Documetação sobre a Análise de Reviews de produtos musicais da Amazon

1. Análise do Negócio
    - Contexto A análise de sentimentos em avaliações de produtos musicais pode ajudar as empresas a entender melhor a percepção dos consumidores sobre seus produtos. Isso pode ser utilizado para melhorar produtos, direcionar marketing e aumentar a satisfação do cliente.
    - Objetivo O objetivo é classificar as avaliações como positivas, negativas ou neutras, permitindo uma análise mais profunda das opiniões dos clientes sobre instrumentos musicais.
2. Compreensão de Dados
    - Descrição das Variáveis reviewerID: ID do revisor -> Categórica; asin: ID do porduto -> Categórica; reviewerName: Nome do revisor -> Categórica; helpful: Classificação de utilidade -> Pode ser classificada entre útil/não útil; reviewText: Texto da revisão do produto -> Categórica; overall: Avaliação do produto (1 a 5) -> Numérica; summary: Resumo da revisão -> Categórica; unixReviewTime: Data da revisão em formato Unix; reviewTime: Data da revisão em formato legível;
3. Método
    - Qual o contexto do problema? O projeto envolve a análise de avaliações de produtos, particularmente instrumentos musicais, com o objetivo de classificar cada avaliação em duas categorias: positiva ou negativa. Esses dados vêm de avaliações textuais feitas por clientes. A ideia é extrair insights das opiniões dos consumidores, auxiliando nas decisões de negócios e compreensão de feedback.
    - Qual o problema? O problema consiste em classificar automaticamente as avaliações dos produtos com base no texto, utilizando algoritmos de aprendizado supervisionado. O objetivo é determinar se uma avaliação é positiva ou negativa, o que pode auxiliar empresas a melhorar seus produtos, serviços e estratégias de marketing.
    - Qual o experimento proposto? O experimento proposto envolve o uso de diferentes modelos de aprendizado de máquina, incluindo redes neurais simples, convolucionais (CNN), LSTM e bidirecionais LSTM, para comparar seu desempenho na tarefa de classificação de sentimentos. Foram testados diversos modelos e hiperparâmetros para identificar a solução que oferece o melhor equilíbrio entre precisão, recall e F1-score.
    - Quais resultados são esperados? Os resultados esperados são que, após o ajuste de hiperparâmetros e a aplicação de diferentes arquiteturas de redes neurais, será identificado um modelo capaz de atingir alta precisão e recall na classificação de sentimentos. A expectativa é que as redes neurais mais complexas, como CNN e LSTM, ofereçam um melhor desempenho, especialmente em termos de precisão

na classe minoritária (negativa), que historicamente apresenta dificuldades em classificadores de aprendizado de máquina.

- Como os dados são preparados? Os dados são preparados por meio de limpeza textual e tokenização. O texto das avaliações passa por um processo de pré-processamento que envolve: - Remoção de stopwords, - Lematização ou stemming, - Tokenização - Conversão em sequências numéricas (representação vetorial) para alimentar os modelos de redes neurais.
- Qual modelo computacional foi escolhido? Por quê? O modelo computacional escolhido foi o CNN. - Apresentou uma acurácia de 90% com um bom equilíbrio entre precisão e recall, especialmente para a classe positiva; - A CNN é bem-sucedida em tarefas de processamento de linguagem natural (NLP) porque pode aprender padrões espaciais e temporais; - De acordo com os resultados, a CNN parece ter um desempenho estável em relação ao modelo LSTM e ao modelo simples, que mostraram sinais de sobreajuste, especialmente com a classe negativa. A capacidade de generalização do CNN pode ser um fator positivo; - O CNN é menos complexo em termos de recursos computacionais comparado aos modelos LSTM; - Os hiperparâmetros, como o número de filtros e o tamanho do kernel, podem ser facilmente ajustados, permitindo otimizar o modelo para o desempenho desejado sem a complexidade adicional de um modelo recurrente

4. Conclusão
   - Os resultados esperados foram encontrados? Os resultados indicam que alguns modelos, especialmente as Redes Neurais Convolucionais (CNN) e LSTM, alcançaram uma precisão considerável. O modelo CNN teve uma precisão em torno de 90%, enquanto o modelo LSTM teve uma precisão um pouco menor, em torno de 87%. No entanto, a classificação da classe negativa (0) apresentou precisão mais baixa em comparação à classe positiva (1), o que sugere que o modelo pode estar tendencioso em relação à classe positiva. Após testes de validação cruzada foi possível encontrar uma média de acurácia de 0.97 e um desvio padrão de 0.03.
   - Quais são as possíveis melhorias no modelo?
     - Ajustes de Hiperparâmetros;
     - Aumento de dados
     - Adição de mais camadas
     - Melhorar o refinamento de limpeza e pré-processamento de dados
     - Combinar diferentes modelos, por exemplo CNN e LSTM, para melhorar os resultados;
   - Próximos Passos -Implementar melhorias;
     - Analisar os casos em que o modelo erra;
     - Melhorar visualização de desempenho;
     - Além da acurácia, avaliar outras métricas;
     - Preparar para produção;

tensorflow-com-redes-neurais

October 1, 2024

[1]:
```
import numpy as np
import pandas as pd
from sklearn.impute import SimpleImputer
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report
import warnings


from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences

from sklearn.preprocessing import LabelEncoder
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Embedding, LSTM, Conv1D,␣
↪MaxPooling1D, GlobalMaxPooling1D, SpatialDropout1D, Bidirectional


warnings.filterwarnings("ignore")
```

[2]:
```
df = pd.read_csv("Musical_instruments_reviews.csv")
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10261 entries, 0 to 10260
Data columns (total 9 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   reviewerID      10261 non-null  object
 1   asin            10261 non-null  object
 2   reviewerName    10234 non-null  object
```

```
 3   helpful         10261 non-null  object
 4   reviewText      10254 non-null  object
 5   overall         10261 non-null  float64
 6   summary         10261 non-null  object
 7   unixReviewTime  10261 non-null  int64
 8   reviewTime      10261 non-null  object
dtypes: float64(1), int64(1), object(7)
memory usage: 721.6+ KB
None
```

[3]:
```python
#Verificando valores ausentes
df.isnull().sum()

print((df.isnull().sum() / len(df)) * 100)
```

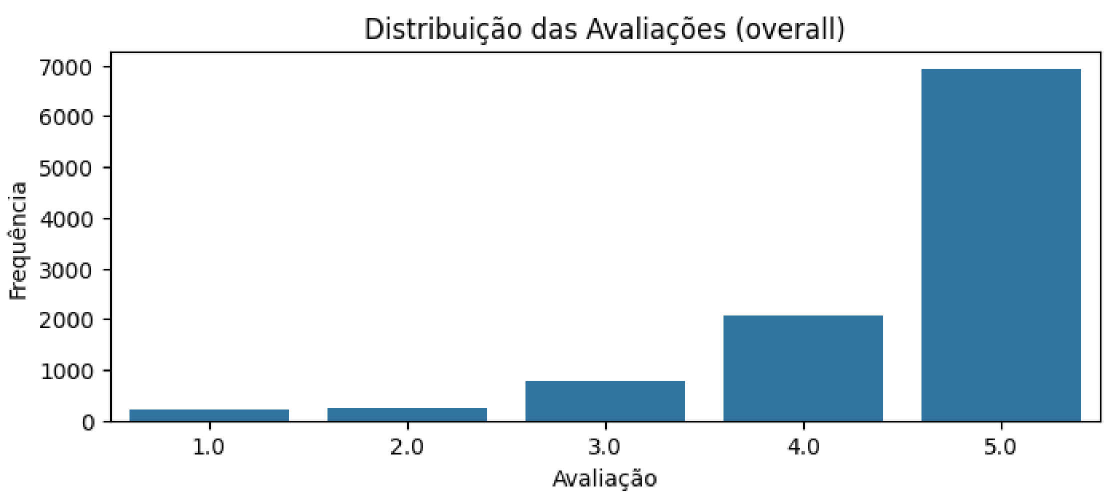
```
reviewerID        0.000000
asin              0.000000
reviewerName      0.263132
helpful           0.000000
reviewText        0.068219
overall           0.000000
summary           0.000000
unixReviewTime    0.000000
reviewTime        0.000000
dtype: float64
```

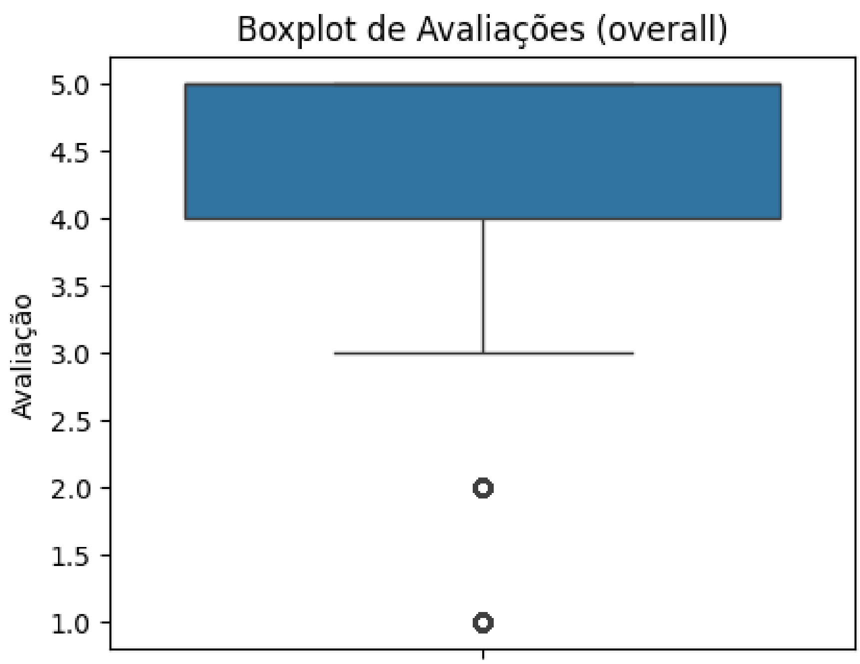
Análise dos Valores Ausentes - reviewerName: 26.3% dos dados estão ausentes. Isso é uma quantidade significativa. - reviewText: 6.8% dos dados estão ausentes. Como essa coluna contém o texto das avaliações, é aconselhável remover essas entradas, pois são essenciais para sua análise.

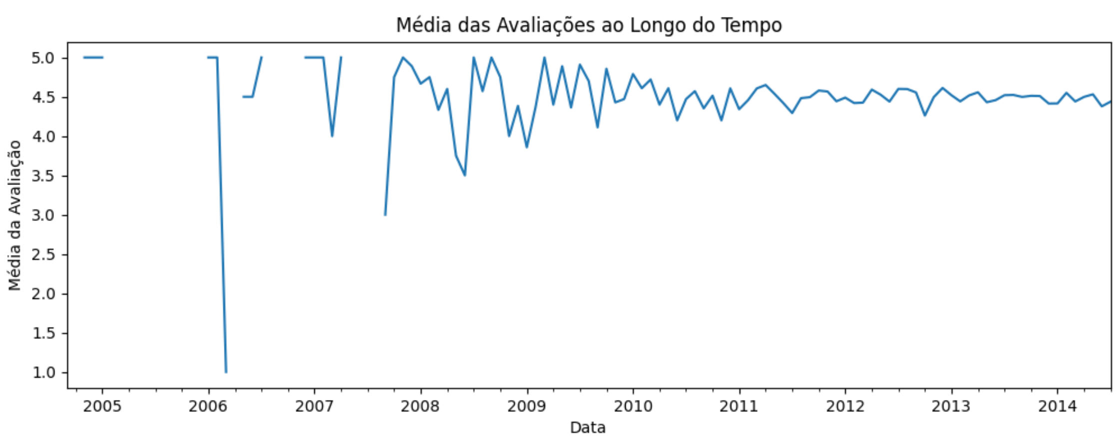
[4]:
```python
#Tratando valores ausentes
df.dropna(subset=['reviewText'], inplace=True)
df.reset_index(drop=True, inplace=True)
df['reviewerName'].fillna('Unknown', inplace=True)

print(df.isnull().sum())
```

```
reviewerID        0
asin              0
reviewerName      0
helpful           0
reviewText        0
overall           0
summary           0
unixReviewTime    0
reviewTime        0
dtype: int64
```

[5]:
```python
#Distribuição das Avaliações (overall)
plt.figure(figsize=(8, 3))
sns.countplot(data=df, x='overall')
plt.title('Distribuição das Avaliações (overall)')
plt.xlabel('Avaliação')
plt.ylabel('Frequência')
plt.show()

plt.figure(figsize=(5, 4))
sns.boxplot(data=df, y='overall')
plt.title('Boxplot de Avaliações (overall)')
plt.ylabel('Avaliação')
plt.show()


# Plotar a distribuição das avaliações ao longo do tempo
df['reviewDate'] = pd.to_datetime(df['unixReviewTime'], unit='s')
plt.figure(figsize=(12, 4))
df.set_index('reviewDate').resample('M')['overall'].mean().plot()
plt.title('Média das Avaliações ao Longo do Tempo')
plt.xlabel('Data')
plt.ylabel('Média da Avaliação')
plt.show()
```







[6]:
```
df["Text"]  = df["summary"] + ". " + df["reviewText"]

df.drop(["summary", "reviewText", "asin", "reviewerName", "reviewerID",␣
 ↪"helpful", "unixReviewTime", "reviewTime"], axis=1, inplace=True)
df.head()
```

[6]:
```
   overall reviewDate                                               Text
0      5.0 2014-02-28  good. Not much to write about here, but it doe…
1      5.0 2013-03-16  Jake. The product does exactly as it should an…
2      5.0 2013-08-28  It Does The Job Well. The primary job of this …
```

```
3      5.0 2014-02-14  GOOD WINDSCREEN FOR THE MONEY. Nice windscreen…
4      5.0 2014-02-21  No more pops when I record my vocals.. This po…
```

[7]:
```python
#Limpeza textual
import nltk
from nltk.corpus import stopwords

nltk.download('stopwords')
stopwords = stopwords.words('english')
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\Michelle\AppData\Roaming\nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
```

[8]:
```python
import string
def clean_text(text):
    text = text.lower()
    text = text.translate(str.maketrans('', '', string.punctuation))
    text = ' '.join([word for word in text.split() if word not in stopwords])
    return text
```

[9]:
```python
df['cleaned_review'] = df['Text'].apply(clean_text)
df.head()
```

[9]:
```
   overall reviewDate                                                Text  \
0      5.0 2014-02-28  good. Not much to write about here, but it doe…
1      5.0 2013-03-16  Jake. The product does exactly as it should an…
2      5.0 2013-08-28  It Does The Job Well. The primary job of this …
3      5.0 2014-02-14  GOOD WINDSCREEN FOR THE MONEY. Nice windscreen…
4      5.0 2014-02-21  No more pops when I record my vocals.. This po…

                                    cleaned_review
0  good much write exactly supposed filters pop s…
1  jake product exactly quite affordablei realize…
2  job well primary job device block breath would…
3  good windscreen money nice windscreen protects…
4  pops record vocals pop filter great looks perf…
```

[10]:
```python
def classify_rating(rating):
    if rating >= 4.0:
        return 'positive'
    elif rating == 3.0:
        return 'neutral'
    else:
        return 'negative'

df['sentiment'] = df['overall'].apply(classify_rating)
```

```
df.head()
```

[10]:
```
   overall reviewDate                                               Text  \
0      5.0 2014-02-28  good. Not much to write about here, but it doe…
1      5.0 2013-03-16  Jake. The product does exactly as it should an…
2      5.0 2013-08-28  It Does The Job Well. The primary job of this …
3      5.0 2014-02-14  GOOD WINDSCREEN FOR THE MONEY. Nice windscreen…
4      5.0 2014-02-21  No more pops when I record my vocals.. This po…

                                    cleaned_review sentiment
0  good much write exactly supposed filters pop s…  positive
1  jake product exactly quite affordablei realize…  positive
2  job well primary job device block breath would…  positive
3  good windscreen money nice windscreen protects…  positive
4  pops record vocals pop filter great looks perf…  positive
```

[11]:
```
X = df["cleaned_review"]
y = df["sentiment"]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)


vectorizer = TfidfVectorizer()

X_train_vectorized = vectorizer.fit_transform(X_train)
X_test_vectorized = vectorizer.transform(X_test)
```

[12]:
```
#Lista de Modelos
models = {
    "Logistic Regression": LogisticRegression(),
    "Decision Tree": DecisionTreeClassifier(),
    "Random Forest": RandomForestClassifier(),
    "Gradient Boosting": GradientBoostingClassifier(),
    "SVM": SVC()
}
results = {}
```

[13]:
```
def fit_model():
    for model_name, model in models.items():
        model.fit(X_train_vectorized, y_train)
        y_pred = model.predict(X_test_vectorized)
        accuracy = accuracy_score(y_test, y_pred)
        results[model_name] = {
            "accuracy": accuracy,
```

```
            "classification_report": classification_report(y_test, y_pred,␣
↪output_dict=True)
        }

def get_model_results():
    for model_name, result in results.items():
        print(f"{model_name}:")
        print(f"Accuracy: {result['accuracy']:.4f}")
        print("Classification Report:")
        print(result['classification_report'])
        print("\n")
```

[14]:
```
fit_model()

get_model_results()
```

```
Logistic Regression:
Accuracy: 0.8874
Classification Report:
{'negative': {'precision': 0.8333333333333334, 'recall': 0.04672897196261682,
'f1-score': 0.08849557522123894, 'support': 107.0}, 'neutral': {'precision':
0.5, 'recall': 0.07518796992481203, 'f1-score': 0.13071895424836602, 'support':
133.0}, 'positive': {'precision': 0.891358024691358, 'recall':
0.9966869133075649, 'f1-score': 0.9410844629822732, 'support': 1811.0},
'accuracy': 0.8873720136518771, 'macro avg': {'precision': 0.7415637860082306,
'recall': 0.3728679517316646, 'f1-score': 0.38676633081729267, 'support':
2051.0}, 'weighted avg': {'precision': 0.8629527300744594, 'recall':
0.8873720136518771, 'f1-score': 0.8440558800217466, 'support': 2051.0}}


Decision Tree:
Accuracy: 0.8376
Classification Report:
{'negative': {'precision': 0.32098765432098764, 'recall': 0.24299065420560748,
'f1-score': 0.2765957446808511, 'support': 107.0}, 'neutral': {'precision':
0.14925373134328357, 'recall': 0.15037593984962405, 'f1-score':
0.149812734082397, 'support': 133.0}, 'positive': {'precision':
0.9106753812636166, 'recall': 0.9232468249585865, 'f1-score':
0.9169180148066904, 'support': 1811.0}, 'accuracy': 0.8376401755241346, 'macro
avg': {'precision': 0.46030558897596263, 'recall': 0.4388711396712727,
'f1-score': 0.44777549785664617, 'support': 2051.0}, 'weighted avg':
{'precision': 0.8305360998290648, 'recall': 0.8376401755241346, 'f1-score':
0.833768582705376, 'support': 2051.0}}


Random Forest:
Accuracy: 0.8849
```

```
Classification Report:
{'negative': {'precision': 0.5, 'recall': 0.009345794392523364, 'f1-score':
0.01834862385321101, 'support': 107.0}, 'neutral': {'precision': 0.75, 'recall':
0.022556390977443608, 'f1-score': 0.043795620437956206, 'support': 133.0},
'positive': {'precision': 0.8855745721271394, 'recall': 1.0, 'f1-score':
0.9393153526970954, 'support': 1811.0}, 'accuracy': 0.8849341784495368, 'macro
avg': {'precision': 0.7118581907090465, 'recall': 0.34396739512332236,
'f1-score': 0.33381986566275423, 'support': 2051.0}, 'weighted avg':
{'precision': 0.856667747499878, 'recall': 0.8849341784495368, 'f1-score':
0.8331975738688355, 'support': 2051.0}}


Gradient Boosting:
Accuracy: 0.8864
Classification Report:
{'negative': {'precision': 0.6875, 'recall': 0.102803738317757, 'f1-score':
0.17886178861788618, 'support': 107.0}, 'neutral': {'precision':
0.35714285714285715, 'recall': 0.07518796992481203, 'f1-score':
0.12422360248447205, 'support': 133.0}, 'positive': {'precision':
0.8953662182361734, 'recall': 0.9922694643843181, 'f1-score':
0.9413305395495024, 'support': 1811.0}, 'accuracy': 0.886396879570941, 'macro
avg': {'precision': 0.6466696917930101, 'recall': 0.39008705754229567,
'f1-score': 0.41480531021728684, 'support': 2051.0}, 'weighted avg':
{'precision': 0.8496200493543199, 'recall': 0.886396879570941, 'f1-score':
0.8485663372192578, 'support': 2051.0}}


SVM:
Accuracy: 0.8820
Classification Report:
{'negative': {'precision': 0.0, 'recall': 0.0, 'f1-score': 0.0, 'support':
107.0}, 'neutral': {'precision': 0.2, 'recall': 0.007518796992481203,
'f1-score': 0.014492753623188406, 'support': 133.0}, 'positive': {'precision':
0.8841075794621027, 'recall': 0.9983434566537824, 'f1-score':
0.9377593360995851, 'support': 1811.0}, 'accuracy': 0.8820087762067285, 'macro
avg': {'precision': 0.3613691931540342, 'recall': 0.3352874178820879,
'f1-score': 0.31741736324092445, 'support': 2051.0}, 'weighted avg':
{'precision': 0.79362205090486, 'recall': 0.8820087762067285, 'f1-score':
0.8289662086339505, 'support': 2051.0}}
```

1 Análise do Modelo

Melhor Acurácia:

A Regressão Logística teve a melhor acurácia (0.8879) entre os modelos testados.

Desempenho em Classes:

- Classe Positiva: A maioria dos modelos apresenta bom desempenho nessa classe, especialmente a
- Classe Neutra: Todos os modelos têm um desempenho fraco nesta classe, especialmente o SVM, qu
- Classe Negativa: O desempenho é consistentemente baixo para todos os modelos, especialmente o

[15]:
```
# Removendo classe neutral
def classify_rating(rating):
    if rating >= 4.0:
        return 1
    else:
        return 0

df['sentiment'] = df['overall'].apply(classify_rating)
```

[16]:
```
X = df["cleaned_review"]
y = df["sentiment"]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)


vectorizer = TfidfVectorizer()

X_train_vectorized = vectorizer.fit_transform(X_train)
X_test_vectorized = vectorizer.transform(X_test)
```

[17]:
```
results = {}
fit_model()

get_model_results()
```

```
Logistic Regression:
Accuracy: 0.8918
Classification Report:
{'0': {'precision': 0.8461538461538461, 'recall': 0.09166666666666666,
'f1-score': 0.16541353383458646, 'support': 240.0}, '1': {'precision':
0.8923456790123456, 'recall': 0.9977912755383765, 'f1-score':
0.9421272158498436, 'support': 1811.0}, 'accuracy': 0.8917601170160897, 'macro
avg': {'precision': 0.8692497625830959, 'recall': 0.5447289711025216,
'f1-score': 0.553770374842215, 'support': 2051.0}, 'weighted avg': {'precision':
0.8869404913545983, 'recall': 0.8917601170160897, 'f1-score':
0.8512392179543479, 'support': 2051.0}}


Decision Tree:
Accuracy: 0.8493
Classification Report:
```

{'0': {'precision': 0.35802469135802467, 'recall': 0.3625, 'f1-score':
0.36024844720496896, 'support': 240.0}, '1': {'precision': 0.9153761061946902,
'recall': 0.913859745996687, 'f1-score': 0.914617297596021, 'support': 1811.0},
'accuracy': 0.8493417844953681, 'macro avg': {'precision': 0.6367003987763574,
'recall': 0.6381798729983434, 'f1-score': 0.637432872400495, 'support': 2051.0},
'weighted avg': {'precision': 0.8501570230348658, 'recall': 0.8493417844953681,
'f1-score': 0.8497472224649373, 'support': 2051.0}}

Random Forest:
Accuracy: 0.8854
Classification Report:
{'0': {'precision': 0.8571428571428571, 'recall': 0.025, 'f1-score':
0.048582995951417005, 'support': 240.0}, '1': {'precision': 0.8855185909980431,
'recall': 0.9994478188845941, 'f1-score': 0.9390402075226978, 'support':
1811.0}, 'accuracy': 0.8854217454900049, 'macro avg': {'precision':
0.8713307240704501, 'recall': 0.512223909442297, 'f1-score': 0.4938116017370574,
'support': 2051.0}, 'weighted avg': {'precision': 0.8821981735795913, 'recall':
0.8854217454900049, 'f1-score': 0.8348423865684766, 'support': 2051.0}}

Gradient Boosting:
Accuracy: 0.8927
Classification Report:
{'0': {'precision': 0.7380952380952381, 'recall': 0.12916666666666668,
'f1-score': 0.2198581560283688, 'support': 240.0}, '1': {'precision':
0.8959681433549029, 'recall': 0.9939260077305356, 'f1-score':
0.9424083769633508, 'support': 1811.0}, 'accuracy': 0.8927352510970259, 'macro
avg': {'precision': 0.8170316907250705, 'recall': 0.5615463371986011,
'f1-score': 0.5811332664958598, 'support': 2051.0}, 'weighted avg':
{'precision': 0.8774944733098909, 'recall': 0.8927352510970259, 'f1-score':
0.8578583754887551, 'support': 2051.0}}

SVM:
Accuracy: 0.8883
Classification Report:
{'0': {'precision': 0.7894736842105263, 'recall': 0.0625, 'f1-score':
0.11583011583011583, 'support': 240.0}, '1': {'precision': 0.8892716535433071,
'recall': 0.9977912755383765, 'f1-score': 0.9404111371324486, 'support':
1811.0}, 'accuracy': 0.8883471477328133, 'macro avg': {'precision':
0.8393726688769167, 'recall': 0.5301456377691882, 'f1-score':
0.5281206264812822, 'support': 2051.0}, 'weighted avg': {'precision':
0.8775936854107534, 'recall': 0.8883471477328133, 'f1-score':
0.8439218903686457, 'support': 2051.0}}

[18]:
```
# Tokenização
max_words = 5000
tokenizer = Tokenizer(num_words=max_words)
tokenizer.fit_on_texts(X_train)
X_train_seq = tokenizer.texts_to_sequences(X_train)
X_test_seq = tokenizer.texts_to_sequences(X_test)

# Padding das sequências
max_length = 100
X_train_pad = pad_sequences(X_train_seq, maxlen=max_length)
X_test_pad = pad_sequences(X_test_seq, maxlen=max_length)
```

[19]:
```
# Dividir os dados em características (X) e rótulos (y)
X = df['cleaned_review']
y = df['sentiment']

# Dividir em conjuntos de treino e teste
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

print(f'Treinamento: {len(X_train)}, Teste: {len(X_test)}')
```

```
Treinamento: 8203, Teste: 2051
```

[20]:
```
# Criar o modelo simples
simple_nn = Sequential()
simple_nn.add(Dense(64, activation='relu', input_shape=(max_length,)))
simple_nn.add(Dense(32, activation='relu'))
simple_nn.add(Dense(1, activation='sigmoid'))  # Saída binária

# Compilar o modelo
simple_nn.compile(loss='binary_crossentropy', optimizer='adam',␣
↪metrics=['accuracy'])

# Resumo do modelo
simple_nn.summary()

# Treinar o modelo
history_simple = simple_nn.fit(X_train_pad, y_train, epochs=5, batch_size=32,␣
↪validation_split=0.2)
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 64)	6,464

```
 dense_1 (Dense)                  (None, 32)                     2,080

 dense_2 (Dense)                  (None, 1)                         33
```

```
 Total params: 8,577 (33.50 KB)

 Trainable params: 8,577 (33.50 KB)

 Non-trainable params: 0 (0.00 B)
```

```
Epoch 1/5
206/206              3s 4ms/step -
accuracy: 0.7301 - loss: 77.8265 - val_accuracy: 0.7672 - val_loss: 18.9013
Epoch 2/5
206/206              1s 3ms/step -
accuracy: 0.8033 - loss: 11.5702 - val_accuracy: 0.8202 - val_loss: 4.1633
Epoch 3/5
206/206              1s 3ms/step -
accuracy: 0.8425 - loss: 2.1662 - val_accuracy: 0.8568 - val_loss: 1.3645
Epoch 4/5
206/206              1s 2ms/step -
accuracy: 0.8675 - loss: 0.8235 - val_accuracy: 0.8641 - val_loss: 0.9040
Epoch 5/5
206/206              1s 3ms/step -
accuracy: 0.8806 - loss: 0.5398 - val_accuracy: 0.8672 - val_loss: 0.7501
```

[21]:

```
from keras.models import Sequential
from keras.layers import Embedding, LSTM, Dense, SpatialDropout1D

# Definindo o modelo LSTM
model_lstm = Sequential()
model_lstm.add(Embedding(max_words, 100, input_length=max_length))
model_lstm.add(SpatialDropout1D(0.2))
model_lstm.add(LSTM(100, dropout=0.2, recurrent_dropout=0.2))
model_lstm.add(Dense(1, activation='sigmoid'))  # Para 2 classes: positiva e␣
 ↪negativa

model_lstm.compile(loss='binary_crossentropy', optimizer='adam',␣
 ↪metrics=['accuracy'])

# Treinando o modelo
model_lstm.fit(X_train_pad, y_train, epochs=5, batch_size=64,␣
 ↪validation_data=(X_test_pad, y_test))
```

```
Epoch 1/5
129/129              19s 116ms/step -
accuracy: 0.8613 - loss: 0.4498 - val_accuracy: 0.8830 - val_loss: 0.3405
Epoch 2/5
129/129              14s 112ms/step -
accuracy: 0.8787 - loss: 0.3053 - val_accuracy: 0.8830 - val_loss: 0.3064
Epoch 3/5
129/129              14s 107ms/step -
accuracy: 0.9274 - loss: 0.2007 - val_accuracy: 0.8869 - val_loss: 0.3034
Epoch 4/5
129/129              15s 113ms/step -
accuracy: 0.9436 - loss: 0.1489 - val_accuracy: 0.8762 - val_loss: 0.3377
Epoch 5/5
129/129              14s 112ms/step -
accuracy: 0.9618 - loss: 0.1160 - val_accuracy: 0.8669 - val_loss: 0.3748
```

[21]:
```
<keras.src.callbacks.history.History at 0x1b72aaf1910>
```

[38]:
```python
# Criar o modelo CNN
cnn_model = Sequential()
cnn_model.add(Embedding(max_words, 128, input_length=max_length))
cnn_model.add(Conv1D(filters=64, kernel_size=5, activation='relu'))
cnn_model.add(MaxPooling1D(pool_size=2))
cnn_model.add(SpatialDropout1D(0.2))
cnn_model.add(GlobalMaxPooling1D())
cnn_model.add(Dense(64, activation='relu'))
cnn_model.add(Dense(1, activation='sigmoid'))  # Saída binária

# Compilar o modelo
cnn_model.compile(loss='binary_crossentropy', optimizer='adam',␣
↪metrics=['accuracy'])

# Resumo do modelo
cnn_model.summary()

# Treinar o modelo
history_cnn = cnn_model.fit(X_train_pad, y_train, epochs=5, batch_size=32,␣
↪validation_split=0.2)
```

Model: "sequential_10"

Layer (type)	Output Shape	Param #
embedding_5 (Embedding)	?	0 (unbuilt)
conv1d_5 (Conv1D)	?	0 (unbuilt)

```
 max_pooling1d_5 (MaxPooling1D)    ?                          0 (unbuilt)

 spatial_dropout1d_5               ?                          0 (unbuilt)
 (SpatialDropout1D)

 global_max_pooling1d_2            ?                          0 (unbuilt)
 (GlobalMaxPooling1D)

 dense_14 (Dense)                  ?                          0 (unbuilt)

 dense_15 (Dense)                  ?                          0 (unbuilt)
```

Total params: 0 (0.00 B)

Trainable params: 0 (0.00 B)

Non-trainable params: 0 (0.00 B)

```
Epoch 1/5
206/206             7s 18ms/step -
accuracy: 0.8573 - loss: 0.4231 - val_accuracy: 0.8757 - val_loss: 0.2973
Epoch 2/5
206/206             3s 15ms/step -
accuracy: 0.9074 - loss: 0.2238 - val_accuracy: 0.8958 - val_loss: 0.2707
Epoch 3/5
206/206             3s 15ms/step -
accuracy: 0.9604 - loss: 0.1085 - val_accuracy: 0.8915 - val_loss: 0.3192
Epoch 4/5
206/206             3s 14ms/step -
accuracy: 0.9888 - loss: 0.0351 - val_accuracy: 0.8927 - val_loss: 0.3868
Epoch 5/5
206/206             3s 15ms/step -
accuracy: 0.9974 - loss: 0.0144 - val_accuracy: 0.8879 - val_loss: 0.5231
```

[23]:

```
# Criar o modelo LSTM
lstm_model = Sequential()
lstm_model.add(Embedding(max_words, 128, input_length=max_length))
lstm_model.add(SpatialDropout1D(0.2))
lstm_model.add(LSTM(64, dropout=0.2, recurrent_dropout=0.2))
lstm_model.add(Dense(1, activation='sigmoid'))  # Saída binária

# Compilar o modelo
```

```python
lstm_model.compile(loss='binary_crossentropy', optimizer='adam',
    metrics=['accuracy'])

# Resumo do modelo
lstm_model.summary()

# Treinar o modelo
history_lstm = lstm_model.fit(X_train_pad, y_train, epochs=5, batch_size=32,
    validation_split=0.2)
```

```
Model: "sequential_3"

 Layer (type)                    Output Shape                  Param #

 embedding_2 (Embedding)         ?                         0 (unbuilt)

 spatial_dropout1d_2             ?                         0 (unbuilt)
 (SpatialDropout1D)

 lstm_1 (LSTM)                   ?                         0 (unbuilt)

 dense_6 (Dense)                 ?                         0 (unbuilt)


 Total params: 0 (0.00 B)

 Trainable params: 0 (0.00 B)

 Non-trainable params: 0 (0.00 B)

Epoch 1/5
206/206              19s 67ms/step -
accuracy: 0.8711 - loss: 0.4213 - val_accuracy: 0.8726 - val_loss: 0.3379
Epoch 2/5
206/206              13s 64ms/step -
accuracy: 0.8858 - loss: 0.2733 - val_accuracy: 0.8818 - val_loss: 0.3195
Epoch 3/5
206/206              14s 68ms/step -
accuracy: 0.9386 - loss: 0.1767 - val_accuracy: 0.8793 - val_loss: 0.3394
Epoch 4/5
206/206              14s 68ms/step -
accuracy: 0.9529 - loss: 0.1335 - val_accuracy: 0.8763 - val_loss: 0.4071
Epoch 5/5
206/206              13s 62ms/step -
```

```
accuracy: 0.9772 - loss: 0.0789 - val_accuracy: 0.8720 - val_loss: 0.4848
```

[24]:

```
# Criar o modelo Bidirectional LSTM
bidir_lstm_model = Sequential()
bidir_lstm_model.add(Embedding(max_words, 128, input_length=max_length))
bidir_lstm_model.add(SpatialDropout1D(0.2))
bidir_lstm_model.add(Bidirectional(LSTM(64, dropout=0.2, recurrent_dropout=0.
 ↪2)))
bidir_lstm_model.add(Dense(1, activation='sigmoid'))  # Saída binária

# Compilar o modelo
bidir_lstm_model.compile(loss='binary_crossentropy', optimizer='adam',␣
 ↪metrics=['accuracy'])

# Resumo do modelo
bidir_lstm_model.summary()

# Treinar o modelo
history_bidir_lstm = bidir_lstm_model.fit(X_train_pad, y_train, epochs=5,␣
 ↪batch_size=32, validation_split=0.2)
```

Model: "sequential_4"

Layer (type)	Output Shape	Param #
embedding_3 (Embedding)	?	0 (unbuilt)
spatial_dropout1d_3 (SpatialDropout1D)	?	0 (unbuilt)
bidirectional (Bidirectional)	?	0 (unbuilt)
dense_7 (Dense)	?	0 (unbuilt)

Total params: 0 (0.00 B)

Trainable params: 0 (0.00 B)

Non-trainable params: 0 (0.00 B)

```
Epoch 1/5
206/206                26s 74ms/step -
accuracy: 0.8600 - loss: 0.3992 - val_accuracy: 0.8726 - val_loss: 0.3309
```

```
Epoch 2/5
206/206            15s 71ms/step -
accuracy: 0.8982 - loss: 0.2543 - val_accuracy: 0.8897 - val_loss: 0.3083
Epoch 3/5
206/206            15s 72ms/step -
accuracy: 0.9386 - loss: 0.1697 - val_accuracy: 0.8800 - val_loss: 0.3486
Epoch 4/5
206/206            14s 69ms/step -
accuracy: 0.9639 - loss: 0.1111 - val_accuracy: 0.8800 - val_loss: 0.3854
Epoch 5/5
206/206            15s 72ms/step -
accuracy: 0.9753 - loss: 0.0762 - val_accuracy: 0.8720 - val_loss: 0.4393
```

[25]:

```python
# Função para avaliar o modelo
def evaluate_model(model, X_test, y_test, model_name):
    y_pred = model.predict(X_test)
    y_pred = (y_pred > 0.5).astype(int)
    print(f"{model_name} Classification Report:")
    print(classification_report(y_test, y_pred))

# Avaliar cada modelo
evaluate_model(simple_nn, X_test_pad, y_test, "Simple Neural Network")
evaluate_model(cnn_model, X_test_pad, y_test, "Convolutional Neural Network")
evaluate_model(lstm_model, X_test_pad, y_test, "Recurrent Neural Network␣
↪(LSTM)")
evaluate_model(bidir_lstm_model, X_test_pad, y_test, "Bidirectional LSTM")
```

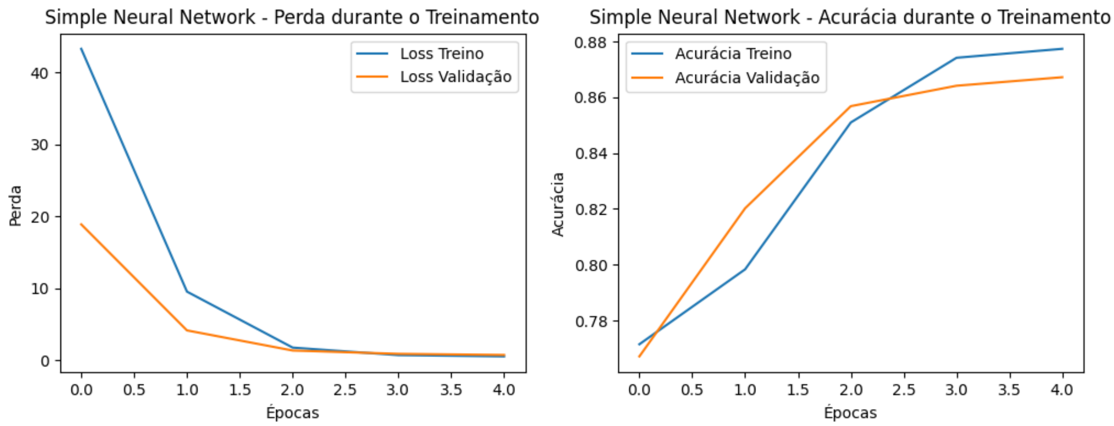
```
65/65            0s 3ms/step
Simple Neural Network Classification Report:
              precision    recall  f1-score   support

           0       0.15      0.02      0.03       240
           1       0.88      0.99      0.93      1811

    accuracy                           0.87      2051
   macro avg       0.52      0.50      0.48      2051
weighted avg       0.80      0.87      0.83      2051

65/65            1s 6ms/step
Convolutional Neural Network Classification Report:
              precision    recall  f1-score   support

           0       0.58      0.38      0.46       240
           1       0.92      0.96      0.94      1811

    accuracy                           0.90      2051
   macro avg       0.75      0.67      0.70      2051
weighted avg       0.88      0.90      0.89      2051
```

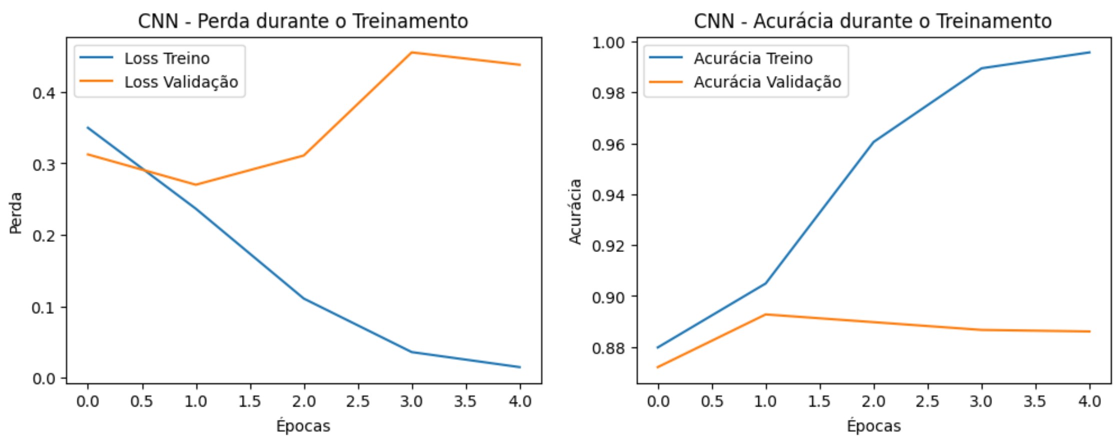
```
65/65              2s 22ms/step
Recurrent Neural Network (LSTM) Classification Report:
              precision    recall  f1-score   support

           0       0.42      0.28      0.34       240
           1       0.91      0.95      0.93      1811

    accuracy                           0.87      2051
   macro avg       0.66      0.62      0.63      2051
weighted avg       0.85      0.87      0.86      2051

65/65              3s 32ms/step
Bidirectional LSTM Classification Report:
              precision    recall  f1-score   support

           0       0.43      0.38      0.40       240
           1       0.92      0.93      0.93      1811

    accuracy                           0.87      2051
   macro avg       0.68      0.66      0.66      2051
weighted avg       0.86      0.87      0.87      2051
```

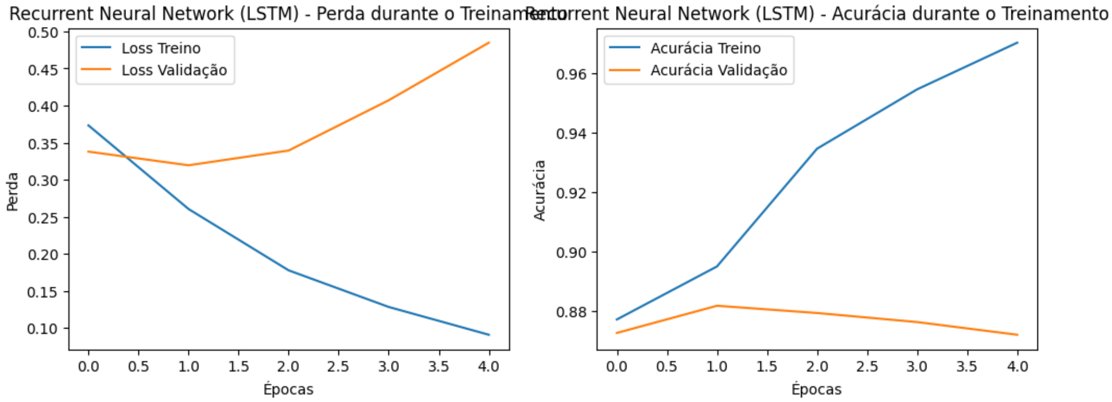
[26]:

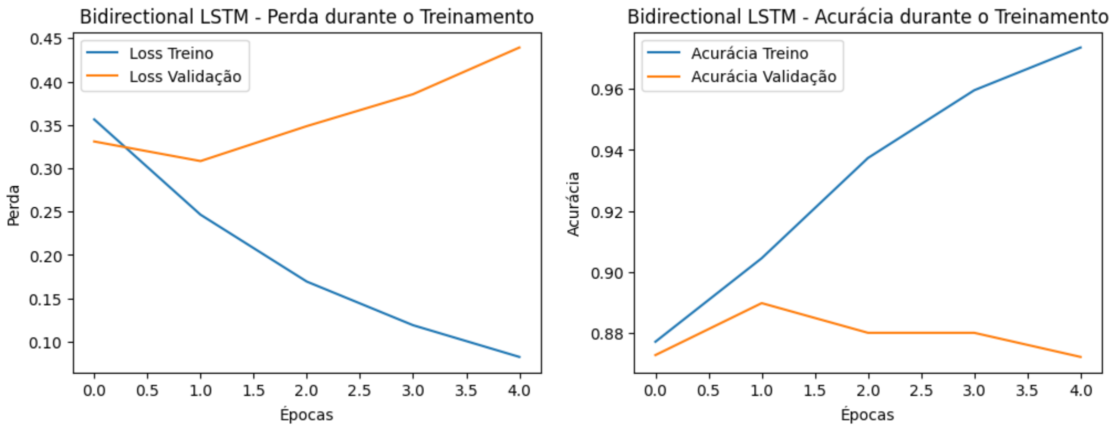
```python
def plot_history(history, model_name):
    plt.figure(figsize=(12,4))

    # Plotar perda
    plt.subplot(1, 2, 1)
    plt.plot(history.history['loss'], label='Loss Treino')
    plt.plot(history.history['val_loss'], label='Loss Validação')
    plt.title(f'{model_name} - Perda durante o Treinamento')
    plt.xlabel('Épocas')
    plt.ylabel('Perda')
    plt.legend()

    # Plotar acurácia
    plt.subplot(1, 2, 2)
    plt.plot(history.history['accuracy'], label='Acurácia Treino')
    plt.plot(history.history['val_accuracy'], label='Acurácia Validação')
    plt.title(f'{model_name} - Acurácia durante o Treinamento')
    plt.xlabel('Épocas')
    plt.ylabel('Acurácia')
    plt.legend()

    plt.show()
```

```python
# Plotar histórico de cada modelo
plot_history(history_simple, "Simple Neural Network")
plot_history(history_cnn, "CNN")
plot_history(history_lstm, "Recurrent Neural Network (LSTM)")
plot_history(history_bidir_lstm, "Bidirectional LSTM")
```





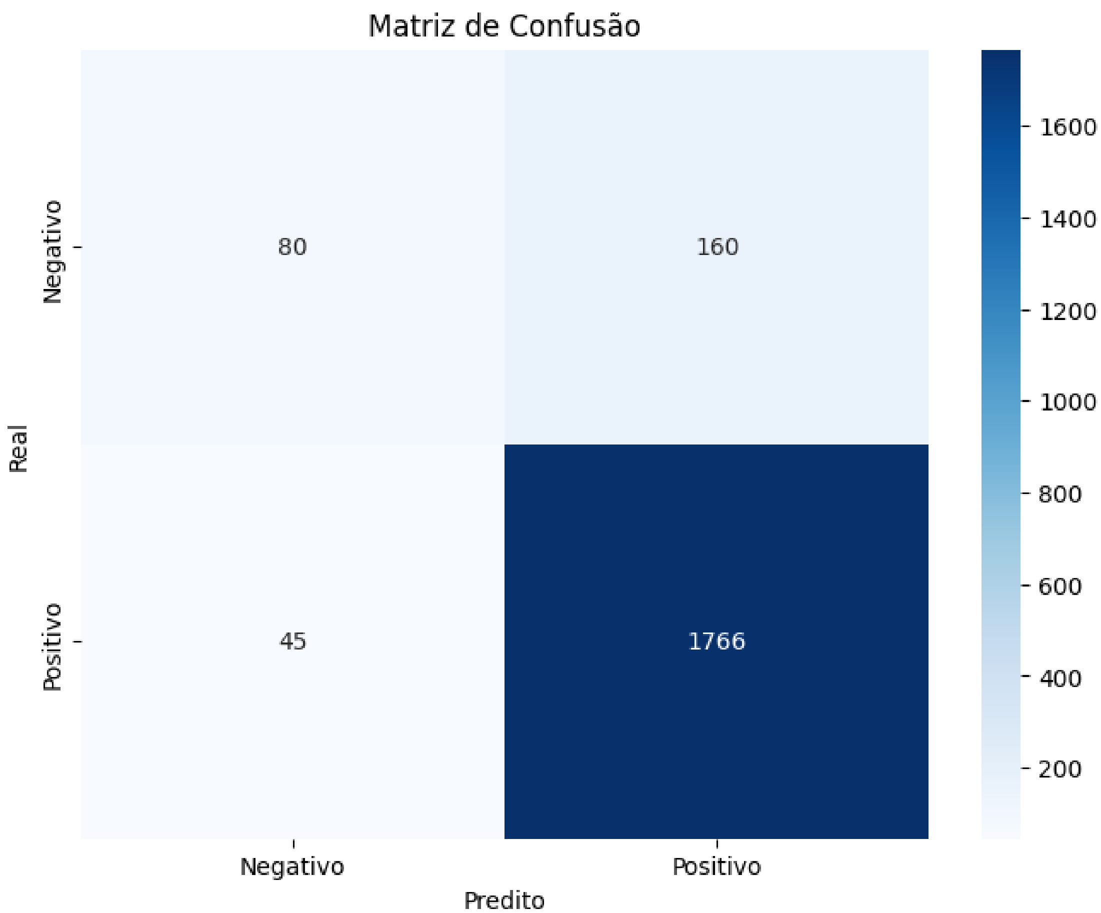




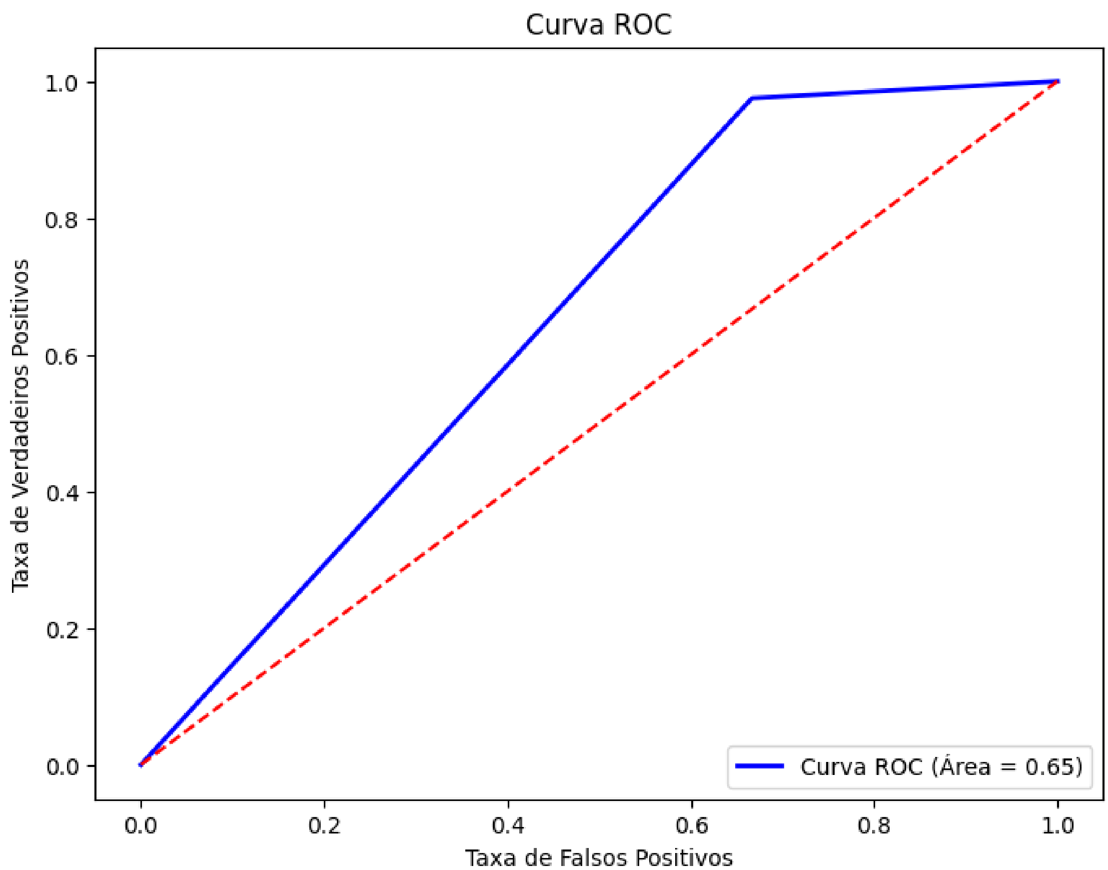
[43]:
```python
y_pred = cnn_model.predict(X_test_pad)
y_pred = (y_pred > 0.5).astype(int)
```

```
65/65                0s 5ms/step
```

[44]:
```python
from sklearn.metrics import confusion_matrix, classification_report

# Matriz de Confusão
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Negativo',␣
 ↪'Positivo'], yticklabels=['Negativo', 'Positivo'])
plt.title('Matriz de Confusão')
plt.ylabel('Real')
plt.xlabel('Predito')
plt.show()
```



[42]:
```python
from sklearn.metrics import roc_curve, auc

# Calcule a curva ROC
fpr, tpr, thresholds = roc_curve(y_test, y_pred)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='Curva ROC (Área = %0.2f)' %␣
↪roc_auc)
plt.plot([0, 1], [0, 1], color='red', linestyle='--')
plt.title('Curva ROC')
plt.xlabel('Taxa de Falsos Positivos')
plt.ylabel('Taxa de Verdadeiros Positivos')
plt.legend(loc='lower right')
plt.show()
```



[50]:
```python
from sklearn.model_selection import cross_val_score
from scikeras.wrappers import KerasClassifier

# Execute validação cruzada
model = KerasClassifier(model=cnn_model, epochs=10, batch_size=32)

cv_scores = cross_val_score(model, X_train_pad, y_train, cv=3)

print(f'Média da Acurácia: {cv_scores.mean():.2f}')
print(f'Desvio Padrão da Acurácia: {cv_scores.std():.2f}')
```

```
Epoch 1/10
171/171              6s 15ms/step -
accuracy: 0.9619 - loss: 0.1369
Epoch 2/10
171/171              3s 15ms/step -
accuracy: 0.9949 - loss: 0.0253
Epoch 3/10
171/171              3s 15ms/step -
accuracy: 0.9996 - loss: 0.0058
```

```
Epoch 4/10
171/171             2s 14ms/step -
accuracy: 0.9986 - loss: 0.0049
Epoch 5/10
171/171             2s 14ms/step -
accuracy: 0.9997 - loss: 0.0018
Epoch 6/10
171/171             3s 15ms/step -
accuracy: 0.9992 - loss: 0.0046
Epoch 7/10
171/171             3s 14ms/step -
accuracy: 1.0000 - loss: 0.0016
Epoch 8/10
171/171             3s 15ms/step -
accuracy: 1.0000 - loss: 9.6167e-04
Epoch 9/10
171/171             3s 16ms/step -
accuracy: 0.9998 - loss: 0.0013
Epoch 10/10
171/171             3s 15ms/step -
accuracy: 1.0000 - loss: 4.5820e-04
86/86            1s 6ms/step
Epoch 1/10
171/171             9s 14ms/step -
accuracy: 0.9615 - loss: 0.1432
Epoch 2/10
171/171             2s 14ms/step -
accuracy: 0.9910 - loss: 0.0297
Epoch 3/10
171/171             2s 14ms/step -
accuracy: 0.9990 - loss: 0.0071
Epoch 4/10
171/171             2s 14ms/step -
accuracy: 0.9998 - loss: 0.0027
Epoch 5/10
171/171             2s 14ms/step -
accuracy: 1.0000 - loss: 0.0021
Epoch 6/10
171/171             3s 15ms/step -
accuracy: 0.9999 - loss: 0.0011
Epoch 7/10
171/171             3s 15ms/step -
accuracy: 0.9999 - loss: 8.9377e-04
Epoch 8/10
171/171             3s 15ms/step -
accuracy: 0.9991 - loss: 0.0015
Epoch 9/10
171/171             3s 14ms/step -
```

```
accuracy: 1.0000 - loss: 5.0944e-04
Epoch 10/10
171/171            3s 15ms/step -
accuracy: 1.0000 - loss: 7.6613e-04
86/86            1s 6ms/step
Epoch 1/10
171/171            5s 16ms/step -
accuracy: 0.9987 - loss: 0.0059
Epoch 2/10
171/171            2s 14ms/step -
accuracy: 0.9990 - loss: 0.0045
Epoch 3/10
171/171            2s 14ms/step -
accuracy: 0.9995 - loss: 0.0021
Epoch 4/10
171/171            3s 15ms/step -
accuracy: 0.9992 - loss: 0.0022
Epoch 5/10
171/171            3s 15ms/step -
accuracy: 0.9992 - loss: 0.0021
Epoch 6/10
171/171            3s 16ms/step -
accuracy: 0.9996 - loss: 0.0013
Epoch 7/10
171/171            3s 15ms/step -
accuracy: 1.0000 - loss: 6.7792e-04
Epoch 8/10
171/171            3s 17ms/step -
accuracy: 1.0000 - loss: 6.9893e-04
Epoch 9/10
171/171            3s 16ms/step -
accuracy: 1.0000 - loss: 3.2870e-04
Epoch 10/10
171/171            2s 14ms/step -
accuracy: 0.9999 - loss: 3.3362e-04
86/86            1s 6ms/step
Média da Acurácia: 0.97
Desvio Padrão da Acurácia: 0.03
```

[53]:

```
cnn_model.save('cnn_model.h5')
```

```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or
`keras.saving.save_model(model)`. This file format is considered legacy. We
recommend using instead the native Keras format, e.g.
`model.save('my_model.keras')` or `keras.saving.save_model(model,
'my_model.keras')`.
```