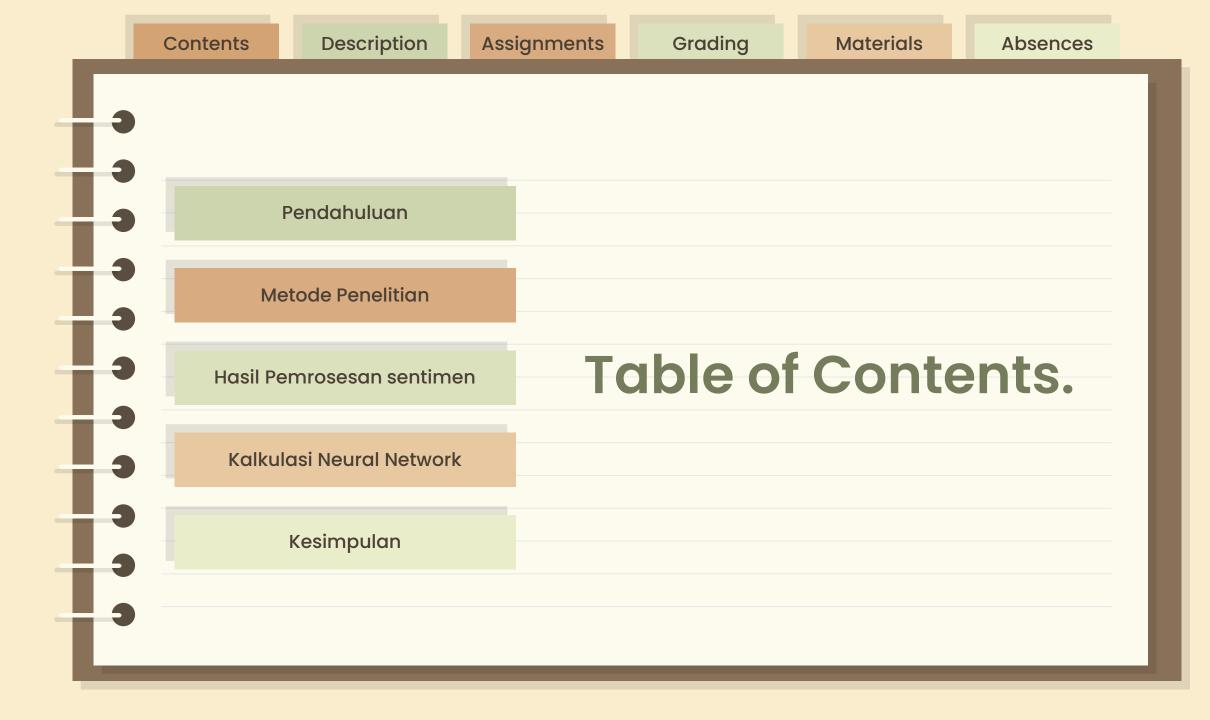
BINAR PLATINUM CHALLENGE

Analisis sentimen melalui flask API



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Contents Description Assignments Grading Materials Absences



Pendahuluan

Kehadiran dunia yang saling berhubungan secara digital menghadirkan celah yang lebih luas dalam membagikan opini berdiskusi secara bebas melewati sosial media dan dunia virtual.

Kecendrungan prilaku manusia untuk mengekspresikan pendapat maupun komentar didukung penuh oleh pemilik sosial media maupun e-commerce untuk menaikan traffic mereka. Mulai dari ruang diskusi, kontroversi, maupun interaksi antar pengguna kerap kali memberikan efek positive maupun negative didalam ruang digital. Nuansa-nuansa didalam sebuah komentar didalam diskusi tersebut dapat diekstraksi dan dapat diimaanfatkan berbagai pihak. Sebagai potensi mendeteksi arus yang terjadi didalam sebuah ruang diskusi virtual untuk menghasilkan user engagement yang lebih baik.

Contents Description Assignments Grading Materials Absences

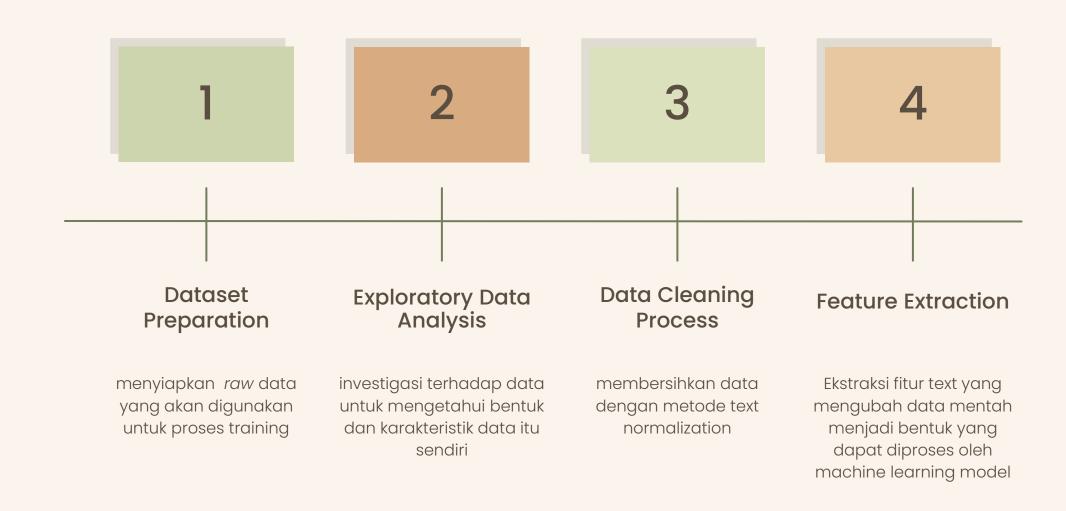
#2

Metode Penelitian

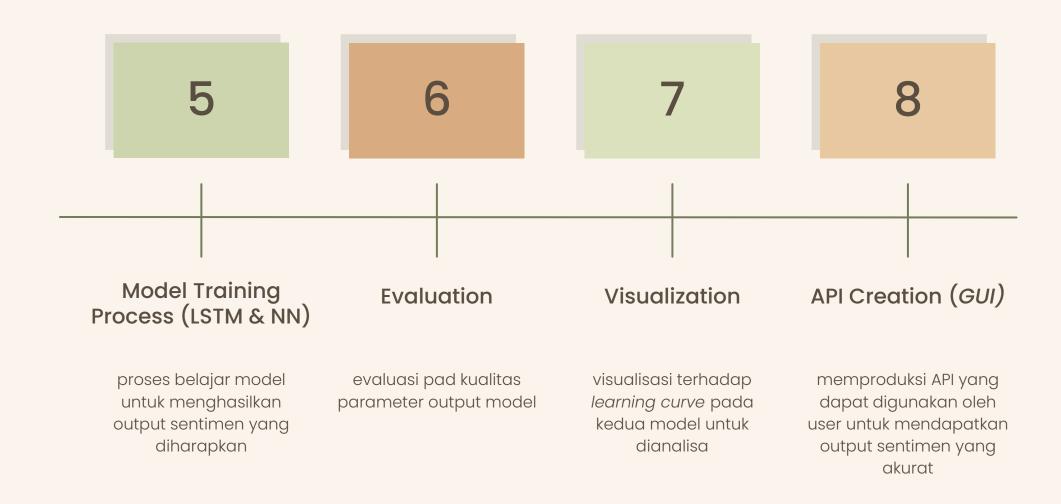
Didalam studi ini kami mencoba untuk membedah lebih dalam dari data yang disediakan dalam bentuk teks yang sudah dilengkapi dengan label sentimen terhadap kalimat-kalimat yang ada.

pada penelitian kali ini, peneliti menggunakan metode LSTM (*Long Short Term Memory*) dan *Neural Network*. Penggunaan LSTM diharapkan dapat memberikan hasil terbaik untuk sequential data dan neural network dipilih dengan pertimbangan model yang dapat ditraining dengan jangka waktu lebih efisien.

Workflow



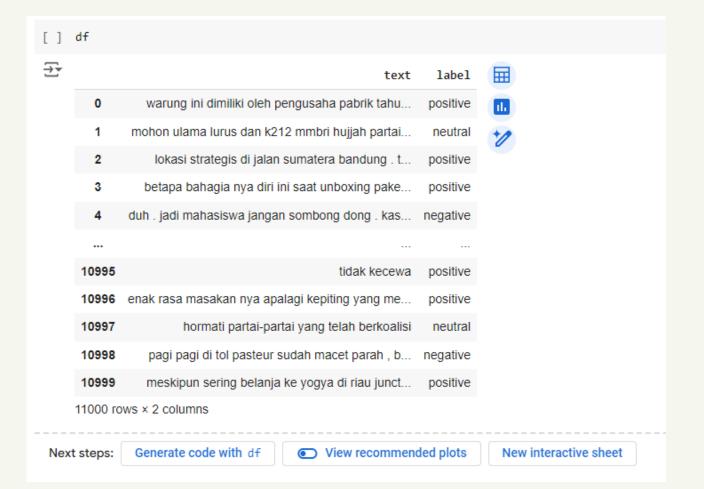
Workflow





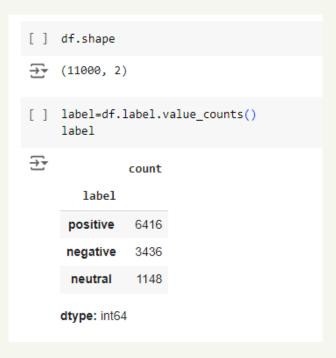
Dataset Preparation

```
[2] # import library yang diperlukan
     # membaca TSV TXT file menggunakan pandas
     import pandas as pd
     import re
     import sklearn
     import nltk
     nltk.download('stopwords')
     !pip install Sastrawi
     from Sastrawi.Stemmer.StemmerFactory import StemmerFactory
     [nltk data] Downloading package stopwords to /root/nltk data...
     [nltk data] Package stopwords is already up-to-date!
     Collecting Sastrawi
       Downloading Sastrawi-1.0.1-py2.py3-none-any.whl.metadata (909 bytes)
     Downloading Sastrawi-1.0.1-py2.py3-none-any.whl (209 kB)
                                               - 209.7/209.7 kB 3.5 MB/s eta 0:00:00
     Installing collected packages: Sastrawi
     Successfully installed Sastrawi-1.0.1
[3] df = pd.read_csv('train_preprocess.tsv.txt', delimiter = "\t", names = ['text', 'label'])
```





EDA (Exploratory Data Analysis)





Data Cleaning Process

```
[] factory = StemmerFactory()
    stemmer = factory.create_stemmer()

[] # fungsi stemming
    def stemming(text):
        text = stemmer.stem(text)
        return text
```

Regex Cleaning

```
def cleaning(text):
      # membuat tulisan lower case
      text = text.lower()
      # menghilangkan whitespaces didepan & belakang
      text = text.strip()
      # menghilangkan USER tag
      text = re.sub('user', ' ', text)
      # menghilangkan URL tag
      text = re.sub('url', ' ', text)
      # menghilangkan "RT" tag
      text = re.sub('rt', ' ', text)
      # menghilangkan random url
      text = re.sub(r'https?:[^\s]+', '', text)
      # menghilangkan tab
      text = re.sub('\t', ' ', text)
      # menghilangkan random /xf character
      text = re.sub('x[a-z0-9]{2}', ' ', text)
      # menghilangkan code "newline"
      text = text.replace('\\n', ' ')
      # menghilangkan symbol tersisa
      text = re.sub(r'[^a-zA-Z0-9]', '', text)
      text = re.sub(r"[-()\"#/@;:{}^+=~|.!?,'0-9]", " ", text)
      # menghilangkan sisa whitespaces
      text = re.sub(r' \s+', ' ',text)
      # menghilangkan whitespaces kembali
      text = text.strip()
      return text
```

Bag of Words

bag of word saya pakai karna memberikan prediksi yang lebih baik pada prediksi sentimen

```
[6] df = pd.read_csv('stemmed.csv')
     data_preprocessed = df.text_clean.tolist()
 [8] from sklearn.feature_extraction.text import CountVectorizer
[9] count_vect = CountVectorizer()
     count vect.fit(data preprocessed)
     X = count vect.transform(data preprocessed)
     print('data exctraction is done')
     data exctraction is done
[10] import pickle
     pickle.dump(count vect, open('feature.p', 'wb'))
```



Feature Extraction

```
LSTM Tokenization Feature Extraction
[ ] import pickle
     import setuptools.dist
     from tensorflow.keras.preprocessing.text import Tokenizer
     from tensorflow.keras.preprocessing.sequence import pad_sequences
     from collections import defaultdict
     max_features = 100000
     tokenizer = Tokenizer(num_words=max_features, split=' ', lower=True)
     tokenizer.fit_on_texts(total_data)
     with open('tokenizer.pickle', 'wb') as handle:
      pickle.dump(tokenizer, handle, protocol=pickle.HIGHEST_PROTOCOL)
      print('tokenizier.pickle has created!')
     X = tokenizer.texts_to_sequences(total_data)
     vocab_size = len(tokenizer.word_index)
     maxlen = max(len(x) for x in X)
     X = pad_sequences(X)
     with open('x_pad_sequences.pickle', 'wb') as handle:
        pickle.dump(X, handle, protocol=pickle.HIGHEST_PROTOCOL)
        print('x_pad_sequences.pickle has been created!')
```



Model Training Process (NN & *LSTM*)

```
[14] from sklearn.neural_network import MLPClassifier
        model = MLPClassifier(activation='logistic')
        model.fit(X_train,y_train)
        print('training is done')
       training is done
[15] import pickle
        pickle.dump(model, open('model-sentiment.p', 'wb'))
```

```
embed_dim = 100
units = 428
modelL = Sequential()
modelL.add(Embedding(max features, embed dim, input length=X.shape[1]))
modelL.add(LSTM(units, dropout=0.5))
modelL.add(Dense(3, activation='softmax'))
modelL.compile(loss = 'binary_crossentropy', optimizer='adam', metrics = ['accuracy'])
print(modelL.summary())
adam = optimizers.Adam(learning rate=0.001)
modelt.compile(loss = 'categorical crossentropy', optimizer = 'adam', metrics = ['accuracy'])
es = EarlyStopping(monitor='val loss', mode='min', verbose=1, patience=4, restore best weights=True)
history = modelL.fit(X train, y train, epochs=12, batch size=15, validation data=(X test, y test), verbose=1, callbacks=[es])
Model: "sequential 12"
```

Layer (type)	Output Shape	Param #
embedding_12 (Embedding)	?	0 (unbuilt)
lstm_12 (LSTM)	?	0 (unbuilt)
dense_12 (Dense)	?	0 (unbuilt)

```
Total params: 0 (0.00 B)
 Trainable params: 0 (0.00 B)
 Non-trainable params: 0 (0.00 B)
Epoch 1/12
587/587
                            - 123s 204ms/step - accuracy: 0.7251 - loss: 0.6713 - val accuracy: 0.8559 - val loss: 0.4098
Epoch 2/12
                           - 126s 215ms/step - accuracy: 0.8976 - loss: 0.2854 - val_accuracy: 0.8700 - val_loss: 0.3499
587/587
Epoch 3/12
587/587
                           - 119s 202ms/step - accuracy: 0.9289 - loss: 0.1853 - val accuracy: 0.8823 - val loss: 0.3590
Epoch 4/12
587/587 -
                           - 119s 202ms/step - accuracy: 0.9615 - loss: 0.1108 - val accuracy: 0.8923 - val loss: 0.3387
Epoch 5/12
                           - 118s 200ms/step - accuracy: 0.9752 - loss: 0.0828 - val accuracy: 0.8905 - val loss: 0.3978
587/587 ·
Enoch 6/12
```

Classification report

positive

accuracy

macro avg weighted avg

```
[16] from sklearn.metrics import classification_report
       test = model.predict(X_test)
       print('testing is done')
       print(classification_report(y_test, test))
   → testing is done
                     precision recall f1-score
                                                   support
           negative
                         0.74
                                            0.73
                                   0.71
                                                       714
            neutral
                         0.70
                                   0.60
                                            0.65
                                                       223
```

0.84

0.76

0.79

0.88

0.73

0.80

0.86

0.80

0.74

0.80

1263

2200

2200

2200



Evaluation & Prediction (NN)

Cross Validation

Training ke -				
	precision	recall	f1-score	support
negative	0.70	0.76	0.73	670
neutral	0.80	0.60	0.69	245
positive	0.86	0.86	0.86	1285
accuracy			0.80	2200
macro avg	0.79	0.74	0.76	2200
weighted avg	0.81	0.80	0.80	2200

Rata-rata Accuracy: 0.7986363636363637

```
    NN Prediction

(25] # original_text = 'mantap sekali rasa syukur dan rasa cukup.'
       original_text = 'suka makan orang'
       # Feature Extraction
       text = count_vect.transform([cleansing(original_text)])
       # Prediksi Sentimenya
       result = model.predict(text)[0]
       print('Text sentiment analysis:')
       print()
       print(result)
   → Text sentiment analysis:
       negative
[26] # original_text = 'mantap sekali rasa syukur dan rasa cukup.'
       original_text = 'Rasa, Syukur kita ucapkan'
```

text = count_vect.transform([cleansing(original_text)])

Feature Extraction

Prediksi Sentimenya

→ Text sentiment analysis:

print()
print(result)

positive

result = model.predict(text)[0]
print('Text sentiment analysis:')



Evaluation & Prediction (NN)



Classification_report

```
[ ] from sklearn import metrics

predictions = modelL.predict(X_test)
y_pred = predictions
matrix_test = metrics.classification_report(y_test.argmax(axis=1), y_pred.argmax(axis=1))

print('testing is done')
print(matrix_test)
```

⊕ 69/69 ——			- 5s 67ms	/step	
testing	LS dor	precision	recall	f1-score	support
	0	0.84	0.89	0.86	685
	1	0.84	0.76	0.80	233
	2	0.93	0.92	0.93	1282
accur	racy			0.89	2200
macro	avg	0.87	0.86	0.86	2200
weighted	avg	0.89	0.89	0.89	2200
	testing i	testing is do	testing is done precision 0 0.84 1 0.84 2 0.93 accuracy macro avg 0.87	testing is done precision recall 0 0.84 0.89 1 0.84 0.76 2 0.93 0.92 accuracy macro avg 0.87 0.86	testing is done precision recall f1-score 0 0.84 0.89 0.86 1 0.84 0.76 0.80 2 0.93 0.92 0.93 accuracy 0.89 macro avg 0.87 0.86 0.86

Evaluation & Prediction (LSTM)

Cross-Validation

Training ke -	5			
	precision	recall	f1-score	support
0	0.85	0.85	0.85	685
1	0.80	0.78	0.79	233
2	0.92	0.93	0.92	1282
accuracy			0.89	2200
macro avg	0.86	0.85	0.85	2200
weighted avg	0.89	0.89	0.89	2200

Rata-rata Accuracy: 0.8795454545454545

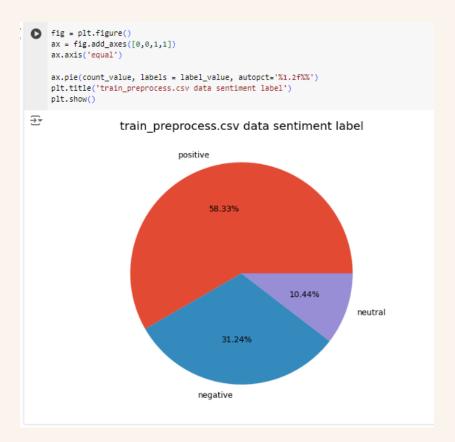
```
#6 activity
```

```
[47] from keras.models import load_model
       input text = ' makan bang, jangan diem diem bae'
       sentiment = ['negative', 'neutral', 'positive']
       text = [cleansing(input_text)]
       predicted = tokenizer.texts_to_sequences(text)
       guess = pad_sequences(predicted, maxlen=X.shape[1])
       model = load_model('modelLSTM.h5')
       prediction = model.predict(guess)
       polarity = np.argmax(prediction[0])
       print('Text: ', text[0])
       print('Sentiment: ', sentiment[polarity])
   🚁 WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you train or evaluate the model.
       1/1 ---- 0s 443ms/step
       Text: makan bang jangan diem diem bae
       Sentiment: positive
[48] from keras.models import load_model
       input_text = ' rasa syukur, cukup'
       sentiment = ['negative', 'neutral', 'positive']
       text = [cleansing(input_text)]
       predicted = tokenizer.texts_to_sequences(text)
       guess = pad sequences(predicted, maxlen=X.shape[1])
       model = load_model('modelLSTM.h5')
       prediction = model.predict(guess)
       polarity = np.argmax(prediction[0])
       print('Text: ', text[0])
       print('Sentiment: ', sentiment[polarity])
  TWARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you train or evaluate the model.
       Text: rasa syukur cukup
       Sentiment: positive
```

Evaluation & Prediction (LSTM)



Visualization



```
label_neutral = df.loc(df['label'] == 'neutral']
text = ' '.join(map(str,(label_neutral['stopwords'])))
wordcloud = WordCloud(width=800, height=400).generate(text)
plt.figure(figsize=(12, 6))
plt.mshow(wordcloud)
plt.axis('off')
plt.show()
```



```
label_positive = df.loc[df['label'] == 'positive']
text = ' '.join(map(str,(label_positive('stopwords'])))
wordcloud = Wordcloud(width=800, height=400).generate(text)
plt.figure(figsize=(12, 6))
plt.imshow(wordcloud)
plt.axis('off')
plt.show()
```



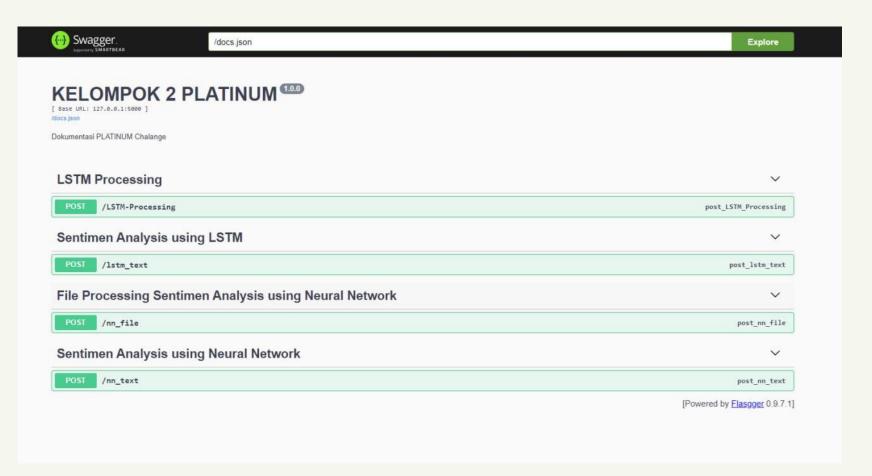


Visualization

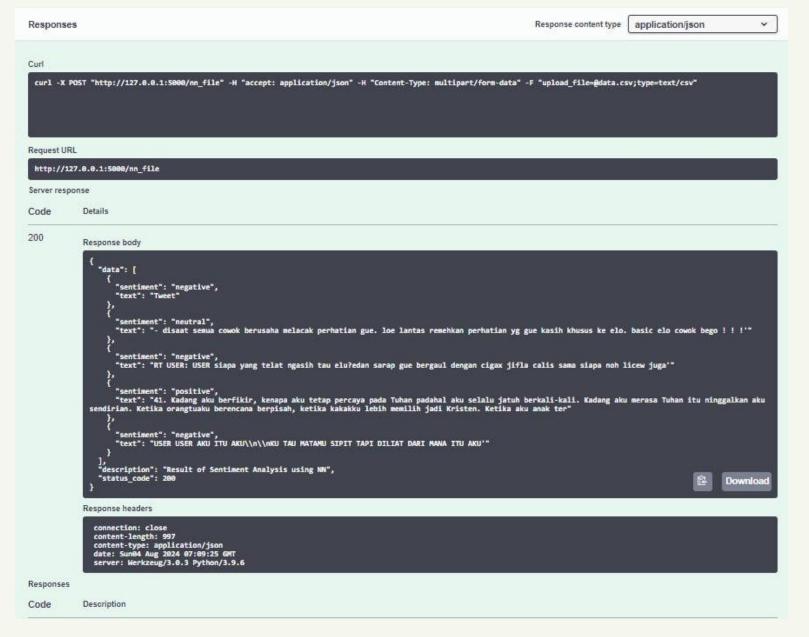


Model Training Confusion Matrix





API Creation



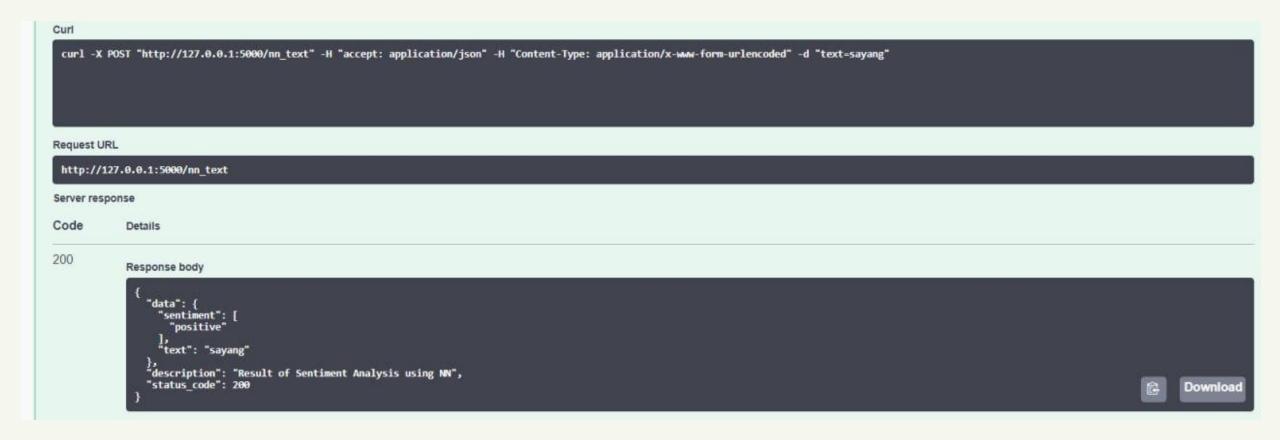


API Creation

Description Assignments Grading Contents Materials **Absences** #4 Hasil dari Pemrosesan Data



Jika kalimat yang dimasukan positive maka akan muncul



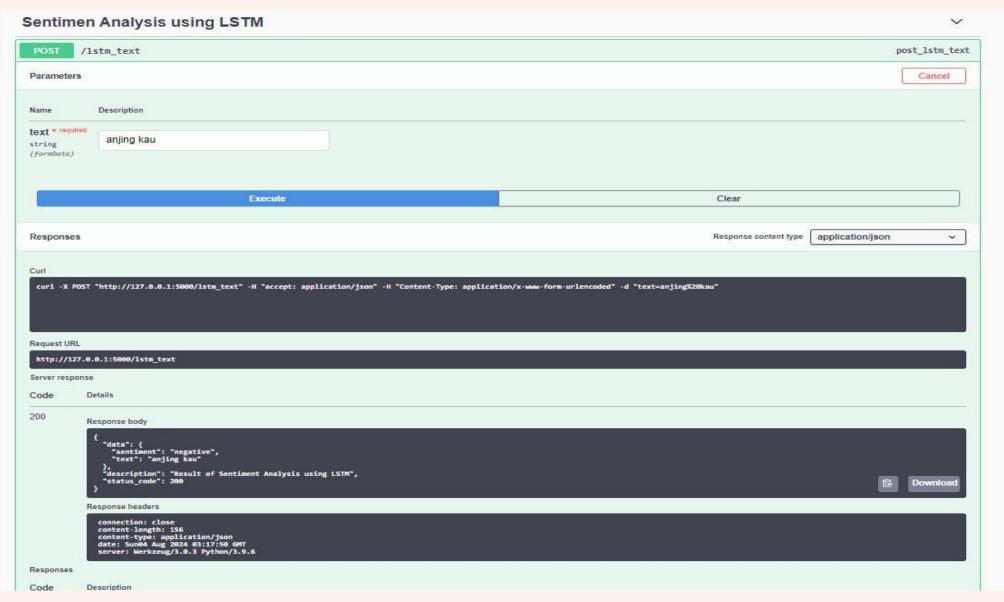
Jika kalimat yang dimasukan negative maka akan muncul



```
Curl
 curl -X POST "http://127.0.0.1:5000/nn text" -H "accept: application/json" -H "Content-Type: application/x-www-form-urlencoded" -d "text-babi%20kau"
Request URL
 http://127.0.0.1:5000/nn text
Server response
Code
            Details
200
            Response body
                "data": {
                   "text": "babi kau"
                },
"description": "Result of Sentiment Analysis using NN",
                "status code": 200
```

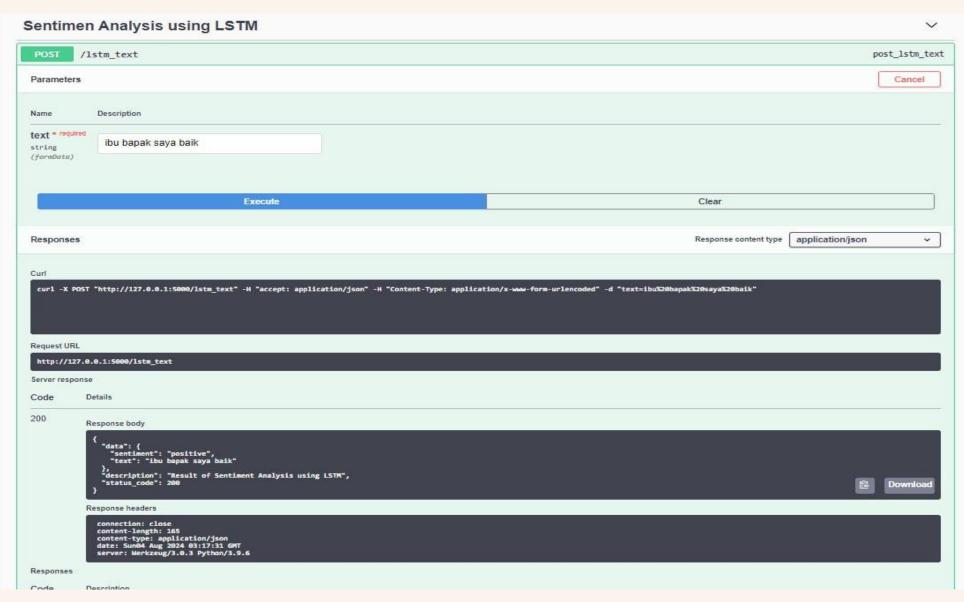
#4

Hasil Deploy Data LSTM negative





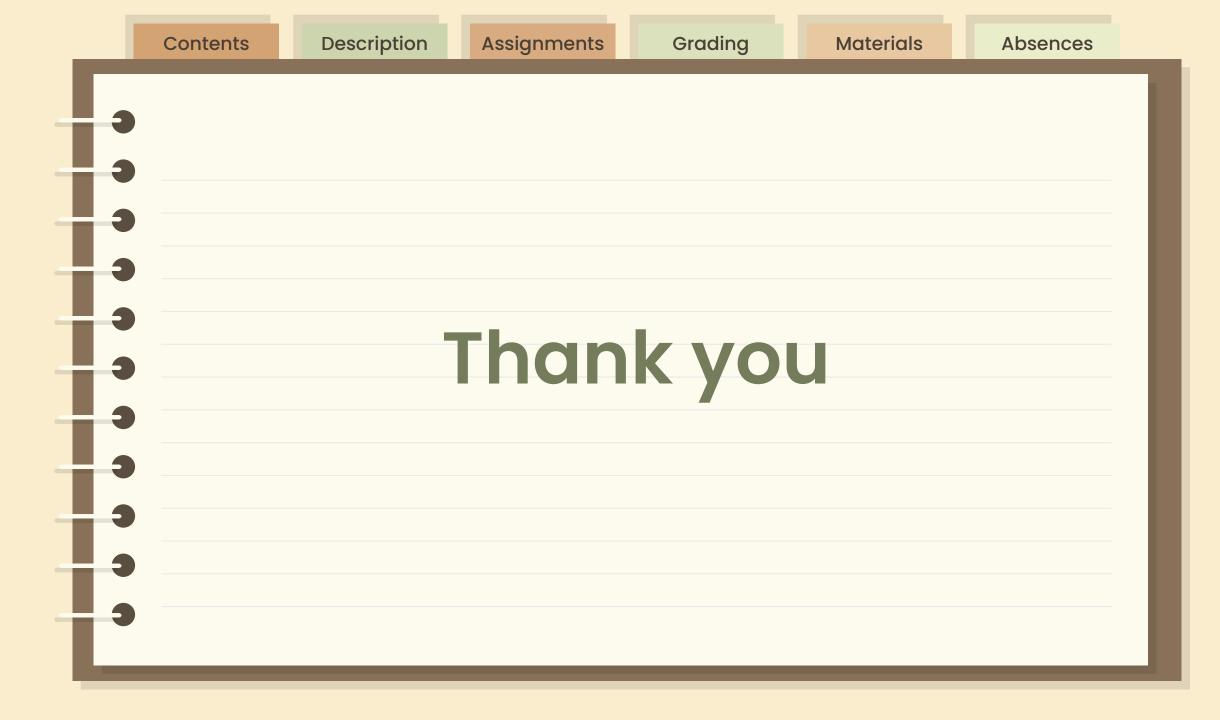
Hasil Deploy Data LSTM positive



Contents Description Assignments Grading Materials Absences

Kesimpulan

Dari hasil prediksi yang dilakukan didalam API terhadap kedua model, menunjukkan hasil yang tidak begitu berbeda. yaitu, memberikan analisis sentimen yang cukup akurat didalam API. nilai akurasi yang dapat dihasilkan model NN sebesar 0.8 dan model LSTM sebesar 0,88-0,89. Dapat disimpulkan dari 100 kali tes, model LSTM seharusnya dapat memberikan prediksi lebih baik dengan ketidakakuratan serendah 12 hasil tes.



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