Classifying noise sounds

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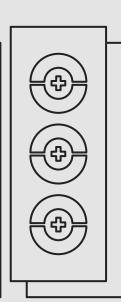
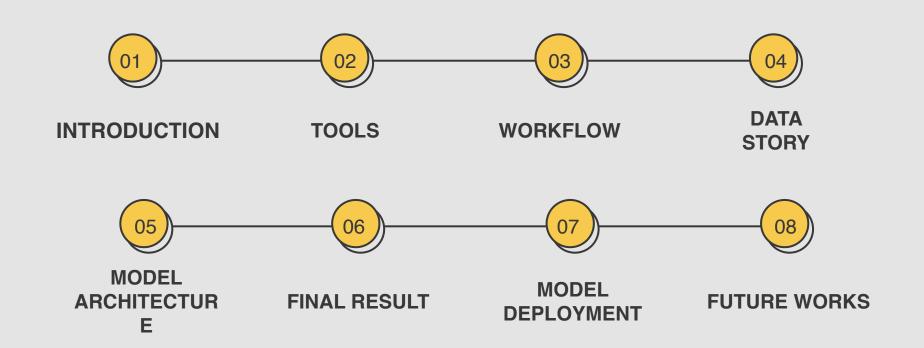


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Introduction

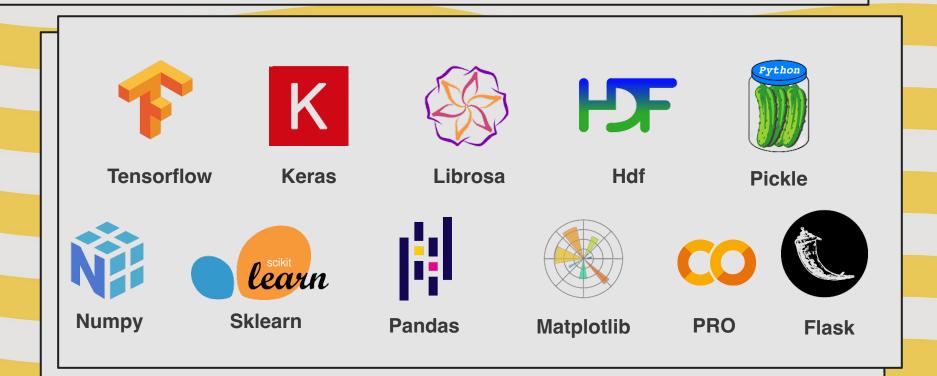
Sounds are all around us. Whether directly or indirectly. Sounds outline the context of our daily activities, conversations, music, noise. The human brain is continuously processing and understanding this audio data, so how the machine can understand it?

Goal:

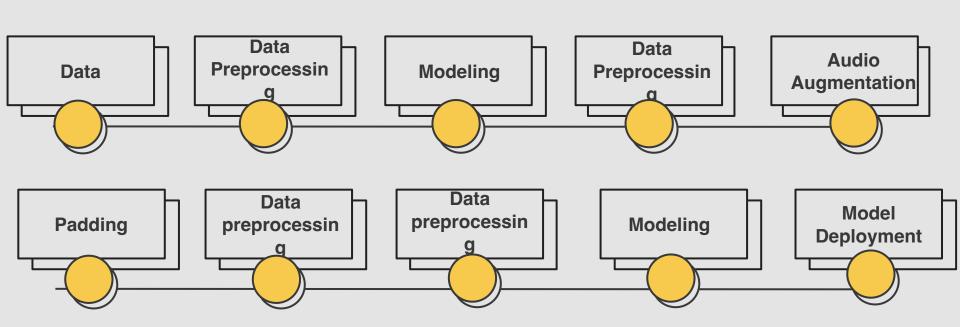
Apply Deep Learning techniques to the classification of environmental sounds:

- Assisting deaf individuals in their daily activities
- Safety and security capabilities
- Smart home use

Tools



workflow



Data Story

Urban sounds classification

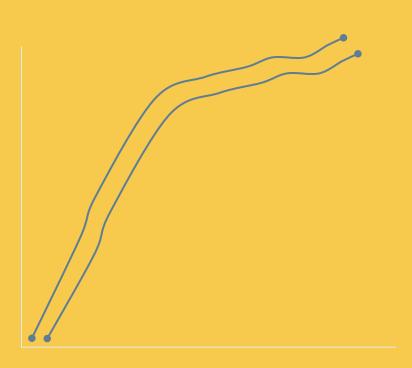


From kaggel

Row = 8733

Class label [10]=

- Air Conditioner
- Car Horn
- Children Playing
- Dog bark
- Drilling
- Engine Idling
- Gun Shot
- Jackhammer
- Siren
- Street Music



Data Story

Urban sounds classification





Row = 8733 Class label [10]=

- Air Conditioner
- Car Horn
- Children Playing
- Dog bark
- Drilling
- Engine Idling
- Gun Shot
- Jackhammer
- Siren
- Street Music

Noise sounds classification



From kaggel

Row =2171
Class label [11]=

- Applause
- Keys_jangling
- Telephone
- Cough
- Microwave oven
- Laughter
- Tearing
- Fireworks
- Bus
- Scissors
- Computer_keyboard'

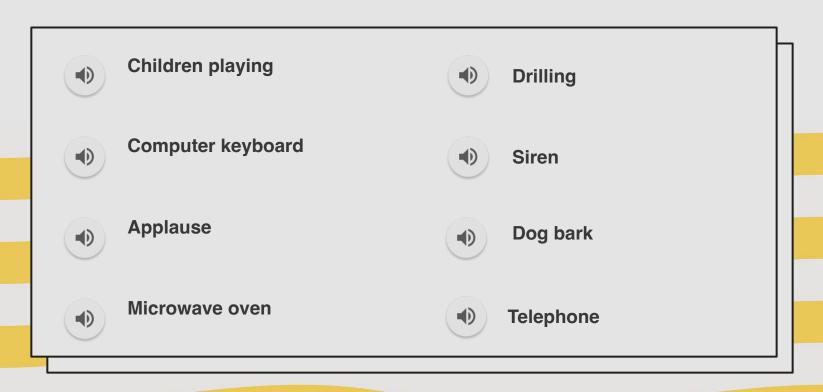
Before = (8733, 10)

After = (10904, 21)

One dataset not enough COMPLEXITY NEEDED!

Data Story

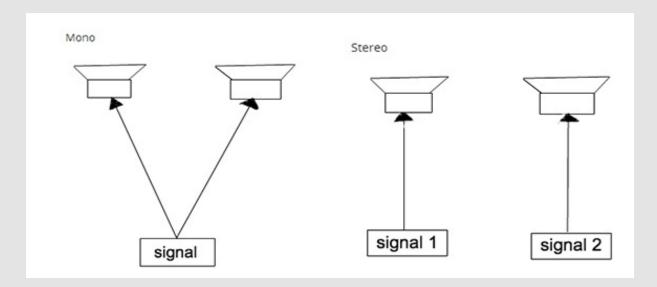
Audio Samples



We heard the audio samples, Do we know now its Properties ?

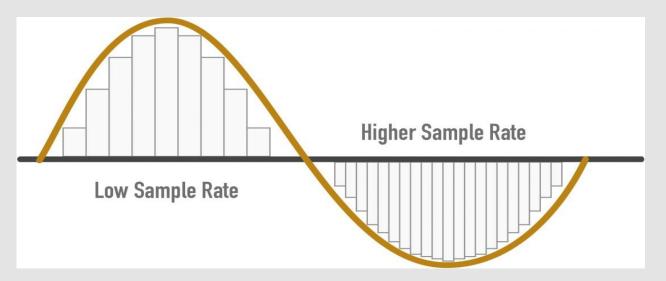
Audio Properties:

Audio Channels



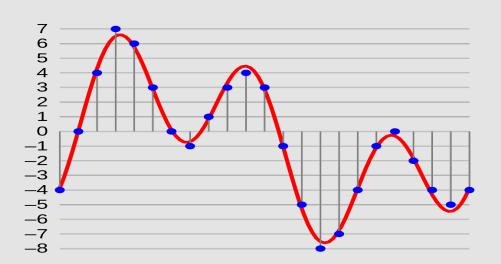
Audio Properties:

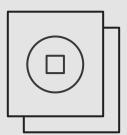
• Sample Rate



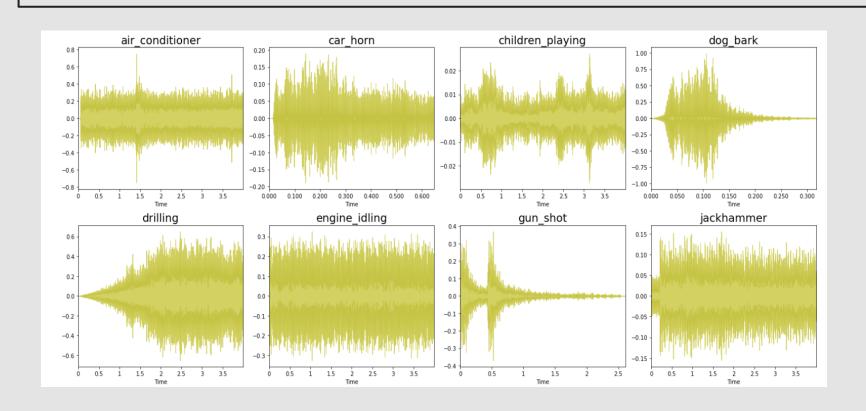
Audio Properties:

• Bit-Depth

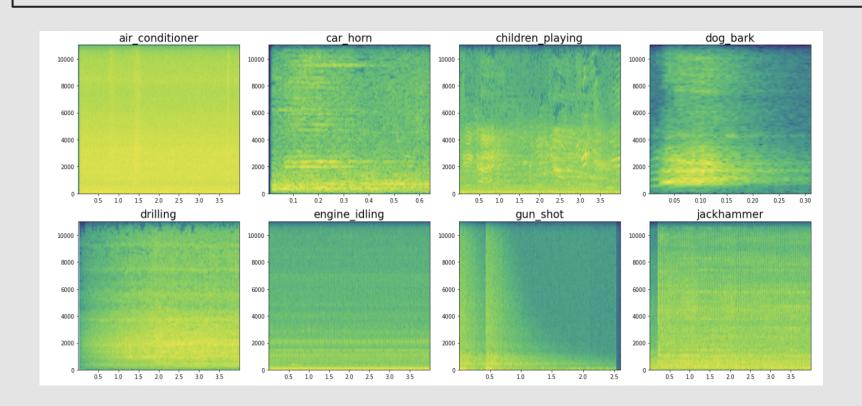




Waveplot



Specgram Plot



but!!



Can we use the spectrum images as input for our model? or something else?

Feature Extraction Method: Mfcc

The MFCC summarises the frequency distribution across the window size, to analyse both the frequency and time characteristics of the sound. These audio representations will allow us to identify features for classification.



```
array([-0.46156558, -0.60931027, -0.7269877 , -0.65179384, -0.45346004
                                -0.35503793, -0.309869 , -0.29231593, -0.3408025 , -0.56441855, -0.668554 , -0.77650434, -0.9077673 .
                                -0.56441855, -0.668554
                                -0.7808625 ,
                                                                                        -0.7378508
                                                                                                                                                   -0.73105305, -0.7016147,
-0.6216891, -0.604039,
                                -0.7165885 , -0.6830154 ,
                                -0.5490541 , -0.5028578 ,
                                                                                                                                                     -0.46407667, -0.4999416 ,
                                -0.8549022
                                                                                                                                                     -0.8369524 , -0.82082754,
                            0.57581935, 0.4758957, 0.64921174, 0.4195482, 0.3389665, 0.47589534, 0.27117366, 0.32846212, 0.31837335, 0.23812626, 0.21767968, 0.2286883, 0.22767977, 0.2672934, 0.38836963, 0.439564936, 0.38856698, 0.44798654, 0.558652, 0.65559697,
                              -0.7478937 -0.7436201 -0.2349931 -0.3383838 -0.34439857 -0.34639867 -0.34639867 -0.34639867 -0.3263864 -0.24638662 -0.254141203 -0.29958154 -0.2663866 -0.25420395 -0.24161993 -0.2581274 -0.2693963 -0.27291867 -0.24633032 -0.21719564 -0.252357889 -0.22331096 -0.22339852
                            -0.39299247, -0.39608532,
                                                                                                                                                     -0.41692922, -0.4035706 ,
                          -0.38559769, -0.36649402; -0.4120001; -0.40582865; -0.38918848; -0.4041523; -0.38918848; -0.4401523; -0.38918848; -0.4401523; -0.44027869; -0.53813744; -0.6076536; -0.6059352; -0.53916515; -0.5426781; -0.53813744; -0.6076536; -0.6059352; -0.53916515; -0.5426781; -0.5426781; -0.542678; -0.5426781; -0.542678; -0.5426781; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678; -0.542678
                               -0.33859769, -0.36949402,
                                                                                                                                                     -0.4120001 , -0.40582865,
```

All we think data now is PERFECT!

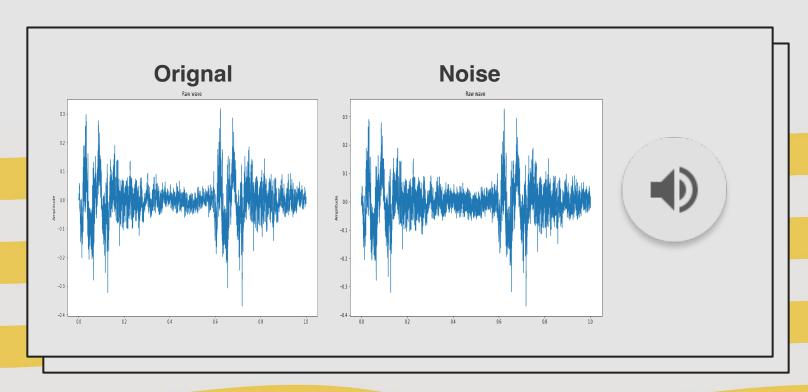
Classes Imbalanced

Solving Classes Imbalanced

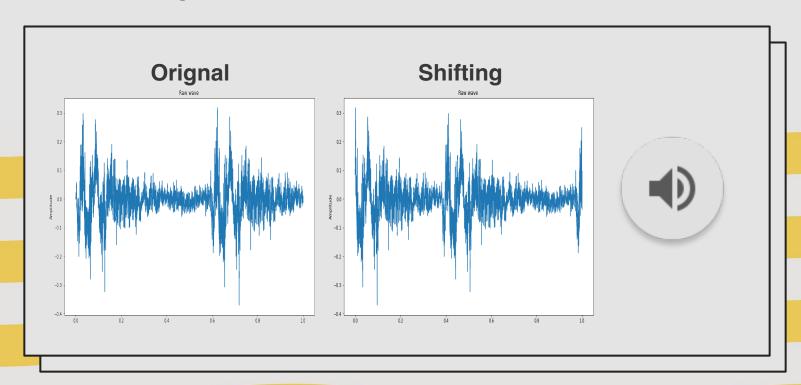
Data Augmentation

The objective is to make our model invariant to those perturbations and enhance its ability to generalize.

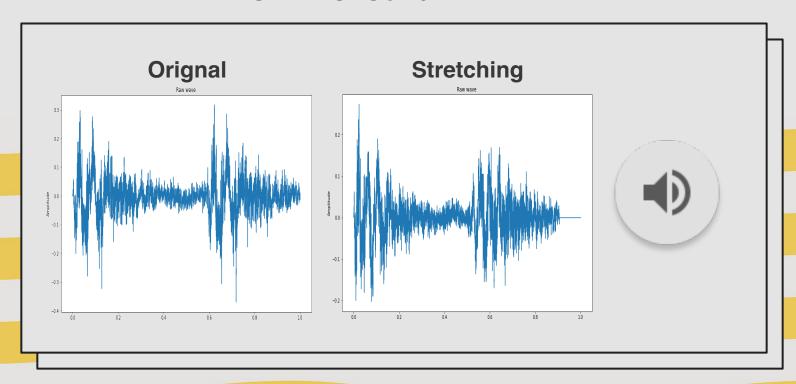
Data Augmentation:



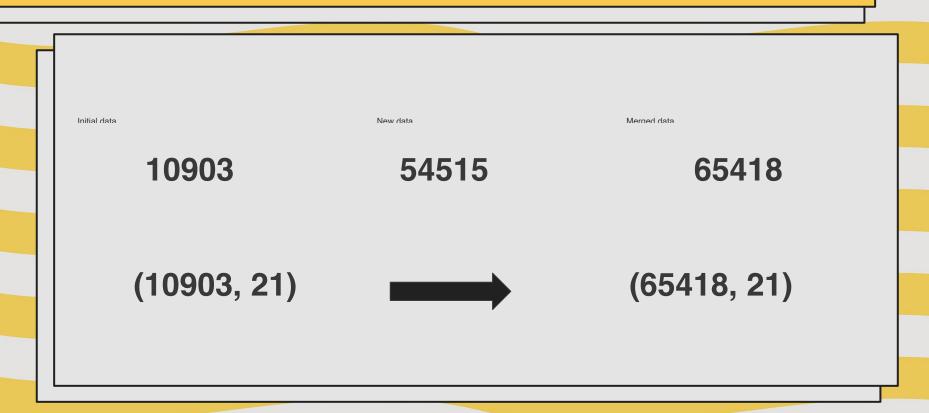
Data Augmentation:

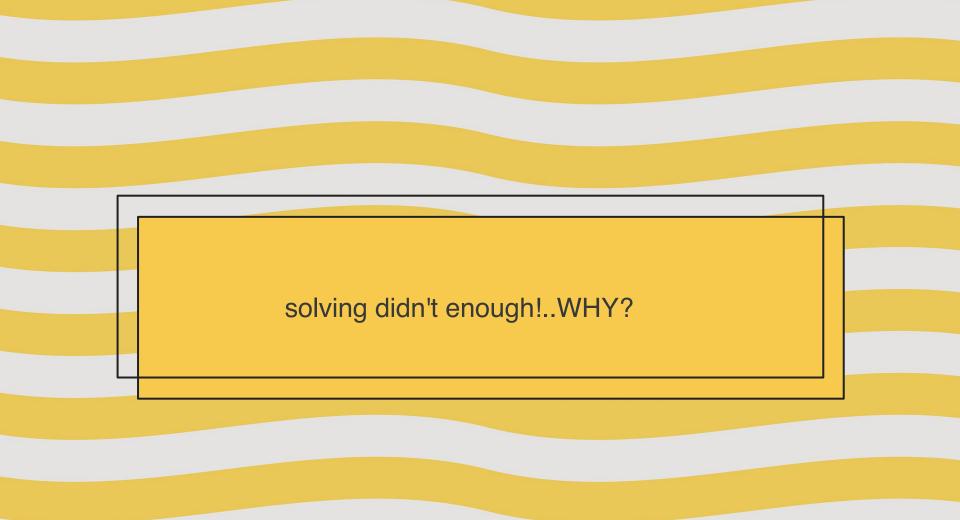


Data Augmentation: (changing play time)

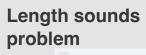


Data Augmentation





Padding



▶ 0:04 / 0:04 **●**

▶ 0:22 / 0:22

Least, why?



Train := 0.8 Test: 0.2

Train :=0.75 Validations:0.25



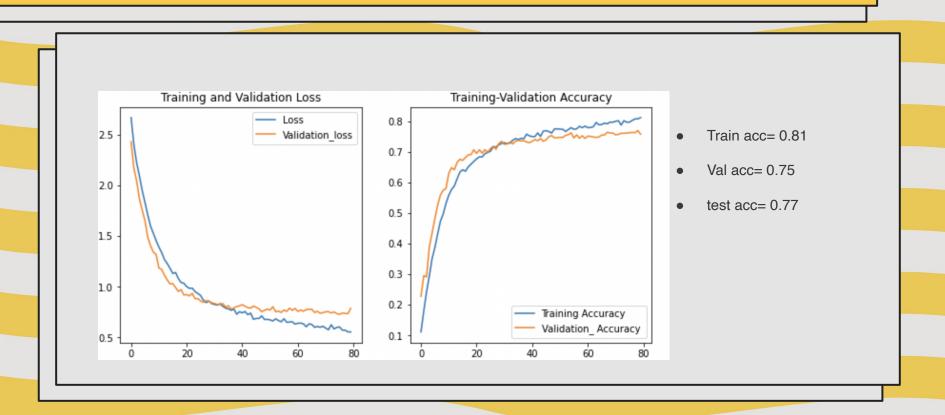
Models result (1)

	Train acc	Val acc	Epochs	batch
Beasline	0.61	0.45	500	50
Cnn2 (1)	0.28	0.25	200	50
Cnn2 (2)	0.60	0.44	1000	50
Cnn2 (3)	0.33	0.21	300	300
Cnn2 (4)	0.48	0.44	500	50

Models result (2)

	Train acc	Val acc	Epochs	batch
Beasline	0.69	0.63	500	50
Cnn2D (1)	0.80	0.77	300	300
Cnn2d (2)	0.89	0.78	300	300
Cnn2d (3)	0.81	0.75	300	300
Cnn1d	0.27	0.3	500	50
Istm	0.3	0.34	500	50

FINAL RESULT



MODEL ARCHITECTURE

Conv2D (Filter size = 128)

MaxPooling2D

Conv2D (Filter size = 128)

MaxPooling2D Droupout (0.8)

Flatten

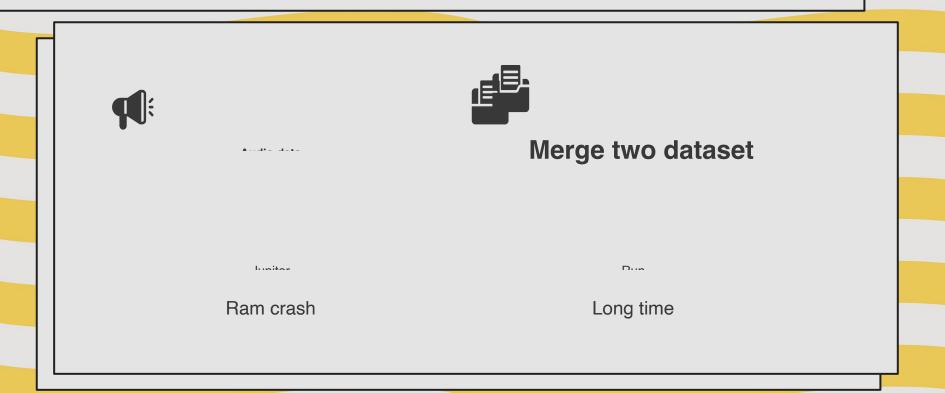
Dense (512, activation = 'relu')
Droupout (0.8)

Dense (512, activation = 'relu')

Droupout (0.8)

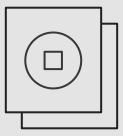
Dense (18, activation = softmax)

Challenges



Future work

- build an app that helps the deaf in their daily life
- Transfer Learning



Model Deployment Demo

