Graduate Project - CSCI 6350

Comparing Deep Learning Transformers To Naive Bayes and Random Forest Models in the Context of Emotion Detection

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In [1]:
```
# Imports of main Libs
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns


# SKlearn
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, f1_score, confusion_matrix


# BERT - Huggingface
from transformers import BertModel
from transformers import BertTokenizer
from transformers import BertForSequenceClassification


# PyTorch Libs
import torch
from torch.utils.data import TensorDataset, DataLoader
import torch.nn.functional as F
from torchmetrics import Accuracy
from torch.optim.lr_scheduler import StepLR
import torch.optim as optim


# Lightning Libs - Primarilry for the Trainer()
import pytorch_lightning as pl
from pytorch_lightning import Trainer
from pytorch_lightning.loggers import CSVLogger
from pytorch_lightning.callbacks.early_stopping import EarlyStopping


# Plotting and Displaying Setup
%matplotlib inline
pd.set_option('display.max_columns', 500) # Allows for up to 500 columns to be displayed when viewing a datafra
pd.set_option('display.max_info_columns', 250) # Allows for up to 250 columns to be displayed when viewing a da
plt.style.use('seaborn-v0_8') # A style that can be used for plots - see style refere nce above


# Set Device
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
device
```

Out[1]:
```
device(type='cuda')
```

Data Loading

In [2]:
```
# Load csv into dataframe
df =  pd.read_csv('pd_en_translated.csv', index_col = None, header=0)

# Display Some details of the Dataset
print("\n*** Emotion Tagged Sentences ***")
display(df.head(5))
```

```
*** Emotion Tagged Sentences ***
```

	emotion_en	sentence_en	emotion_de	sentence_de
0	sadness	sorry mum, will treat you well from now on	Traurigkeit	Entschuldigung, Mama, werde Sie von nun an gut...
1	hate	i hate snoring. remind me if my future husband...	Ekel	Ich hasse es zu schnarchen.Erinnern Sie mich d...
2	surprise	And I end up in privilege... Oh well, at least...	Überraschung	Und ich lande im Privileg ... na ja, zumindest...
3	worry	Tasha's really bad haircut. She's being treate...	Angst	Tasha ist wirklich schlechter Haarschnitt.Sie ...
4	sadness	I miss my mom.. "May angels lead you in&...	Traurigkeit	Ich vermisse meine Mutter.

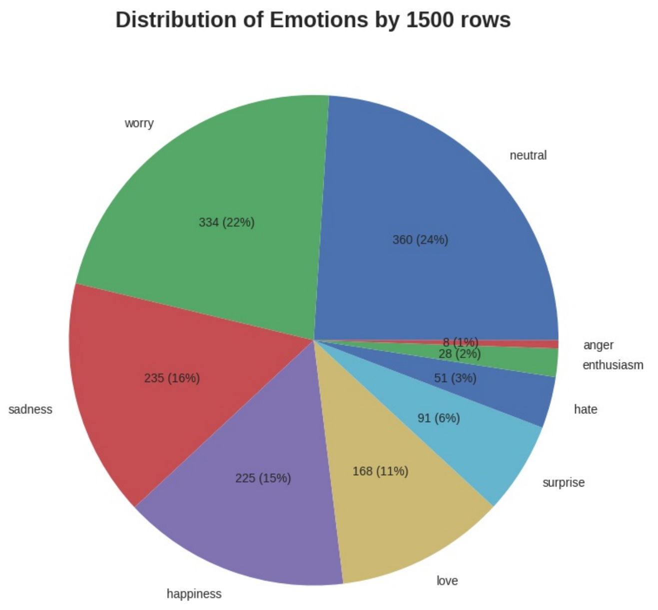
In [3]:

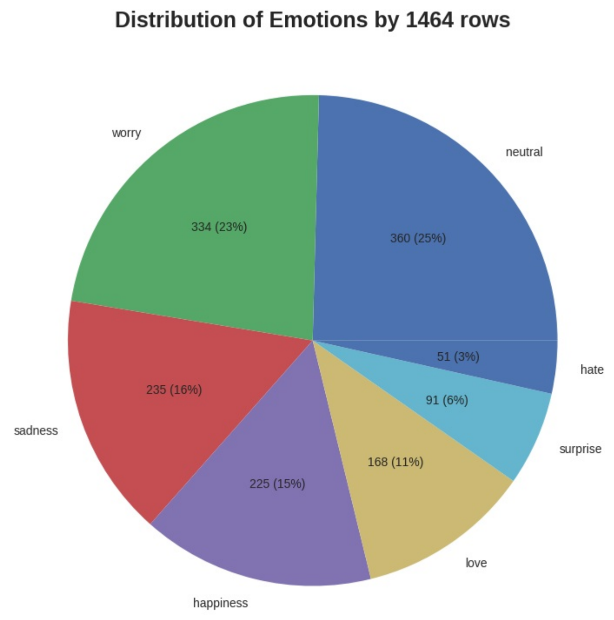
```
# Drop Columns Not Needed
df.drop(["emotion_de", "sentence_de"], axis=1, inplace=True)
```

Plot Pie Chart of Emotion Distribution

In [4]:

```
# Group by Emotions
emotion_count = df["emotion_en"].value_counts()

# Make sure we use the entire width
plt.figure(figsize=(20, 10))


# Custom function to show both count and percentage on the pie chart
def autopct_format(values):
    def my_format(pct):
        total = sum(values)
        val = int(round(pct*total/100.0))
        return '{v:d} ({p:.0f}%)'.format(p=pct,v=val)
    return my_format


# Group by Emotions
emotion_count = df["emotion_en"].value_counts()

# First - Raw Pie Chart
plt.subplot(121)
plt.pie(emotion_count,
        labels = emotion_count.index,
        autopct = autopct_format(emotion_count)
       )

# Setup Title
plt.title(f'Distribution of Emotions by {len(df)} rows',
          fontweight='bold',
          fontsize='18',
          horizontalalignment='center')



# Remove rows where 'emotion_en' is 'anger' and 'enthusiasm'
df = df[df['emotion_en'] != 'anger']
df = df[df['emotion_en'] != 'enthusiasm']

# Group by Emotions
emotion_count = df["emotion_en"].value_counts()

# Second - Updated Pie Chart
plt.subplot(122)
plt.pie(emotion_count,
        labels = emotion_count.index,
        autopct = autopct_format(emotion_count)
       )

# Setup Title
plt.title(f'Distribution of Emotions by {len(df)} rows',
          fontweight='bold',
          fontsize='18',
          horizontalalignment='center')

# Save & Show the Plot
plt.savefig('fig_distribution.png')
plt.show()
```

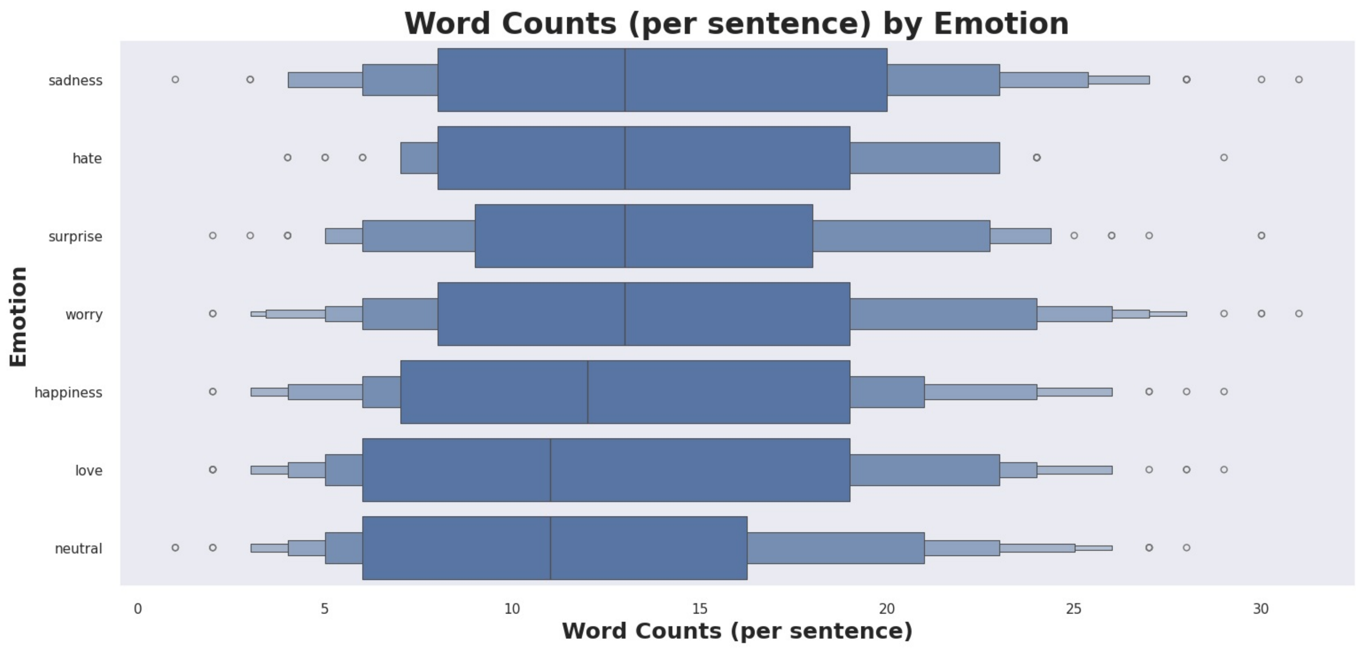




Review Max Length and Disttibution of Sentence Counts

In [5]:

```
df["word_count"] = df["sentence_en"].str.split().apply(len)

# Setting the Style of Seaborn
sns.set(style='dark')

# Make sure we use the entire width
plt.figure(figsize=(18, 8))

sns.boxenplot(
    data = df,
    x = "word_count",
    y = "emotion_en")

# Setup Title, and Axis Lables
plt.title('Word Counts (per sentence) by Emotion',
          fontweight='bold',
          fontsize='24',
          horizontalalignment='center')

plt.xlabel('Word Counts (per sentence)',
           fontweight='bold',
           fontsize='18',
           horizontalalignment='center')

plt.ylabel('Emotion',
           fontweight='bold',
           fontsize='18')


# Save & Show the Plot
plt.savefig('fig_word_counts.png')
plt.show()
```



Label Encoding of Emotions

In [6]:
```
# Label Encoding the Emotions
label_encoder = LabelEncoder()

# Encode labels in column 'emotion_en'
df['label'] = label_encoder.fit_transform(df['emotion_en'])

# Show Updated Dataframe
display(df.head(10))
```

	emotion_en	sentence_en	word_count	label
0	sadness	sorry mum, will treat you well from now on	9	4
1	hate	i hate snoring. remind me if my future husband...	15	1
2	surprise	And I end up in privilege... Oh well, at least...	15	5
3	worry	Tasha's really bad haircut. She's being treate...	18	6
4	sadness	I miss my mom.. "May angels lead you in&...	9	4
5	surprise	@laurenceobrien Thank you xo	4	5
6	surprise	The chicken noodle soup I made for lunch to fe...	21	5
7	worry	Being dragged round Ikea this morning Bad times!	8	6
8	happiness	seniors done 5 more days!! woohoo!! going out...	11	0
9	worry	...wait, I lied.	3	6

In [7]:
```
# Setup / Instantiate the Tokenizer
tokenizer = BertTokenizer.from_pretrained("bert-base-uncased", do_lower_case=True)

# Show Detail on the BERT Tokenizer
print(f'Vocab size: {tokenizer.vocab_size}')
print(f'Max length: {tokenizer.model_max_length}')
print(f'Tokenizer Model Input: {tokenizer.model_input_names}')
```

```
Vocab size: 30522
Max length: 512
Tokenizer Model Input: ['input_ids', 'token_type_ids', 'attention_mask']
```

Encoding / Tokenization Stage

In [8]:
```
# Example of Tokenizer
print('Encoded text')
encoded_text = tokenizer("Hello World!",
                         add_special_tokens = True,
                         max_length = 10,
                         truncation=True,
                         padding=True)
print(encoded_text,'\n')
```

```
Encoded text
{'input_ids': [101, 7592, 2088, 999, 102], 'token_type_ids': [0, 0, 0, 0, 0], 'attention_mask': [1, 1, 1, 1, 1]}
```

In [9]:

```
# Set the maximum sequence length.
MAX_LEN = 64 # This is derived by the above details!
SEED = 42

# Create the Level and Sentence List (Arrays)
emotions  = df.emotion_en.values
sentences = df.sentence_en.values
labels    = df.label.values
tokens    = [ tokenizer(sent, add_special_tokens = True, max_length = MAX_LEN, truncation=True, pad_to_max_leng

# Example Index - Just for Demo Info
IDX = 20

print("\nSentence:\n->", sentences[IDX])
print("\nTokens:\n->", tokens[IDX])
print("\nLabel:\n->", labels[IDX])
print("\nEmotion:\n->", emotions[IDX])
```

```
/opt/conda/lib/python3.11/site-packages/transformers/tokenization_utils_base.py:2618: FutureWarning: The `pad_to
_max_length` argument is deprecated and will be removed in a future version, use `padding=True` or `padding='lon
gest'` to pad to the longest sequence in the batch, or use `padding='max_length'` to pad to a max length. In thi
s case, you can give a specific length with `max_length` (e.g. `max_length=45`) or leave max_length to None to p
ad to the maximal input size of the model (e.g. 512 for Bert).
  warnings.warn(
Sentence:
-> @Desert_Star95 oh so you know how I feel then  Damn representative for bank of america tried to make it sound
like I did it. What a b ...

Tokens:
-> {'input_ids': [101, 1030, 5532, 1035, 2732, 2683, 2629, 2821, 2061, 2017, 2113, 2129, 1045, 2514, 2059, 4365,
4387, 2005, 2924, 1997, 2637, 2699, 2000, 2191, 2009, 2614, 2066, 1045, 2106, 2009, 1012, 2054, 1037, 1038, 1012
, 1012, 1012, 102, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0], 'token_type_id
s': [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0], 'attention_mask': [1, 1, 1,
1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0
, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]}

Label:
-> 6

Emotion:
-> worry
```

Split into a training set and a test set using a stratified k fold

In [10]:

```
# Get Classes
n_classes = len(df["label"].unique())
print(f"Unique Classes: {n_classes}")

# Settings
PCT_TRAIN = 0.8 # => 80%

X_train, X_test, y_train, y_test = train_test_split(tokens,
                                                    labels,
                                                    test_size=(1-PCT_TRAIN),
                                                    random_state=SEED,
                                                    stratify=labels)


X_val, X_test, y_val, y_test = train_test_split(X_test,
                                                y_test,
                                                test_size=0.5, # Split in Half (50%)
                                                random_state=SEED,
                                                stratify= y_test )

# Show Count Details - Small Dataset!!!
print(len(X_train))
print(len(y_train))
print(len(X_val))
print(len(y_val))
print(len(X_test))
print(len(y_test))
```

```
Unique Classes: 7
1171
1171
146
146
147
147
```

Build Datasets into Tensors

In [11]:
```python
# Create Tensors for Training and Testing

# Training Data
train_input_ids_tensors = torch.tensor([d['input_ids'] for d in X_train])
train_attention_mask_tensors = torch.tensor([d['attention_mask'] for d in X_train])
train_labels_tensors = torch.tensor(y_train)

# Validation Data
val_input_ids_tensors = torch.tensor([d['input_ids'] for d in X_val])
val_attention_mask_tensors = torch.tensor([d['attention_mask'] for d in X_val])
val_labels_tensors = torch.tensor(y_val)

# Test Data
test_input_ids_tensors = torch.tensor([d['input_ids'] for d in X_test])
test_attention_mask_tensors = torch.tensor([d['attention_mask'] for d in X_test])
test_labels_tensors = torch.tensor(y_test)
```

Creating the DataLoaders for the Trainer()

In [12]:
```python
# Select a batch size for training. For fine-tuning BERT on a specific task, the authors recommend a batch size
BATCH_SIZE = 10
NUM_WORKERS = 3

train_data = TensorDataset(train_input_ids_tensors,
                           train_attention_mask_tensors,
                           train_labels_tensors)

train_dataloader = DataLoader(train_data,
                              batch_size = BATCH_SIZE,
                              num_workers = NUM_WORKERS,
                              shuffle = True)

val_data = TensorDataset(val_input_ids_tensors,
                         val_attention_mask_tensors,
                         val_labels_tensors)

val_dataloader = DataLoader(val_data,
                            batch_size = BATCH_SIZE,
                            num_workers = NUM_WORKERS,
                            shuffle = False)

test_data = TensorDataset(test_input_ids_tensors,
                          test_attention_mask_tensors,
                          test_labels_tensors)

test_dataloader = DataLoader(test_data,
                             batch_size = BATCH_SIZE,
                             num_workers = NUM_WORKERS,
                             shuffle = False)
```

BERT Model Design

This model inherits from the `pl.LightningModule` to allow fro the `Trainer()` to handle learing rate and early stopping.

In [13]:
```python
class BertClassifier(pl.LightningModule):
    def __init__(self, n_classes: int, learning_rate:float):
        super().__init__()
        self.bert = BertForSequenceClassification.from_pretrained("bert-base-uncased", num_labels=n_classes)
        self.learning_rate = learning_rate
        self.accuracy = Accuracy(num_classes = n_classes, task='multiclass')


    def forward(self, input_ids, attention_mask, labels=None):
        output = self.bert(input_ids, attention_mask=attention_mask, labels=labels)
        return output
```

```python
    def predict(self, input_ids, attention_mask):
        self.eval()  # Set the model to evaluation mode
        with torch.no_grad():  # Disable gradient calculation
            outputs = self.bert(input_ids, attention_mask=attention_mask)
            logits = outputs.logits
            probs = F.softmax(logits, dim=1)  # Convert logits to probabilities
            return probs

    def training_step(self, batch, batch_idx):
        input_ids, attention_mask, labels = batch
        output = self.forward(input_ids, attention_mask, labels)

        # Get Loss
        loss = output.loss
        self.log('train_loss', loss, on_step=False, on_epoch=True)

        # Get Acc
        logits = output.logits
        preds = torch.argmax(logits, dim=1)
        acc = self.accuracy(preds, labels)
        self.log('train_acc', acc, on_step=False, on_epoch=True)

        # Get Learing Rate (for Logging)
        lr = self.trainer.optimizers[0].param_groups[0]['lr']
        self.log('lr', lr, on_step=False, on_epoch=True)

        return loss

    def validation_step(self, batch, batch_idx):
        input_ids, attention_mask, labels = batch
        output = self.forward(input_ids, attention_mask, labels)

        # Get Loss
        loss = output.loss
        self.log('val_loss', loss, on_step=False, on_epoch=True)

        # Get Acc
        logits = output.logits
        preds = torch.argmax(logits, dim=1)
        acc = self.accuracy(preds, labels)
        self.log('val_acc', acc, on_step=False, on_epoch=True)

        return loss

    def test_step(self, batch, batch_idx):
        input_ids, attention_mask, labels = batch
        output = self.forward(input_ids, attention_mask, labels)

        # Get Loss
        loss = output.loss
        self.log('test_loss', loss, on_step=False, on_epoch=True)

        # Get Acc
        logits = output.logits
        preds = torch.argmax(logits, dim=1)
        acc = self.accuracy(preds, labels)
        self.log('test_acc', acc, on_step=False, on_epoch=True)

        return loss

    def configure_optimizers(self):
        # Define Optimizer
        optimizer = torch.optim.Adam(self.parameters(), lr=self.learning_rate)

        # Define LR scheduler
        scheduler = {
            'scheduler': StepLR(optimizer,
                                step_size = 1, # Drop Each Epoch
                                gamma = 0.95), # 5% Drop in LR
            'interval': 'epoch',  # or 'step' for step-wise
            'frequency': 2,
        }
        # Return the Optimizer and Scheduler in Dictionary List
        return [optimizer], [scheduler]
```

In [14]:

```python
# Settings / Configurations
NUM_EPOCHS  = 10
NUM_CLASSES = n_classes
L_RATE      = 0.000005
LOG_DIR     = "logs"
LOG_NAME    = "Classifier"
ES_PATIENCE = 3
```

```python
# Instantiate the Logger
csv_logger = CSVLogger(name = LOG_NAME, save_dir = LOG_DIR)


# Instantiate Model with Class Count
model = BertClassifier(n_classes = NUM_CLASSES, learning_rate = L_RATE)


# Initialize the EarlyStopping callback
early_stopping = EarlyStopping(
    monitor = 'val_loss',    # Monitor validation loss for early stopping
    patience = ES_PATIENCE,  # Number of epochs to wait for improvement before stopping
    verbose = True,          # Print messages when stopping
    mode = 'min'             # The direction is automatically inferred if not set but it's good practice to inc
)


# Setup Trainer with Logger Included
trainer = pl.Trainer(logger = csv_logger,
                     max_epochs = NUM_EPOCHS,
                     enable_progress_bar = True,
                     callbacks=[early_stopping])


# Start Training / Fine-Tuning the Model
trainer.fit(model, train_dataloader, val_dataloader)
```

```
Some weights of BertForSequenceClassification were not initialized from the model checkpoint at bert-base-uncase
d and are newly initialized: ['classifier.weight', 'classifier.bias']
You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.
GPU available: True (cuda), used: True
TPU available: False, using: 0 TPU cores
IPU available: False, using: 0 IPUs
HPU available: False, using: 0 HPUs
LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES: [0]

  | Name     | Type                          | Params
-----------------------------------------------------------
0 | bert     | BertForSequenceClassification | 109 M
1 | accuracy | MulticlassAccuracy            | 0
-----------------------------------------------------------
109 M     Trainable params
0         Non-trainable params
109 M     Total params
437.950   Total estimated model params size (MB)
SLURM auto-requeueing enabled. Setting signal handlers.
Sanity Checking: |          | 0/? [00:00<?, ?it/s]
Training: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Metric val_loss improved. New best score: 1.779
Validation: |          | 0/? [00:00<?, ?it/s]
Metric val_loss improved by 0.074 >= min_delta = 0.0. New best score: 1.705
Validation: |          | 0/? [00:00<?, ?it/s]
Metric val_loss improved by 0.051 >= min_delta = 0.0. New best score: 1.653
Validation: |          | 0/? [00:00<?, ?it/s]
Metric val_loss improved by 0.141 >= min_delta = 0.0. New best score: 1.512
Validation: |          | 0/? [00:00<?, ?it/s]
Metric val_loss improved by 0.030 >= min_delta = 0.0. New best score: 1.482
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Validation: |          | 0/? [00:00<?, ?it/s]
Monitored metric val_loss did not improve in the last 3 records. Best score: 1.482. Signaling Trainer to stop.
```

In [15]:

```python
# Actual Model (no Trainer) to Predict!
pred_output = model.predict(test_input_ids_tensors, test_attention_mask_tensors)

# Show Tensor Output Probailities!
print(pred_output)
```

```
tensor([[0.6053, 0.0123, 0.2501,  ..., 0.0112, 0.0404, 0.0141],
        [0.1246, 0.0130, 0.0440,  ..., 0.0193, 0.0788, 0.0202],
        [0.0800, 0.0165, 0.0297,  ..., 0.0445, 0.0749, 0.0389],
        ...,
        [0.0145, 0.0898, 0.0216,  ..., 0.3688, 0.0394, 0.4252],
        [0.0450, 0.0356, 0.0283,  ..., 0.2031, 0.0684, 0.4416],
        [0.0132, 0.0727, 0.0182,  ..., 0.3354, 0.0376, 0.4805]])
```

In [16]:

```python
# Get Predictions
y_preds = np.argmax(pred_output, axis=1)
```

```python
# Get the F1-Score and Accuracy of the Correlation Matrix Details
f1 = f1_score(test_labels_tensors, y_preds, average="weighted")
acc = accuracy_score(test_labels_tensors, y_preds)

print(f"Acc: {acc}")
print(f"F1-Score: {f1}")
print("|")
print(f'Output Prediction:{y_preds.shape}')
print(f'Pred\n: {y_preds}')
print(f'Label\n: {test_labels_tensors}')
```

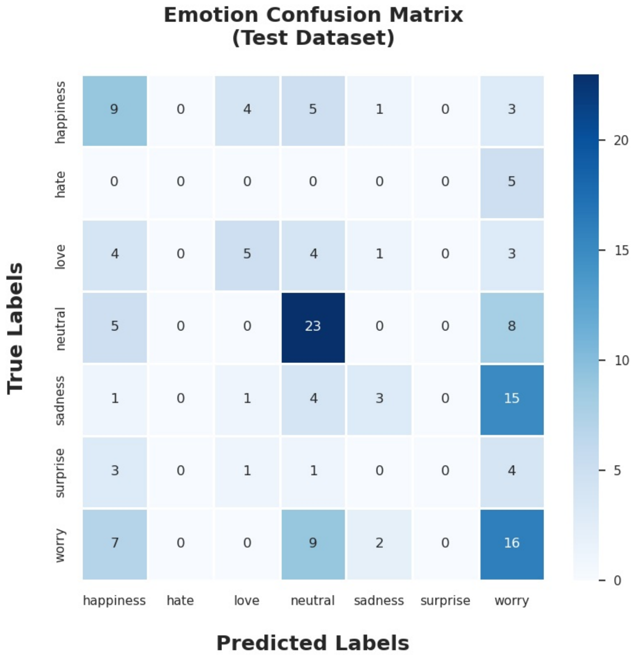
```
Acc: 0.38095238095238093
F1-Score: 0.3472112521017685
|
Output Prediction:torch.Size([147])
Pred
: tensor([0, 3, 3, 3, 3, 3, 0, 0, 6, 0, 2, 3, 0, 3, 3, 6, 6, 3, 3, 3, 6, 6, 0, 2,
        3, 3, 6, 6, 6, 0, 0, 0, 3, 6, 6, 3, 0, 3, 2, 6, 2, 6, 3, 3, 2, 0, 6, 3,
        6, 3, 3, 6, 3, 4, 6, 3, 3, 6, 0, 0, 3, 3, 3, 2, 0, 6, 0, 6, 6, 2, 0, 2,
        0, 2, 0, 6, 6, 6, 0, 6, 6, 6, 2, 6, 6, 4, 3, 6, 2, 3, 6, 3, 6, 6, 4, 0,
        6, 0, 3, 3, 6, 0, 3, 4, 6, 4, 6, 3, 4, 6, 6, 6, 6, 3, 0, 6, 3, 6, 3, 3,
        3, 6, 0, 6, 3, 3, 3, 6, 6, 6, 0, 6, 3, 0, 0, 6, 6, 6, 4, 3, 0, 0, 3, 3,
        6, 6, 6])
Label
: tensor([3, 3, 6, 3, 3, 6, 0, 2, 4, 0, 2, 3, 0, 5, 0, 4, 1, 3, 4, 3, 3, 5, 2, 0,
        2, 3, 2, 4, 4, 3, 0, 0, 2, 0, 1, 3, 0, 6, 0, 4, 5, 4, 3, 3, 0, 5, 0, 4,
        3, 3, 3, 2, 6, 0, 6, 2, 3, 4, 2, 3, 3, 0, 3, 2, 2, 5, 6, 3, 6, 2, 3, 0,
        6, 2, 0, 1, 4, 0, 6, 6, 6, 6, 4, 3, 6, 4, 0, 6, 2, 2, 4, 6, 4, 6, 6, 5,
        5, 6, 4, 3, 6, 6, 3, 2, 3, 4, 4, 3, 6, 1, 3, 3, 4, 0, 3, 6, 3, 4, 3, 0,
        6, 6, 5, 4, 4, 3, 6, 6, 4, 2, 0, 6, 6, 6, 6, 1, 3, 6, 4, 3, 4, 0, 3, 6,
        6, 5, 6])
```

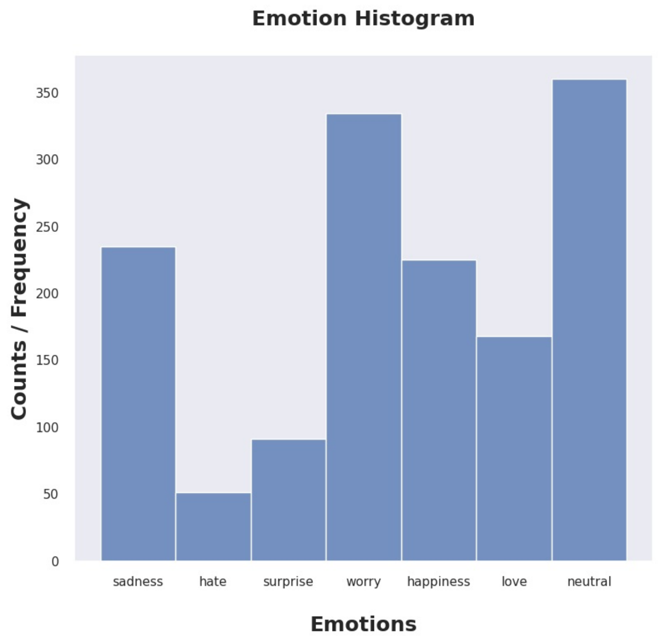
In [17]:

```python
# Create Confusion Matrix
conf_matrix = confusion_matrix(test_labels_tensors, y_preds)

# Show Details
print(conf_matrix)
print()

# Get Class Names based on teh Label Idx
sorted_df = df.sort_values(by='label').drop_duplicates(subset=['emotion_en'])
class_names = sorted_df['emotion_en'].tolist()
# Something like this: class_names = ['Happiness', 'Hate', 'Love', 'Neutral', 'Sadness', 'Surprise', 'Worry']

plt.figure(figsize=(20, 8))

# Create Seaborn Heatmap for Display Confusion Matrix
plt.subplot(121)
sns.heatmap(conf_matrix,
            annot=True,
            fmt='g',
            cmap='Blues',
            linewidth=1,
            xticklabels=class_names,
            yticklabels=class_names)


# Setup Title and Axis Lables
plt.title('Emotion Confusion Matrix\n(Test Dataset)\n',
          fontweight='bold',
          fontsize='18',
          horizontalalignment='center')

plt.xlabel('\nPredicted Labels',
           fontweight='bold',
           fontsize='18',
           horizontalalignment='center')

plt.ylabel('True Labels\n',
           fontweight='bold',
           fontsize='18')


plt.subplot(122)
sns.histplot(data=df, x='emotion_en')

# Setup Title and Axis Lables
plt.title('Emotion Histogram\n',
          fontweight='bold',
          fontsize='18',
          horizontalalignment='center')

plt.xlabel('\nEmotions',
           fontweight='bold',
```

```
            fontsize='18',
            horizontalalignment='center')

plt.ylabel('Counts / Frequency',
            fontweight='bold',
            fontsize='18')


# Save & Show the Plot
plt.savefig('fig_confusion_matrix.png')
plt.show()
```

```
[[ 9  0  4  5  1  0  3]
 [ 0  0  0  0  0  0  5]
 [ 4  0  5  4  1  0  3]
 [ 5  0  0 23  0  0  8]
 [ 1  0  1  4  3  0 15]
 [ 3  0  1  1  0  0  4]
 [ 7  0  0  9  2  0 16]]
```





Display Validation & Testing Results

In [18]:
```
trainer.validate(model, dataloaders=val_dataloader)
trainer.test(model, test_dataloader)
```

```
LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES: [0]
SLURM auto-requeueing enabled. Setting signal handlers.
Validation: |          | 0/? [00:00<?, ?it/s]
```

Validate metric	DataLoader 0
val_acc	0.39726027846336365
val_loss	1.5434670448303223

```
LOCAL_RANK: 0 - CUDA_VISIBLE_DEVICES: [0]
SLURM auto-requeueing enabled. Setting signal handlers.
Testing: |          | 0/? [00:00<?, ?it/s]
```

Test metric	DataLoader 0
test_acc	0.380952388048172
test_loss	1.7607795000076294

Out[18]: [{'test_loss': 1.7607795000076294, 'test_acc': 0.380952388048172}]

Plot Training Parameters

In [19]:
```
results = pd.read_csv(csv_logger.log_dir + "/metrics.csv")
results
```

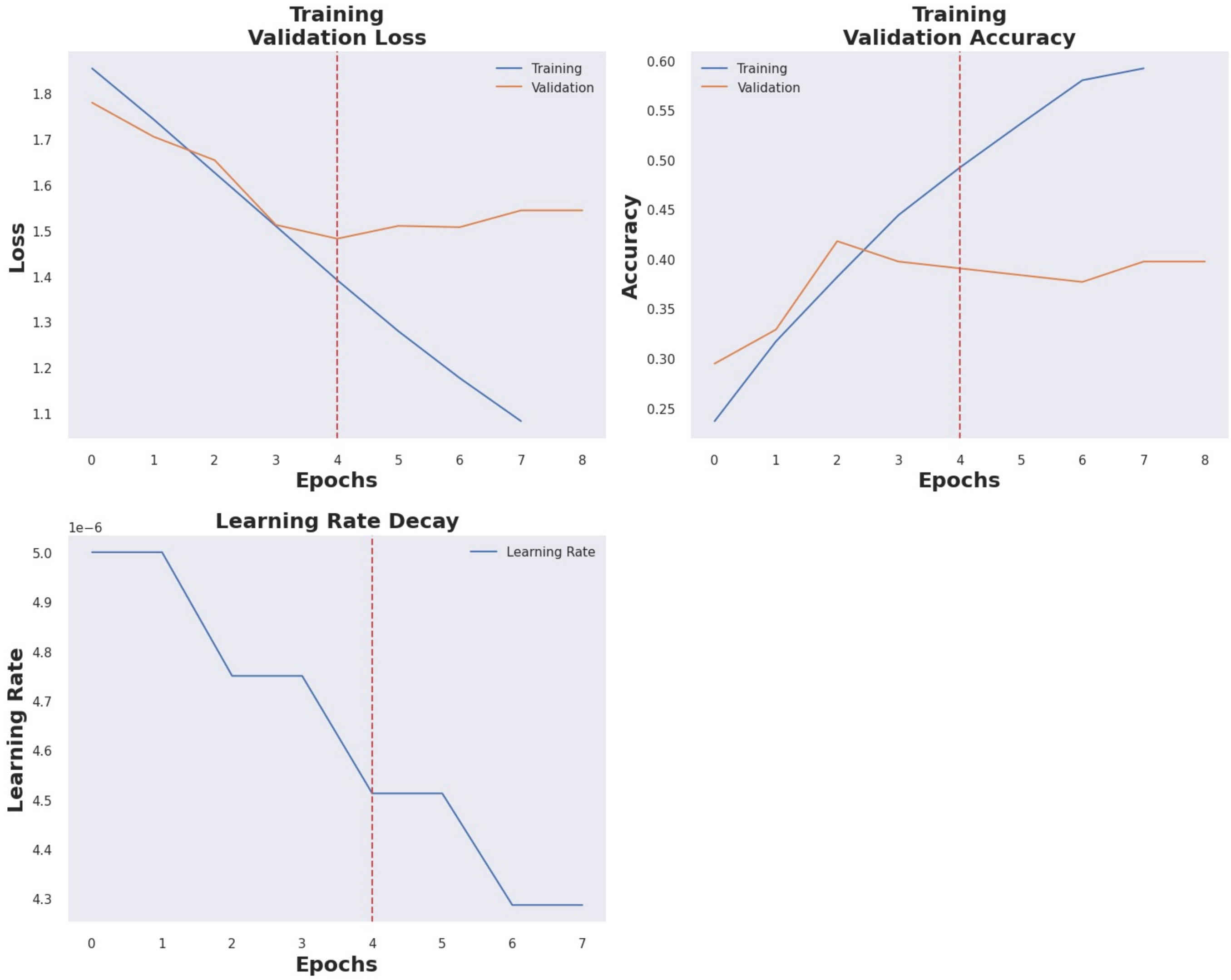
Out[19]:

	val_loss	step	epoch	val_acc	train_loss	lr	train_acc	test_loss	test_acc
0	1.778817	117	0	0.294521	NaN	NaN	NaN	NaN	NaN
1	NaN	117	0	NaN	1.853640	0.000005	0.236550	NaN	NaN
2	1.704656	235	1	0.328767	NaN	NaN	NaN	NaN	NaN
3	NaN	235	1	NaN	1.742712	0.000005	0.316823	NaN	NaN
4	1.653244	353	2	0.417808	NaN	NaN	NaN	NaN	NaN
5	NaN	353	2	NaN	1.625816	0.000005	0.381725	NaN	NaN
6	1.511819	471	3	0.397260	NaN	NaN	NaN	NaN	NaN
7	NaN	471	3	NaN	1.509168	0.000005	0.444065	NaN	NaN
8	1.481664	589	4	0.390411	NaN	NaN	NaN	NaN	NaN
9	NaN	589	4	NaN	1.391266	0.000005	0.491887	NaN	NaN
10	1.509674	707	5	0.383562	NaN	NaN	NaN	NaN	NaN
11	NaN	707	5	NaN	1.279503	0.000005	0.536294	NaN	NaN
12	1.506783	825	6	0.376712	NaN	NaN	NaN	NaN	NaN
13	NaN	825	6	NaN	1.177210	0.000004	0.579846	NaN	NaN
14	1.543467	943	7	0.397260	NaN	NaN	NaN	NaN	NaN
15	NaN	943	7	NaN	1.083147	0.000004	0.591802	NaN	NaN
16	1.543467	944	8	0.397260	NaN	NaN	NaN	NaN	NaN
17	NaN	944	8	NaN	NaN	NaN	NaN	1.76078	0.380952

In [20]:

```python
# Set Chart Sizing
plt.figure(figsize=(15, 12))

# Best EPOCH
BEST_EPOCH = 4

# Loss Plot
plt.subplot(221)
plt.plot(results["epoch"][np.logical_not(np.isnan(results["train_loss"]))],
         results["train_loss"][np.logical_not(np.isnan(results["train_loss"]))],
         label="Training")

plt.plot(results["epoch"][np.logical_not(np.isnan(results["val_loss"]))],
         results["val_loss"][np.logical_not(np.isnan(results["val_loss"]))],
         label="Validation")

plt.legend()
plt.title('Training\nValidation Loss',
          fontweight='bold',
          fontsize='18',
          horizontalalignment='center')

plt.xlabel('Epochs',
           fontweight='bold',
           fontsize='18',
           horizontalalignment='center')

plt.ylabel('Loss',
           fontweight='bold',
           fontsize='18')

# Show Epoch that was best!
plt.axvline(x=BEST_EPOCH, color='r', linestyle='--')

# Accuracy Plot
plt.subplot(222)
plt.plot(results["epoch"][np.logical_not(np.isnan(results["train_acc"]))],
         results["train_acc"][np.logical_not(np.isnan(results["train_acc"]))],
         label="Training")

plt.plot(results["epoch"][np.logical_not(np.isnan(results["val_acc"]))],
         results["val_acc"][np.logical_not(np.isnan(results["val_acc"]))],
         label="Validation")

plt.legend()
plt.title('Training\nValidation Accuracy',
          fontweight='bold',
          fontsize='18',
```

```
          horizontalalignment='center')

plt.xlabel('Epochs',
           fontweight='bold',
           fontsize='18',
           horizontalalignment='center')

plt.ylabel('Accuracy',
           fontweight='bold',
           fontsize='18')

# Show Epoch that was best!
plt.axvline(x=BEST_EPOCH, color='r', linestyle='--')


# LR Plot
plt.subplot(223)
plt.plot(results["epoch"][np.logical_not(np.isnan(results["lr"]))],
         results["lr"][np.logical_not(np.isnan(results["lr"]))],
         label="Learning Rate")

plt.legend()
plt.title('Learning Rate Decay',
          fontweight='bold',
          fontsize='18',
          horizontalalignment='center')

plt.xlabel('Epochs',
           fontweight='bold',
           fontsize='18',
           horizontalalignment='center')

plt.ylabel('Learning Rate',
           fontweight='bold',
           fontsize='18')

# Show Epoch that was best!
plt.axvline(x=BEST_EPOCH, color='r', linestyle='--')

plt.tight_layout(h_pad=1.5)

# Save & Show the Plot
plt.savefig('fig_training.png')
plt.show()
```


Training
Validation Loss
Loss
Epochs
Training
Validation
Training
Validation Accuracy
Accuracy
Epochs
Training
Validation
Learning Rate Decay
Learning Rate
Epochs
Learning Rate
1e−6

In [ ]: