Sinteza vorbirii pornind de la mișcarea buzelor

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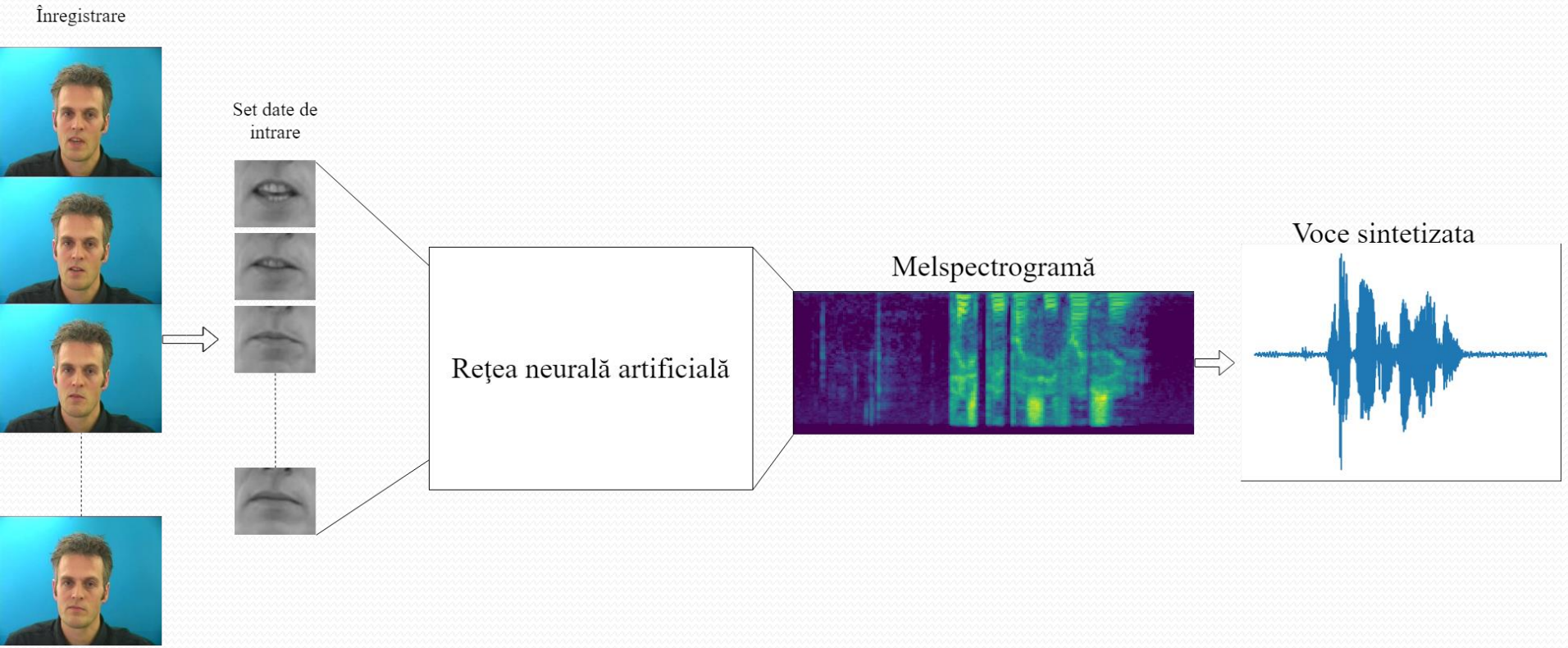
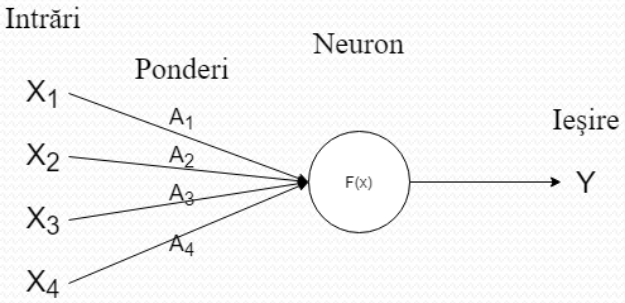
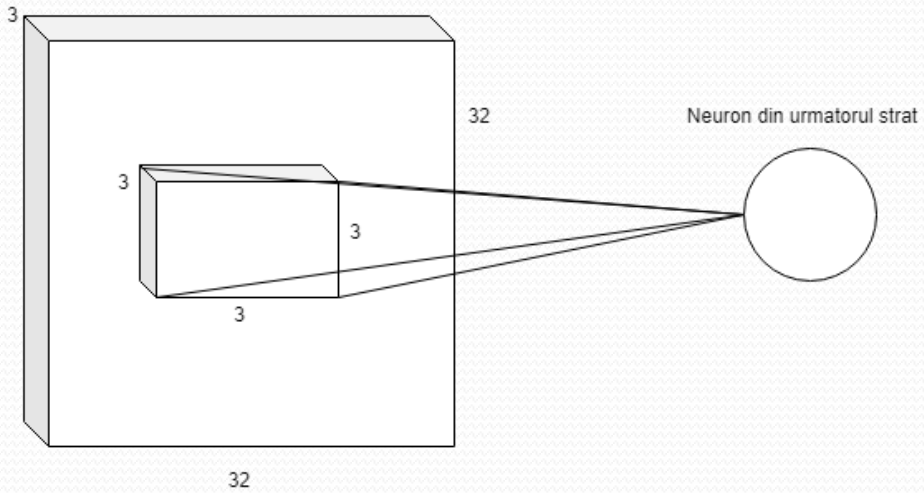
Scopul şi structura lucrării



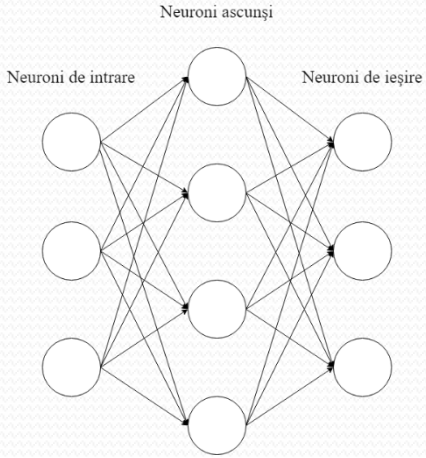
Noţiuni teoretice



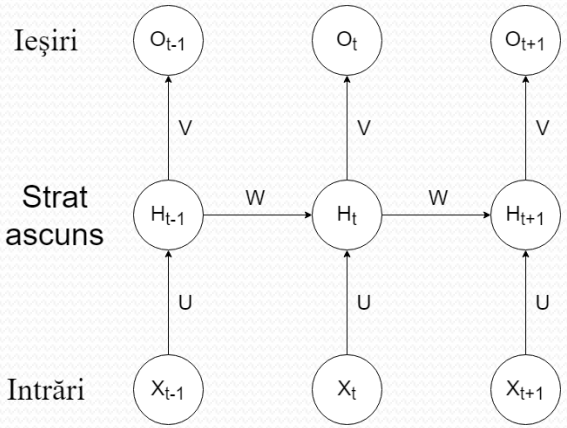
Reţea neurală convoluţională



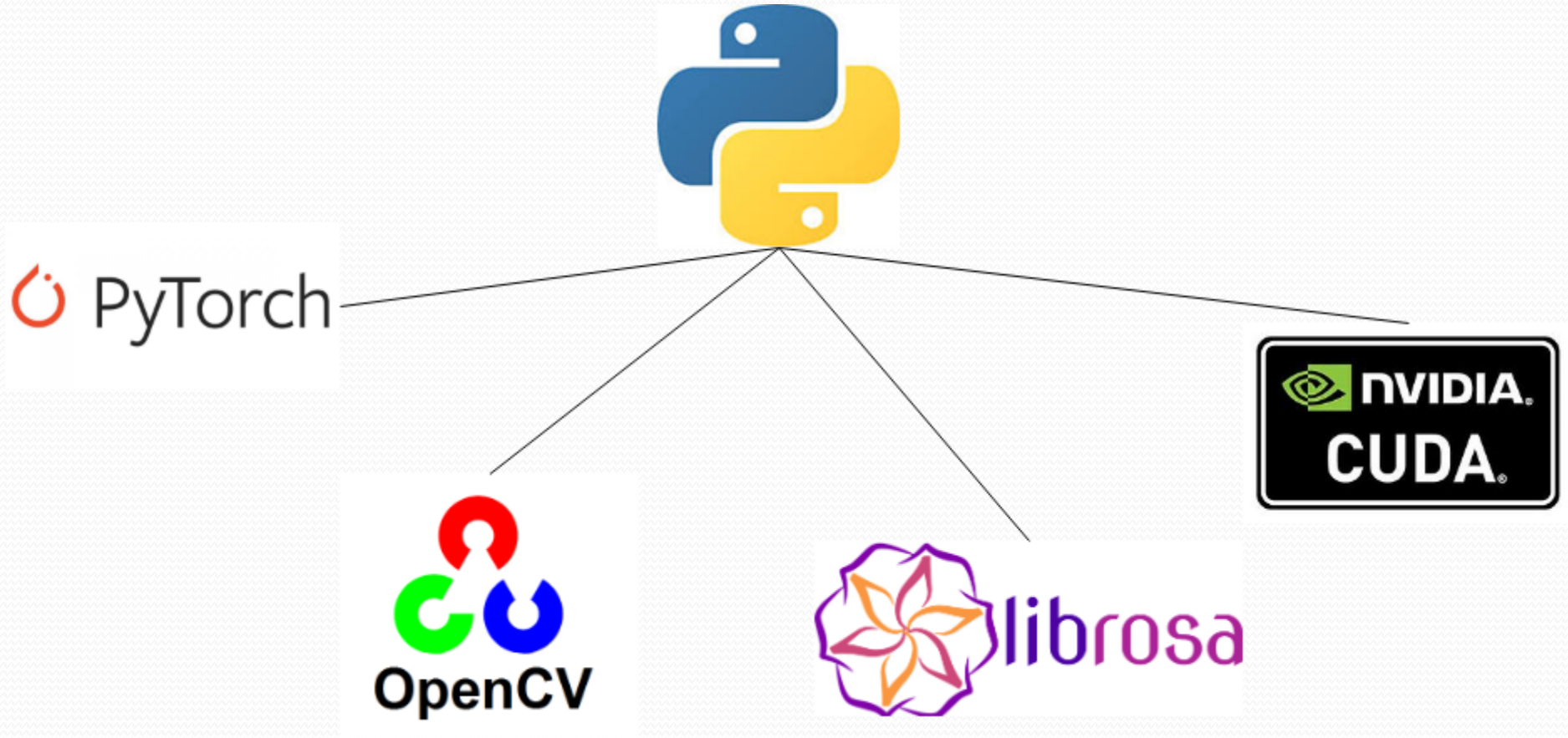
Reţea neurală tradiţională



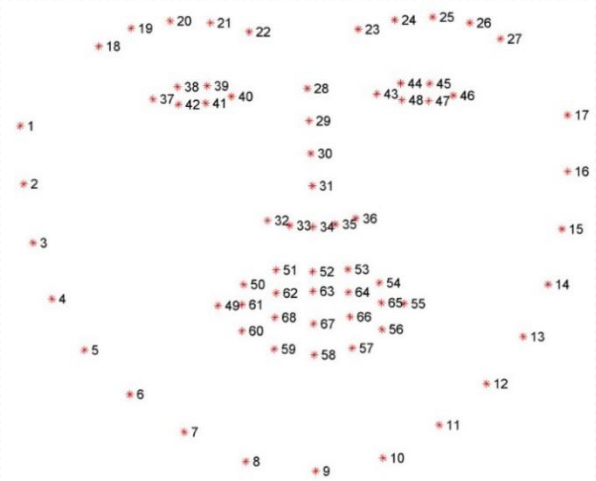
Reţea neurală recurentă



Tehnologii folosite

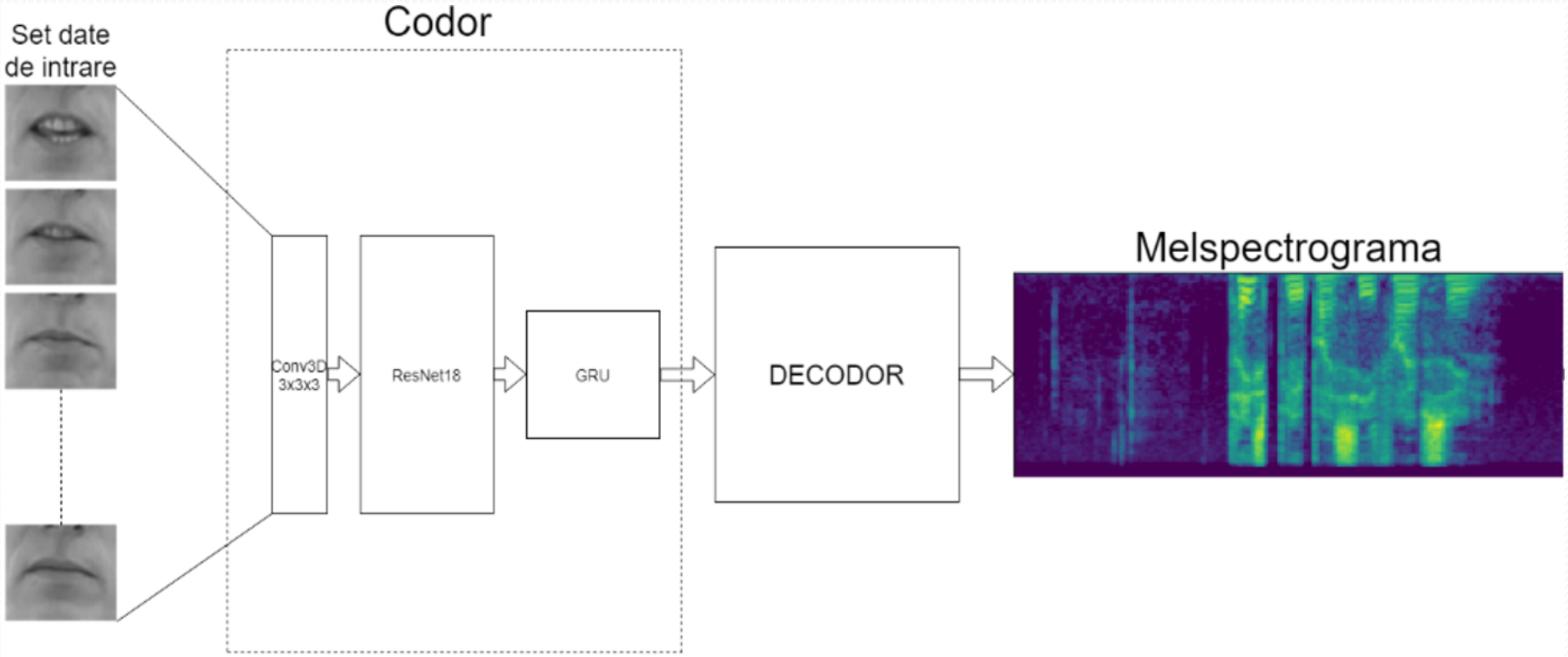


Prelucrarea imaginilor



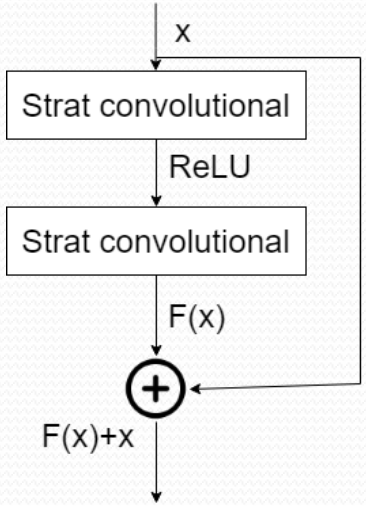
*model preantrenat de detectie feţe Sursa: [1]

Arhitectura folosită



ResNet18

Conexiune reziduală



Structura ResNet18

Layer Name	Output Size	ResNet-18
conv1	$112 \times 112 \times 64$	7×7, 64, stride 2
conv2_x	$56 \times 56 \times 64$	3×3 max pool, stride 2
		$\begin{bmatrix} 3 \times 3, 64 \\ 3 \times 3, 64 \end{bmatrix} \times 2$
conv3_x	$28 \times 28 \times 128$	$\begin{bmatrix} 3 \times 3, 128 \\ 3 \times 3, 128 \end{bmatrix} \times 2$
conv4_x	$14 \times 14 \times 256$	$\begin{bmatrix} 3 \times 3, 256 \\ 3 \times 3, 256 \end{bmatrix} \times 2$
conv5_x	$7 \times 7 \times 512$	$\begin{bmatrix} 3 \times 3, 512 \\ 3 \times 3, 512 \end{bmatrix} \times 2$
average pool	$1 \times 1 \times 512$	7×7 average pool
fully connected	1000	512×1000 fully connections
softmax	1000	

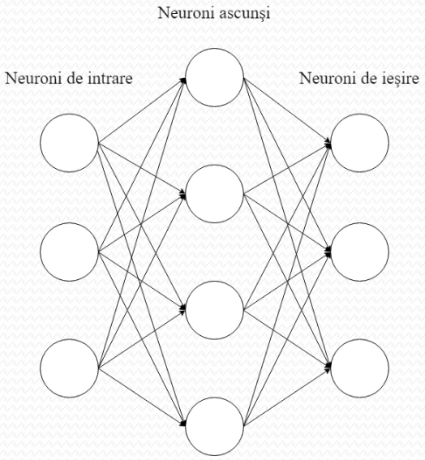
Implementare software

```
168         self.encoder = resnet18()
169         self.encoder.conv1 = nn.Conv2d(
170             K,
171             64,
172             kernel_size=(7, 7),
173             stride=(2, 2),
174             padding=(3, 3),
175             bias=False,
176         )
177
178         self.encoder = nn.Sequential(*list(self.encoder.children())[:-1])
```

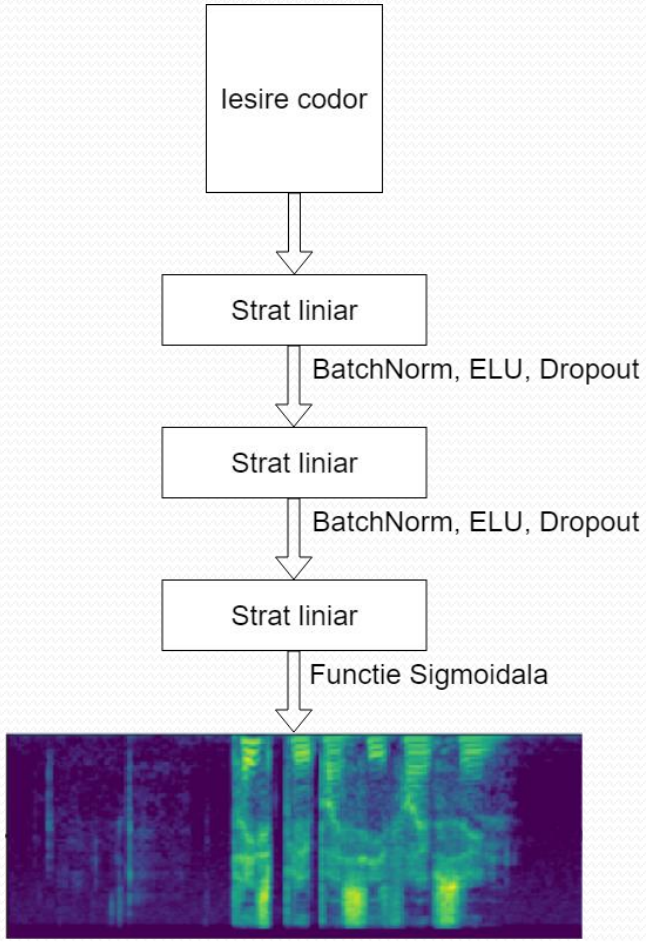
*Resnet18 Sursa:[2]

Decodor MLP

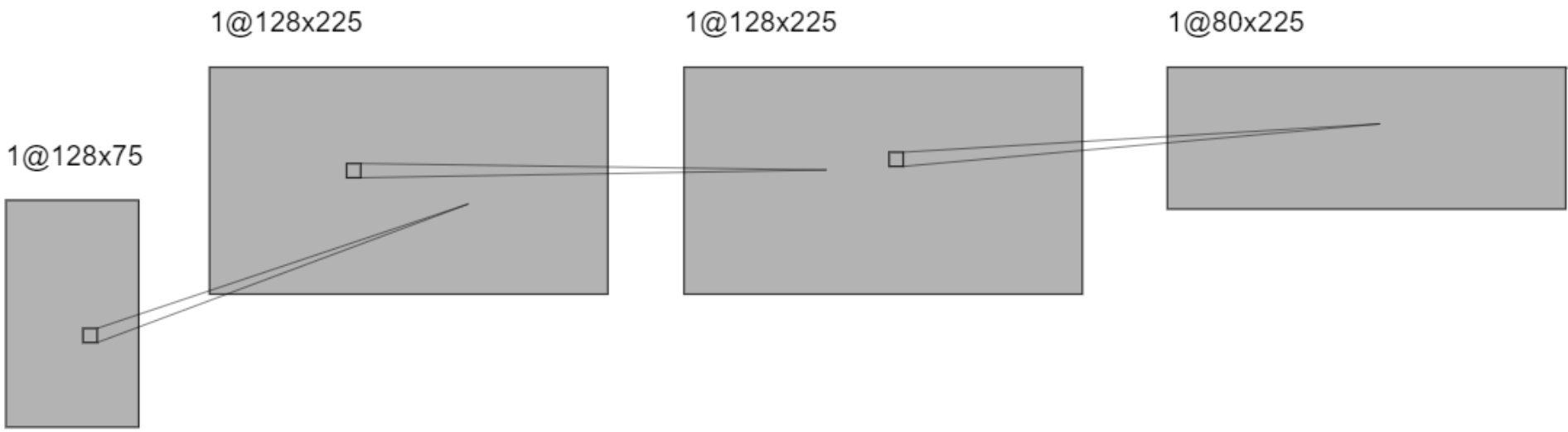
Strat liniar MLP



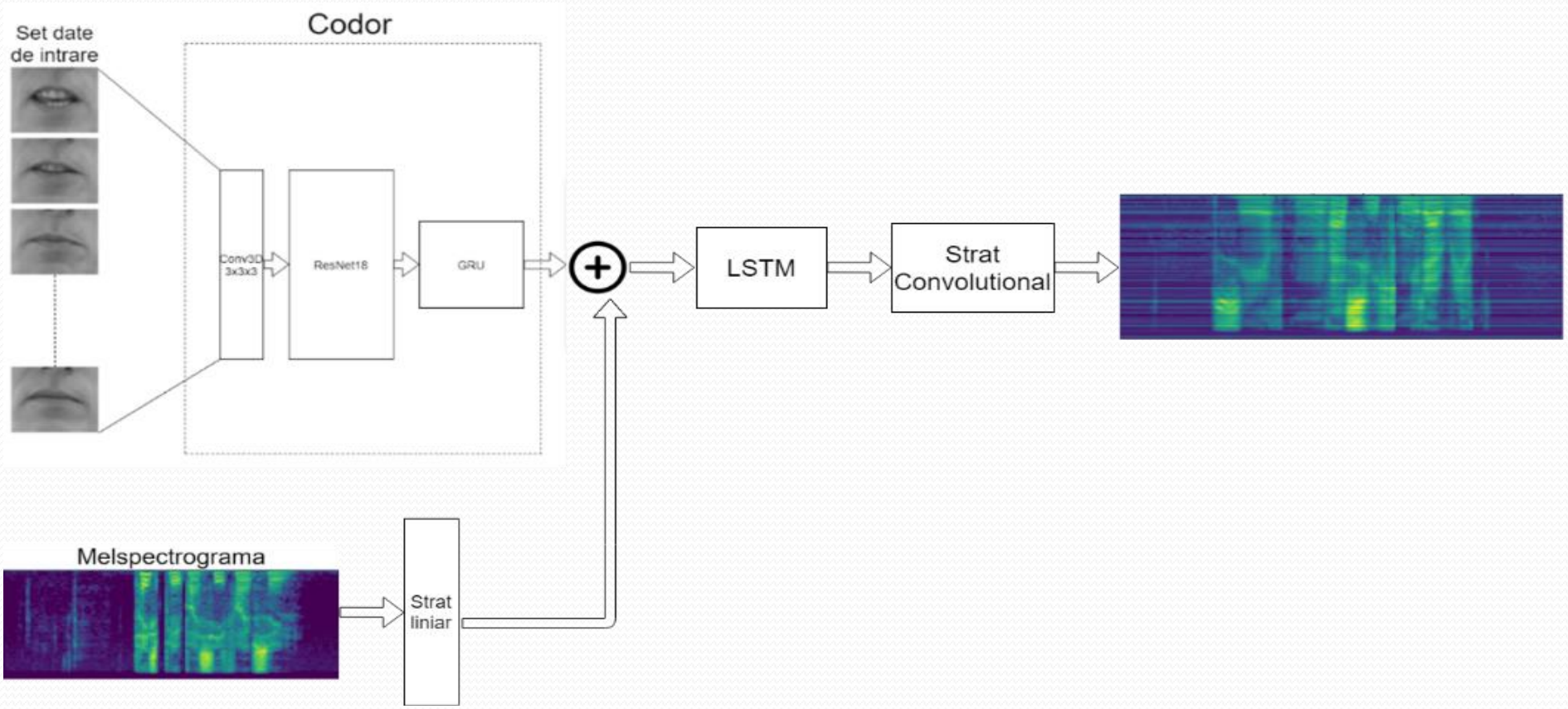
Structura decodorului



Decodor convoluţional



Decodor “Flowtron”



*Flowtron Sursa:[3]

Prelucrarea datelor pentru imbunătăţirea rezultatelor

- Padding
- Derivate de ordinul 1 si 2
- Normalizare

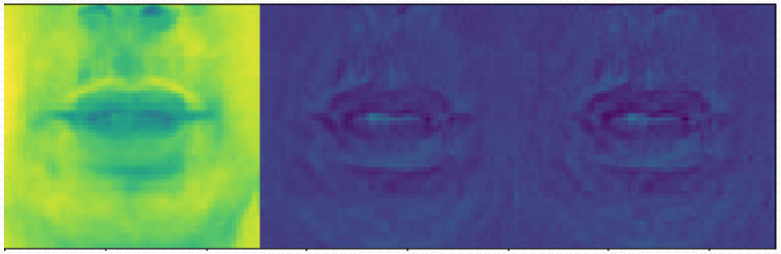
Padding

Eroarea medie patrată:

$$L(y, \hat{y}) = \frac{1}{N} \sum_{i=0}^{N} (y - \hat{y}_i)^2$$

num. subjects	padding	first and second derivatives	normalization	decoder	sampling frequency	MSE ↓
1	10	yes	standardization	MLP	22 KHz	0.0058
1	25	yes	standardization	MLP	22 KHz	0.0059

Derivate de ordinul 1 si 2



num. subjects	padding	first and second derivatives	decoder	MSE ↓
1	10	no	MLP	0.00575
1	10	yes	MLP	0.00577
2	10	no	MLP	0.0056
2	10	yes	MLP	0.0053
5	10	no	MLP	0.0056
5	10	yes	MLP	0.0053

num. subjects	padding	first and second derivatives	decoder	MSE ↓
1	10	no	conv	0.0052
1	10	yes	conv	0.0052
2	10	no	conv	0.0053
2	10	yes	conv	0.0052

Normalizare

Formula folosită:
Rezultat = (intrare – medie) / abaterea medie standard

num. subjects	padding	first and second derivatives	normalization	decoder	sampling frequency	MSE ↓
2	10	yes	[0, 1]	MLP	22 KHz	0.0060
2	10	yes	standardization	MLP	22 KHz	0.0053

Implementare Software:

```
57      for data_, _ in train_loader:
58          batch_samples = data.size(0)
59          data = data.view(batch_samples, data.size(1), -1)
60          mean += data.mean(2).sum(0)
61          std += data.std(2).sum(0)
62          nb_samples += batch_samples
63
64      mean /= nb_samples
65      std /= nb_samples
```

Rezultate finale

num. subjects	padding	first and second derivatives	normalization	decoder	sampling frequency	MCD ↓
1	10	yes	standardization	MLP	22 KHz	183
1	10	yes	standardization	conv	19.3 KHz	169
1	10	yes	standardization	autoregressive	19.3 Khz	182

num. subjects	padding	first and second derivatives	normalization	decoder	sampling frequency	MCD
2	10	yes	standardization	conv	19.3 KHz	169
2	10	yes	standardization	autoregressive	19.3 Khz	191
2	10	yes	standardization	MLP	22 KHz	195

Mel Cepstral Distortion:

$$\frac{10\sqrt{2}}{\ln 10}\frac{1}{T}\sum_{t=1}^{T}\sqrt{\sum_{i}\left(C_{ti}-\hat{C}_{ti}\right)^2}$$

Contribuţii personale

- Preprocesarea datelor
- Stabilirea arhitecturii generale
- Stabilirea si implementarea codorului si a decodoarelor
- Implementarea metodelor de procesare a datelor pentru imbunatăţirea rezultatelor
- Modificarea hiperparametrilor pentru potrivirea complexităţii arhitecturilor cu setul de date de intrare

Concluzii

- Scop inițial atins, reproducerea vocii este inteligibilă pentru:
  - Decodor convoluțional
  - Decodor autoregresiv
- Dezvoltari ulterioare
  - Integrarea posibilitații de a lucra in timp real
  - Identificarea emoțiilor si influențarea vocii pe baza lor

Demonstrarea funcţionalităţii

Audio original

Decodor MLP:

Decodor convolutional:

Decodor autoregresiv:

Cuvinte: “Set white at v1 again”

Bibliografie

- [1] J. Wang, K. Sun, T. Cheng, B. Jiang. Deep High-Resolution Representation Learning for Visual Recognition. 2020

- [2] K. He, X. Zhang, S. Ren, J. Sun. Deep Residual Learning for Image Recognition. Microsoft Research, 2015

- [3] R. Valle, K. Shih, R. Prenger, B. Catanzero. Flowtron: an autoregressive Flow-based Generative Network for Text-to-Speech Synthesis. 2020