57298 |
valid balanced accuracy: 0.374 | 0:03:58s
epoch 36 | loss: 0.83231 | train balanced accuracy: 0.56677 |
valid balanced accuracy: 0.38235 | 0:04:04s
epoch 37 | loss: 0.82796 | train_balanced_accuracy: 0.58484 |
valid_balanced_accuracy: 0.36922 | 0:04:10s
epoch 38 | loss: 0.82502 | train_balanced_accuracy: 0.58426 |
valid_balanced_accuracy: 0.36818 | 0:04:17s
epoch 39 | loss: 0.81531 | train_balanced_accuracy: 0.57663 |
valid_balanced_accuracy: 0.36517 | 0:04:23s
epoch 40 | loss: 0.82914 | train_balanced_accuracy: 0.58323 |
valid_balanced_accuracy: 0.37707 | 0:04:29s
epoch 41 | loss: 0.81902 | train_balanced_accuracy: 0.5873 |
valid_balanced_accuracy: 0.37172 | 0:04:36s
epoch 42 | loss: 0.81443 | train_balanced_accuracy: 0.58255 |
valid_balanced_accuracy: 0.38053 | 0:04:43s
epoch 43 | loss: 0.80589 | train balanced accuracy: 0.59259 |
valid balanced accuracy: 0.40054 | 0:04:49s
epoch 44 | loss: 0.80995 | train balanced accuracy: 0.59656 |
valid_balanced_accuracy: 0.3901 | 0:04:56s
epoch 45 | loss: 0.79916 | train_balanced_accuracy: 0.59152 |
valid_balanced_accuracy: 0.39101 | 0:05:02s
epoch 46 | loss: 0.7951 | train_balanced_accuracy: 0.59592 |
valid_balanced_accuracy: 0.37794 | 0:05:09s
epoch 47 | loss: 0.78743 | train_balanced_accuracy: 0.57897 |
valid_balanced_accuracy: 0.39122 | 0:05:15s
epoch 48 | loss: 0.79812 | train_balanced_accuracy: 0.60352 |
valid_balanced_accuracy: 0.37721 | 0:05:22s
epoch 49 | loss: 0.79636 | train_balanced_accuracy: 0.61286 |
valid_balanced_accuracy: 0.37466 | 0:05:28s
```

```
epoch 50 | loss: 0.79574 | train_balanced_accuracy: 0.59492 |
valid_balanced_accuracy: 0.39868 | 0:05:34s
epoch 51 | loss: 0.7922 | train_balanced_accuracy: 0.61761 |
valid_balanced_accuracy: 0.387 | 0:05:41s
epoch 52 | loss: 0.78775 | train balanced accuracy: 0.60871 |
valid balanced accuracy: 0.39676 | 0:05:47s
epoch 53 | loss: 0.78033 | train balanced accuracy: 0.61305 |
valid_balanced_accuracy: 0.39993 | 0:05:53s
epoch 54 | loss: 0.79279 | train balanced accuracy: 0.59919 |
valid_balanced_accuracy: 0.39267 | 0:06:00s
epoch 55 | loss: 0.79476 | train_balanced_accuracy: 0.58554 |
valid_balanced_accuracy: 0.40512 | 0:06:06s
epoch 56 | loss: 0.79529 | train_balanced_accuracy: 0.57335 |
valid_balanced_accuracy: 0.36169 | 0:06:12s
epoch 57 | loss: 0.78514 | train_balanced_accuracy: 0.59644 |
valid_balanced_accuracy: 0.39014 | 0:06:19s
epoch 58 | loss: 0.77798 | train_balanced_accuracy: 0.61522 |
valid_balanced_accuracy: 0.39945 | 0:06:25s
epoch 59 | loss: 0.78279 | train_balanced_accuracy: 0.60367 |
valid balanced accuracy: 0.37908 | 0:06:31s
epoch 60 | loss: 0.7816 | train balanced accuracy: 0.61073 |
valid balanced accuracy: 0.37613 | 0:06:38s
epoch 61 | loss: 0.77906 | train_balanced_accuracy: 0.60585 |
valid_balanced_accuracy: 0.39357 | 0:06:45s
epoch 62 | loss: 0.77346 | train_balanced_accuracy: 0.6147 |
valid_balanced_accuracy: 0.39014 | 0:06:51s
epoch 63 | loss: 0.76619 | train_balanced_accuracy: 0.61722 |
valid_balanced_accuracy: 0.379
                               | 0:06:58s
epoch 64 | loss: 0.76873 | train_balanced_accuracy: 0.60593 |
valid_balanced_accuracy: 0.38366 | 0:07:04s
epoch 65 | loss: 0.76239 | train_balanced_accuracy: 0.6151 |
valid_balanced_accuracy: 0.38979 | 0:07:10s
epoch 66 | loss: 0.76005 | train_balanced_accuracy: 0.59914 |
valid_balanced_accuracy: 0.38029 | 0:07:17s
epoch 67 | loss: 0.76569 | train balanced accuracy: 0.62932 |
valid balanced accuracy: 0.39355 | 0:07:24s
epoch 68 | loss: 0.76006 | train balanced accuracy: 0.6195 |
valid_balanced_accuracy: 0.39069 | 0:07:30s
epoch 69 | loss: 0.76618 | train_balanced_accuracy: 0.61029 |
valid_balanced_accuracy: 0.40029 | 0:07:36s
epoch 70 | loss: 0.75801 | train_balanced_accuracy: 0.60774 |
valid_balanced_accuracy: 0.36723 | 0:07:43s
epoch 71 | loss: 0.76232 | train_balanced_accuracy: 0.61565 |
valid_balanced_accuracy: 0.38205 | 0:07:49s
epoch 72 | loss: 0.75112 | train_balanced_accuracy: 0.61485 |
valid_balanced_accuracy: 0.38412 | 0:07:56s
epoch 73 | loss: 0.75863 | train_balanced_accuracy: 0.59589 |
valid_balanced_accuracy: 0.37215 | 0:08:03s
```

```
epoch 74 | loss: 0.75479 | train_balanced_accuracy: 0.60204 |
valid_balanced_accuracy: 0.39199 | 0:08:09s
epoch 75 | loss: 0.76071 | train_balanced_accuracy: 0.62331 |
valid_balanced_accuracy: 0.39126 | 0:08:15s
epoch 76 | loss: 0.75277 | train balanced accuracy: 0.62375 |
valid balanced accuracy: 0.39737 | 0:08:22s
epoch 77 | loss: 0.75332 | train balanced accuracy: 0.59101 |
valid_balanced_accuracy: 0.38389 | 0:08:28s
epoch 78 | loss: 0.7528 | train balanced accuracy: 0.60685 |
valid_balanced_accuracy: 0.3768 | 0:08:35s
epoch 79 | loss: 0.75348 | train_balanced_accuracy: 0.6036 |
valid_balanced_accuracy: 0.37572 | 0:08:41s
epoch 80 | loss: 0.74556 | train_balanced_accuracy: 0.61106 |
valid_balanced_accuracy: 0.36929 | 0:08:48s
epoch 81 | loss: 0.75218 | train_balanced_accuracy: 0.59921 |
valid_balanced_accuracy: 0.38006 | 0:08:54s
epoch 82 | loss: 0.7429 | train_balanced_accuracy: 0.59807 |
valid_balanced_accuracy: 0.37381 | 0:09:01s
epoch 83 | loss: 0.74328 | train_balanced_accuracy: 0.62759 |
valid balanced accuracy: 0.38178 | 0:09:07s
epoch 84 | loss: 0.7386 | train_balanced_accuracy: 0.61717 |
valid balanced accuracy: 0.3739 | 0:09:13s
epoch 85 | loss: 0.75087 | train_balanced_accuracy: 0.61999 |
valid_balanced_accuracy: 0.39013 | 0:09:20s
epoch 86 | loss: 0.75104 | train_balanced_accuracy: 0.62011 |
valid_balanced_accuracy: 0.38935 | 0:09:27s
epoch 87 | loss: 0.75049 | train_balanced_accuracy: 0.60756 |
valid_balanced_accuracy: 0.37154 | 0:09:33s
epoch 88 | loss: 0.73765 | train_balanced_accuracy: 0.60142 |
valid_balanced_accuracy: 0.37245 | 0:09:40s
epoch 89 | loss: 0.7395 | train_balanced_accuracy: 0.59368 |
valid_balanced_accuracy: 0.37856 | 0:09:46s
epoch 90 | loss: 0.7403 | train_balanced_accuracy: 0.60837 |
valid_balanced_accuracy: 0.38233 | 0:09:52s
epoch 91 | loss: 0.74567 | train balanced accuracy: 0.61556 |
valid balanced accuracy: 0.37167 | 0:09:59s
epoch 92 | loss: 0.74558 | train balanced accuracy: 0.61199 |
valid_balanced_accuracy: 0.38302 | 0:10:06s
epoch 93 | loss: 0.73227 | train_balanced_accuracy: 0.60764 |
valid_balanced_accuracy: 0.37717 | 0:10:12s
epoch 94 | loss: 0.73832 | train_balanced_accuracy: 0.60615 |
valid_balanced_accuracy: 0.38735 | 0:10:19s
epoch 95 | loss: 0.73214 | train_balanced_accuracy: 0.63771 |
valid_balanced_accuracy: 0.38581 | 0:10:25s
epoch 96 | loss: 0.72661 | train_balanced_accuracy: 0.63612 |
valid_balanced_accuracy: 0.38305 | 0:10:31s
epoch 97 | loss: 0.73308 | train_balanced_accuracy: 0.64282 |
valid_balanced_accuracy: 0.38917 | 0:10:38s
```

```
epoch 98 | loss: 0.73029 | train_balanced_accuracy: 0.61611 |
valid_balanced_accuracy: 0.37151 | 0:10:45s
epoch 99 | loss: 0.73767 | train_balanced_accuracy: 0.64017 |
valid_balanced_accuracy: 0.39671 | 0:10:51s
epoch 100 | loss: 0.74229 | train balanced accuracy: 0.59897 |
valid_balanced_accuracy: 0.37954 | 0:10:57s
epoch 101 | loss: 0.73277 | train balanced accuracy: 0.60913 |
valid_balanced_accuracy: 0.38695 | 0:11:04s
epoch 102 | loss: 0.73808 | train_balanced_accuracy: 0.62746 |
valid_balanced_accuracy: 0.37431 | 0:11:10s
epoch 103 | loss: 0.73009 | train_balanced_accuracy: 0.60618 |
valid_balanced_accuracy: 0.39121 | 0:11:17s
epoch 104 | loss: 0.72669 | train_balanced_accuracy: 0.61565 |
valid_balanced_accuracy: 0.38722 | 0:11:23s
epoch 105 | loss: 0.72675 | train_balanced_accuracy: 0.62828 |
valid_balanced_accuracy: 0.36445 | 0:11:30s
epoch 106 | loss: 0.72745 | train_balanced_accuracy: 0.64856 |
valid_balanced_accuracy: 0.38814 | 0:11:36s
epoch 107 | loss: 0.72924 | train_balanced_accuracy: 0.64804 |
valid balanced accuracy: 0.39742 | 0:11:43s
epoch 108 | loss: 0.72524 | train balanced accuracy: 0.642
valid balanced accuracy: 0.39709 | 0:11:49s
epoch 109 | loss: 0.73933 | train_balanced_accuracy: 0.63137 |
valid_balanced_accuracy: 0.37966 | 0:11:55s
epoch 110 | loss: 0.72338 | train_balanced_accuracy: 0.64403 |
valid_balanced_accuracy: 0.38482 | 0:12:02s
epoch 111 | loss: 0.72852 | train_balanced_accuracy: 0.62995 |
valid_balanced_accuracy: 0.38325 | 0:12:08s
epoch 112 | loss: 0.7201 | train_balanced_accuracy: 0.62729 |
valid_balanced_accuracy: 0.36838 | 0:12:15s
epoch 113 | loss: 0.72654 | train_balanced_accuracy: 0.61102 |
valid_balanced_accuracy: 0.37809 | 0:12:21s
epoch 114 loss: 0.72222 | train_balanced_accuracy: 0.62514 |
valid_balanced_accuracy: 0.37412 | 0:12:28s
epoch 115 | loss: 0.71867 | train balanced accuracy: 0.6302 |
valid_balanced_accuracy: 0.37747 | 0:12:34s
epoch 116 | loss: 0.72453 | train balanced accuracy: 0.62727 |
valid_balanced_accuracy: 0.37794 | 0:12:40s
epoch 117 | loss: 0.72526 | train_balanced_accuracy: 0.60387 |
valid_balanced_accuracy: 0.37015 | 0:12:47s
epoch 118 | loss: 0.71324 | train_balanced_accuracy: 0.63403 |
valid_balanced_accuracy: 0.36995 | 0:12:53s
epoch 119 | loss: 0.72227 | train_balanced_accuracy: 0.64801 |
valid_balanced_accuracy: 0.38905 | 0:13:00s
epoch 120| loss: 0.71987 | train_balanced_accuracy: 0.65199 |
valid_balanced_accuracy: 0.36964 | 0:13:07s
epoch 121 | loss: 0.72485 | train_balanced_accuracy: 0.62439 |
valid_balanced_accuracy: 0.36822 | 0:13:13s
```

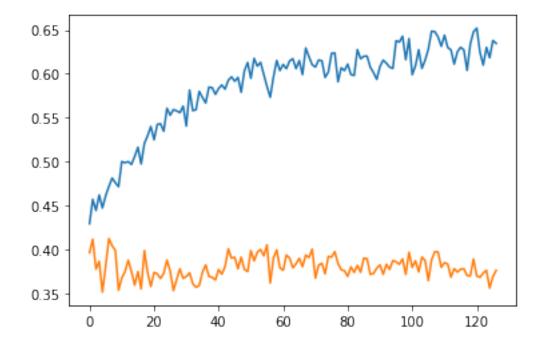
```
epoch 122 | loss: 0.71824 | train_balanced_accuracy: 0.60993 | valid_balanced_accuracy: 0.37306 | 0:13:20s epoch 123 | loss: 0.70235 | train_balanced_accuracy: 0.6301 | valid_balanced_accuracy: 0.37618 | 0:13:26s epoch 124 | loss: 0.7161 | train_balanced_accuracy: 0.61837 | valid_balanced_accuracy: 0.35595 | 0:13:33s epoch 125 | loss: 0.72457 | train_balanced_accuracy: 0.63801 | valid_balanced_accuracy: 0.36894 | 0:13:39s epoch 126 | loss: 0.71504 | train_balanced_accuracy: 0.63463 | valid_balanced_accuracy: 0.37613 | 0:13:46s
```

Early stopping occurred at epoch 126 with best_epoch = 6 and best_valid_balanced_accuracy = 0.4123

```
[]:  # plot losses  # plt.plot(clf1_nopreproc.history['valid_logloss'])
```

```
[]: # plot accuracy
plt.plot(clf1_nopreproc.history['train_balanced_accuracy'])
plt.plot(clf1_nopreproc.history['valid_balanced_accuracy'])
```

[]: [<matplotlib.lines.Line2D at 0x7f06ecddb790>]



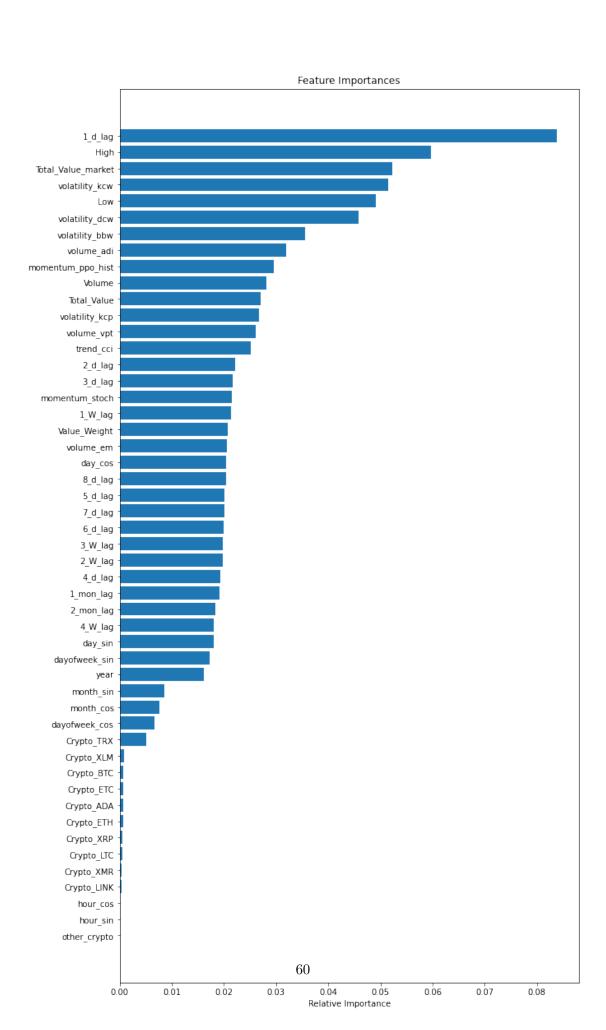
```
[]: # Saving the file import pickle
```

```
temp_file_path = '/content/drive/MyDrive/MADS_23_DL_final_project/data/
      \# clf1_nopreproc.save(temp_file_path + '/Tabnet_model.h5') \# creates a HDF5_{\square}
     ⇔file 'my model.h5'
     with open(temp_file_path + '/tabnet_v2.pkl', 'wb') as f: # Python 3: open(..., u
        pickle.dump(clf1_nopreproc, f)
[]: nn pred= clf1 nopreproc.predict(norm test df.fillna(0).values)
[]: nn_pred.value_counts()
                                                Traceback (most recent call last)
     AttributeError
     <ipython-input-257-d3a82199df5b> in <module>
     ---> 1 nn_pred.value_counts()
     AttributeError: 'numpy.ndarray' object has no attribute 'value_counts'
[]: df = pd.DataFrame(nn_pred)
     nn_pred = df.idxmax(axis=1)
[]: generate_model_report(test_target, nn_pred, 'micro')
     generate_model_report(test_target, nn_pred, 'macro')
     generate_model_report(test_target, nn_pred, 'weighted')
[]: print('\nClassification Report\n')
     print(classification_report(test_target, nn_pred))
[]: # Creating a confusion matrix, which compares the y_test and y_pred
     cm = confusion_matrix(test_target, nn_pred)
     # Creating a dataframe for a array-formatted Confusion matrix, so it will be \Box
     →easy for plotting.
     cm df = pd.DataFrame(cm,
                          index = ['below_0', 'above_0', 'above_market'],
                          columns = ['below_0', 'above_0', 'above_market'])
     #Plotting the confusion matrix
     plt.figure(figsize=(10,10))
     sns.heatmap(cm_df, annot=True)
     plt.title('Confusion Matrix')
```

```
plt.ylabel('Actal Values')
    plt.xlabel('Predicted Values')
    plt.show()
   End of the Notebook
[]:
   5.8 Random forest classifier
[]: # fitting the model
    model = RandomForestClassifier(n_estimators=500,__
     →random_state=1,max_depth=8,n_jobs=-1)
    model.fit(norm_train_df.fillna(0), target)
[]: RandomForestClassifier(max_depth=8, n_estimators=500, n_jobs=-1, random_state=1)
[]: target_test_pred = model.predict(norm_test_df.fillna(0))
[]: generate_model_report(test_target, target_test_pred, 'micro')
    generate_model_report(test_target, target_test_pred, 'macro')
    generate_model_report(test_target, target_test_pred, 'weighted')
   =======Printing the micro metrics=========
   Accuracy = 0.506
   Precision = 0.506
   Recall = 0.506
   F1 Score = 0.506
   _____
   Precision = 0.338
   Recall = 0.354
   F1 Score = 0.345
   _____
   =======Printing the weighted metrics=========
   Precision = 0.485
   Recall = 0.506
   F1 Score = 0.494
[]: # Feature importance
    features=norm_train_df.columns
    importances = model.feature_importances_
    indices = np.argsort(importances)
    plt.figure(figsize=(10,20))
    plt.title('Feature Importances')
```

```
plt.barh(range(len(indices)), importances[indices])
plt.yticks(range(len(indices)), features[indices])
plt.xlabel('Relative Importance')
```

[]: Text(0.5, 0, 'Relative Importance')



```
[]:
[]:
[]:
    5.9 LGBM tuning with optuna
[]: from verstack import LGBMTuner
     tuned_lgbm = LGBMTuner(metric = 'f1_macro', trials = 20)
     tuned_lgbm.fit(norm_train_df.fillna(0), target)
     * Initiating LGBMTuner.fit
         . Settings:
         .. Trying 20 trials
         .. Evaluation metric: f1_macro
         .. Study direction: minimize log_loss
         . Trial number: 0 finished
         .. Optimization score (lower-better): log_loss: 0.7677924794265247
         .. Evaluation score (greater-better): f1_macro: 0.5203214698753702
         . Trial number: 1 finished
         .. Optimization score (lower-better): log_loss: 0.7593523232768736
         .. Evaluation score (greater-better): f1_macro: 0.5097983602870538
         . Trial number: 2 finished
         .. Optimization score (lower-better): log_loss: 0.774663563326048
         .. Evaluation score (greater-better): f1_macro: 0.5199973165458244
         . Trial number: 3 finished
         .. Optimization score (lower-better): log_loss: 0.774393559693144
         .. Evaluation score (greater-better): f1_macro: 0.5144030968450225
         . Trial number: 4 finished
         .. Optimization score (lower-better): log_loss: 0.7750818256537647
         .. Evaluation score (greater-better): f1_macro: 0.5209124315021884
         . Trial number: 11 finished
         .. Optimization score (lower-better): log_loss: 0.7556247573923124
         .. Evaluation score (greater-better): f1_macro: 0.5387465284643207
         . Trial number: 15 finished
         .. Optimization score (lower-better): log_loss: 0.761536687537761
```

```
.. Evaluation score (greater-better): f1_macro: 0.5309296563380371
...

. Trial number: 19 finished
.. Optimization score (lower-better): log_loss: 0.7584679418238669
.. Evaluation score (greater-better): f1_macro: 0.5328100292785513
...

- Tune n_estimators with early_stopping
Training until validation scores don't improve for 200 rounds
```

[100] train's multi_logloss: 0.501566 valid's multi_logloss: 0.798502 [200] train's multi_logloss: 0.313777 valid's multi_logloss: 0.765368

[300] train's multi_logloss: 0.208219 valid's multi_logloss: 0.758456 train's multi_logloss: 0.142102 valid's multi_logloss: 0.759817

[500] train's multi_logloss: 0.0987624 valid's multi_logloss: 0.767103

Early stopping, best iteration is:

[319] train's multi_logloss: 0.193157 valid's multi_logloss: 0.757329

- Fitting optimized model with the follwing params:

task : train learning_rate : 0.02 num_leaves : 177

colsample_bytree : 0.6277217293825994 subsample : 0.9154787443696969

bagging_freq : 1
max_depth : -1
verbosity : -1

reg_alpha : 1.2005946274475368e-08 reg_lambda : 1.210727364048483e-08

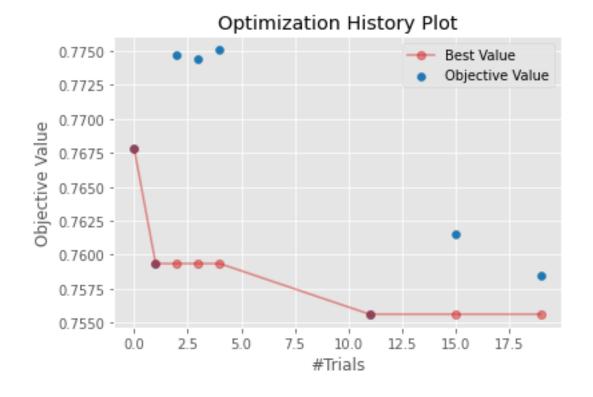
min_split_gain: 0.0zero_as_missing: Falsemax_bin: 255min_data_in_bin: 3random_state: 42num_classes: 3

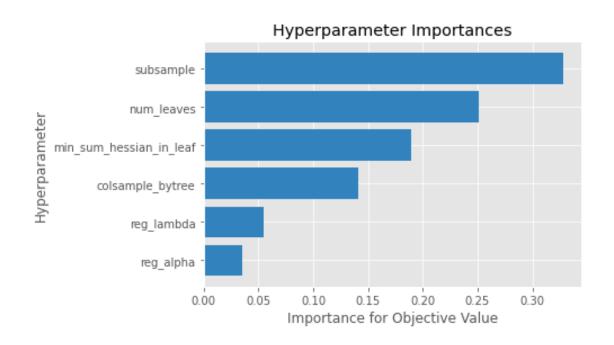
objective : multiclass metric : multi_logloss

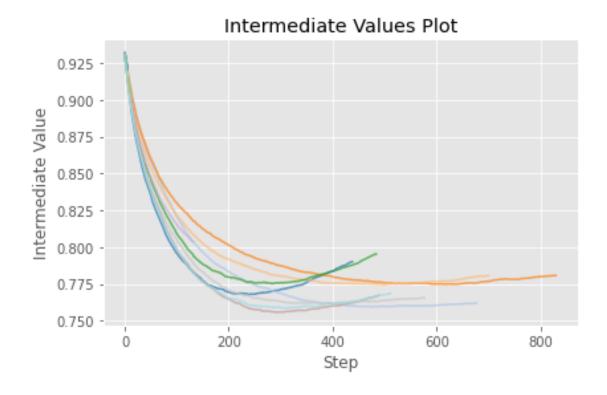
num_threads : 0

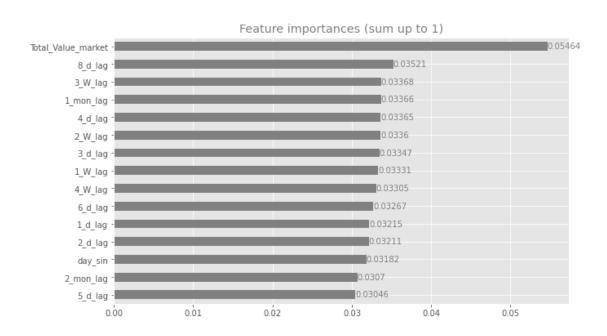
min_sum_hessian_in_leaf : 0.1610128003061735

n_estimators : 319









. Optuna hyperparameters optimization finished
.. Best trial number:11 | log_loss: 0.7556247573923124

```
.. best iteration: 319
                                      multi_logloss:
                                                              0.7573285095803589
     ______
    Time elapsed for fit execution: 6 min 3.876 sec
[]: tuned_lgbm.best_params
[]: {'task': 'train',
     'learning_rate': 0.02,
     'num_leaves': 177,
     'colsample_bytree': 0.6277217293825994,
     'subsample': 0.9154787443696969,
     'bagging_freq': 1,
     'max_depth': -1,
     'verbosity': -1,
     'reg_alpha': 1.2005946274475368e-08,
     'reg_lambda': 1.210727364048483e-08,
     'min_split_gain': 0.0,
     'zero_as_missing': False,
     'max_bin': 255,
     'min_data_in_bin': 3,
     'random_state': 42,
     'num_classes': 3,
     'objective': 'multiclass',
     'metric': 'multi_logloss',
     'num_threads': 0,
     'min_sum_hessian_in_leaf': 0.1610128003061735,
     'n_estimators': 319}
[]: tuned_lgbm
[]: LGBMTuner(Evaluation metric: f1_macro
             trials: 20
              refit: True
              verbosity: 1
              visualization: True)
[]: tuned_lgbm_pred = tuned_lgbm.predict(norm_test_df)
[]: generate_model_report(test_target, tuned_lgbm_pred, 'micro')
    generate_model_report(test_target, tuned_lgbm_pred, 'macro')
    generate_model_report(test_target, tuned_lgbm_pred, 'weighted')
    ========Printing the micro metrics========
    Accuracy = 0.518
    Precision = 0.518
    Recall = 0.518
```

. n_estimators optimization finished

```
F1 Score = 0.518
   _____
   ======Printing the macro metrics========
   Precision = 0.433
   Recall = 0.379
   F1 Score = 0.376
   _____
   =======Printing the weighted metrics=========
   Precision = 0.517
   Recall = 0.518
   F1 Score = 0.501
   []: # Saving the file
   import pickle
   temp_file_path = '/content/drive/MyDrive/MADS_23_DL_final_project/data/
    →model_files/LGBM_hourly'
   with open(temp_file_path + '/tuned_lgbm_f13_final.pkl', 'wb') as f: # Python 3:
    → open(..., 'wb')
      pickle.dump(tuned_lgbm, f)
```

5.10 LGBM After Optimisation

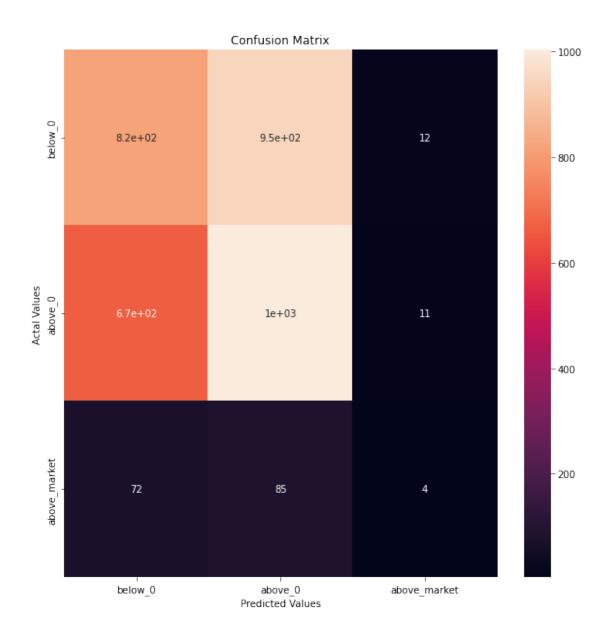
```
[]: import lightgbm as lgb
     untuned_lgbm = lgb.LGBMClassifier( learning_rate= 0.02,
     num_leaves= 185,
      colsample_bytree= 0.9973006775338719,
      subsample= 0.8626362747879762,
      bagging_freq= 1,
      max_depth = -1,
      verbosity= -1,
      reg_alpha= 0.6849391813640976,
      reg_lambda= 1.4776089934723414e-08,
      min_split_gain= 0.0,
      zero_as_missing= False,
      max_bin=255,
      min_data_in_bin= 3,
     random_state= 42,
      num_classes= 3,
      objective= 'multiclass',
      metric= 'multi_logloss',
      num_threads= 0,
      min_sum_hessian_in_leaf= 8.698870626111832,
      n_estimators= 780)
     untuned_lgbm.fit(norm_train_df.fillna(0), target)
```

[LightGBM] [Warning] num_threads is set=0, n_jobs=-1 will be ignored. Current

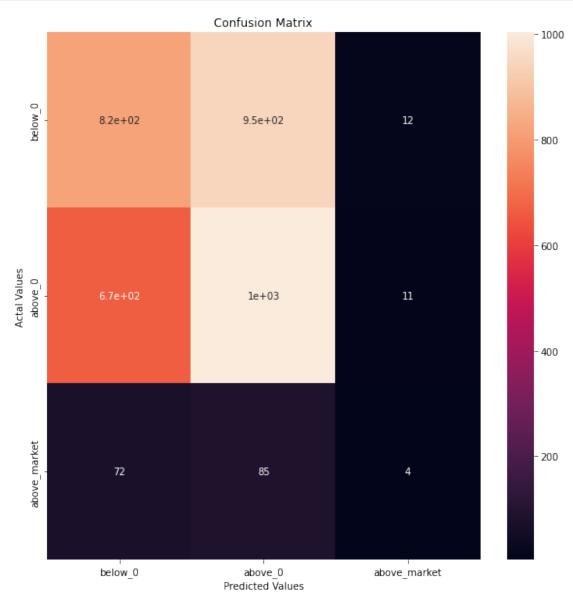
```
value: num_threads=0
    [LightGBM] [Warning] min_sum_hessian_in_leaf is set=8.698870626111832,
   min_child_weight=0.001 will be ignored. Current value:
   min_sum_hessian_in_leaf=8.698870626111832
    [LightGBM] [Warning] bagging freq is set=1, subsample freq=0 will be ignored.
   Current value: bagging_freq=1
[]: LGBMClassifier(bagging_freq=1, colsample_bytree=0.9973006775338719,
                  learning_rate=0.02, max_bin=255, metric='multi_logloss',
                  min_data_in_bin=3, min_sum_hessian_in_leaf=8.698870626111832,
                  n_estimators=780, num_classes=3, num_leaves=185, num_threads=0,
                  objective='multiclass', random_state=42,
                  reg_alpha=0.6849391813640976, reg_lambda=1.4776089934723414e-08,
                  subsample=0.8626362747879762, verbosity=-1,
                  zero_as_missing=False)
[]: |lgbm_pred=untuned_lgbm.predict(norm_test_df)
[]:
   5.10.1 Test Metrics
[]: generate_model_report(test_target, lgbm_pred, 'micro')
    generate_model_report(test_target, lgbm_pred, 'macro')
    generate_model_report(test_target, lgbm_pred, 'weighted')
   =======Printing the micro metrics========
   Accuracy = 0.508
   Precision = 0.508
   Recall = 0.508
   F1 Score = 0.508
    _____
   ======Printing the macro metrics========
   Precision = 0.402
   Recall = 0.391
   F1 Score = 0.385
    _____
   =======Printing the weighted metrics=========
   Precision = 0.512
   Recall = 0.508
   F1 Score = 0.495
    _____
   5.10.2 Confusion matrix
[]: from sklearn.metrics import classification_report
    print('\nClassification Report\n')
    print(classification_report(test_target, lgbm_pred))
```

Classification Report

	precision	recall	f1-score	support
0	0.55	0.38	0.45	1778
1	0.50	0.68	0.58	1682
2	0.15	0.11	0.13	161
accuracy			0.51	3621
macro avg	0.40	0.39	0.39	3621
weighted avg	0.51	0.51	0.49	3621



```
plt.xlabel('Predicted Values')
plt.show()
```



```
[]: # Saving the file
import pickle
temp_file_path = '/content/drive/MyDrive/MADS_23_DL_final_project/data/
→model_files/LGBM_hourly'
with open(temp_file_path + '/Tuned_lgbm_v13_final2.pkl', 'wb') as f: # Python
→3: open(..., 'wb')
pickle.dump(untuned_lgbm, f)
```

6 End of the Notebook