Files

main

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Speech Emotion Recognition - S...

dataset

AmanAgrahari1314 Add files via upload 412f8f1 · 3 minutes ago History

Import Modules

In [30]:
```
import pandas as pd
import numpy as np
import os
import seaborn as sns
import matplotlib.pyplot as plt
import librosa
import librosa.display
from IPython.display import Audio
import warnings
warnings.filterwarnings('ignore')
```

Load the Dataset

In [31]:
```
paths = []
labels = []
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        paths.append(os.path.join(dirname, filename))
        label = filename.split('_')[-1]
        label = label.split('.')[0]
        labels.append(label.lower())
    if len(paths) == 2800:
        break
print('Dataset is Loaded')
```

```
Dataset is Loaded
```

In [32]:
```
len(paths)
```

Out[32]:
```
2800
```

In [33]:
```
paths[:5]
```

Out[33]:
```
['/kaggle/input/toronto-emotional-speech-set-tess/TESS Toronto emotional speech set data/YAF_fear/YAF_home_fear.wav',
 '/kaggle/input/toronto-emotional-speech-set-tess/TESS Toronto emotional speech set data/YAF_fear/YAF_youth_fear.wav',
 '/kaggle/input/toronto-emotional-speech-set-tess/TESS Toronto emotional speech set data/YAF_fear/YAF_near_fear.wav',
 '/kaggle/input/toronto-emotional-speech-set-tess/TESS Toronto emotional speech set data/YAF_fear/YAF_search_fear.wav',
 '/kaggle/input/toronto-emotional-speech-set-tess/TESS Toronto emotional speech set data/YAF_fear/YAF_pick_fear.wav']
```

In [34]:
```
labels[:5]
```

Out[34]:
```
['fear', 'fear', 'fear', 'fear', 'fear']
```

In [35]:
```
## Create a dataframe
df = pd.DataFrame()
df['speech'] = paths
df['label'] = labels
df.head()
```

Out[35]:

	speech	label
0	/kaggle/input/toronto-emotional-speech-set-tes...	fear
1	/kaggle/input/toronto-emotional-speech-set-tes...	fear
2	/kaggle/input/toronto-emotional-speech-set-tes...	fear
3	/kaggle/input/toronto-emotional-speech-set-tes...	fear
4	/kaggle/input/toronto-emotional-speech-set-tes...	fear

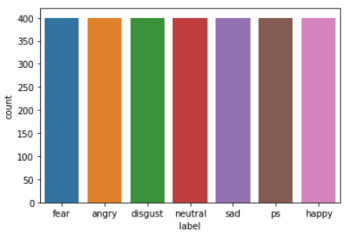
In [36]:
```
df['label'].value_counts()
```

Out[36]:
```
fear       400
angry      400
disgust    400
neutral    400
sad        400
ps         400
happy      400
Name: label, dtype: int64
```

Exploratory Data Analysis

In [37]:
```
sns.countplot(data=df, x='label')
```

Out[37]:
```
<AxesSubplot:xlabel='label', ylabel='count'>
```

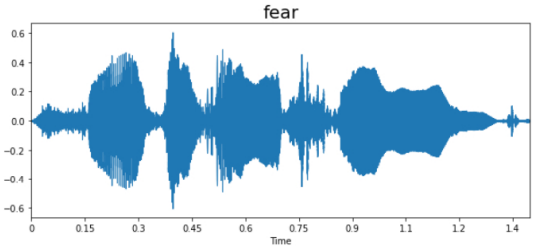


In [38]:
```
def waveplot(data, sr, emotion):
    plt.figure(figsize=(10,4))
    plt.title(emotion, size=20)
    librosa.display.waveshow(data, sr=sr)
    plt.show()

def spectogram(data, sr, emotion):
    x = librosa.stft(data)
```

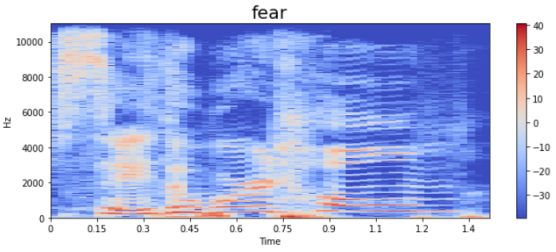
```
    xdb = librosa.amplitude_to_db(abs(x))
    plt.figure(figsize=(11,4))
    plt.title(emotion, size=20)
    librosa.display.specshow(xdb, sr=sr, x_axis='time', y_axis='hz')
    plt.colorbar()
```

In [39]:

```
emotion = 'fear'
path = np.array(df['speech'][df['label']==emotion])[0]
data, sampling_rate = librosa.load(path)
waveplot(data, sampling_rate, emotion)
spectogram(data, sampling_rate, emotion)
Audio(path)
```

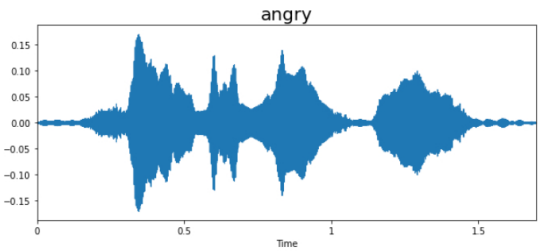


Out[39]:

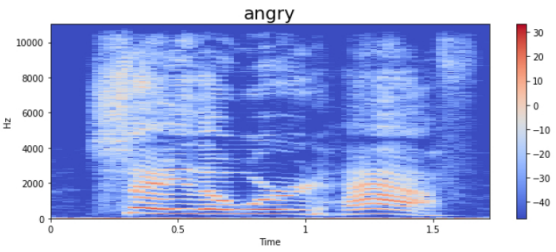


In [40]:

```
emotion = 'angry'
path = np.array(df['speech'][df['label']==emotion])[1]
data, sampling_rate = librosa.load(path)
waveplot(data, sampling_rate, emotion)
spectogram(data, sampling_rate, emotion)
Audio(path)
```

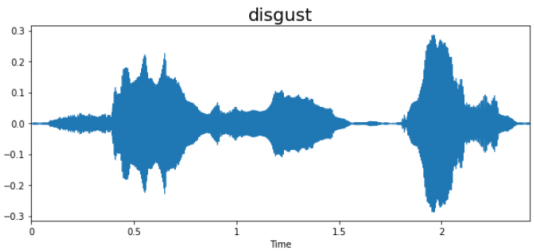


Out[40]:

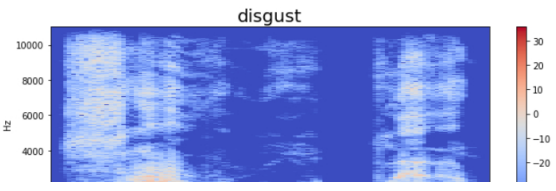


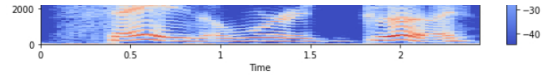
In [41]:

```
emotion = 'disgust'
path = np.array(df['speech'][df['label']==emotion])[0]
data, sampling_rate = librosa.load(path)
waveplot(data, sampling_rate, emotion)
spectogram(data, sampling_rate, emotion)
Audio(path)
```



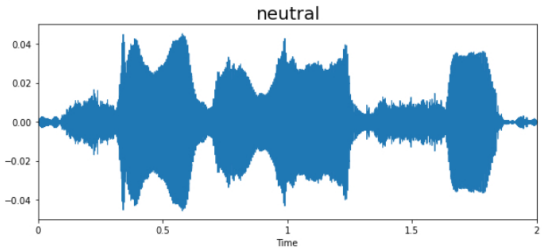
Out[41]:



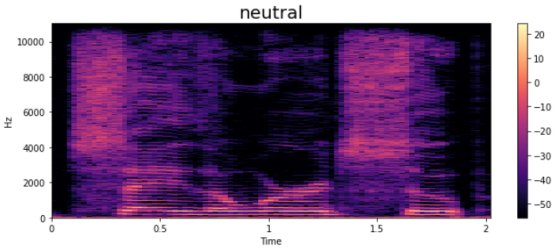


In [42]:

```
emotion = 'neutral'
path = np.array(df['speech'][df['label']==emotion])[0]
data, sampling_rate = librosa.load(path)
waveplot(data, sampling_rate, emotion)
spectogram(data, sampling_rate, emotion)
Audio(path)
```

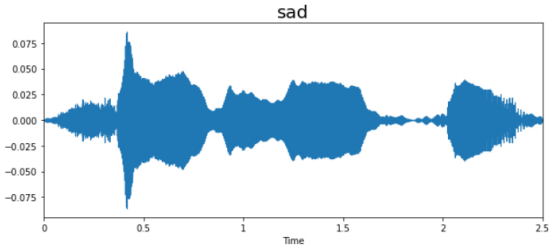


Out[42]:

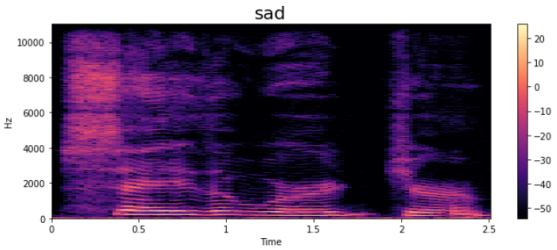


In [43]:

```
emotion = 'sad'
path = np.array(df['speech'][df['label']==emotion])[0]
data, sampling_rate = librosa.load(path)
waveplot(data, sampling_rate, emotion)
spectogram(data, sampling_rate, emotion)
Audio(path)
```

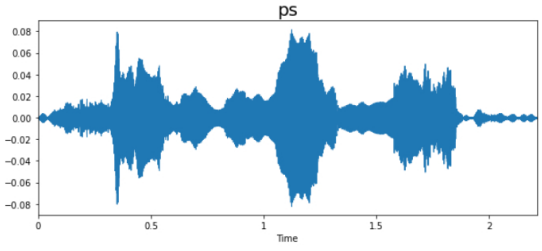


Out[43]:

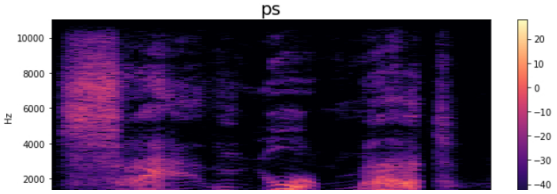


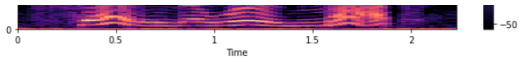
In [44]:

```
emotion = 'ps'
path = np.array(df['speech'][df['label']==emotion])[0]
data, sampling_rate = librosa.load(path)
waveplot(data, sampling_rate, emotion)
spectogram(data, sampling_rate, emotion)
Audio(path)
```

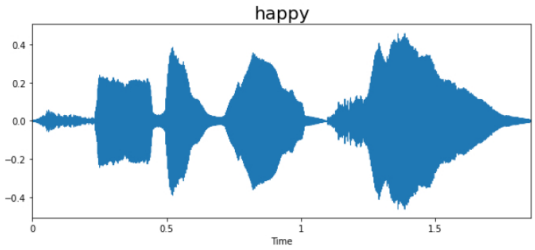


Out[44]:

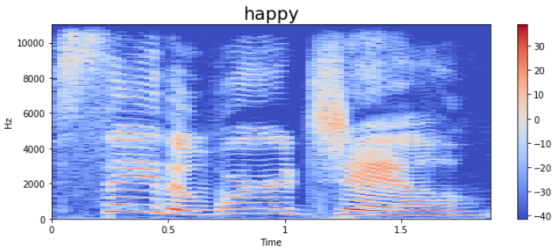




In [45]:
```
emotion = 'happy'
path = np.array(df['speech'][df['label']==emotion])[0]
data, sampling_rate = librosa.load(path)
waveplot(data, sampling_rate, emotion)
spectogram(data, sampling_rate, emotion)
Audio(path)
```



Out[45]:



Feature Extraction

In [46]:
```
def extract_mfcc(filename):
    y, sr = librosa.load(filename, duration=3, offset=0.5)
    mfcc = np.mean(librosa.feature.mfcc(y=y, sr=sr, n_mfcc=40).T, axis=0)
    return mfcc
```

In [47]:
```
extract_mfcc(df['speech'][0])
```

Out[47]:
```
array([-285.2542    ,   86.24267   ,   -2.7735834 ,   22.61731   ,
       -15.214631   ,   11.602871  ,   11.931779  ,   -2.5318177 ,
         0.65986294,   11.62756    ,  -17.814924  ,   -7.5654893 ,
         6.2167835  ,   -3.7255652 ,   -9.563306  ,    3.899267  ,
       -13.657834   ,   14.420068  ,   19.243341  ,   23.024492  ,
        32.129776   ,   16.585697  ,   -4.137755  ,    1.2746525 ,
       -11.517016   ,    7.0145273 ,   -2.8494127 ,   -7.415011  ,
       -11.150621   ,   -2.1190548 ,   -5.4515266 ,    4.473824  ,
       -11.377713   ,   -8.931878  ,   -3.8482094 ,    4.950994  ,
        -1.7254968  ,    2.659218  ,   11.390564  ,   11.3327265 ],
      dtype=float32)
```

In [48]:
```
X_mfcc = df['speech'].apply(lambda x: extract_mfcc(x))
```

In [49]:
```
X_mfcc
```

Out[49]:
```
0       [-285.2542, 86.24267, -2.7735834, 22.61731, -1...
1       [-348.23337, 35.60242, -4.365128, 15.534869, 6...
2       [-339.50308, 54.41241, -14.795754, 21.566118, ...
3       [-306.92944, 21.973307, -5.1588626, 7.6269317,...
4       [-344.88586, 47.05694, -24.83122, 20.24406, 1....
                              ...
2795    [-374.1317, 61.859463, -0.41998756, 9.31088, -...
2796    [-314.12222, 40.262157, -6.7909045, -3.2963052...
2797    [-357.65854, 78.49201, -15.684815, 3.644915, -...
2798    [-352.78336, 102.219765, -14.560364, -11.48181...
2799    [-389.80002, 54.120773, 0.8988281, -0.6595729,...
Name: speech, Length: 2800, dtype: object
```

In [50]:
```
X = [x for x in X_mfcc]
X = np.array(X)
X.shape
```

Out[50]:
```
(2800, 40)
```

In [51]:
```
## input split
X = np.expand_dims(X, -1)
X.shape
```

Out[51]:
```
(2800, 40, 1)
```

In [52]:
```
from sklearn.preprocessing import OneHotEncoder
enc = OneHotEncoder()
y = enc.fit_transform(df[['label']])
```

In [53]:
```
y = y.toarray()
```

In [54]:
```
y.shape
```

Out[54]:
```
(2800, 7)
```

Create the LSTM Model

In [101…
```
from keras.models import Sequential
from keras.layers import Dense, LSTM, Dropout

model = Sequential([
    LSTM(256, return_sequences=False, input_shape=(40,1)),
    Dropout(0.2),
    Dense(128, activation='relu'),
    Dropout(0.2),
    Dense(64, activation='relu'),
    Dropout(0.2),
```

```
    Dense(7, activation='softmax')
])

model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
model.summary()
```

```
Model: "sequential_24"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_30 (LSTM)               (None, 256)               264192
_________________________________________________________________
dropout_62 (Dropout)         (None, 256)               0
_________________________________________________________________
dense_72 (Dense)             (None, 128)               32896
_________________________________________________________________
dropout_63 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_73 (Dense)             (None, 64)                8256
_________________________________________________________________
dropout_64 (Dropout)         (None, 64)                0
_________________________________________________________________
dense_74 (Dense)             (None, 7)                 455
=================================================================
Total params: 305,799
Trainable params: 305,799
Non-trainable params: 0
_________________________________________________________________
```

In [102…

```
# Train the model
history = model.fit(X, y, validation_split=0.2, epochs=50, batch_size=64)
```

```
Epoch 1/50
35/35 [==============================] - 2s 18ms/step - loss: 1.0892 - accuracy: 0.6201 - val_loss: 2.0684 - val_accuracy: 0.
2946
Epoch 2/50
35/35 [==============================] - 0s 7ms/step - loss: 0.3742 - accuracy: 0.8598 - val_loss: 2.4078 - val_accuracy: 0.2
054
Epoch 3/50
35/35 [==============================] - 0s 8ms/step - loss: 0.1671 - accuracy: 0.9487 - val_loss: 1.9055 - val_accuracy: 0.4
446
Epoch 4/50
35/35 [==============================] - 0s 8ms/step - loss: 0.1672 - accuracy: 0.9442 - val_loss: 2.7364 - val_accuracy: 0.3
179
Epoch 5/50
35/35 [==============================] - 0s 7ms/step - loss: 0.1107 - accuracy: 0.9683 - val_loss: 1.8414 - val_accuracy: 0.5
607
Epoch 6/50
35/35 [==============================] - 0s 8ms/step - loss: 0.1082 - accuracy: 0.9585 - val_loss: 2.7303 - val_accuracy: 0.4
679
Epoch 7/50
35/35 [==============================] - 0s 9ms/step - loss: 0.1275 - accuracy: 0.9656 - val_loss: 1.2245 - val_accuracy: 0.7
232
Epoch 8/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0765 - accuracy: 0.9786 - val_loss: 2.9995 - val_accuracy: 0.3
893
Epoch 9/50
35/35 [==============================] - 0s 8ms/step - loss: 0.0577 - accuracy: 0.9795 - val_loss: 3.5068 - val_accuracy: 0.3
679
Epoch 10/50
35/35 [==============================] - 0s 8ms/step - loss: 0.0531 - accuracy: 0.9826 - val_loss: 2.3169 - val_accuracy: 0.4
786
Epoch 11/50
35/35 [==============================] - 0s 8ms/step - loss: 0.0357 - accuracy: 0.9888 - val_loss: 3.8930 - val_accuracy: 0.4
321
Epoch 12/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0554 - accuracy: 0.9835 - val_loss: 1.5915 - val_accuracy: 0.6
607
Epoch 13/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0684 - accuracy: 0.9790 - val_loss: 3.4805 - val_accuracy: 0.4
589
Epoch 14/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0453 - accuracy: 0.9835 - val_loss: 2.4777 - val_accuracy: 0.4
661
Epoch 15/50
35/35 [==============================] - 0s 8ms/step - loss: 0.0874 - accuracy: 0.9737 - val_loss: 4.4744 - val_accuracy: 0.2
446
Epoch 16/50
35/35 [==============================] - 0s 8ms/step - loss: 0.0530 - accuracy: 0.9853 - val_loss: 2.9993 - val_accuracy: 0.5
232
Epoch 17/50
35/35 [==============================] - 0s 6ms/step - loss: 0.0421 - accuracy: 0.9839 - val_loss: 4.3298 - val_accuracy: 0.4
714
Epoch 18/50
35/35 [==============================] - 0s 8ms/step - loss: 0.0514 - accuracy: 0.9857 - val_loss: 2.2161 - val_accuracy: 0.5
946
Epoch 19/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0310 - accuracy: 0.9897 - val_loss: 3.7546 - val_accuracy: 0.4
071
Epoch 20/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0301 - accuracy: 0.9897 - val_loss: 2.7526 - val_accuracy: 0.5
036
Epoch 21/50
35/35 [==============================] - 0s 8ms/step - loss: 0.0342 - accuracy: 0.9875 - val_loss: 4.7068 - val_accuracy: 0.2
839
Epoch 22/50
35/35 [==============================] - 0s 8ms/step - loss: 0.0295 - accuracy: 0.9893 - val_loss: 3.4425 - val_accuracy: 0.4
054
Epoch 23/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0213 - accuracy: 0.9933 - val_loss: 2.8260 - val_accuracy: 0.5
607
Epoch 24/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0255 - accuracy: 0.9933 - val_loss: 4.4797 - val_accuracy: 0.4
696
Epoch 25/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0236 - accuracy: 0.9915 - val_loss: 4.2527 - val_accuracy: 0.4
143
Epoch 26/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0223 - accuracy: 0.9920 - val_loss: 3.5158 - val_accuracy: 0.4
429
Epoch 27/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0245 - accuracy: 0.9929 - val_loss: 3.9560 - val_accuracy: 0.4
661
Epoch 28/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0238 - accuracy: 0.9902 - val_loss: 4.4557 - val_accuracy: 0.3
893
Epoch 29/50
35/35 [==============================] - 0s 8ms/step - loss: 0.0702 - accuracy: 0.9772 - val_loss: 3.5628 - val_accuracy: 0.3
839
Epoch 30/50
35/35 [==============================] - 0s 8ms/step - loss: 0.0165 - accuracy: 0.9951 - val_loss: 3.8458 - val_accuracy: 0.4
089
Epoch 31/50
35/35 [==============================] - 0s 8ms/step - loss: 0.0080 - accuracy: 0.9978 - val_loss: 3.8509 - val_accuracy: 0.4
339
Epoch 32/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0091 - accuracy: 0.9964 - val_loss: 3.8585 - val_accuracy: 0.4
786
Epoch 33/50
35/35 [==============================] - 0s 6ms/step - loss: 0.0146 - accuracy: 0.9960 - val_loss: 4.4246 - val_accuracy: 0.3
554
Epoch 34/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0075 - accuracy: 0.9969 - val_loss: 4.4920 - val_accuracy: 0.3
911
Epoch 35/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0072 - accuracy: 0.9982 - val_loss: 3.6941 - val_accuracy: 0.4
232
```

```
Epoch 36/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0244 - accuracy: 0.9933 - val_loss: 2.6108 - val_accuracy: 0.5
000
Epoch 37/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0115 - accuracy: 0.9969 - val_loss: 3.3635 - val_accuracy: 0.5
750
Epoch 38/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0519 - accuracy: 0.9853 - val_loss: 5.5903 - val_accuracy: 0.2
554
Epoch 39/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0369 - accuracy: 0.9906 - val_loss: 3.8724 - val_accuracy: 0.4
018
Epoch 40/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0122 - accuracy: 0.9964 - val_loss: 4.3779 - val_accuracy: 0.4
250
Epoch 41/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0124 - accuracy: 0.9973 - val_loss: 3.4232 - val_accuracy: 0.4
893
Epoch 42/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0095 - accuracy: 0.9969 - val_loss: 4.3362 - val_accuracy: 0.3
804
Epoch 43/50
35/35 [==============================] - 0s 8ms/step - loss: 0.0089 - accuracy: 0.9978 - val_loss: 3.9718 - val_accuracy: 0.4
911
Epoch 44/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0058 - accuracy: 0.9987 - val_loss: 3.5679 - val_accuracy: 0.5
018
Epoch 45/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0074 - accuracy: 0.9982 - val_loss: 4.0037 - val_accuracy: 0.4
607
Epoch 46/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0030 - accuracy: 0.9991 - val_loss: 4.6531 - val_accuracy: 0.3
982
Epoch 47/50
35/35 [==============================] - 0s 8ms/step - loss: 0.0076 - accuracy: 0.9982 - val_loss: 5.2379 - val_accuracy: 0.3
571
Epoch 48/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0082 - accuracy: 0.9973 - val_loss: 4.3685 - val_accuracy: 0.4
357
Epoch 49/50
35/35 [==============================] - 0s 7ms/step - loss: 0.0155 - accuracy: 0.9964 - val_loss: 4.8508 - val_accuracy: 0.3
804
Epoch 50/50
35/35 [==============================] - 0s 6ms/step - loss: 0.0079 - accuracy: 0.9982 - val_loss: 5.0355 - val_accuracy: 0.3
750
```

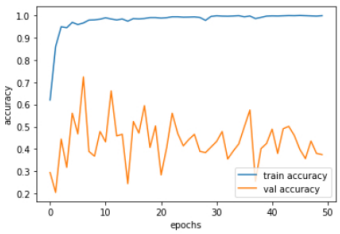
In [ ]:

```
# best val accuracy: 72.32
# use checkpoint to save the best val accuracy model
# adjust learning rate for slow convergence
```

Plot the results

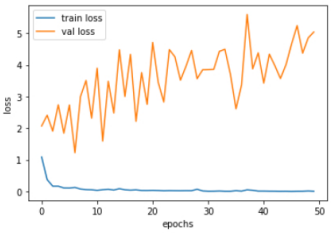
In [103…

```
epochs = list(range(50))
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

plt.plot(epochs, acc, label='train accuracy')
plt.plot(epochs, val_acc, label='val accuracy')
plt.xlabel('epochs')
plt.ylabel('accuracy')
plt.legend()
plt.show()
```



In [104…

```
loss = history.history['loss']
val_loss = history.history['val_loss']

plt.plot(epochs, loss, label='train loss')
plt.plot(epochs, val_loss, label='val loss')
plt.xlabel('epochs')
plt.ylabel('loss')
plt.legend()
plt.show()
```



In [ ]:

In [ ]: