# INFORMATICS INSTITUTE OF TECHNOLOGY

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## ROBERT GORDON UNIVERSITY

## ABERDEEN

# Deep Learning - CM3604

# Coursework Report

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GIT Repository link - [https://github.com/AnuttaraR/deep-learning-coursework](https://github.com/AnuttaraR/deep-learning-coursework)

## 1. Introduction

In recent times, deep learning techniques have been rapidly growing, especially in understanding language. This report shares our journey in a university group project where we focused on analyzing the meaning of Yelp reviews.

Yelp, a place known for user reviews, gives us a diverse dataset to explore sentiments and meaning in what users write. By using Hugging Face models, known for their effectiveness in understanding language, our project aims to find patterns and sentiments hidden in the words of Yelp reviews. This report gives a thorough overview of how we went about it—covering steps like preparing the data, choosing models, training them, and measuring their success

## 2. Sentiment Analysis with bert- based-uncased

Bert - based - uncased model is a neural network language model that uses BERT(Bidirectional Encoder Representations from Transformers) architecture. Tasks involving natural language processing are the focus of BERT. "Uncased" denotes that there is no distinction made by the model between lowercase and uppercase letters. It bidirectionally records contextualized word representations improving comprehension in a range of language-related tasks, including named entity recognition, sentiment analysis, and question answering.

In sentiment analysis, the Bert-based- uncased model proves that it is effective due to its ability to capture contextualized word representations. It understands the specifics of the language, considering the order and the meaning of words in a sentence. Due to this reason we are using bert-based- model for our use case.

## a. Corpus preparation

After the essential libraries are loaded, the first dataset to be loaded is the review dataset from the yelp academic dataset. The Yelp dataset is a comprehensive collection of data from the Yelp platform, a popular online review platform for businesses. In this model we are using the two datasets for review and business information, these are stored in json format.

When we first load the review dataset we can see that there are several rows present.

| | review_id | user_id | business_id | stars | useful | funny | cool | text | date |
|---|---|---|---|---|---|---|---|---|---|
| 0 | KU_O5udG6zpxOg-VcAEodg | mh_-eMZ6K5RLWhZyISBhwA | XQfwVwDr-v0ZS3_CbbE5Xw | 3 | 0 | 0 | 0 | If you decide to eat here, just be aware it is... | 2018-07-07 22:09:11 |
| 1 | BiTunyQ73aT9WBnpR9DZGw | OyoGAe7OKpv6SyGZT5g77Q | 7ATYjTIgM3jUlt4UM3IypQ | 5 | 1 | 0 | 1 | I've taken a lot of spin classes over the year... | 2012-01-03 15:28:18 |
| 2 | saUsX_uimxRlCVr67Z4Jig | 8g_iMtfSiwikVnbP2etR0A | YjUWPpI6HXG530lwP-fb2A | 3 | 0 | 0 | 0 | Family diner. Had the buffet. Eclectic assortm... | 2014-02-05 20:30:30 |
| 3 | AqPFMleE6RsU23_auESxiA | _7bHUi9Uuf5__HHc_Q8guQ | kxX2SOes4o-D3ZQBkiMRfA | 5 | 1 | 0 | 1 | Wow! Yummy, different, delicious. Our favo... | 2015-01-04 00:01:03 |

*Initial Review Dataset*

Upon initial review, the length of the dataset is 10000.

We can see that some columns of data won't be necessary for our model so we will remove them.

| | business_id | stars | text |
|---|---|---|---|
| 0 | XQfwVwDr-v0ZS3_CbbE5Xw | 3 | If you decide to eat here, just be aware it is... |
| 1 | 7ATYjTIgM3jUlt4UM3IypQ | 5 | I've taken a lot of spin classes over the year... |
| 2 | YjUWPpI6HXG530lwP-fb2A | 3 | Family diner. Had the buffet. Eclectic assortm... |
| 3 | kxX2SOes4o-D3ZQBkiMRfA | 5 | Wow! Yummy, different, delicious. Our favo... |
| 4 | e4Vwtrqf-wpJfwesgvdgxQ | 4 | Cute interior and owner (?) gave us tour of up... |

*Review Dataset after columns dropped*

After loading the business dataset, we see that it contains these rows of data also with columns we don't need:

| | business_id | name | address | city | state | postal_code | latitude | longitude | stars | review_count | is_op |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | Pns2l4eNsfO8kk83dixA6A | Abby Rappoport, LAC, CMQ | 1616 Chapala St, Ste 2 | Santa Barbara | CA | 93101 | 34.426679 | -119.711197 | 5.0 | 7 | |
| 1 | mpf3x-BjTdTEA3yCZrAYPw | The UPS Store | 87 Grasso Plaza Shopping Center | Affton | MO | 63123 | 38.551126 | -90.335695 | 3.0 | 15 | |
| 2 | tUFrWirKiKi_TAnsVWINQQ | Target | 5255 E Broadway Blvd | Tucson | AZ | 85711 | 32.223236 | -110.880452 | 3.5 | 22 | |

*Initial business dataset*

Then we filter out rows with null 'categories' and create a subset, df_business_new, containing only businesses labelled as restaurants. The resulting DataFrame is refined to include only 'business_id' and 'categories,'

| | business_id | categories |
|---|---|---|
| 3 | MTSW4McQd7CbVtyjqoe9mw | Restaurants, Food, Bubble Tea, Coffee & Tea, B... |
| 5 | CF33F8-E6oudUQ46HnavjQ | Burgers, Fast Food, Sandwiches, Food, Ice Crea... |
| 8 | k0hlBqXX-Bt0vf1op7Jr1w | Pubs, Restaurants, Italian, Bars, American (Tr... |

*Business labeled as restaurants*

Then we move on to merging the two dataframes, df_review and df_business_new, using an inner join operation based on the common 'business_id' column. The resulting dataframe, df_joined, combines information from both DataFrames, linking reviews with corresponding restaurant details.

| | business_id | stars | text | categories |
|---|---|---|---|---|
| 0 | XQfwVwDr-v0ZS3_CbbE5Xw | 3 | If you decide to eat here, just be aware it is... | Restaurants, Breakfast & Brunch, Food, Juice B... |
| 1 | XQfwVwDr-v0ZS3_CbbE5Xw | 2 | This is the second time we tried turning point... | Restaurants, Breakfast & Brunch, Food, Juice B... |
| 2 | XQfwVwDr-v0ZS3_CbbE5Xw | 4 | The place is cute and the staff was very frien... | Restaurants, Breakfast & Brunch, Food, Juice B... |
| 3 | XQfwVwDr-v0ZS3_CbbE5Xw | 3 | We came on a Saturday morning after waiting a ... | Restaurants, Breakfast & Brunch, Food, Juice B... |
| 4 | kxX2SOes4o-D3ZQBkiMRfA | 5 | Wow! Yummy, different, delicious. Our favo... | Halal, Pakistani, Restaurants, Indian |

*Merged dataset*

Next, it renames the 'text' column to 'restaurant_reviews' and drops the 'business_id' column. The language of each review in the 'restaurant_reviews' column is detected using the langdetect library. Rows where the detected language is not English ('en') are removed, ensuring analysis is focused on English reviews, and NaN values are checked. Duplicate rows are removed to ensure data integrity, and reviews with a 3-star rating are excluded.

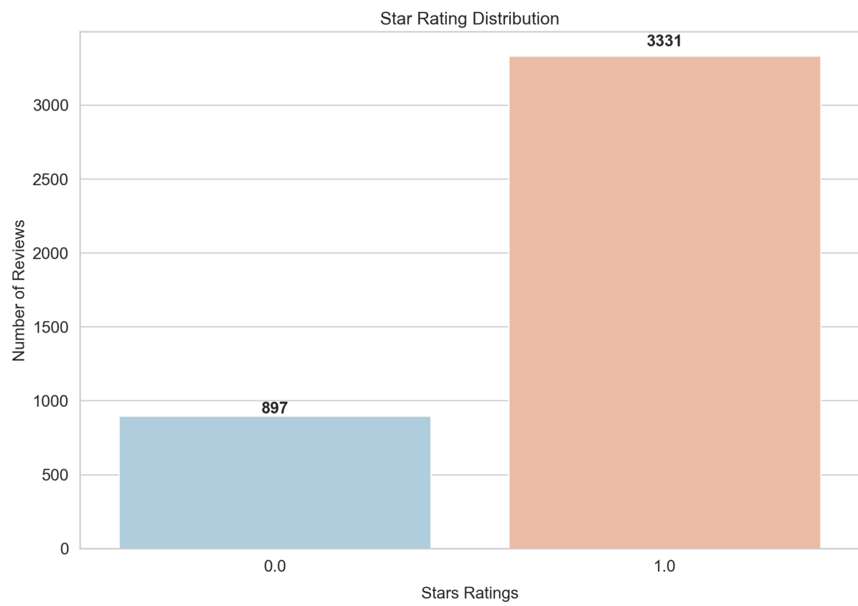
Now our dataset is down to 4228 rows.

Furthermore, sentiment labels are assigned to the DataFrame df_joined based on review ratings. Reviews with a rating of fewer than 3 stars are labelled as 0, indicating a negative sentiment, while those with a rating greater than 3 stars are labelled as 1, denoting a positive sentiment. The 'stars' column is then dropped from the DataFrame, leaving behind a refined dataset where each review is associated with a binary sentiment label.

| | restaurant_reviews | categories | detect | sentiment |
|---|---|---|---|---|
| 1 | This is the second time we tried turning point... | Restaurants, Breakfast & Brunch, Food, Juice B... | en | 0.0 |
| 2 | The place is cute and the staff was very frien... | Restaurants, Breakfast & Brunch, Food, Juice B... | en | 1.0 |
| 4 | Wow! Yummy, different, delicious. Our favo... | Halal, Pakistani, Restaurants, Indian | en | 1.0 |
| 5 | Dine-in gets 2 stars. Disappointing service & ... | Halal, Pakistani, Restaurants, Indian | en | 0.0 |
| 6 | After a long hiatus from reviewing I have awak... | Halal, Pakistani, Restaurants, Indian | en | 1.0 |

*Df with binary sentimental classification*

For visualization purposes, we added a bar plot, created with seaborn to display the count of reviews for each sentiment category. The x-axis represents the sentiment labels (0 for negative, 1 for positive), and the y-axis shows the corresponding number of reviews. This provides a visual overview of the sentiment distribution in the dataset.




*Star ratings vs number of reviews*

This shows that the positive and negative reviews are imbalanced. So to resolve this we had to resample the negative reviews to match the positive reviews.

```
sentiment
0.0    3331
1.0    3331
Name: count, dtype: int64
```

Once that's done, spaCy is utilized to remove stopwords from a restaurant review dataset. The English language model (en_core_web_sm) is loaded, and the default set of spaCy stopwords is retrieved. Specific stopwords, such as 'no' and 'not', are excluded from the set. The text preprocessing function text_preprocessing is defined to clean raw restaurant reviews. This function removes non-alphabetic characters, converts text to lowercase, tokenizes words, and filters out spaCy stopwords.

The cleaning process is applied to the 'restaurant_reviews' column, and the preprocessed reviews are stored in a new 'cleaned_reviews' column in the DataFrame df_clean. The final DataFrame df is then reset with a new index for subsequent analysis on the cleaned reviews.

| | restaurant_reviews | categories | detect | sentiment | cleaned_reviews |
|---|---|---|---|---|---|
| 0 | Wow have things changed at this location. I us... | Vegetarian, American (New), Mediterranean, San... | en | 0.0 | wow things changed location come regular basis... |
| 1 | The service was great and the restaurant was c... | Restaurants, Italian, Pizza | en | 0.0 | service great restaurant clean food okay lingu... |
| 2 | Decent, quick serve food. Certainly not gourme... | Mexican, Tacos, Restaurants, Tex-Mex, Fast Foo... | en | 0.0 | decent quick serve food certainly gourmet taco... |
| 3 | Please be careful when you order food to go f... | Restaurants, American (New), Southern, Chinese | en | 0.0 | careful order food restaurant website updated ... |
| 4 | i wish i could have given it a zero or a negat... | Vegetarian, American (New), Mediterranean, San... | en | 0.0 | wish given zero negative experience pleasant o... |

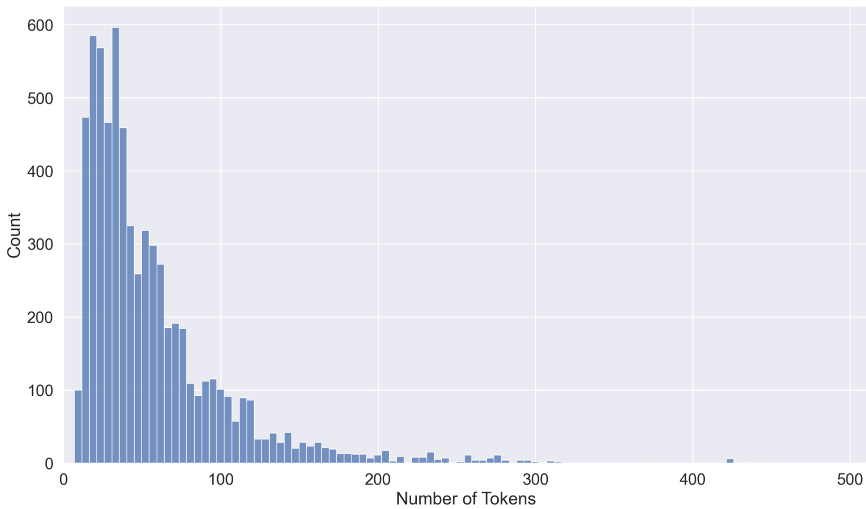
*Final cleaned dataset*

### b. Solution methodology

Now for the model. We utilize the BERT (Bidirectional Encoder Representations from Transformers) tokenizer from the 'bert-base-uncased' pre-trained model to analyze the distribution of token lengths in the cleaned restaurant reviews.

The variable token_lens is created to store the length of tokens for each review. The loop iterates over the cleaned reviews, encoding them with the BERT tokenizer while considering a maximum length of 512 tokens.

To analyze the number of tokens used to craft reviews, it can be visualized using a histogram plot. The x-axis represents the number of tokens, and the y-axis shows the frequency of reviews with a specific token length. The plot is configured to limit the x-axis range to 512 tokens.




The BERT tokenizer is used to tokenize the cleaned restaurant reviews, and the maximum sequence length is set to 260 tokens by our choice because most of the reviews seems to have less than 260 tokens.

We will use 70% of the dataset for training, then 15% each for validation and testing. This ensures that the distribution of observations across different classes in each subset mirrors the original dataset's proportions, maintaining consistency with the initial distribution.

Once the sets are converted to lists, we generate a set of token IDs (input IDs) for each review through the tokenizer. The conversion was done, which translates a string into a series of integer input IDs by utilizing the tokenizer and vocabulary. This process involves tokenizing the string and assigning each token its respective ID. For classification tasks, we added special tokens—[CLS] and [SEP]—to enhance the input sequence's representation.

We ensured uniformity in sequence lengths through both padding and truncating techniques. For padding, zeros were added as needed to extend sequences to the specified length of MAX_SEQ_LENGTH. In cases where sequences surpassed this length, we employed truncation to ensure they conformed to the maximum length constraint

For attention masks, we distinguish genuine tokens from placeholder [PAD] tokens. We then transform all lists containing input IDs, labels, and attention masks into Torch tensors.

We implemented a DataLoader to efficiently handle the loading of our datasets, functioning as an iterator and significantly conserving memory during the training process as opposed to traditional for loops.

Our approach involves leveraging the BertForSequenceClassification model to address our classification task. This model extends the Bert Model transformer by incorporating an additional layer specifically designed for classification purposes.

To optimize our Bert Classifier, we opted for the AdamW optimizer due to its incorporation of gradient bias correction and weight decay. Additionally, we adopted a linear scheduler devoid of warm-up steps. In the fine-tuning process, we considered various settings recommended by the authors:

- Batch size: Choices included 16 and 32.
- Learning rate (Adam): Options were 5e-5, 3e-5, and 2e-5.
- Number of epochs: We deliberated on 2, 3, or 4 epochs.

Ultimately, our selections were a batch size of **16**, a learning rate of **3e-5**, and a duration of **2** epochs, aligning with the given recommendations.

Throughout each epoch, we collect and record the training and validation loss and accuracy metrics. By doing so, we have the ability to visually represent the progress of the training loop using plots or tables.

## 3. Sentiment Analysis with Convolutional Neural Network

Convolutional Neural Networks (CNNs) are used in sentiment analysis, which uses deep learning methods to identify and analyse sentiments in textual data. CNNs are especially good at recognising hierarchical patterns and dependencies in word sequences, which sets them apart from traditional methods and enables them to automatically learn pertinent features for sentiment classification. Convolutional layers give the model the ability to recognise important local patterns in the text, which makes it a good fit for tasks such as sentiment analysis. CNNs are able to identify subtleties in sentiment expressions by extracting meaningful features and representations. This allows CNNs to provide a strong framework for interpreting the emotional tone of a given text.

### a. Corpus preparation

First we checked for the null values, duplicates and missing values. Since there were no null

```
Null Values:
review_id      0
user_id        0
business_id    0
stars          0
useful         0
funny          0
cool           0
text           0
date           0
dtype: int64

Duplicates:
Empty DataFrame
Columns: [review_id, user_id, business_id, stars, useful, funny, cool, text, date]
Index: []

Missing Values:
Empty DataFrame
Columns: [review_id, user_id, business_id, stars, useful, funny, cool, text, date]
Index: []
```

values, duplicates and missing values we had no requirement to do a data cleaning. Therefore we decided to proceed with the dataset.

Once the data cleaning part was completed, We also created a code to convert the JSON data into .csv data format for ease of use, and also decided to use only 100,000 rows of data for efficiency.

The YELP dataset typically have 9 columns but we decided to drop the rest and use only the needed 5 columns.

DL_SVM.ipynb | dataset_analysis.py | json_csv.py | yelp_csv_dataset.csv

```python
import pandas as pd
import json

# Specify the paths
json_file_path = 'yelp_academic_dataset_review.json'
csv_output_path = 'yelp_csv_dataset.csv'

# Open the JSON file and read lines
with open(json_file_path, 'r', encoding='utf-8') as json_file:
    # Read the first 10,000 lines from the JSON file
    json_lines = [json_file.readline() for _ in range(100000)]

# Parse each JSON line and store the data in a list
data = [json.loads(line) for line in json_lines]

# Convert the list of dictionaries to a DataFrame
df = pd.DataFrame(data)

# Save the DataFrame to a CSV file
df.to_csv(csv_output_path, index=False)

# Display the first few rows of the resulting CSV file
print(f"Subset of Yelp dataset saved to '{csv_output_path}':")
print(df.head())

```

| | review_id | business_id | user_id | text | stars |
|---|---|---|---|---|---|
| **0** | KU_O5udG6zpxOg-VcAEodg | XQfwVwDr-v0ZS3_CbbE5Xw | mh_-eMZ6K5RLWhZyISBhwA | If you decide to eat here, just be aware it is... | 3.0 |
| **1** | BiTunyQ73aT9WBnpR9DZGw | 7ATYjTIgM3jUlt4UM3IypQ | OyoGAe7OKpv6SyGZT5g77Q | I've taken a lot of spin classes over the year... | 5.0 |
| **2** | saUsX_uimxRlCVr67Z4Jig | YjUWPpI6HXG530lwP-fb2A | 8g_iMtfSiwikVnbP2etR0A | Family diner. Had the buffet. Eclectic assortm... | 3.0 |
| **3** | AqPFMleE6RsU23_auESxiA | kxX2SOes4o-D3ZQBkiMRfA | _7bHUi9Uuf5__HHc_Q8guQ | Wow! Yummy, different, delicious. Our favo... | 5.0 |
| **4** | Sx8TMOWLNuJBWer-0pcmoA | e4Vwtrqf-wpJfwesgvdgxQ | bcjbaE6dDog4jkNY91ncLQ | Cute interior and owner (?) gave us tour of up... | 4.0 |

*Datasets after dropping unnecessary columns*

To facilitate NLP, a cleaning function (get_clean_text) was implemented, encompassing lowercase conversion, special character removal, punctuation elimination, and stopword exclusion.

Additionally, a tokenization function (get_words) was defined to extract a list of words from the cleaned text. TF-IDF vectorization was employed using scikit-learn's TfidfVectorizer, transforming the cleaned text into numerical vectors.

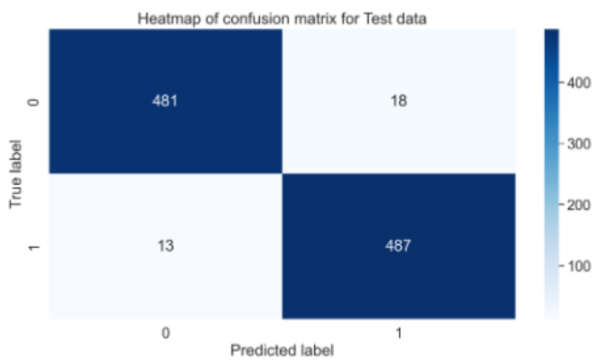
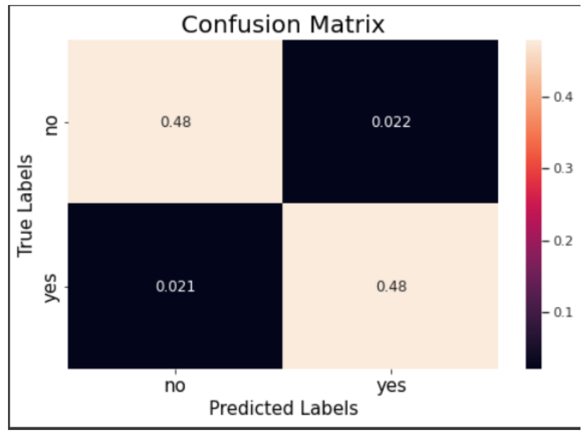
### b. Solution methodology

The project approach starts with a thorough examination and preprocessing of Yelp review data, concentrating on important columns and using efficient text cleaning methods. Feature engineering uses the cleaned text's TF-IDF vectorization to produce numerical representations. The main goal is to use Convolutional Neural Networks (CNN) implemented with Keras to perform sentiment analysis on Yelp reviews. Embedding, Dropout, Conv1D, MaxPooling1D, LSTM, and Dense are some of the layers in the CNN model architecture that enable the extraction of complex features from the text's sequential structure. In order to avoid overfitting, the model is trained over a maximum of three epochs with a batch size of 100 and early stopping. To evaluate the effectiveness of the CNN model, evaluation metrics such as confusion matrices, accuracy, precision, and recall are used.

## 4. Evaluation metrics

The evaluation metrics for the sentiment analysis models include accuracy, precision, recall, and F1 score for multi-class sentiment analysis. These metrics provide a detailed understanding of the models' performance in predicting star ratings, and the ability to correctly classify reviews into various sentiment classes. The confusion matrix visually encapsulates these metrics. In the binary sentiment classification, metrics like accuracy, precision, recall, provide a nuanced evaluation of the model's proficiency in distinguishing positive from negative sentiments. The classification report dissects these metrics further. Visualization of a confusion matrix helps in showing true positives, true negatives, false positives, and false negatives.

## 5. Evaluation metrics comparison

<table>
<tr><th></th><th>Bert-based-uncased model</th><th>Convolutional Neural Network</th></tr>
<tr><td>Confusion matrix</td><td>
</td><td>
</td></tr>
<tr><td>Classification report</td><td><table>
<tr><th></th><th>precision</th><th>recall</th><th>f1-score</th><th>support</th></tr>
<tr><td>0</td><td>0.974</td><td>0.964</td><td>0.969</td><td>499</td></tr>
<tr><td>1</td><td>0.964</td><td>0.974</td><td>0.969</td><td>500</td></tr>
<tr><td>accuracy</td><td></td><td></td><td>0.969</td><td>999</td></tr>
<tr><td>macro avg</td><td>0.969</td><td>0.969</td><td>0.969</td><td>999</td></tr>
<tr><td>weighted avg</td><td>0.969</td><td>0.969</td><td>0.969</td><td>999</td></tr>
</table></td><td>Accuracy on testing set: 0.9571052631578948<br>Precision on testing set: 0.9568421052631579<br>Recall on testing set: 0.957345971563981</td></tr>
<tr><td>Accuracy</td><td>accuracy 0.969</td><td>Accuracy on testing set: 0.9571052631578948</td></tr>
</table>

## 6. Limitations and future enhancements

### a. Limitations

Both Bert-based-uncased and Linear SVM are computationally expensive and require substantial resources for training and inference. The representation and quality of the training data have a major impact on these models' performance. Performance may be impacted by training set biases or constraints.

BERT- based models are deep neural networks, which means that their decisions are difficult to interpret. As such, they are frequently referred to as "black box" models.

**Limitations of bert-based-uncased algorithm**

Due to the size, BERT models require a lot of memory and may not be feasible to implement in settings with limited resources. It can take a lot of effort and time to train BERT models from scratch. Although fine-tuning is common , significant processing power may still be needed.

**Limitation of Convolutional Neural Network**

Because Convolutional Neural Networks (CNNs) are inherently designed for spatial hierarchies in data, such as images, they have limitations when it comes to sentiment analysis. Their local feature-capturing fixed-size receptive fields might not be able to handle the complex and varied sentiment expression lengths found in textual data. It can be difficult to adjust CNN hyperparameters like filter size and stride for the best sentiment analysis. Furthermore, CNN interpretability is frequently worse than that of traditional models, which makes it challenging to identify the precise textual elements influencing sentiment predictions.

### b. Future Enhancements

The focus of sentiment analysis's upcoming improvements is on solving current problems and bringing in fresh ideas. The main goal is to reduce model biases and guarantee impartial and fair predictions for a wide range of user demographics. Subsequent investigation focuses on incorporating contextual data to enhance comprehension of complex emotional expressions. The goal of domain adaptation and transfer learning advances is to make models more flexible in response to changing language usage and dynamic content. A more thorough understanding of sentiment in multimedia content is made possible by the investigation of multimodal sentiment analysis, which incorporates both visual and auditory cues. Furthermore, the search for interpretable deep learning models and techniques for real-time sentiment analysis opens the door to the development of sentiment analysis systems that are more precise, flexible, and morally upright.

## 7. Conclusion

In summary, the BERT-based-uncased model achieved a higher accuracy of 96.9%, outperforming the convolutional neural network model which has an accuracy of 9%.47%. The BERT model performs better than other models because it can capture complex language patterns that take word order and context into account. Depending on the needs of the particular application, we can choose between these models; BERT provides a reliable solution for complex sentiment analysis.

## 8. Appendix

### a. Bert-based-uncased model

```
!pip install transformers langdetect spacy
import pandas as pd
import numpy as np
import seaborn as sns
from matplotlib import rc
from pylab import rcParams
import matplotlib.pyplot as plt
from textwrap import wrap
from collections import defaultdict
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report,
accuracy_score,f1_score,precision_score, recall_score
import nltk
import re
import spacy
from nltk.tokenize import word_tokenize
import transformers
```

```
from transformers import BertModel, BertTokenizer, BertForSequenceClassification
from transformers import AdamW, get_linear_schedule_with_warmup
import torch
from torch import nn,optim
from torch.utils.data import Dataset,DataLoader,TensorDataset, RandomSampler,
SequentialSampler
import torch.nn as nn
import torch.nn.functional as F
import time
import datetime
import tensorflow as tf
import sys
import os
import warnings

sp = spacy.load('en_core_web_sm')
nltk.download('punkt')
device=torch.device('cuda:0' if torch.cuda.is_available() else 'cpu')

%matplotlib inline
%config InlineBackend.figure_format='retina'

sns.set(style='whitegrid',palette='muted',font_scale=1.2)
color_palette=['#ffb6c1','#add8e6','#98fb98','#fffacd','#dcb4e4','#ffdab9']
sns.set_palette(sns.color_palette(color_palette))

rcParams['figure.figsize']= 10,5
```

```
seed=42
np.random.seed(seed)
torch.manual_seed(seed)

if not sys.warnoptions:
    warnings.simplefilter("ignore")
    os.environ["PYTHONWARNINGS"] = "ignore"
#%%
df_review =
pd.read_json("C:/Users/USER/Downloads/yelp_dataset/yelp_academic_dataset_review
.json", nrows=10000, lines=True)
#%%
df_review.head()
#%%
len(df_review)
#%%
cols_to_drop = ['review_id', 'user_id', 'useful', 'funny', 'cool', 'date']
df_review.drop(cols_to_drop, axis=1, inplace=True)
#%%
df_review.head()
#%%
df_business =
pd.read_json("C:/Users/USER/Downloads/yelp_dataset/yelp_academic_dataset_busine
ss.json", nrows=10000, lines=True)
#%%
df_business.head()
#%%
```

```
df_business = df_business[df_business['categories'].notnull()]
df_business_new = df_business[df_business['categories'].str.contains('Restaurant')]

df_business_new =  df_business_new[['business_id', 'categories']]

#%%
df_business_new.head()
#%%
df_joined = df_review.merge(df_business_new, how='inner', on='business_id')
#%%
df_joined.head()
#%%
# Rename and drop columns
df_joined.rename(columns={'text':'restaurant_reviews'}, inplace=True)
df_joined.drop('business_id', axis=1, inplace=True)

#%%
# Analyze only English reviews
from langdetect import detect

df_joined['detect'] = df_joined['restaurant_reviews'].apply(detect)
df_joined = df_joined[df_joined['detect'] == 'en'].reset_index(drop=True)

#%%
# Check for NaN values
df_joined.isnull().values.any()
```

```
# Remove duplicate rows
df_joined.drop_duplicates(inplace=True)

# Remove 3-star reviews
df_joined = df_joined[df_joined['stars'] != 3]
#%%
df_joined.head()
#%%
len(df_joined)
#%%
# Label reviews as positive or negative
df_joined.loc[df_joined['stars'] < 3, 'sentiment'] = 0 # negative lable given to rating lower than 3 stars
df_joined.loc[df_joined['stars'] > 3, 'sentiment'] = 1 # positive label given to ratings higher than 3 stars
df_joined.drop('stars', axis=1, inplace=True)
#%%
df_joined.head()
#%%
warnings.simplefilter(action='ignore', category=FutureWarning)
plt.figure(figsize=(12,8))
grouped = df_joined.sentiment.value_counts().sort_index()
sns.barplot(x=grouped.index, y=grouped.values, palette=sns.color_palette("RdBu_r", len(grouped)))
plt.xlabel('Stars Ratings', labelpad=10, fontsize=14)
plt.ylabel('Number of Reviews', fontsize=14)
plt.title('Star Rating Distribution', fontsize=15)
```

```
plt.tick_params(labelsize=14)
for  i, v in enumerate(grouped):
        plt.text(i,  v*1.02,  str(v),  horizontalalignment  ='center',fontweight='bold',
fontsize=14)

#%%
from sklearn.utils import resample

df_more = df_joined[(df_joined['sentiment']==1)]
df_less = df_joined[(df_joined['sentiment']==0)]



df_less_resampled = resample(df_less,
                             replace=True,
                             n_samples= len(df_more), # to match majority class
                             random_state=42)
df_clean = pd.concat([df_less_resampled, df_more])

df_clean.sentiment.value_counts()
#%%
# Remove spaCy stopwords
sp = spacy.load('en_core_web_sm')
stopwords = sp.Defaults.stop_words
exclude_stopwords = ['no', 'not']
for word in exclude_stopwords:
   stopwords.remove(word)
#%%
```

```
# Define text preprocessing function
# The input is a single string (a raw restaurant review), and the output is a single string
(a preprocessed restaurant review)

def text_preprocessing( raw_review ):
    # 1. Remove non-letters
    review_text_letters_only = re.sub("[^a-zA-Z]", " ", raw_review)
    # 2. Convert to lower case
    review_preprocessed = review_text_letters_only.lower()
    # 3. Word tokenization
    review_tokens = word_tokenize(review_preprocessed)
    # 4. Filter the stopwords
    filtered_sentence =[]
    for word in review_tokens:
        lexeme = sp.vocab[word]
        if lexeme.is_stop == False:
            filtered_sentence.append(word)

    return " ".join(filtered_sentence)
#%%
# Apply text preprocessing to create cleaned_reviews column
df_clean['cleaned_reviews'] = df_clean['restaurant_reviews'].apply(text_preprocessing)
df = df_clean.reset_index(drop=True)
#%%
df.head()
#%%
pre_trained_model='bert-base-uncased'
```

```
tokenizer=BertTokenizer.from_pretrained(pre_trained_model)
#%%
token_lens = []

for txt in df.cleaned_reviews:
  tokens = tokenizer.encode(txt, max_length=512, truncation=True)
  token_lens.append(len(tokens))

sns.set(font_scale=1.4)
plt.rcParams["figure.figsize"] = (14,8)
sns.histplot(token_lens)
plt.xlim([0, 512])
plt.xlabel('Number of Tokens')
plt.show()
#%%
#Deciding max length based on the lengths
MAX_SEQ_LENGTH = 260
#%%
x_train, x_test, y_train, y_test = train_test_split(df['cleaned_reviews'],df.sentiment,
test_size=0.3, random_state = 42, stratify=df.sentiment)
#%%
x_test, x_val, y_test, y_val = train_test_split(x_test, y_test, test_size=0.5, random_state
= 42, stratify= y_test)
#%%
# Create TensorDatasets
y_train = y_train.astype(int)
y_val = y_val.astype(int)
```

```
y_test = y_test.astype(int)

train_reviews = x_train.tolist()
val_reviews = x_val.tolist()
test_reviews = x_test.tolist()
#%%
# Train dataset
train_input_ids = [tokenizer.encode(train_reviews[i],add_special_tokens = True, max_length=MAX_SEQ_LENGTH, truncation=True) for i in range(0,len(train_reviews))]
# Val dataset
val_input_ids = [tokenizer.encode(val_reviews[i],add_special_tokens = True, max_length=MAX_SEQ_LENGTH, truncation=True) for i in range(0,len(val_reviews))]
# Test dataset
test_input_ids = [tokenizer.encode(test_reviews[i],add_special_tokens = True, max_length=MAX_SEQ_LENGTH, truncation=True) for i in range(0,len(test_reviews))]


#%%
from keras.preprocessing.sequence import pad_sequences   # Pad utility function to pad sequences to maximum length.

# Padding value: is optional, the default is 0.

# Train dataset
```

```
train_input_ids = pad_sequences(train_input_ids, maxlen=MAX_SEQ_LENGTH, dtype="long",
                    value=0, truncating="post", padding="post")

# Validation dataset
val_input_ids = pad_sequences(val_input_ids, maxlen=MAX_SEQ_LENGTH, dtype="long",
                    value=0, truncating="post", padding="post")

# Test dataset
test_input_ids = pad_sequences(test_input_ids, maxlen=MAX_SEQ_LENGTH, dtype="long",
                    value=0, truncating="post", padding="post")
#%%
# Create attention masks

# Train dataset
train_attention_masks = [[int(token_id > 0) for token_id in review]
                    for review in train_input_ids]
# dev dataset
val_attention_masks = [[int(token_id > 0) for token_id in review]
                    for review in val_input_ids]
# Test dataset
test_attention_masks = [[int(token_id > 0) for token_id in review]
                    for review in test_input_ids]
#%%
# input_ids
```

```
train_inputs = torch.tensor(train_input_ids)
val_inputs = torch.tensor(val_input_ids)
test_inputs = torch.tensor(test_input_ids)
# labels
train_labels = torch.tensor(y_train.values)
val_labels = torch.tensor(y_val.values)
test_labels = torch.tensor(y_test.values)
# attention masks
train_masks = torch.tensor(train_attention_masks)
val_masks = torch.tensor(val_attention_masks)
test_masks = torch.tensor(test_attention_masks)
#%%
batch_size = 16

# Create the DataLoader for our training set.
train_data = TensorDataset(train_inputs, train_masks, train_labels)
train_sampler = RandomSampler(train_data)
train_dataloader = DataLoader(train_data, sampler=train_sampler,
batch_size=batch_size)

# Create the DataLoader for our validation set.
val_data = TensorDataset(val_inputs, val_masks, val_labels)
val_sampler = SequentialSampler(val_data)
val_dataloader = DataLoader(val_data, sampler=val_sampler, batch_size=batch_size)

# Create the DataLoader for our test set.
test_data = TensorDataset(test_inputs, test_masks, test_labels)
```

```
test_sampler = SequentialSampler(test_data)
test_dataloader = DataLoader(test_data, sampler=test_sampler, batch_size=batch_size)
#%%
# Number of classes / labels
n_classes = y_train.nunique()
n_classes
#%%
from transformers import logging
logging.set_verbosity_error()

model = BertForSequenceClassification.from_pretrained(
    "bert-base-uncased", # The 12-layer BERT model with an uncased vocab
    num_labels = 2, # For binary classification
    output_attentions = False, # Not to return attentions weights
    output_hidden_states = False, # Not to return all hidden-states
)
#%%
model = model.to(device)
#%%
epochs=2

optimizer=AdamW(model.parameters(),lr=3e-5)
total_steps=len(train_dataloader)*epochs

# Create the learning rate scheduler
scheduler=get_linear_schedule_with_warmup(
    optimizer,
```

```
    num_warmup_steps=0,
    num_training_steps=total_steps
)
 # Define loss function and move it to GPU
loss_fn=nn.CrossEntropyLoss().to(device)
#%%
def format_time(elapsed):
    # Round to the nearest second
    elapsed_round = int(round(elapsed))
    # Format time in hh:mm:ss
    return str(datetime.timedelta(seconds = elapsed_round))


def accuracy(preds, labels):
    preds = np.argmax(preds, axis=1).flatten()
    labels = labels.flatten()
    return np.sum(preds == labels) / len(labels)
#%%
from tqdm import tqdm
import time

# Assuming you have already imported the necessary libraries and defined your model, dataloaders, etc.

# Store for each epoch
loss_train_values = []
acc_train_values = []
loss_val_values = []
```

```
acc_val_values = []

# Training loop
for epoch in range(epochs):
    # --- Train ---

    # Perform forward pass over the training dataset
    print("\n Epoch {:}/{:} :".format(epoch + 1, epochs))
    print('Training....')

    # Measure how long the training epoch takes
    t0 = time.time()
    # Reset total loss and accuracy for this epoch
    total_loss = 0
    total_acc = 0

    # Put the model in training mode
    model.train()

    # For each batch of training data
        for step, batch in enumerate(tqdm(train_dataloader, desc=f'Epoch {epoch + 1}/{epochs}')):
        # Update progress for each 100 steps
        if (step % 100 == 0) and (not step == 0):
            # Calculate elapsed time in minutes
            elapsed = format_time((time.time() - t0))
            # Report progress
```

```
            print(' Batch {:>5,} of {:>5,}. Elapsed:{:}.'.format(step, len(train_dataloader), elapsed))

        # Unpack training batch from trainloader and move to GPU
        b_input_ids = batch[0].to(device)  # 0 - input ids tensor
        b_attention_mask = batch[1].to(device)  # 1 - input masks tensor
        b_labels = batch[2].long().to(device)  # Convert to torch.long

        # Clear any previously calculated gradients in PyTorch before performing a backward pass
        model.zero_grad()

        # Output the results
        outputs = model(input_ids=b_input_ids, attention_mask=b_attention_mask, labels=b_labels)  # Return tuple
        # Loss value from output
        loss = outputs.loss  # Loss

        # Update total loss
        total_loss += loss.item()

        preds = outputs.logits  # Output probabilities
        # Move logits and labels to CPU
        preds = preds.detach().cpu().numpy()
        label_ids = b_labels.to('cpu').numpy()

        # Calculate the accuracy for this batch
```

```
        tmp_train_accuracy = accuracy(preds, label_ids)

        # Accumulate the total accuracy
        total_acc += tmp_train_accuracy

        # Perform a backward pass to calculate gradients
        loss.backward()

        # To avoid exploding vanishing gradients problem, clip the norm of the gradients
to 1.0
        torch.nn.utils.clip_grad_norm_(model.parameters(), 1.0)

        # Update the parameters (weights)
        optimizer.step()

        # Update the learning rate
        scheduler.step()

    # Calculate the average loss over training data
    avg_total_loss = total_loss / len(train_dataloader)

    # Store the loss values
    loss_train_values.append(avg_total_loss)

    # Calculate the average accuracy over the training data
    avg_train_acc = total_acc / len(train_dataloader)
```

```
# Store the accuracy values
acc_train_values.append(avg_train_acc)

print("")
print("\nAverage training accuracy: {0:.2f}".format(avg_train_acc))

print('Average training loss : {0:.2f}'.format(avg_total_loss))
print('Training epoch took: {:}'.format(format_time(time.time() - t0)))

# --- VALIDATION ---

# After each epoch perform validation to check model performance
print('\n Running validation...')

t0 = time.time()
# Put model in evaluation mode
model.eval()

# Tracking variables
total_eval_accuracy = 0
total_eval_loss = 0

# Unpack validation batch from trainloader and move to GPU
for batch in tqdm(val_dataloader, desc='Validation'):
    b_input_ids = batch[0].to(device)
    b_input_mask = batch[1].to(device)
    b_labels = batch[2].long().to(device)  # Convert to torch.long
```

```
        # Tell model not to compute gradients to save memory and accelerate validation
        with torch.no_grad():
            # Forward pass, calculate logit prediction
                                    outputs = model(b_input_ids, token_type_ids=None,
attention_mask=b_input_mask, labels=b_labels)
        loss = outputs.loss
        logits = outputs.logits
        # Update total evaluation loss
        total_eval_loss += loss.item()

        # Move logits and labels to CPU
        logits = logits.detach().cpu().numpy()
        label_ids = b_labels.to('cpu').numpy()

        # Calculate the accuracy for this batch and accumulate it over all batches
        total_eval_accuracy += accuracy(logits, label_ids)

    # Compute the average accuracy over all of the batches
    avg_val_accuracy = total_eval_accuracy / len(val_dataloader)

    # Store the accuracy values
    acc_val_values.append(avg_val_accuracy)

    # Compute the average loss over all of the batches
    avg_val_loss = total_eval_loss / len(val_dataloader)
```

```
    # Store the loss values
    loss_val_values.append(avg_val_loss)

    # Measure how long the validation run took.
    validation_time = format_time(time.time() - t0)
    print("  Accuracy: {0:.2f}".format(avg_val_accuracy))
    print("  Validation Loss: {0:.2f}".format(avg_val_loss))
    print("  Validation took: {:}".format(validation_time))

#%%
import os

model_save_path = 'Saved_models/sentiment_model.pth'
os.makedirs('Saved_models/', exist_ok=True)  # Create the directory if it doesn't exist
torch.save(model.state_dict(), model_save_path)
print(f'Model saved to {model_save_path}')
#%%
import pickle

# Assuming you have the lists you want to save: loss_train_values, acc_train_values, loss_val_values, acc_val_values

# Save the lists to a file
with open('Saved_models/training_metrics.pkl', 'wb') as f:
    pickle.dump({
        'loss_train_values': loss_train_values,
        'acc_train_values': acc_train_values,
```

```
        'loss_val_values': loss_val_values,
        'acc_val_values': acc_val_values
    }, f)
#%%
# Load the lists from the file
with open('Saved_models/training_metrics.pkl', 'rb') as f:
    loaded_metrics = pickle.load(f)

# Access the loaded lists
loaded_loss_train_values = loaded_metrics['loss_train_values']
loaded_acc_train_values = loaded_metrics['acc_train_values']
loaded_loss_val_values = loaded_metrics['loss_val_values']
loaded_acc_val_values = loaded_metrics['acc_val_values']
#%%
model_save_path = 'Saved_models/sentiment_model.pth'
model.load_state_dict(torch.load(model_save_path))

# Move the model to the device (GPU or CPU)
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model.to(device)

# Set the model to evaluation mode
model.eval()
#%%
df_acc = pd.DataFrame(acc_val_values,columns=['Accuracy'])
df_acc.index+=1
#%%
```

```
# Use plot styling from seaborn
sns.set(style='darkgrid')

# Increase the plot size and font size
sns.set(font_scale=1.5)
plt.rcParams["figure.figsize"] = (12,6)

# Plot the learning curve
sns.lineplot(data=df_acc,x=df_acc.index,y=df_acc.Accuracy)

# Label the plot
plt.title("Validation Accuracy")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")

plt.show()

#%%

df_loss = pd.DataFrame(loss_val_values,columns=['Loss'])
df_loss.index+=1
#%%


# Use plot styling from seaborn
sns.set(style='darkgrid')
```

```
# Increase the plot size and font size
sns.set(font_scale=1.5)
plt.rcParams["figure.figsize"] = (12,6)

# Plot the learning curve
sns.lineplot(data=df_loss,x=df_loss.index,y=df_loss.Loss)

# Label the plot
plt.title("Validation Loss")
plt.xlabel("Epoch")
plt.ylabel("Loss")

plt.show()



#%%
# Put model in evaluation mode
model.eval()

# Tracking variables
predictions, true_labels = [], []

# Create a tqdm progress bar for the test dataloader
for batch in tqdm(test_dataloader, desc='Predicting', leave=False):
    # Move batch to GPU
    batch = tuple(t.to(device) for t in batch)
    # Unpack inputs from test dataloader
```

```
    b_input_ids, b_attention_mask, b_labels = batch
    # Tell model not to compute gradients to save memory and accelerate validation
    with torch.no_grad():
        # Forward pass, calculate logit prediction
        outputs = model(input_ids=b_input_ids, attention_mask=b_attention_mask)
    # logits are class probabilities and get them from outputs
    logits = outputs[0]

    # Store predictions and true labels
    predictions.extend(logits.tolist())
    true_labels.extend(b_labels.tolist())

print('Predictions Done')

#%%



import torch.nn.functional as F
preds = torch.tensor(predictions)

preds = F.softmax(preds,dim=1)



preds = np.array(preds)
true_labels = np.array(true_labels)
```

```
#%%


def evaluate(y_test, predictions):
    cf_matrix = confusion_matrix(true_labels, preds.argmax(1))
    sns.heatmap(cf_matrix, annot = True, fmt = 'd',cmap="Blues")
    plt.title('Heatmap of confusion matrix for Test data')
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
evaluate(true_labels, preds.argmax(1))


#%%


class_report= classification_report(true_labels, preds.argmax(1), digits=3)
print(class_report)
```

**b. Linear Convolutional Neural Network**

```
# Sentiment Analysis for YELP Reviews data using CNN
""""
```

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer

from sklearn.metrics import accuracy_score, precision_score, recall_score, confusion_matrix, roc_curve, auc, classification_report
from sklearn.svm import LinearSVC
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
from datetime import datetime

train = pd.read_csv('yelp_csv_dataset.csv', nrows= 5000, names= ('class','text'))
test = pd.read_csv('yelp_csv_dataset.csv', nrows= 5000, names= ('class','text'))

train

train.loc[train["class"] == 1, "class"] = 0
train.loc[train["class"] == 2, "class"] = 1
test.loc[test["class"] == 1, "class"] = 0
test.loc[test["class"] == 2, "class"] = 1
```

```
"""Let's look at how many words in each review by counting spaces in the text."""

train["word_count"] = train["text"].str.split().str.len()
train["word_count"].hist()

X_train = train['text']
y_train = train['class']
X_test = test['text']
y_test = test['class']

"""Tokenize the text in training and testing data: choose the 20,000 most common words and set vector size as 300."""

from keras.preprocessing.text import Tokenizer

max_vocab = 20000
tokenizer = Tokenizer(num_words=max_vocab)

X_train = [str(text) for text in X_train]
X_test = [str(text) for text in X_test]

tokenizer.fit_on_texts(X_train)
X_train = tokenizer.texts_to_sequences(X_train)
X_test = tokenizer.texts_to_sequences(X_test)

X_train = tf.keras.preprocessing.sequence.pad_sequences(X_train, padding='post',
```

```
maxlen=300)
X_test = tf.keras.preprocessing.sequence.pad_sequences(X_test, padding='post', maxlen=300)

"""## Convolutional Neural Networks (CNN)

Build model and add layers:

"""

model_cnn = tf.keras.Sequential([
    tf.keras.layers.Embedding(max_vocab, 128, input_length=300),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Conv1D(64, 5, activation='relu'),
    tf.keras.layers.MaxPooling1D(pool_size=4),
    tf.keras.layers.LSTM(128),
    tf.keras.layers.Dense(1, activation='sigmoid')
])

model_cnn.summary()

"""### Train model

Since the data set contains 5000 rows, so we run 2 epochs maximum, with batch size of 32, and use early stop that automatically stops training when a monitored metric "val_loss" has stopped improving.
"""
```

```
!pip install --upgrade tensorflow

import tensorflow as tf
from sklearn.preprocessing import LabelEncoder



label_encoder = LabelEncoder()
y_train_encoded = label_encoder.fit_transform(y_train)
early_stop = tf.keras.callbacks.EarlyStopping(monitor='val_loss', patience=2, restore_best_weights=True)

model_cnn.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

# Make sure X_train and y_train are NumPy arrays or TensorFlow tensors
X_train = tf.convert_to_tensor(X_train)
y_train = tf.convert_to_tensor(y_train)

history_cnn = model_cnn.fit(X_train, y_train_encoded, epochs=2, validation_split=0.3, batch_size=32, shuffle=True, callbacks=[early_stop])

"""### Evaluation"""

model_cnn.evaluate(X_test, y_test)

pred_cnn = model_cnn.predict(X_test)
```

```
predictions_cnn = []

for i in pred_cnn:
    if i >= 0.5:
        predictions_cnn.append(1)
    else:
        predictions_cnn.append(0)

print('Accuracy on testing set:', accuracy_score(predictions_cnn, y_test))
print('Precision on testing set:', precision_score(predictions_cnn, y_test))
print('Recall on testing set:', recall_score(predictions_cnn, y_test))

matrix = confusion_matrix(predictions_cnn, y_test, normalize='all')
plt.figure(figsize=(8, 5))
ax= plt.subplot()
sns.set(font_scale=1)
sns.heatmap(matrix, annot=True, ax = ax)

ax.set_xlabel('Predicted Labels', size=15)
ax.set_ylabel('True Labels', size=15)
ax.set_title('Confusion Matrix', size=20)
ax.xaxis.set_ticklabels(["no","yes"], size=15)
ax.yaxis.set_ticklabels(["no","yes"], size=15)
```

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