Deep learning for Cla
crying with hands-or

Rabeya Tus Sadia · Follow

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Crying is the primary means of communication between the baby and the outside world. When a baby is crying, it is difficult for a novice parent to understand the

baby's needs immediately. If parents can accurately determine the cause of the baby's cry, they can understand the baby's emotional and physiological changes and needs.

In this article, I will discuss how deep learning can be utilized to categorize better and label audio. I'll use my attempt at labeling a baby's cries as an illustration of this problem. In addition to being an entertaining experiment in CNN-based audio classification, this could be useful in the development of a monitor to alert parents that their baby is crying. Here is the notebook for this coding implementation of the baby cry classification.

Building dataset

Obtaining a useful dataset was the first step in the classifier construction process. I was unable to locate a readily accessible dataset to create a model. So I decided to build one from data I collected from the internet. I used the Donate-A-Cry corpus for samples of sounds of babies crying. The dataset has about ~1000 sound clips of 7 secs in length. The dataset has five classes. They are 'hungry,' 'burping,' 'discomfort,' 'belly_pain,' and 'tired.'

Building a model

The audio clips have a sample rate of 16000 Hz and a duration of about ~7 secs. This means there are about 16000*7 numbers per second representing the audio data. We take a fast fourier transform (FFT) of a 2048 sample window, slide it by 512 samples and repeat the process of the 7-sec clip. The resulting representation can be shown as a 2D image and is called a Short-Time Fourier Transform (STFT). Since humans perceive sound on a logarithmic scale, we'll convert the STFT to the mel scale. The librosa library lets us load an audio file and convert it to a melspectrogram.

Coding Implementation

Import necessary libraries for the implementation.

```
import matplotlib.pyplot as plt
from scipy import signal
from scipy.io import wavfile as wav
import numpy as np
from numpy.lib import stride_tricks
import torch
import torchvision
import cv2
import librosa
import librosa.display
import numpy as np
from sklearn.model_selection import train_test_split
import pandas as pd
import os
import pandas as pd
import matplotlib.pyplot as plt
from torch.utils.data import Dataset, DataLoader
from sklearn.model_selection import train_test_split
import cv2
from torchvision import transforms
import numpy as np
```

Import libraries

Utility functions to convert from audio to image.

Utility functions for Audio-to-image

```
# Reading the audio file and applying some transformations (trimming, padding...)

def read_audio(conf, pathname, trim_long_data):
    y, sr = librosa.load(pathname, sr=conf.sampling_rate)
    # trim silence
    if 0 < len(y): # workaround: 0 length causes error
        y, _ = librosa.effects.trim(y) # trim, top_db=default(60)
    # make it unified length to conf.samples
    if len(y) > conf.samples: # long enough
        if trim_long_data:
            y = y[0:0+conf.samples]
    else: # pad blank
        padding = conf.samples - len(y)    # add padding at both ends
        offset = padding // 2
        y = np.pad(y, (offset, conf.samples - len(y) - offset), 'constant')
```

Convert audio to image

Utilizing librosa library, generating the mel-spectogram from the audio file.

```
def audio_to_melspectrogram(conf, audio):
    spectrogram = librosa.feature.melspectrogram(audio,
                                                 sr=conf.sampling_rate,
                                                 n_mels=conf.n_mels,
                                                 hop_length=conf.hop_length,
                                                 n_fft=conf.n_fft,
                                                 fmin=conf.fmin,
                                                 fmax=conf.fmax)
    spectrogram = librosa.power_to_db(spectrogram)
    spectrogram = spectrogram.astype(np.float32)
    return spectrogram
```

A set of settings that you can adapt to fit your audio files (frequency, average duration, number of Fourier transforms)

```
class conf:
    # Preprocessing settings
    sampling_rate = 16000
    duration = 7
    hop_length = 100*duration
    fmin = 20
    fmax = sampling_rate // 2
    n_mels = 128
    n_fft = n_mels * 20
    samples = sampling_rate * duration
```

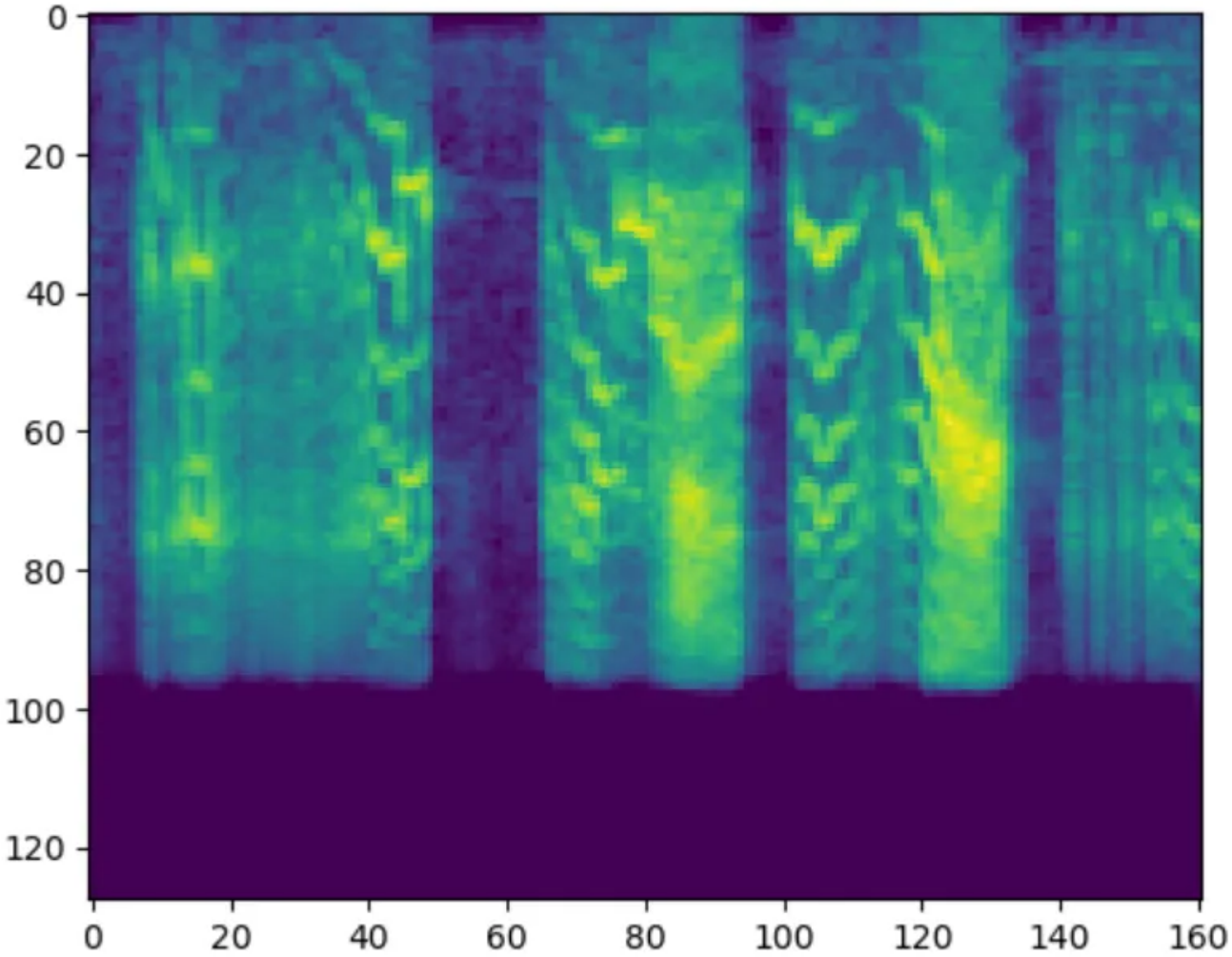
To generate the image dataset, we first need to remove the .wav extension and add the .jpg.

```
def rename_file(img_name):
    img_name = img_name.split("/")[-1]
    img_name = img_name[:-4]
    img_name += ".jpg"
    return img_name
```

Set the converted image to categorized folder.

```
to_folders=['hungry', 'burping', 'discomfort', 'belly_pain', 'tired']
for to_folder in to_folders:
    try:
        os.makedirs('/kaggle/working/'+to_folder)
    except:
        continue
    for i, fn in enumerate(os.listdir('/kaggle/input/donate-cry-updated-dataset/d
        path = '/kaggle/input/donate-cry-updated-dataset/donateacry-corpus-master
        save_image_from_sound(path,to_folder)
```

The melspectrogram of a baby crying looks like the image below:



The dataset is divided into train and test(75:25) into their respective folders.

Train_test_split

```
# Take the source folder
source = r'/kaggle/input/donateacrycorpusfeaturesdataset/donateacrycorpus_features

X_train,X_test,Y_train,Y_test=train_test_split(all_img,all_img_label,train_size=0.
X_train = np.array(X_train)
X_test = np.array(X_test)
Y_train= np.array(Y_train)
Y_test= np.array(Y_test)
print(X_train.shape,Y_train.shape)
print(X_test.shape,Y_test.shape)
print(Y_train[0])
```

```
(342,) (342,)
(115,) (115,)
3
```

Training Model

```
model = models.resnet50(pretrained=True)
num_ftrs = model.fc.in_features
model.fc = torch.nn.Linear(num_ftrs,5)
device=torch.device('cuda' if torch.cuda.is_available() else 'cpu')
model=model.to(device)
```

```
Downloading: "https://download.pytorch.org/models/resnet50-0676ba61.pth" to /root/.cach
checkpoints/resnet50-0676ba61.pth
100% 97.8M/97.8M [00:00<00:00, 106MB/s]
```

Training accuracy:

```
epoch: 0 Accuracy = 81.28655242919922
epoch:  0  loss:  12.92688517398201
epoch: 1 Accuracy = 84.21052551269531
epoch:  1  loss:  8.40015251338482
epoch: 2 Accuracy = 84.50292205810547
epoch:  2  loss:  7.265490334481001
epoch: 3 Accuracy = 85.67251586914062
epoch:  3  loss:  6.4702746033668515
epoch: 4 Accuracy = 89.18128967285156
epoch:  4  loss:  5.418753217160702
epoch: 5 Accuracy = 91.52046966552734
epoch:  5  loss:  3.588867117650807
epoch: 6 Accuracy = 93.85964965820312
epoch:  6  loss:  3.1710626550018786
epoch: 7 Accuracy = 95.6140365600586
epoch:  7  loss:  2.2358758419752123
epoch: 8 Accuracy = 97.36842346191406
epoch:  8  loss:  1.6652651662006974
epoch: 9 Accuracy = 98.83040618896484
epoch:  9  loss:  0.9571665681432933
Finished Training
```

Testing accuracy

```
    correct=0.0
    for i,(inputs,labels) in enumerate(dataloader['test']):
        inputs=inputs.to(device)
        labels=labels.to(device)

        # zero the parameter gradients
        outputs = model(inputs)

        _, predicted = torch.max(outputs.data, 1)
        correct += (predicted == labels).float().sum()
#         print(correct)

    accuracy = 100 * correct / len(test_set)

    print("epoch:",epoch,"Accuracy = {}".format(accuracy))
        # print statistics
        ## e.g:dataset=500, batch_size=10, #batch=50
#         print("Loss: ", loss.item())
    print('Finished Test')
```

```
epoch: 0 Accuracy = 80.0
```

Finally, the accuracy of the baby crying classification is 80%. After a lot of tuning and modification, this accuracy could be increased.

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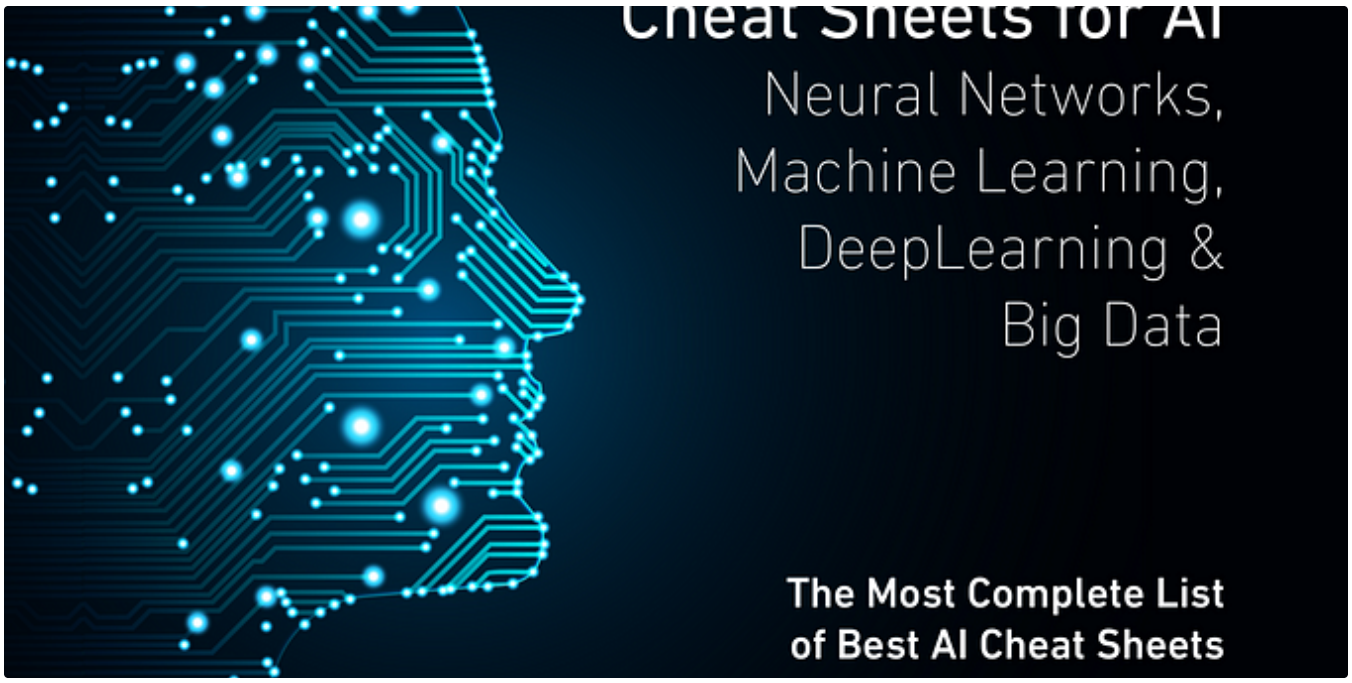

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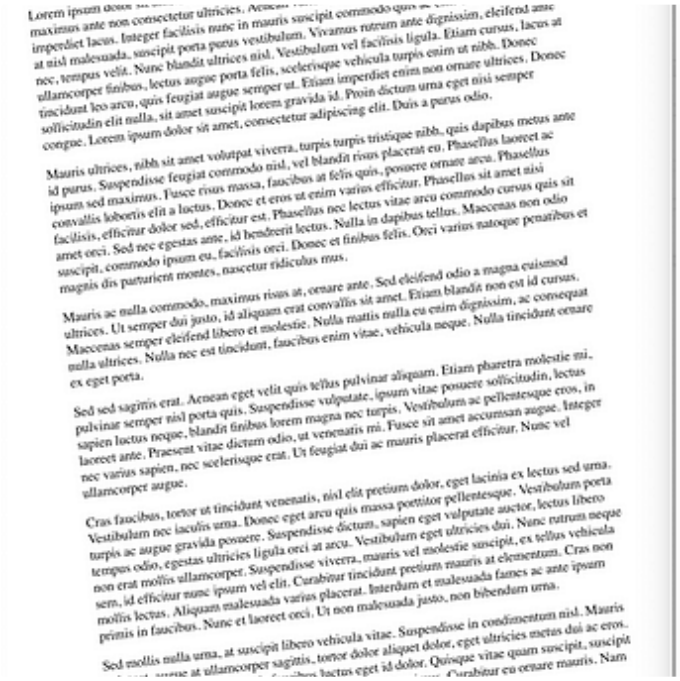

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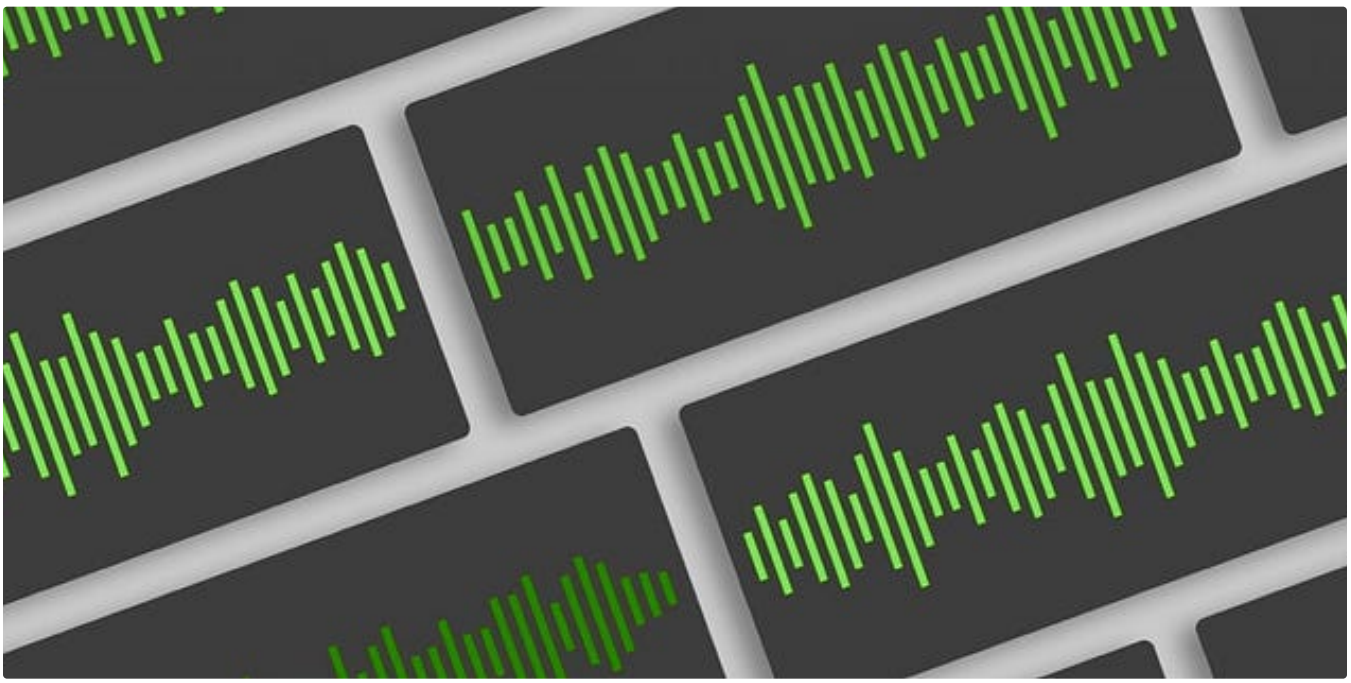

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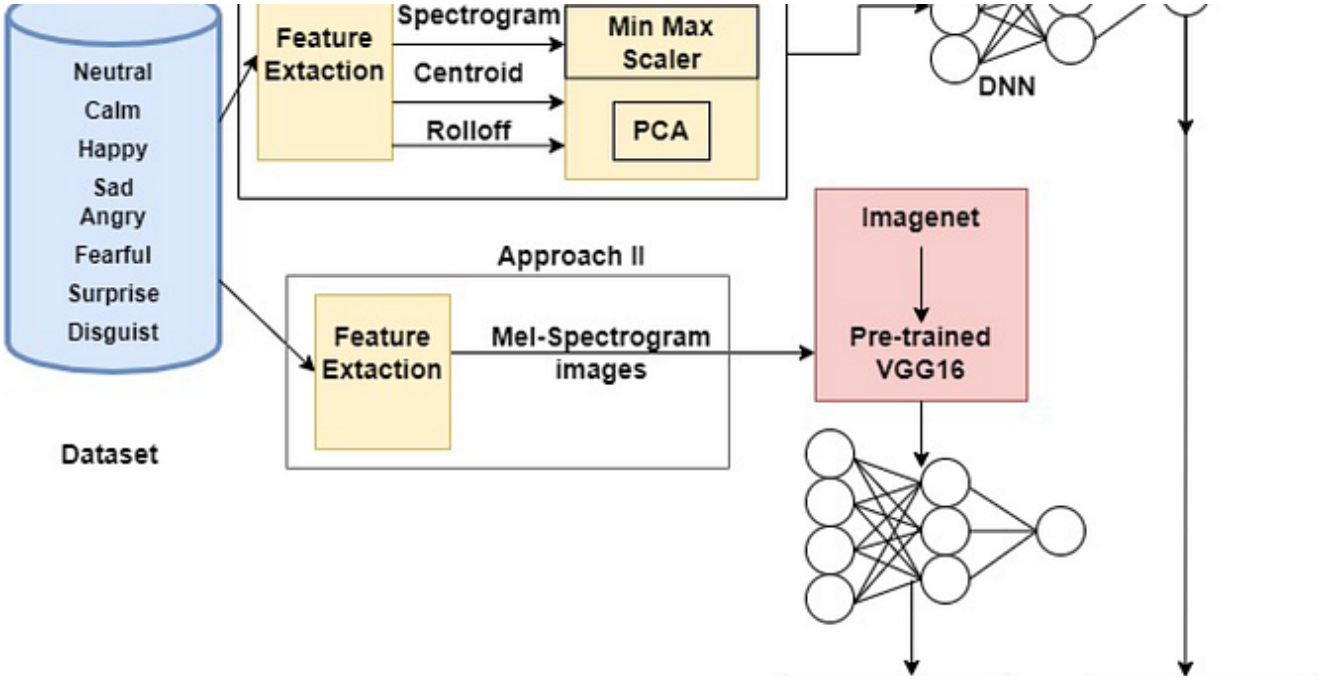

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