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Master Level in Big Data Analysis

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MSIS-822 Advanced Data Analytic Techniques

Honorable Prof. Mohammad ALsarim

December 2025

Detection of AI-Generated Arabic Text:

A Data Mining Approach

Abstract

When Prof. Alsarim share his vision with the Class of M4 regarding this 822 Course, along the way he interpret the significant aspect of this project regarding our development in the Big Data Analysis. When I first start working on the project, it felt like I am in the middle of no-where. Now after finishing it, the degree I've reached so far make me proud of all the hard work and effort I managed to achieve. The deeper we dive the wider it gets.

Introduction:

Detection of AI-Generated Media has storm the public every day browsing among social media, which significantly mean that the digital work-force in both side, Generating and Detection contexts achieving massive results, yet the NLP are reaching OK level regarding English Language, Thus more work needed to reach an OK level in the ladder of Arabic Language NLP. This project aim to achieve a proud effort regarding this subject.

Dataset Description:

As directed by Prof. AL-sarim this project rely on

KFUPM-JRCAI/arabic-generated-abstracts Available on Hugging Face:

(https://huggingface.co/datasets/KFUPM-JRCAI/arabic-generated-abstracts)

This is publicly available Arabic machine generated text dataset hosted on Hugging Face . it contains pairs of academic abstract in Arabic, part is human presented under the label Original abstract, and part is AI, generated by many language models which are:

- Allam_generated_abstract
- Jais_generated_abstract
- Llama_generated_abstract
- Open_ai_generated_abstract

- **Total samples:** 41,940
- **Features:**
  - `abstract_text` – the raw abstract
  - `source_split` – originating data source identifier
  - `generated_by` – human or model name
  - `label` – 0 for human, 1 for AI

Additional Remark:

fun facts, to interpret what is name stands for:

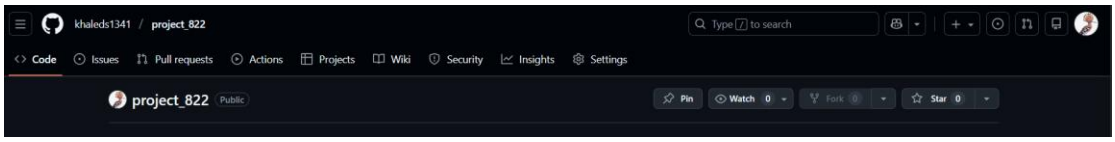
ALLAM : Arabic Language Large Model

LLAM: Large Language Model

JAIS: from the mountain in UAE named Jais.

PHASE 1

- **Task 1.1:** Establish a project repository (e.g., on GitHub) to host all code, reports, and results.



https://github.com/khaleds1341

https://github.com/khaleds1341/project_822

- **Task 1.2:** Use the datasets library from Hugging Face to download the arabic-generated-abstracts dataset directly into a Python environment (e.g., Jupyter Notebook, Google Colab).

```
from datasets import load_dataset
import pandas as pd

# Load the dataset
dataset = load_dataset("KFUPM-JRCAI/arabic-generated-abstracts")
```

Checking for Noise:

```
66    # 1. Missing values
```

```
71    # 2. Duplicates
```

```
80    # 3. Inconsistencies: empty strings or only spaces
```

At the top of the code< I've listed almost all pipeline needed to run the code

```
# pip install datasets
# pip install numpy
# pip install pandas
# pip install regex
# pip install textstat
# pip install spacy
# pip install spacy-arabic
# pip install camel-tools
# pip install transformers
#لتصدير الملف لفتحه في اكسل لكي تظهر الخطوط العربية بشكل افضل من تيرمنال # pip install openpyxl
# pip install scipy
# pip install sentence-transformers
# pip install tensorflow
# pip install tf_keras

# pip install sentence_transformers

# pip install torch torchvision torchaudio --index-url https://download.pytorch.org/whl/cpu

```

PHASE 2

Preprocessing:

Arabic Language is the richest language, many word might have the same shape but due to a simple symbol the meaning and spilling might chang; thus there are

- Diacritics (Tashkeel ًٌٍَُِّْ)
- Long Vowel (Madd ـا ـي ـو)

And as many languages

- Punctuation Marks.

In order to make the dataset ready for mining, the dataset had been preprocessed as:

❖ Remove Diacritics (Tashkeel)

```
172  # 2.1.2 aiming to remove altashkeel
173  def remove_diacritics(text):
174      arabic_diacritics = re.compile('[\u0617-\u061A\u064B-\u0652]')
175      return re.sub(arabic_diacritics, '', text)
```

❖ Normalize: the first letter in Arabic is " ALEF" it has 3 pronounciation based on three sumbol it has called " "HAMZA", [أ , إ , آ] removing HAMZA is an example of how normalize used.

```
161  def normalize_arabic(text):
162      text = re.sub("[إأآا]", "ا", text)
163      text = re.sub("ى", "ي", text)
164      text = re.sub("ؤ", "و", text)
165      text = re.sub("ئ", "ي", text)
166      text = re.sub("ة", "ه", text)
167      text = re.sub("+[ ـ^]", " ", text)  # remove non-Arabic chars
168      return text
169      #2.1.1 Normalization
```

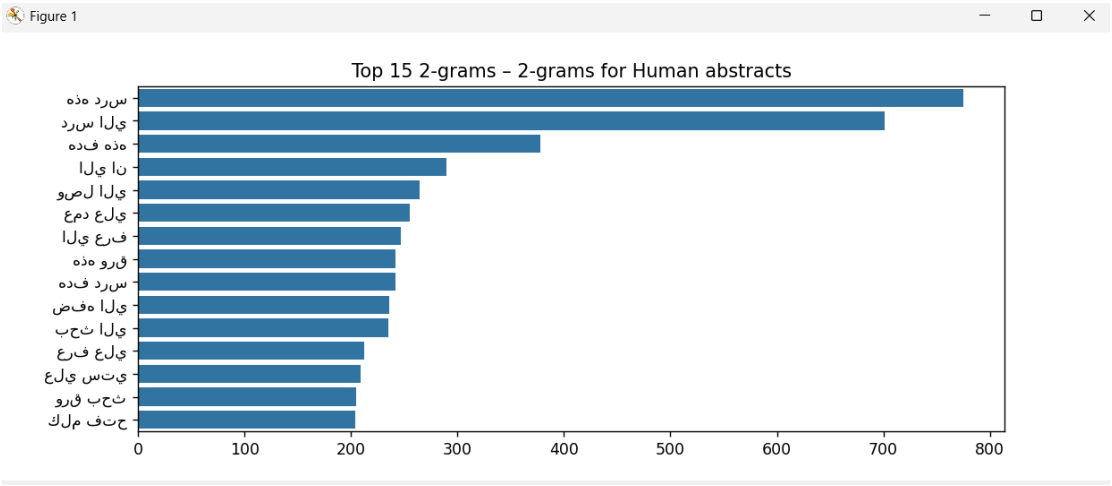
❖ Stopwords such as full stop or question mark or !

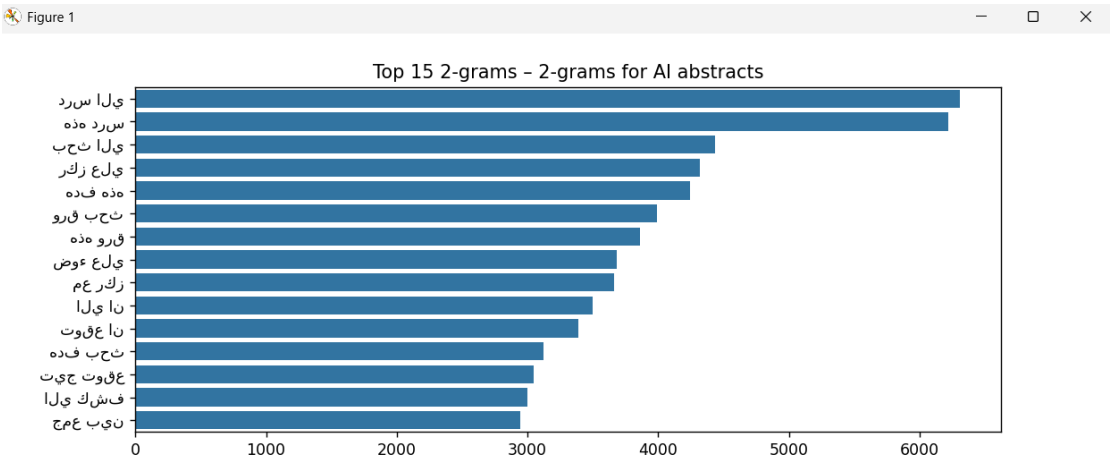
```
#2.1.3 & 2.1.4
arabic_stopwords = set(stopwords.words("arabic"))
stemmer = ISRIStemmer()
```

❖ Additional remark:::

```
192  # to overcome a struggle I had to import this library
193  from nltk.corpus import stopwords
194  arabic_stopwords = set(stopwords.words("arabic"))
195
196  #enhanced the solution via this line
197  arabic_stopwords = {
198      "في", "من", "على", "عن", "إلى", "و", "كما", "أن", "إن", "ما", "هو", "هي","الذي","هذا", "ذلك"
199  }
200
```

VISUALIZATION





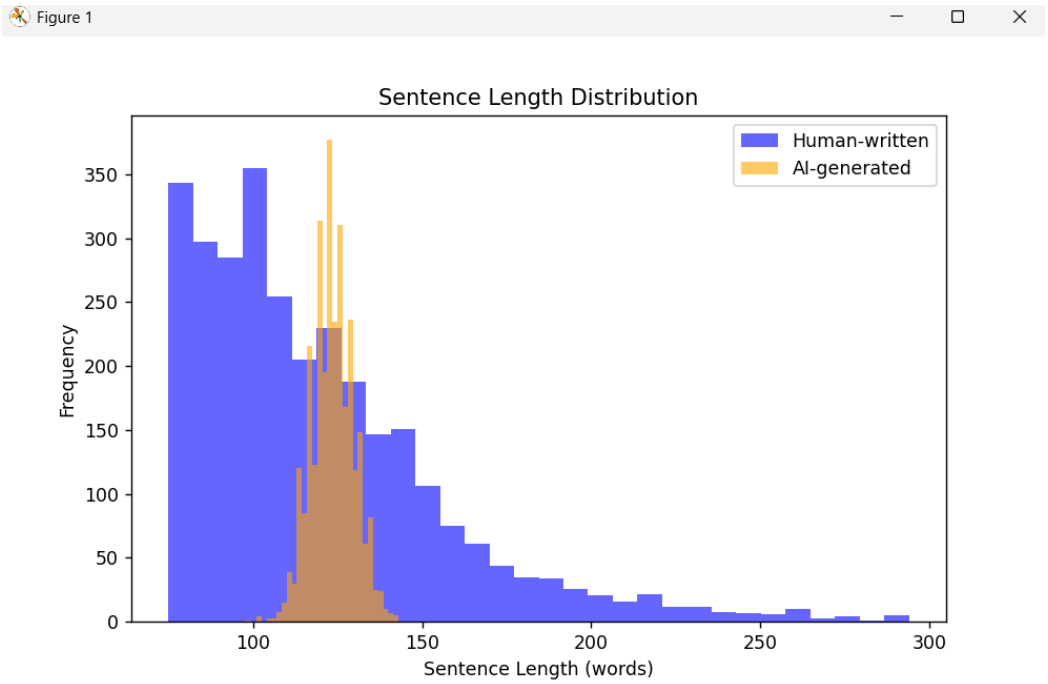


Figure 1
Sentence Length Distribution
Human-written
AI-generated
Frequency
Sentence Length (words)
0
50
100
150
200
250
300
350
100
150
200
250
300

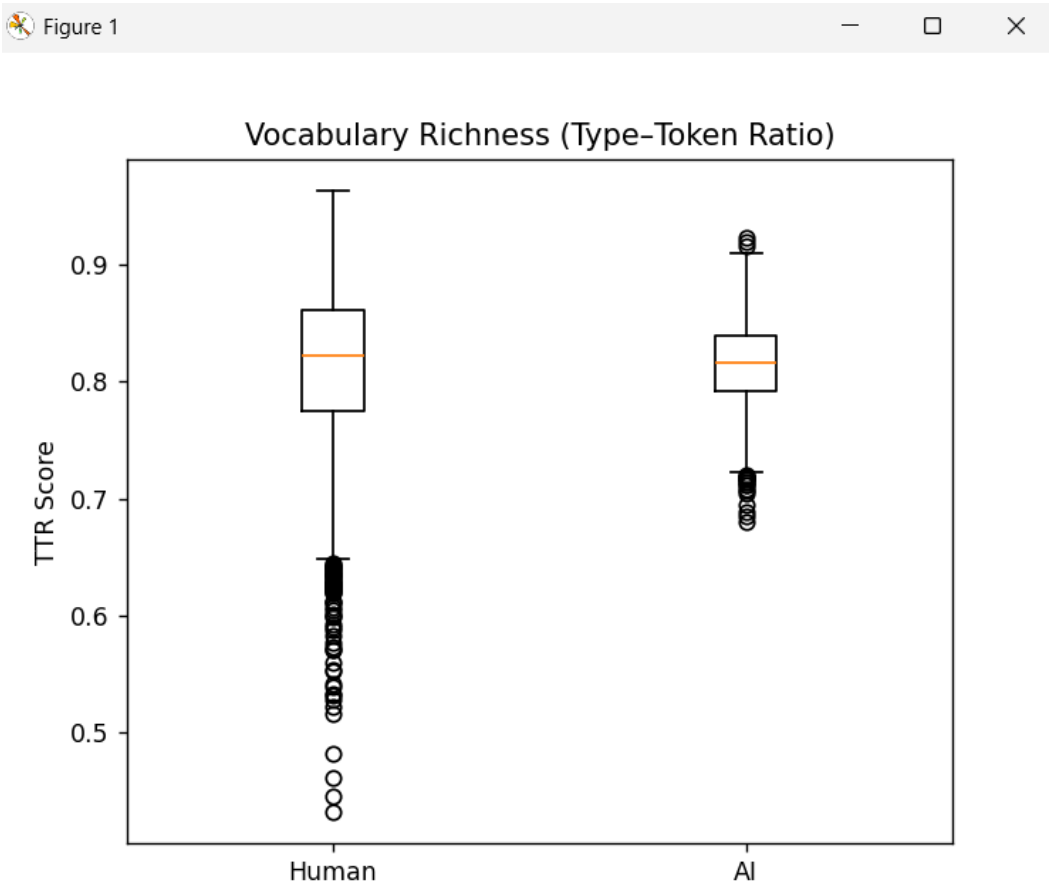


Figure 1
Vocabulary Richness (Type–Token Ratio)
TTR Score
0.5
0.6
0.7
0.8
0.9
Human
AI

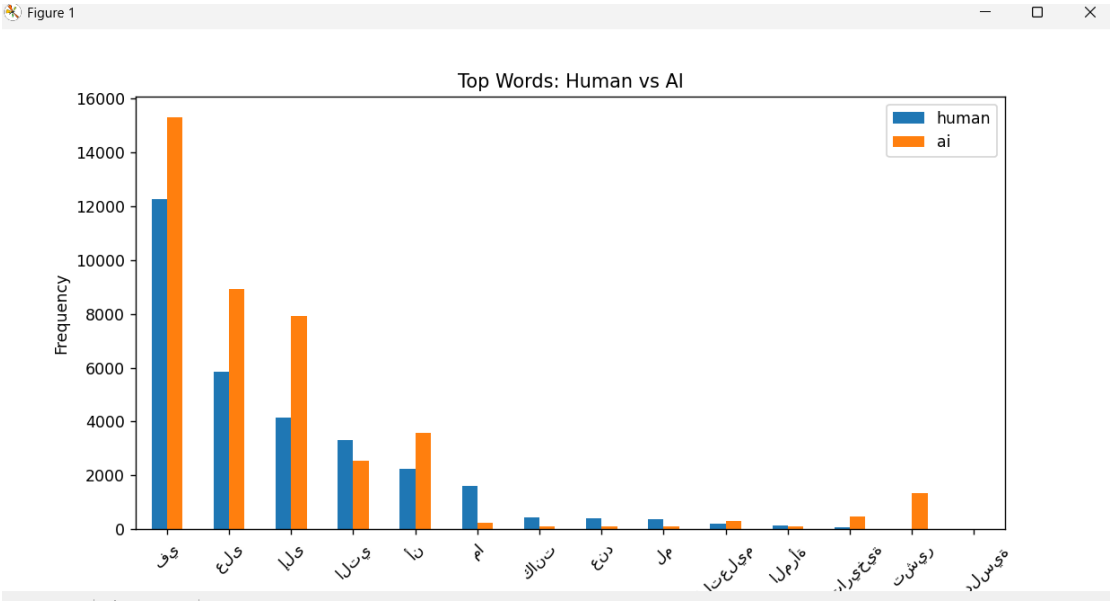


Figure 1
Top Words: Human vs AI
human
ai
Frequency
16000
14000
12000
10000
8000
6000
4000
2000
0

- **Lexical Analysis:** Comparing the use of function words, punctuation, and specific terms.

  - Function Words removal/comparison

```
173     arabic_diacritics = re.compile('[\u0617-\u061A\u064B-\u0652]')
174     return re.sub(arabic_diacritics, '', text)
```

  - Vocabulary Richness

```
319 def type_token_ratio(text):
320     words = text.split()
321     return len(set(words)) / len(words) if words else 0
```

```
original_abstract_tokens          [كثيرا, ما, ترتبط, الموارد, التاريخية, في, ال...
original_abstract_words           [كثيرا, ما, ترتبط, الموارد, التاريخية, في, ال...
original_abstract_sentences       [كثيرا ما ترتبط الموارد التاريخية في الأدبيات ...
allam_generated_abstract_tokens   [يهدف, هذا, البحث, إلى, دراسة, مظاهر, التعليم, ...
allam_generated_abstract_words    [يهدف, هذا, البحث, إلى, دراسة, مظاهر, التعليم, ...
allam_generated_abstract_sentences [يهدف هذا البحث إلى دراسة مظاهر التعليم عند الم...
jais_generated_abstract_tokens    [تدرس, هذه, الورقة, البحثية, مظاهر, التعليم, لد...
jais_generated_abstract_words     [تدرس, هذه, الورقة, البحثية, مظاهر, التعليم, لد...
jais_generated_abstract_sentences [تدرس هذه الورقة البحثية مظاهر التعليم لدى المر...
llama_generated_abstract_tokens   [تهدف, هذه, الورقة, البحثية, إلى, استكشاف, صور...
llama_generated_abstract_words    [تهدف, هذه, الورقة, البحثية, إلى, استكشاف, صور...
llama_generated_abstract_sentences [تهدف هذه الورقة البحثية إلى استكشاف صور مظ ...
openai_generated_abstract_tokens  [البحث, يستكشف, مظاهر, التعليم, عند, المرأة, ال...
openai_generated_abstract_words   [البحث, يستكشف, مظاهر, التعليم, عند, المرأة, ال...
openai_generated_abstract_sentences [البحث يستكشف مظاهر التعليم عند المرأة الأندلسي...
```

TOKENs: smallest units after splitting text into word and punctuation

WORDs: cleaned of preprocessed tokens

SENTENCEs: text split into sentences

PHASE 3

Functions used based on Prof. ALsarim direction start from number 5

خالد سعد بن شاهر المطرفي	4714248	**5**

Added by 23 number of students in M4 class

4. You are responsible for the feature at this index and the subsequent four features. Therefore, your full set of features is: $f_{k+i} = (k \times n) + i$, where $k = 0,1,2,3,$ so on

5. Number of elongations

```
466  # Feature 5: Number of elongations
467  import re
468  TATWEEL = '\u0640'
469  for col in original_text_columns:
470      feature = f'{col}_f005_num_elongations'
471      def _elong_count(t):
472          s = str(t) if pd.notna(t) else ""
473          tat = s.count(TATWEEL)
474          repeats = len(re.findall(r'(.)\1{2,}', s))
475          return tat + repeats
476      df[feature] = df[col].apply(_elong_count)
```

28. Number of colons

```
479     # Feature 28 : Number of colons
480   #لحساب عدد (:) في الجمل
481   for col in original_text_columns:
482       base = col
483       df[f'f028_colons_{base}'] = df[base].apply(
484           lambda t: t.count(":") if isinstance(t, str) else 0
485       )
486
```

51. Number of abbreviations

```
490   #51. Number of abbreviations
491   import re
492
493   def count_abbreviations(text):
```

74. Number of definitive

```
562   #المعرفات بالألف و اللام occurrences (-ال) Feature 74: Number of definitive
563   #(ـــال) Feature 74: Number of definitives
564   for col in original_text_columns:
565       df[f'{col}_f074_num_definitive'] = df[col].apply(
566           lambda t: len(re.findall(r'\bال[\u0621-\u064A]+', t)) if isinstance(t, str) else 0
567       )
568
569   import os
570   print("Saving Excel...")
571   print(os.getcwd())  # shows where the file will be saved
572
573   df.to_excel("output.xlsx", index=False)
574   print("Excel saved!")
```

97. **BERT Embedding Similarity:** Mean cosine similarity of BERT embeddings.

```
554  #97. BERT Embedding Similarity
555  #.لكل جملة embeddings بين Mean Cosine Similarity احسب
556  from transformers import AutoTokenizer, AutoModel
557  import torch
558  import numpy as np
559  from sklearn.metrics.pairwise import cosine_similarity
560
561      (variable) device: Literal['cuda', 'cpu']
562  device = 'cuda' if torch.cuda.is_available() else 'cpu'
563  print(f"Using device: {device}")
564
```

Transformer: library that contain BERT and many AI Language models

When I run the code and reach BERT Embedding… since my computer does not has GPU, running the code was heavy on CPU, it took about more than 20 minutes.

- **Task 3.2:** Split the data into training, validation, and test sets (e.g., 70/15/15). Crucially, ensure this split is done at the very beginning and the test set is never used for training or feature selection to avoid data leakage.

```
599  # task3.2
600
601  # Train (70%) / Temp (30%) → then Temp → Validation (15%) / Test (15%)
602  from sklearn.model_selection import train_test_split
603
604  # First split: 70% Train, 30% Temp
605  train_df, temp_df = train_test_split(
606      df,
607      test_size=0.30,
608      random_state=42,
609      shuffle=True
610  )
611
612  # Second split: Split Temp into 15% Validation + 15% Test
613  # Since temp_df is 30% of total, splitting it 50/50 → 15% each
614  val_df, test_df = train_test_split(
615      temp_df,
```

PHASE 4

- **Task 4.1: Baseline Model**
  - Train a simple baseline model (e.g., Naïve Bayes or Logistic Regression). This sets a performance benchmark.

Necessity preparation needed to be able to conduct task 4.1.

Libraries:

Data handling

- Pandas: to manage dataframes
- numpy: numeric computation
- os

text preprocessing and NLP

- re and regex as re2: for Arabic aware regex operation
- ntlk for stopwords and stemming(ISRIStemmer)
- datasets

feature extraction

- TF-IDF VECTORIZATION

```
654    from sklearn.feature_extraction.text import TfidfVectorizer
```

- SCIPY to handle numeric + sparse TF-IDF features

```
876  # final features
877  X_train = hstack([X_train_tfidf, X_train_num]).tocsr()
878  X_val   = hstack([X_val_tfidf, X_val_num]).tocsr()
879  X_test  = hstack([X_test_tfidf, X_test_num]).tocsr()
880
881  y_train = train_df['label'].values
882  y_val   = val_df['label'].values
883  y_test  = test_df['label'].values
884
885  print('Final feature shapes ->', X_train.shape, X_val.shape, X_test.shape)
```

Methods & preprocessing steps

- **Dataset preparation**
  - Converted dataset into **long format**: one abstract per row
  - Created a **binary label** (0 = human, 1 = AI)
- **Text preprocessing (Arabic-specific)**
  - **Normalization**: unified letters (ه, ي, ا, etc.)
  - **Diacritics removal**: removed tashkeel marks
  - **Stopwords removal**: removed common Arabic words
  - **Stemming**: using ISRIStemmer to reduce words to root form
- **Derived features** (optional numeric features for ML):
  - Number of **elongations** (tatweel & repeated chars)
  - Number of **colons**
  - Number of **abbreviations**
  - Number of **definitive "ال-" occurrences**
  - **Sentence-level embedding similarity** (BERT, optional)
- **Text vectorization**
  - TF-IDF (TfidfVectorizer) for cleaned text (abstract_text_clean)
  - Created final feature matrices:
    - X_train_tfidf, X_val_tfidf, X_test_tfidf
    - Numeric features combined via hstack to form X_train, X_val, X_test
- **Train/Validation/Test split**
  - Stratified splitting using sklearn.model_selection.train_test_split

Snippet

```
Loaded split 'by_polishing' with 2851 rows
Unified dataset rows: 14255 (human=2851, ai=11404)
Computed bert_sentence_sim feature.
Split sizes -> train: 9978, val: 2138, test: 2139
TF-IDF vector shapes: (9978, 5000) (2138, 5000) (2139, 5000)
Final feature shapes -> (9978, 5005) (2138, 5005) (2139, 5005)
LR val acc: 0.9354536950420954
```

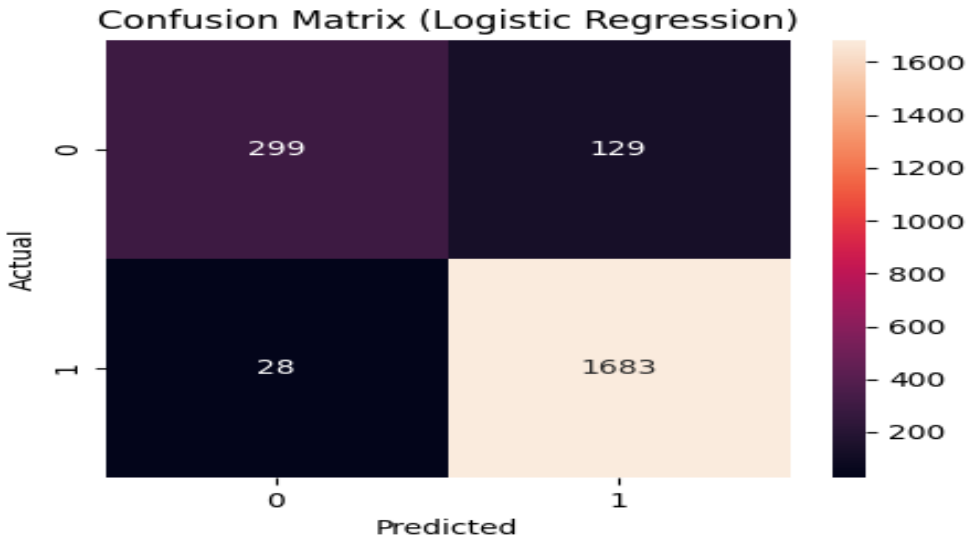
```
=== lr Test Results ===
Accuracy: 0.9266012155212716
              precision    recall  f1-score   support

           0       0.91      0.70      0.79       428
           1       0.93      0.98      0.96      1711

    accuracy                           0.93      2139
   macro avg       0.92      0.84      0.87      2139
weighted avg       0.93      0.93      0.92      2139

Confusion matrix:
 [[ 299  129]
 [  28 1683]]
```

Test Evaluation for Logistic Regression Model

Class 0 = Human written

Class 1 = AI generated

Metric	Class 0	Class 1	Notes
Precision	0.91	0.93	How many predicted as class x are correct
Recall	0.70	0.98	How many actual class x were correctly predicted
F1-score	0.79	0.96	Mean of P & R
Support	428	1711	Number of samples



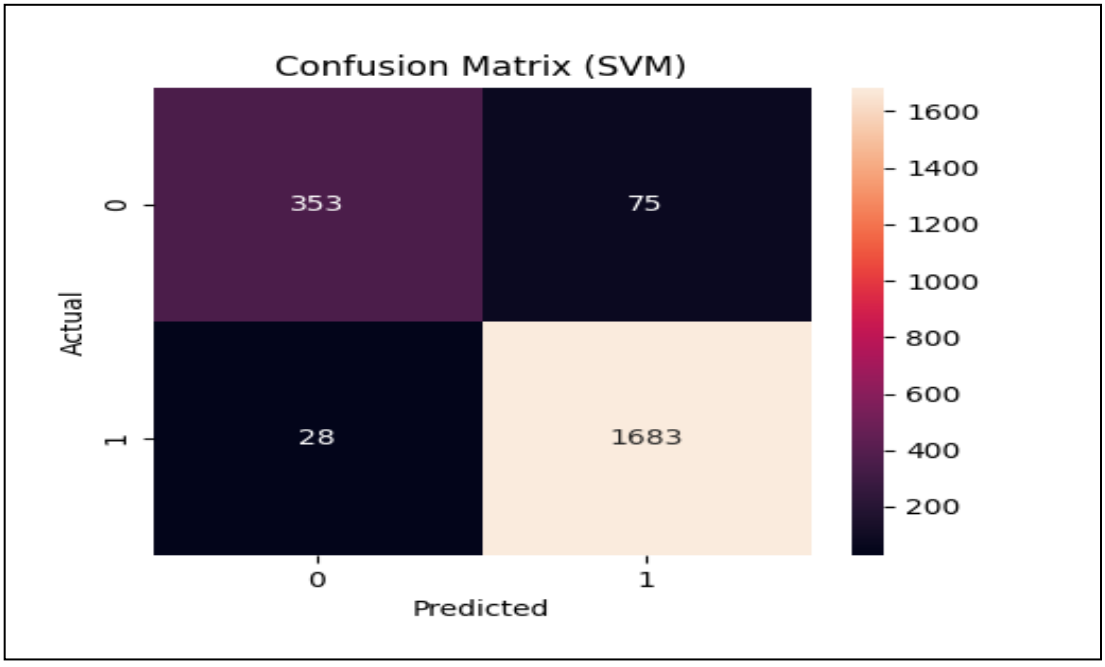
```
=== svm Test Results ===
Accuracy: 0.9518466573165031
              precision    recall  f1-score   support

           0       0.93      0.82      0.87       428
           1       0.96      0.98      0.97      1711

    accuracy                           0.95      2139
   macro avg       0.94      0.90      0.92      2139
weighted avg       0.95      0.95      0.95      2139

Confusion matrix:
 [[ 353   75]
 [  28 1683]]
```

Test Evaluation for Support Vector Machine Model

Class 0 = Human written

Class 1 = AI generated

Metric	Class 0	Class 1	Notes
Precision	0.93	0.96	How many predicted as class x are correct
Recall	0.82	0.98	How many actual class x were correctly predicted
F1-score	0.87	0.97	Mean of P & R
Support	428	1711	Number of samples



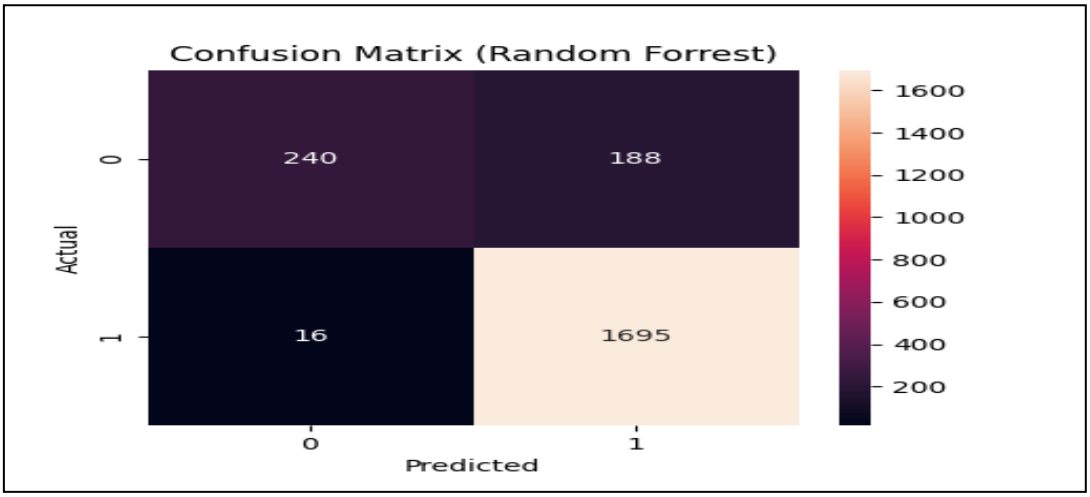
```
=== rf Test Results ===
Accuracy: 0.9046283309957924
              precision    recall  f1-score   support

           0       0.94      0.56      0.70       428
           1       0.90      0.99      0.94      1711

    accuracy                           0.90      2139
   macro avg       0.92      0.78      0.82      2139
weighted avg       0.91      0.90      0.89      2139

Confusion matrix:
 [[ 240  188]
 [  16 1695]]
```

Test Evaluation for Random Forrest Model

Class 0 = Human written

Class 1 = AI generated

Metric	Class 0	Class 1	Notes
Precision	0.94	0.90	How many predicted as class x are correct
Recall	0.56	0.99	How many actual class x were correctly predicted
F1-score	0.70	0.94	Mean of P & R
Support	428	1711	Number of samples



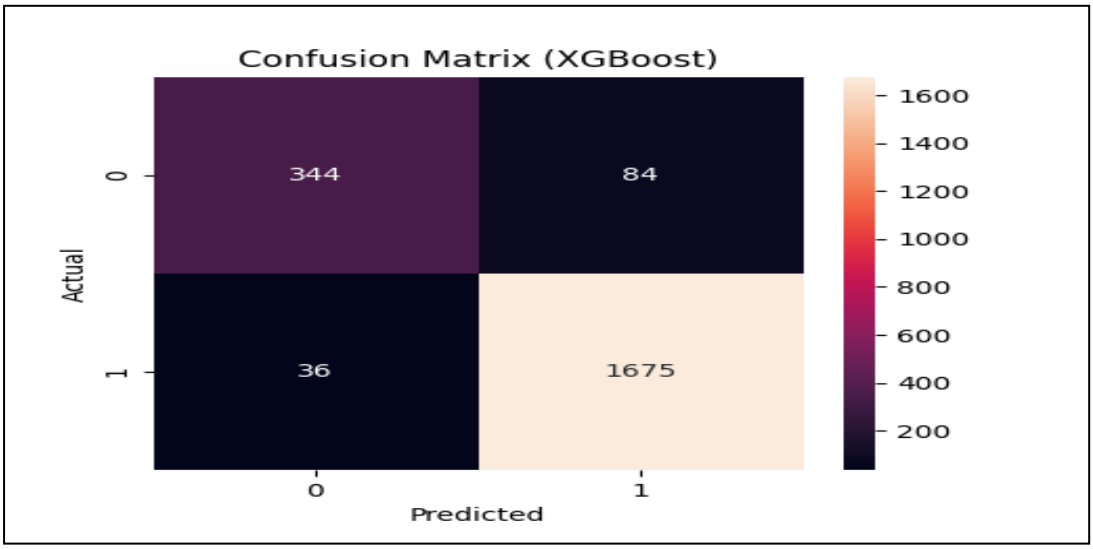
```
=== xgb Test Results ===
Accuracy: 0.9438990182328191
              precision    recall  f1-score   support

           0       0.91      0.80      0.85       428
           1       0.95      0.98      0.97      1711

    accuracy                           0.94      2139
   macro avg       0.93      0.89      0.91      2139
weighted avg       0.94      0.94      0.94      2139

Confusion matrix:
 [[ 344   84]
 [  36 1675]]
```

Test Evaluation for Genetic Programing XGP Model

Class 0 = Human written

Class 1 = AI generated

Metric	Class 0	Class 1	Notes
Precision	0.91	0.95	How many predicted as class x are correct
Recall	0.80	0.98	How many actual class x were correctly predicted
F1-score	0.85	0.97	Mean of P & R
Support	428	1711	Number of samples



Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 256)	98,560
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 128)	32,896
dropout_1 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 1)	129

Total params: 131,585 (514.00 KB)
Trainable params: 131,585 (514.00 KB)
Non-trainable params: 0 (0.00 B)

2. Layers

Layer	Output Shape	Params	Description
`dense`	(None, 256)	98,560	Fully connected layer with 256 neurons. "None" means batch size is flexible.
`dropout`	(None, 256)	0	Dropout layer (for regularization, randomly sets some inputs to 0 during training).
`dense_1`	(None, 128)	32,896	Fully connected layer with 128 neurons.
`dropout_1`	(None, 128)	0	Another dropout layer.
`dense_2`	(None, 1)	129	Output layer with 1 neuron (likely for **binary regression/classification**).

3. Parameters

- **Total params:** 131,585 → total number of trainable weights in the model.
- **Trainable params:** 131,585 → all parameters are adjustable during training.
- **Non-trainable params:** 0 → no frozen layers.

The numbers in **Param #** come from the formula for dense layers:

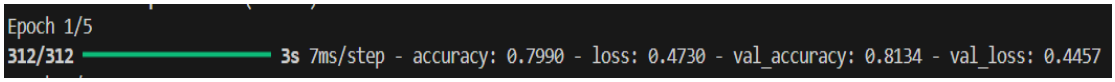
$$\text{Params} = (\text{input units} \times \text{output units}) + \text{output units (bias)}$$

For example, first dense layer:

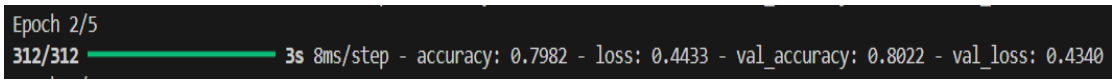
$$(384 \times 256) + 256 = 98,560$$

(where 384 is the input dimension from your dataset).

The Feedforward Neural Network (FFNN) was trained for 5 epochs using the training dataset, and performance was evaluated on a separate validation set after each epoch.

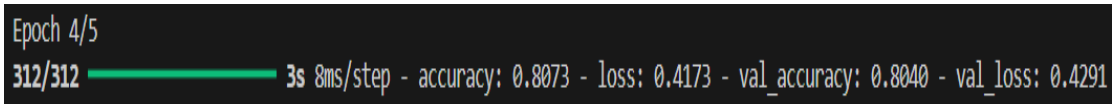


In Epoch 1, the model has achieved a training accuracy of (79.83%) with a loss of (47.50%), while the validation accuracy was (80.03%) and validation loss (44%).

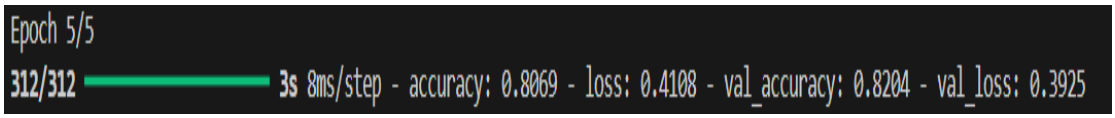


In Epoch 2, the training accuracy slightly increased to (80%) and the loss decreased to (44.13%), with validation accuracy improving to (81.34%) and validation loss at (44.18%).

Epoch 3 showed further improvement in training accuracy (80.53%) and a lower loss (42.84%), while validation accuracy remained high at (80.87%) and validation loss decreased to (40.39%).



During Epoch 4, the training accuracy reached (80.61%) with a loss of (41. 59%) and the validation metrics were (80.22%) accuracy and 40.82%) loss.



Finally, in Epoch 5, the model achieved its best performance with (81.42%) training accuracy and (40.80%) loss, while the validation accuracy was (82.69%) and validation loss (39.78%), indicating that the model learned effectively over successive epochs with no significant overfitting.

```
FFNN Test Acc: 0.8106591865357644
              precision    recall  f1-score   support

           0       0.73      0.09      0.15       428
           1       0.81      0.99      0.89      1711

    accuracy                           0.81      2139
   macro avg       0.77      0.54      0.52      2139
weighted avg       0.80      0.81      0.75      2139
```

Test Evaluation for Feedforward Neural Network (FFNN) Model

Class 0 = Human written

Class 1 = AI generated

Metric	Class 0	Class 1	Notes
Precision	0.73	0.81	How many predicted as class x are correct
Recall	0.09	0.99	How many actual class x were correctly predicted
F1-score	0.15	0.89	Mean of P & R
Support	428	1711	Number of samples

- Additional remark:::

I try so many times to find solution for the shortage of the FFNN code. But this is the best I could've done. I will try to improve my ability repeatedly.

conclusion

Between the five models listed above, SVM has achieved the strongest overall predictive performance, Yet the imbalance in the dataset caused all model to act bias in favor of CLASS 1; which results in low detection of CLASS 0. While the SVM performs best in accuracy and CLASS 0, F1-score, Logistic Regression or SVM may offer more balanced macro-level performance once data imbalance techniques are applied. Future work should focus on balancing methods to improve minority-class detection.

Resources

1. https://www.researchgate.net/publication/394621406_Detecting_Machine-Generated_Arabic_Text_Using_AraBERT_and_LSTM_Toward_Trustworthy_NLP_in_Low-Resource_Languages.
2. https://arxiv.org/abs/2407.15390
3. CHATGPT.com
4. Data Mining Concepts and Techniques Third Edition by Jiawei Han er al