**NATIONAL ENGINEERING COLLEGE, K.R.NAGAR, KOVILPATTI-628503**

***(An Autonomous Institution, Affiliated to Anna University, Chennai)***

**Department of Artificial intelligence and Data Science**

**Text Emotion Analyzer**

**A Deep Learning Model for Emotion Detection in Text**

**19AD55C – DEEP LEARNING LABORATORY**

**MINI PROJECT**

**By**

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**B.Tech (AI&DS)**

**III rd Year / V Sem**

**AIM :**

The aim of this project is to build a deep learning-based Emotion Classification System that can identify and categorize emotions from textual data. The model will help in understanding user sentiment across various categories like joy, sadness, fear, anger, love, and surprise.

**ALGORITHM:**

* **Data Loading and Preparation:**
* Load dataset containing messages and corresponding emotional states.
* Rename target column for clarity.
* Visualize the distribution of emotional states using a count plot to assess balance in the dataset.
* **Text Preprocessing:**
* Tokenization: Split each message into individual words.
* Stopword Removal: Remove common stopwords (e.g., "the," "is") to reduce noise.
* Punctuation Removal: Strip punctuation marks from the tokenized words.
* Lowercasing: Convert all words to lowercase for uniformity.
* Generate word clouds for each emotion to visualize the most frequent words associated with each category.
* **Text Vectorization:**
* Convert text data into sequences of integers using a tokenizer, where each word is mapped to a unique integer.
* Pad sequences to a fixed length to ensure uniform input size for the model.
* **Label Encoding:**
* Encode categorical emotional states (e.g., "joy," "sadness") into numerical values using a label encoder for model compatibility.
* **Model Architecture:**
* **Embedding Layer:** Convert integer sequences into dense vectors to capture semantic relationships between words.
* **SimpleRNN Layers:** Stack of recurrent layers to capture temporal relationships in the text sequences, with outputs feeding into subsequent layers.
* **Dropout Layers**: Add dropout layers between RNN layers to prevent overfitting by randomly dropping units during training.
* **Dense Layer:** Final layer with softmax activation to output probabilities for each emotion category, enabling multi-class classification.
* **Model Compilation:**
* Use AdamW optimizer for training, incorporating weight decay to improve generalization.
* Apply sparse categorical cross-entropy as the loss function, suitable for multi-class classification with integer-encoded labels.
* Track accuracy as a performance metric.
* **Training the Model:**
* Train the model on the training data over a set number of epochs.
* Plot the training accuracy to visualize learning progress and convergence.
* **Evaluation:**
* Evaluate the model on a test set and generate predictions.
* Create a confusion matrix to compare actual vs. predicted emotional states, highlighting the model's performance for each category.
* **Prediction:**
* Preprocess new, unseen text in real-time (tokenization, padding) and pass it through the model.
* Output the predicted emotion, demonstrating the model’s practical application for emotion recognition in real-world tasks like sentiment analysis.

**SOURCE CODE:**

import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

import missingno as msn

import tensorflow as tf

from tensorflow.keras.preprocessing.text import Tokenizer

from tensorflow.keras.preprocessing.sequence import pad\_sequences

from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import Dense, Dropout, Flatten, SimpleRNN, Embedding, Activation

import nltk

from nltk.corpus import stopwords

from nltk.tokenize import word\_tokenize

from nltk.stem import PorterStemmer, WordNetLemmatizer

from wordcloud import WordCloud

from collections import Counter

from textblob import TextBlob

import string

from sklearn.preprocessing import LabelEncoder, StandardScaler

from sklearn.metrics import confusion\_matrix

from sklearn.model\_selection import train\_test\_split, cross\_val\_predict, cross\_val\_score, RandomizedSearchCV

df = pd.read\_csv(r"/kaggle/input/emotions-dataset-for-nlp/train.txt", sep=";")

df.columns = ["message", "state"]

df.to\_csv("train.csv", index=False)

print("File converted and saved as train.csv")

plt.figure(figsize=(10, 7))

sns.countplot(df, x="state", order=df["state"].value\_counts().index)

plt.title("Target Category Count")

plt.xlabel("State")

plt.ylabel("Count")

plt.show()

def preprocessing(text):

pre\_text = word\_tokenize(text)

pre\_text = [word for word in pre\_text if word not in string.punctuation]

pre\_text = [word for word in pre\_text if word not in set(stopwords.words("english"))]

return pre\_text

sadness\_words = df[df["state"] == "sadness"]["message"].apply(preprocessing).sum()

anger\_words = df[df["state"] == "anger"]["message"].apply(preprocessing).sum()

love\_words = df[df["state"] == "love"]["message"].apply(preprocessing).sum()

surprise\_words = df[df["state"] == "surprise"]["message"].apply(preprocessing).sum()

fear\_words = df[df["state"] == "fear"]["message"].apply(preprocessing).sum()

joy\_words = df[df["state"] == "joy"]["message"].apply(preprocessing).sum()

sadness\_words = " ".join(sadness\_words)

anger\_words = " ".join(anger\_words)

love\_words = " ".join(love\_words)

surprise\_words = " ".join(surprise\_words)

fear\_words = " ".join(fear\_words)

joy\_words = " ".join(joy\_words)

sadness\_words = WordCloud(width=800, height=400, background\_color='white').generate(sadness\_words)

anger\_words = WordCloud(width=800, height=400, background\_color='white').generate(anger\_words)

love\_words = WordCloud(width=800, height=400, background\_color='white').generate(love\_words)

surprise\_words = WordCloud(width=800, height=400, background\_color='white').generate(surprise\_words)

fear\_words = WordCloud(width=800, height=400, background\_color='white').generate(fear\_words)

joy\_words = WordCloud(width=800, height=400, background\_color='white').generate(joy\_words)

plt.imshow(joy\_words, interpolation='bilinear')

plt.title('Joy Word Cloud')

plt.axis('off')

plt.show()

def text\_preprocessing(text):

pre\_txt = word\_tokenize(text)

pre\_txt = [word.lower() for word in pre\_txt if word not in string.punctuation]

pre\_txt = [word for word in pre\_txt if word not in set(stopwords.words("english"))]

pre\_txt = " ".join(pre\_txt)

return pre\_txt

df["processed\_text"] = df["message"].apply(text\_preprocessing)

X = df.drop(columns=["message", "state"])

y = df["state"]

train\_data, test\_data, train\_target, test\_target = train\_test\_split(X, y, random\_state=42, test\_size=0.3, shuffle=True)

train\_data = train\_data.squeeze()

test\_data = test\_data.squeeze()

train\_data\_token = tokenizer.texts\_to\_sequences(train\_data)

test\_data\_token = tokenizer.texts\_to\_sequences(test\_data)

tokenizer = Tokenizer(num\_words=5000, oov\_token="<OOV>")

tokenizer.fit\_on\_texts(train\_data)

train\_data\_token\_padd = pad\_sequences(train\_data\_token, maxlen=200)

test\_data\_token\_padd = pad\_sequences(test\_data\_token, maxlen=200)

encoder = LabelEncoder()

train\_target\_encode = encoder.fit\_transform(train\_target)

test\_target\_encode = encoder.transform(test\_target)

model = Sequential()

model.add(Embedding(input\_dim=5000, output\_dim=64, input\_length=200))

model.add(Dropout(0.1))

model.add(SimpleRNN(units=128, activation="relu", return\_sequences=True))

model.add(Dropout(0.1))

model.add(SimpleRNN(units=64, activation="relu", return\_sequences=True))

model.add(Dropout(0.1))

model.add(SimpleRNN(units=32, activation="relu", return\_sequences=True))

model.add(Dropout(0.1))

model.add(SimpleRNN(units=16, activation="relu", return\_sequences=True))

model.add(Dropout(0.1))

model.add(SimpleRNN(units=8, activation="relu"))

model.add(Dropout(0.1))

model.add(Dense(len(np.unique(train\_target\_encode)) + 1, activation="softmax"))

model.build(input\_shape=(None, 200))

model.summary()

opt = tf.keras.optimizers.AdamW(learning\_rate=0.001)

model.compile(loss="sparse\_categorical\_crossentropy", optimizer=opt, metrics=["accuracy"])

history = model.fit(train\_data\_token\_padd, train\_target\_encode, epochs=15)

plt.figure(figsize=(10, 7))

plt.plot(history.history["accuracy"])

plt.title("Train accuracy")

plt.xlabel("Epochs")

plt.show()

y\_pred = model.predict(test\_data\_token\_padd)

predictions = []

for i in y\_pred:

predictions.append(np.argmax(i))

confusion = confusion\_matrix(test\_target\_encode, predictions)

# Create a heatmap with Seaborn

plt.figure(figsize=(8, 6))

sns.heatmap(confusion, annot=True, fmt='d', cmap='Blues', cbar=False)

# Customize labels and title

plt.xlabel('Predicted', fontsize=14, fontweight='bold')

sent = "i am feeling good"

sent\_pre = text\_preprocessing(sent)

sent\_pre = tokenizer.texts\_to\_sequences([sent\_pre])

sent\_pre = pad\_sequences(sent\_pre, maxlen=200)

pred = model.predict(sent\_pre)

the\_pred = encoder.classes\_[np.argmax(pred)]

**Output:**

**A screenshot of a computer program

Description automatically generated**

**A screenshot of a computer

Description automatically generated**

**Sentence :** "i am feeling good"

**Prediction :** ‘Joy’

**OPTIMIZATION MODEL PERFORMANCE:**

* **Learning Rate Tuning:** The AdamW optimizer with a learning rate of 0.001 is used for better weight updates. Adjusting this could improve performance further.
* **Batch Size and Epochs:** Experimenting with batch sizes and the number of epochs could lead to improvements in model accuracy.
* **Regularization Techniques:** Dropout layers are already used to avoid overfitting. Additional techniques such as L2 regularization could also be applied.
* **Data Augmentation:** Data augmentation techniques, such as adding synonyms, can be used to generate more training samples for underrepresented classes.

**FUTURE WORK:**

* **Incorporate More Advanced Models:** Experiment with more advanced models like LSTM, GRU, or Transformer-based models (e.g., BERT) to improve the sequence processing capabilities of the model.
* **Fine-Tuning Pretrained Models:** Fine-tuning state-of-the-art language models like GPT or BERT could lead to better contextual understanding of text and hence improve emotion classification**.**
* **Cross-Lingual Emotion Detection:** Extending the system to support multi-language inputs could increase its applicability in diverse environments.
* **Real-Time Emotion Detection:** The system could be enhanced to detect emotions in real-time for applications in chatbots, virtual assistants, or sentiment analysis tools.

**REFERENCE:**

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**CONCLUSION:**

The emotion classification system is able to identify different emotions from textual data with 98% accuracy, as demonstrated by the results from the confusion matrix and accuracy scores during training. The model's ability to learn word patterns associated with emotions is key to its classification performance.