

# **Self drives me crazy: from 0 to autonomous car in 150 hours**

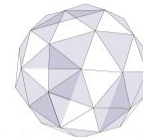
**Felipe  
Salvatore**



**Paula  
Moraes**

## Quem somos:

- **Felipe Salvatore**: doutorando em Deep Learning/NLP
- **Paula Moraes**: mestranda com foco em Robótica Probabilística



**LIAMF**

**Laboratório de IA do IME-USP**

## Por que montar um carro autônomo?

- Desmistificar a implementação dessa tecnologia
- Porque é divertido :)



**IME-USP**

## Desafio

Implementar o artigo: **End to End Learning for Self-Driving Cars (2016)**

# Por que carros autônomos?

- Carros autônomos são os robôs que vão diretamente impactar nosso **dia a dia no futuro próximo**: atualmente há 51,3 milhões de veículos rodando no Brasil.
- Esse problema é rico para a inteligência artificial, pois junta diferentes áreas como **machine learning, computer vision, path planning** e **reinforcement learning**

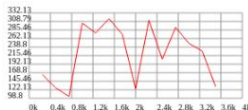
# Por que carros autônomos?

## DeepTesla - End-to-End Steering Model

[Main Page](#) - [About DeepTesla](#)

### Training

Forward pass (ms): 4      Backward pass (ms): 8  
Total examples seen / unique: 3689      Network Status: training



```
1 {
2   "network": [
3     { "type": "input", "out_sx": 200, "out_sy": 66, "out_depth": 3 },
4     { "type": "conv", "sx": 3, "filters": 8, "stride": 3, "pad": 2, "activation": "relu" },
5     { "type": "conv", "sx": 3, "filters": 8, "stride": 3, "pad": 2, "activation": "relu" },
6     { "type": "conv", "sx": 3, "filters": 8, "stride": 3, "pad": 2, "activation": "relu" },
7     { "type": "pool", "sx": 4, "stride": 2 },
8     { "type": "regression", "num_neurons": 1 }
9   ],
10  "trainer": { "method": "adadelta", "batch_size": 4, "l2_decay": 0.0001 }
11 }
```

### Layer Visualization

Input (200x66x3)

Activations (actual angle: 0.5, predicted angle: 0.1)



VIDEO VISUALIZATION



## DeepTraffic: Deep Reinforcement Learning

### DeepTraffic

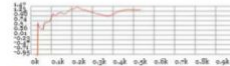
[Main Page](#) - [Leaderboard](#) - [About DeepTraffic](#)

Americans spend 8 billion hours stuck in traffic every year.  
Deep neural networks can help!

```
5 laneside = 3;
6 patchesAhead = 30;
7 patchesBehind = 10;
8 trainIterations = 10000;
9
10 // the number of other autonomous vehicles controlled by your network
11 otherAgents = 0; // max of 9
12
13 var num_inputs = (laneside * 2 + 1) * (patchesAhead + patchesBehind);
```

[Apply Code/Reset Net](#) [Save Code/Net to File](#) [Load Code/Net from File](#)

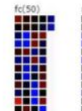
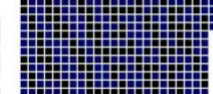
[Submit Model to Competition](#)



[Run Training](#) [Start Evaluation/Run](#)

Value Function Approximating Neural Network:

Input(280)



[LOAD CUSTOM IMAGE](#)

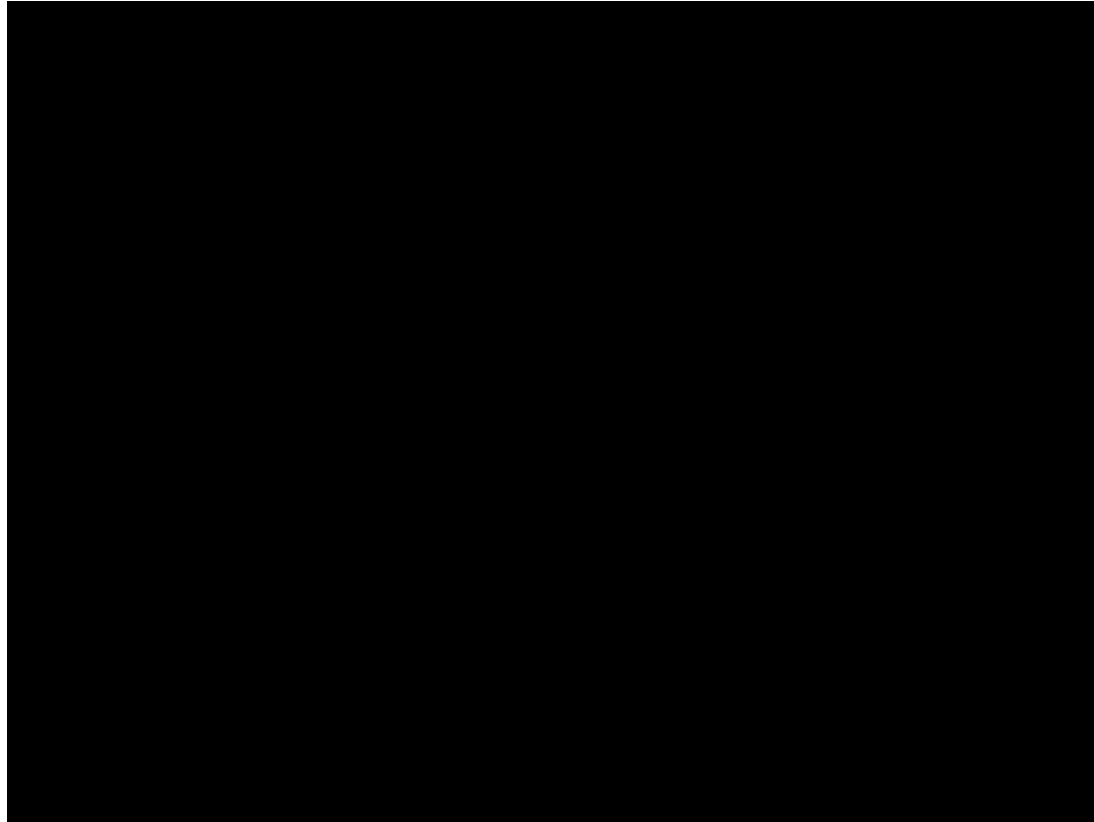
red

[REQUEST VISUALIZATION](#)

[vehicle skins](#)

Fonte: MIT 6.S094: Deep Learning for Self-Driving Cars

# Carro autônomo no Brasil: um breve histórico



# End to End Learning for Self-Driving Cars

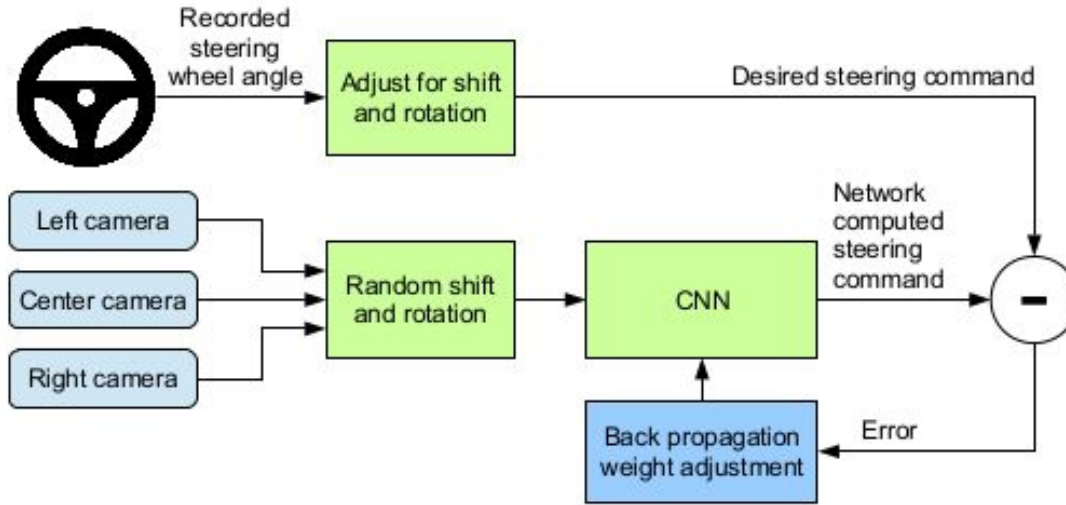


Figure 2: Training the neural network.

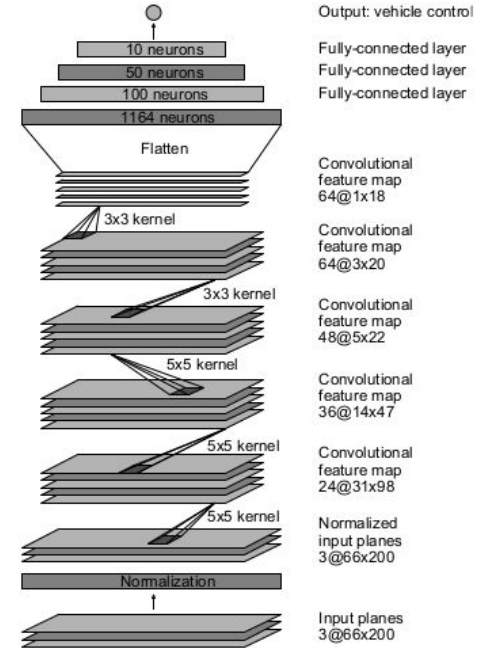
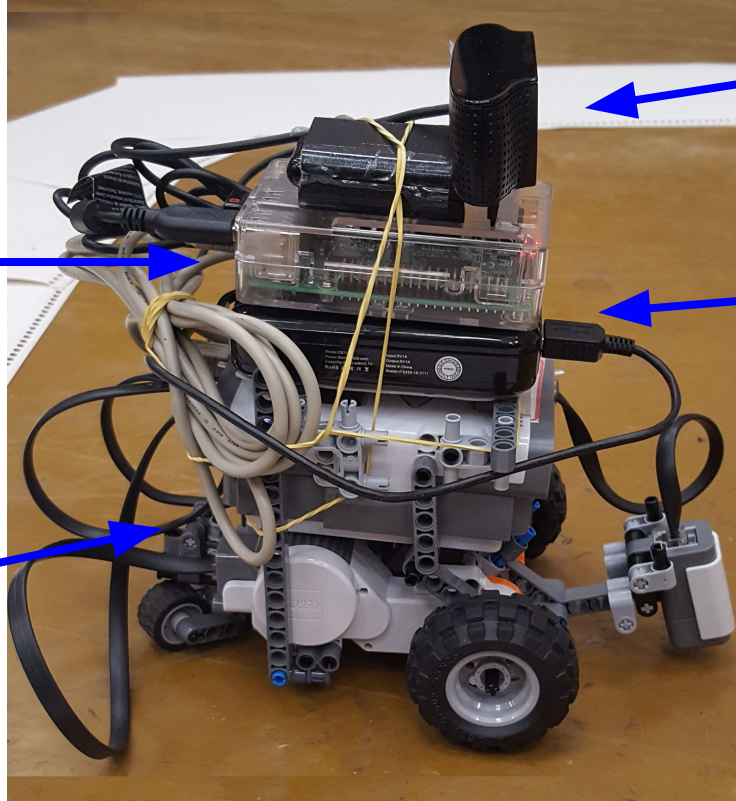


Figure 4: CNN architecture. The network has about 27 million connections and 250 thousand parameters.

# Recursos utilizados



Webcam

Power bank

Raspberry Pi

Lego NXT

custo total: \$ 60

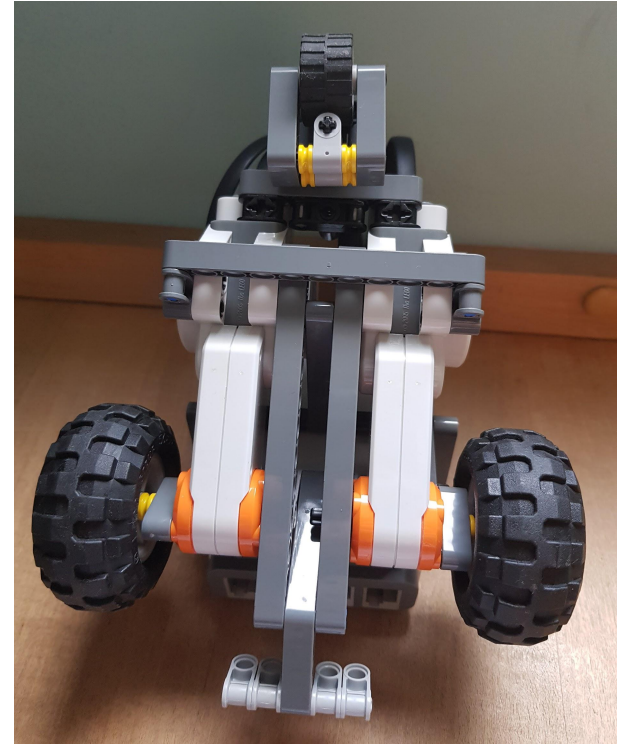
 TensorFlow™

 NXT-PYTHON



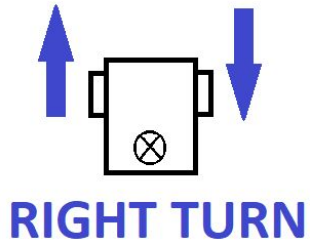
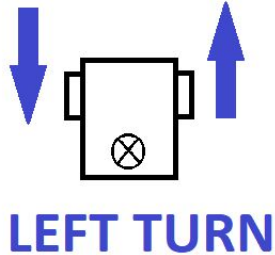
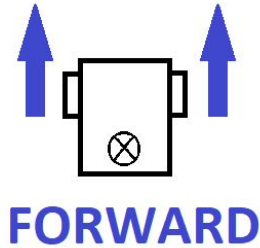
# Robô com acionamento diferencial

- Sistema com duas rodas controladas por **atuadores independentes**
- Possui uma roda passiva (***castor wheel***) para maior estabilidade
- Benefícios:
  - simplicidade
  - permite girar no próprio eixo
- Movimentação baseada na **diferença de velocidade** entre os motores





# Robô com acionamento diferencial



```
self.leftMotor = nxt.Motor(self.brick, nxt.PORT_B)
self.rightMotor = nxt.Motor(self.brick, nxt.PORT_A)
self.both = nxt.SynchronizedMotors(self.leftMotor,
                                    self.rightMotor,
                                    turn_ratio)

def move_up(self):
    """
    Execute action of moving up
    """
    self.both.run(self.power_up)

def move_left(self):
    """
    Execute action of moving left for tacho_left degrees
    """
    self.rightMotor.weak_turn(self.power_left, self.tacho_left)
    self.leftMotor.weak_turn(- self.power_left, self.tacho_left)

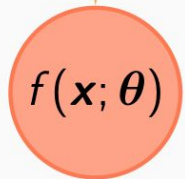
def move_right(self):
    """
    Execute action of moving right for tacho_right degrees
    """
    self.rightMotor.weak_turn(- self.power_right, self.tacho_right)
    self.leftMotor.weak_turn(self.power_right, self.tacho_right)
```

# Controle como regressão

$x$



$132 \times 400 \times 3$



$\hat{y}$

$\begin{bmatrix} 0.005236 \\ 10.150000 \\ 0.147433 \end{bmatrix}$	<b>steering angle</b>
	<b>speed</b>
	<b>brake</b>

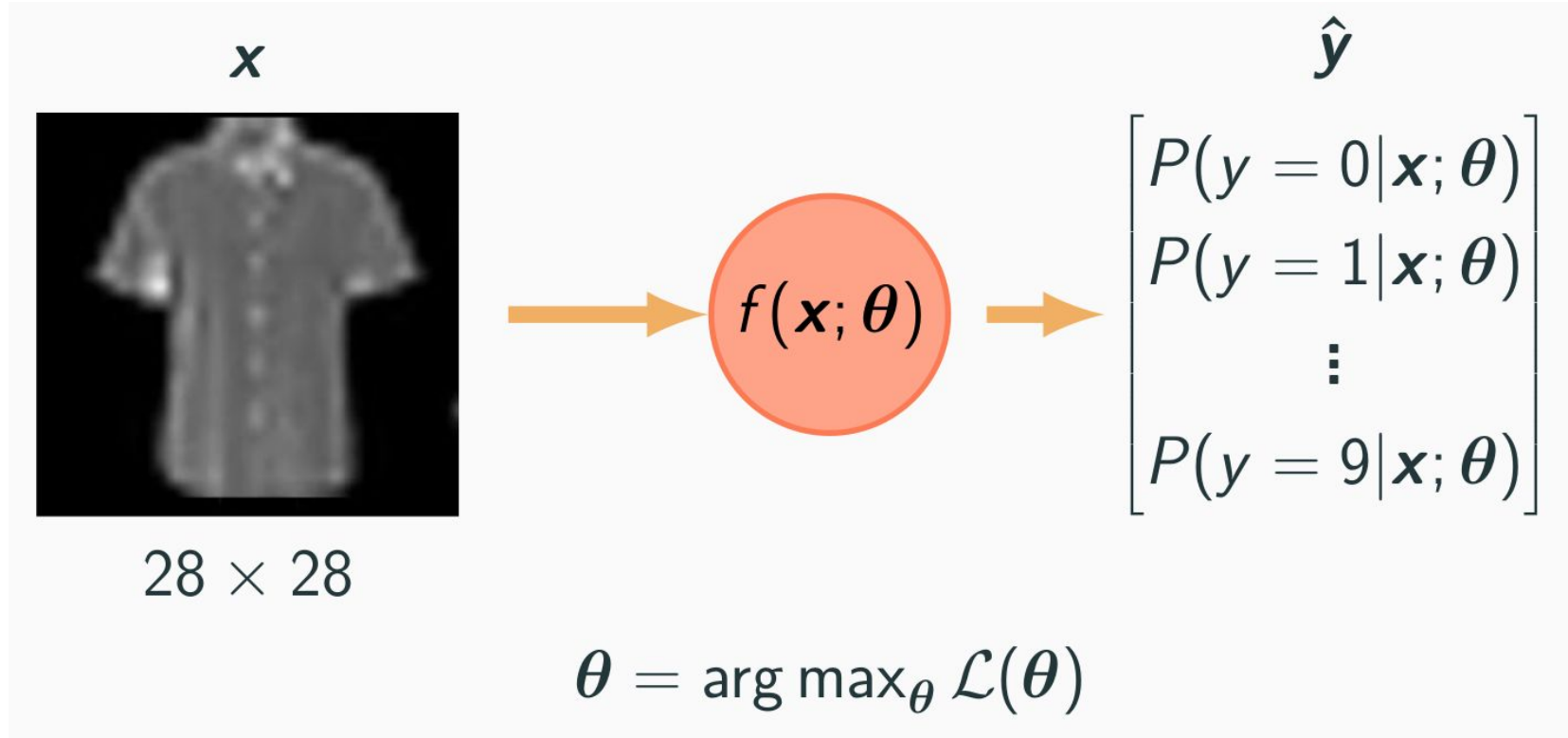
$$\theta = \arg \min_{\theta} J(\theta)$$

Exemplos:

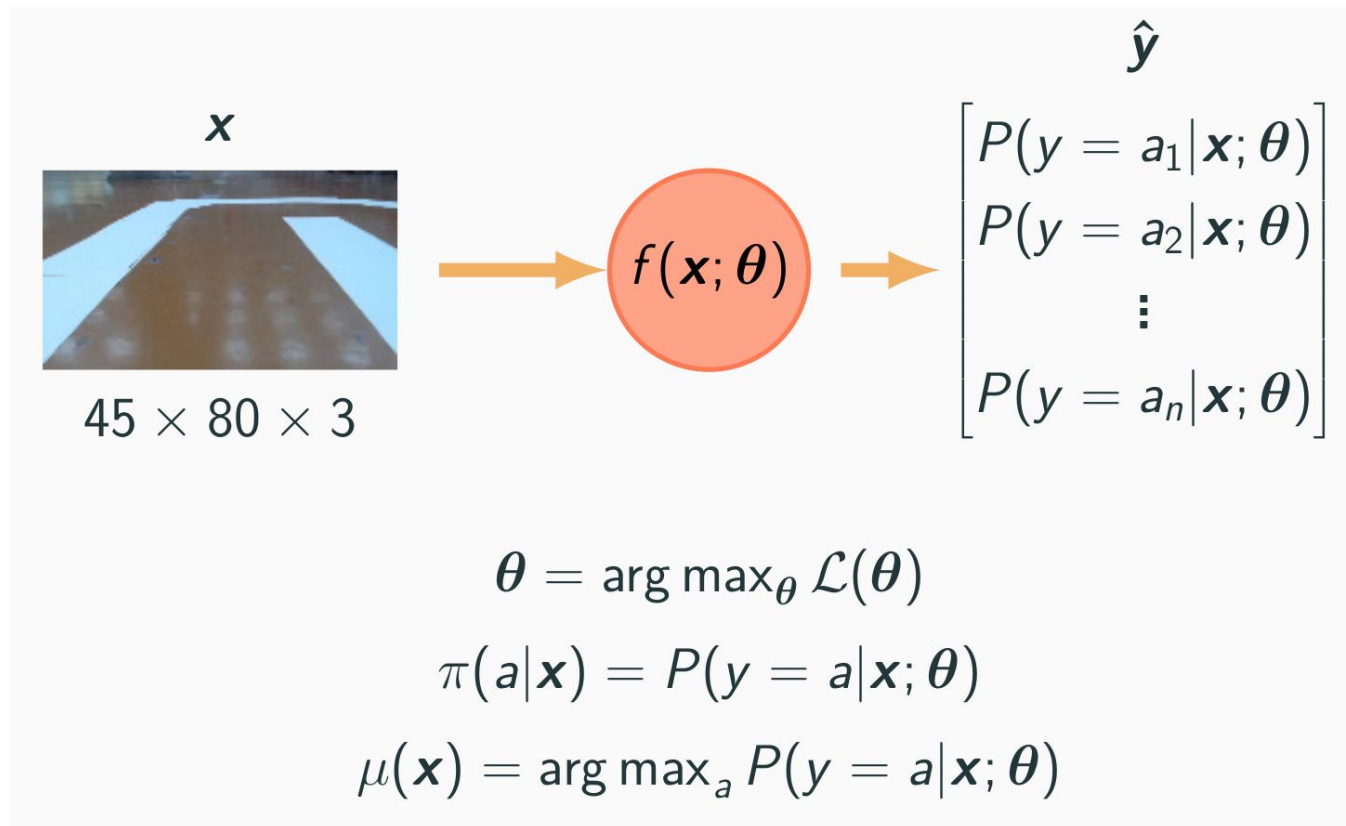
Udacity's Lincoln MKZ

DeepTesla

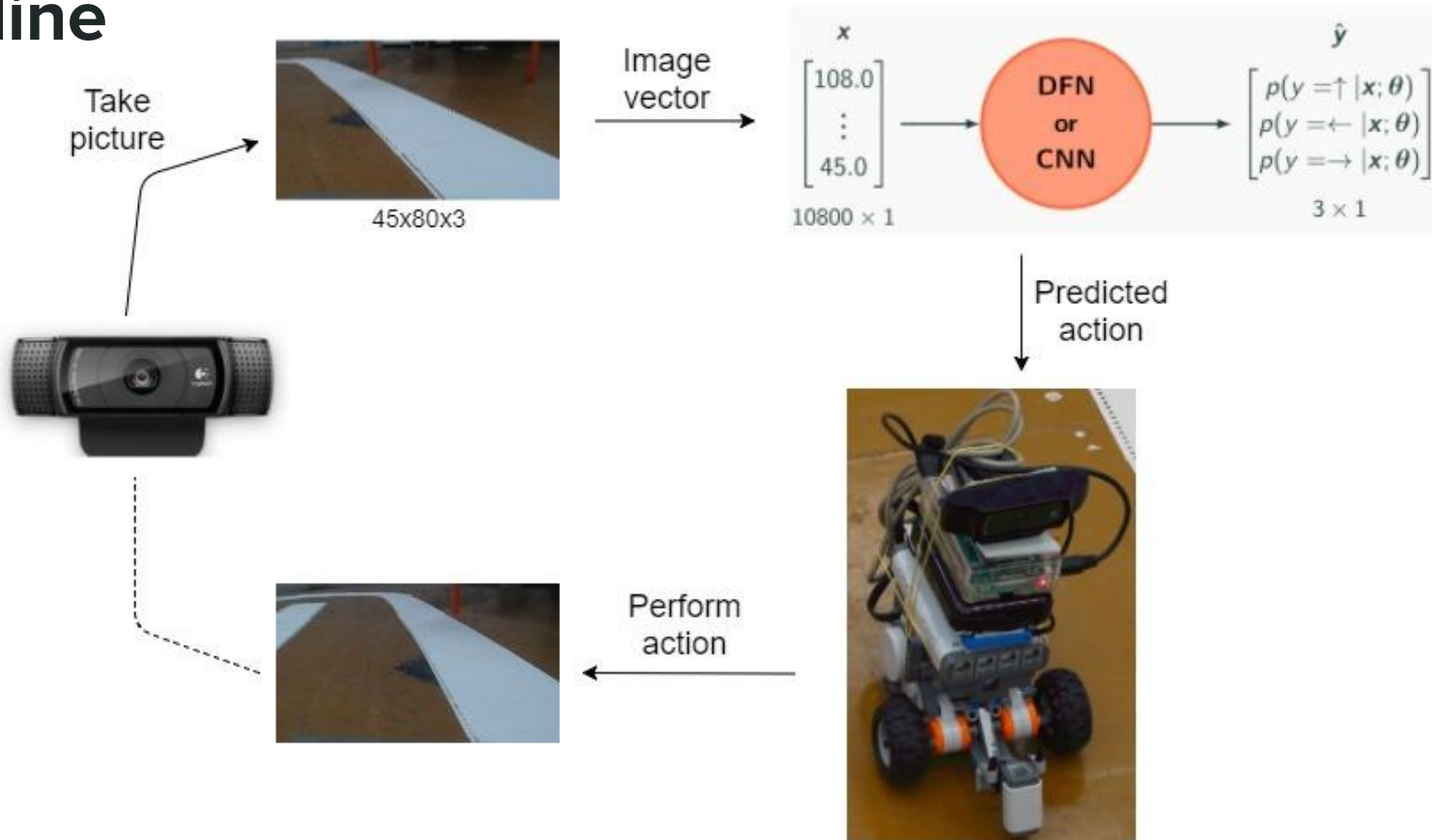
# Classificação de imagens



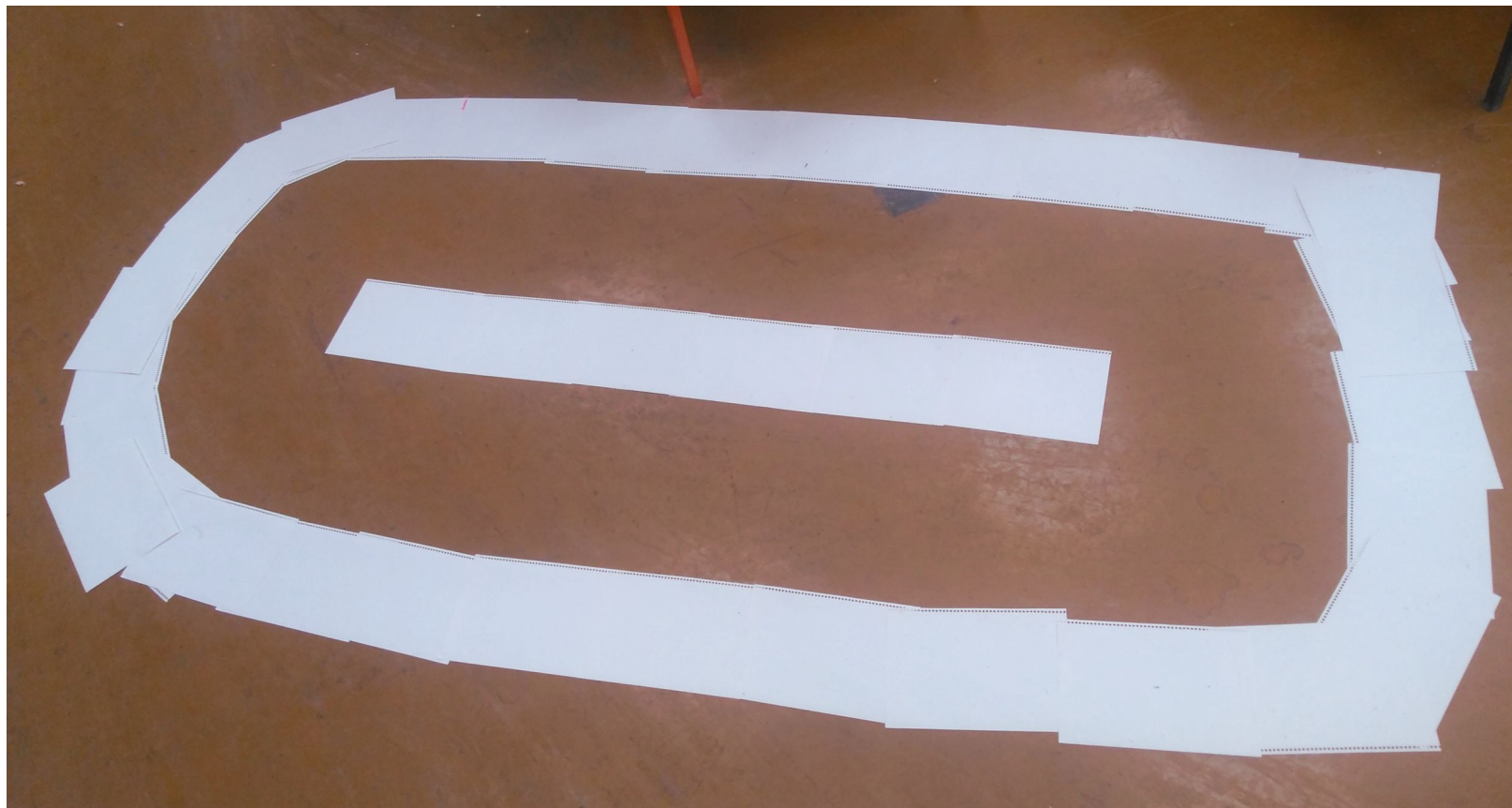
# Controle como classificação de imagens



# Pipeline

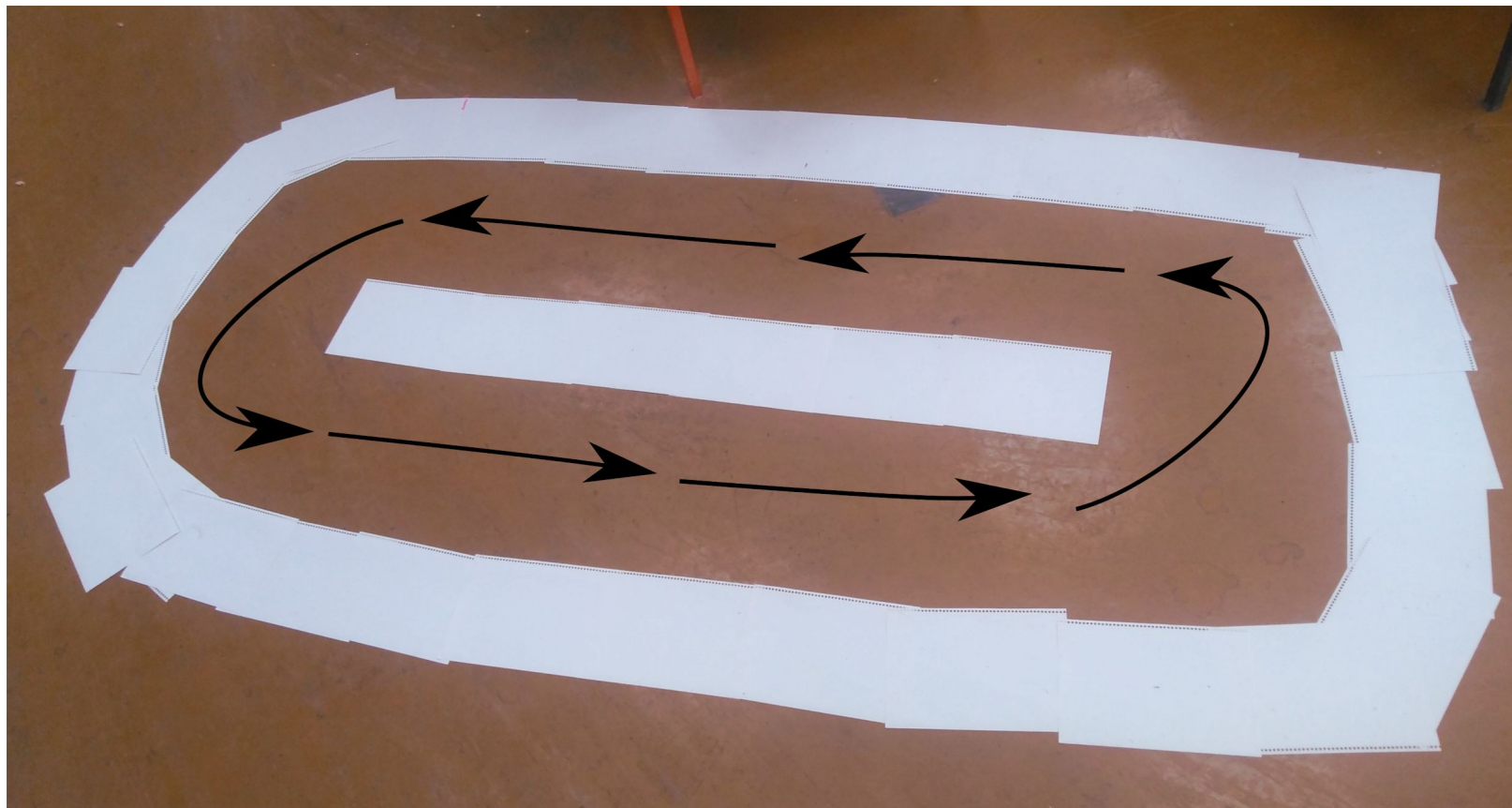


# Coleta de dados



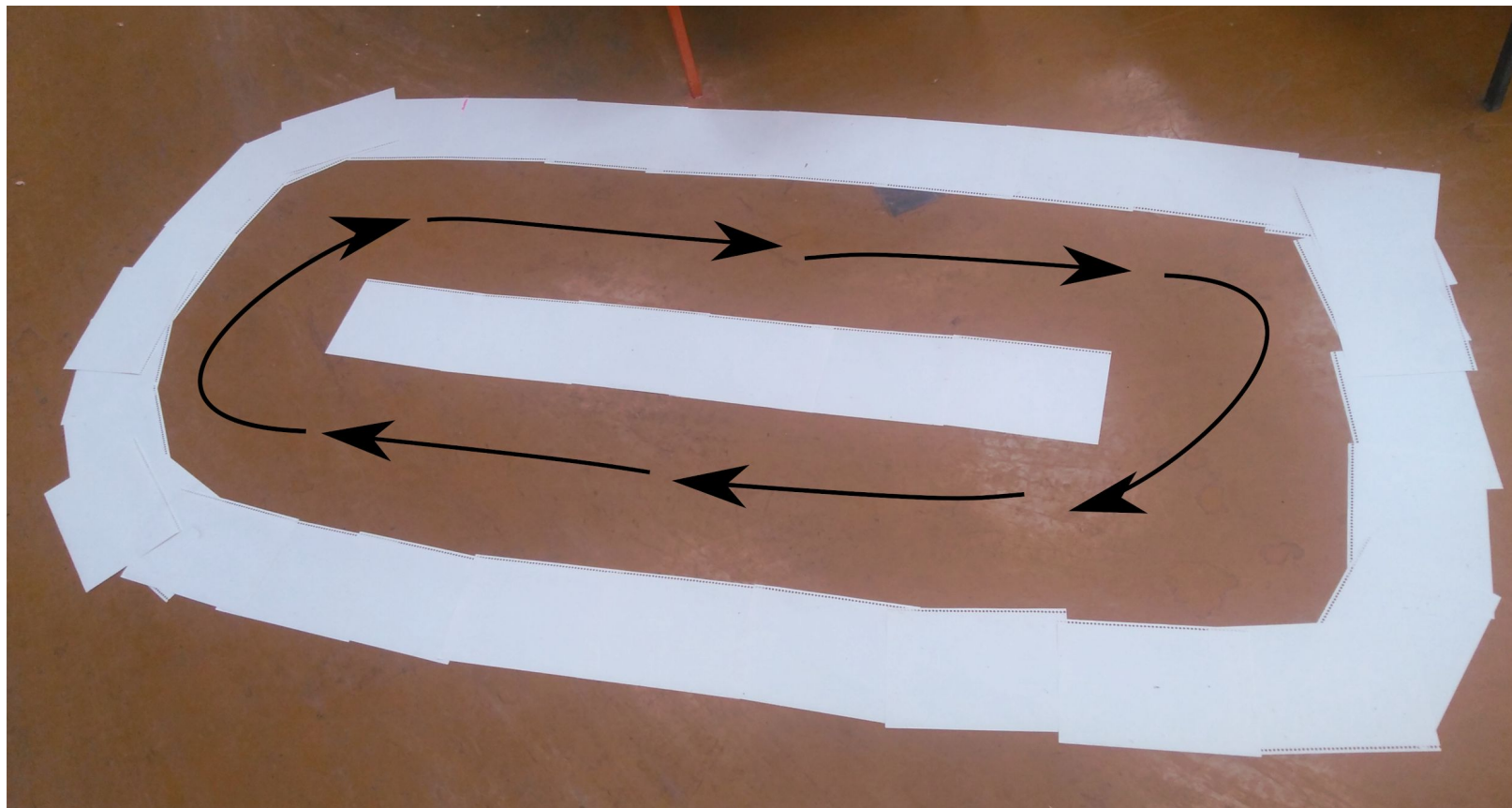


# Coleta de dados

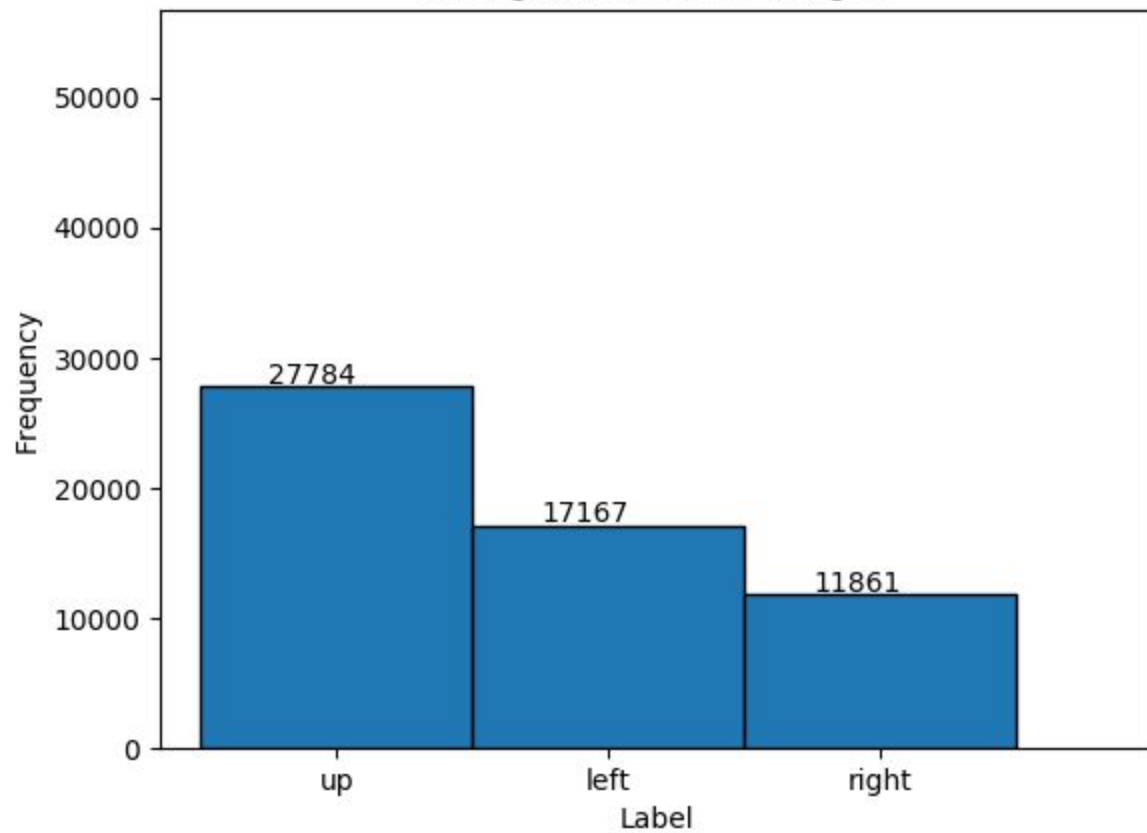




# Coleta de dados



Histogram of 56812 images



# Manipulação de imagens



Original



Binary



Random shadow

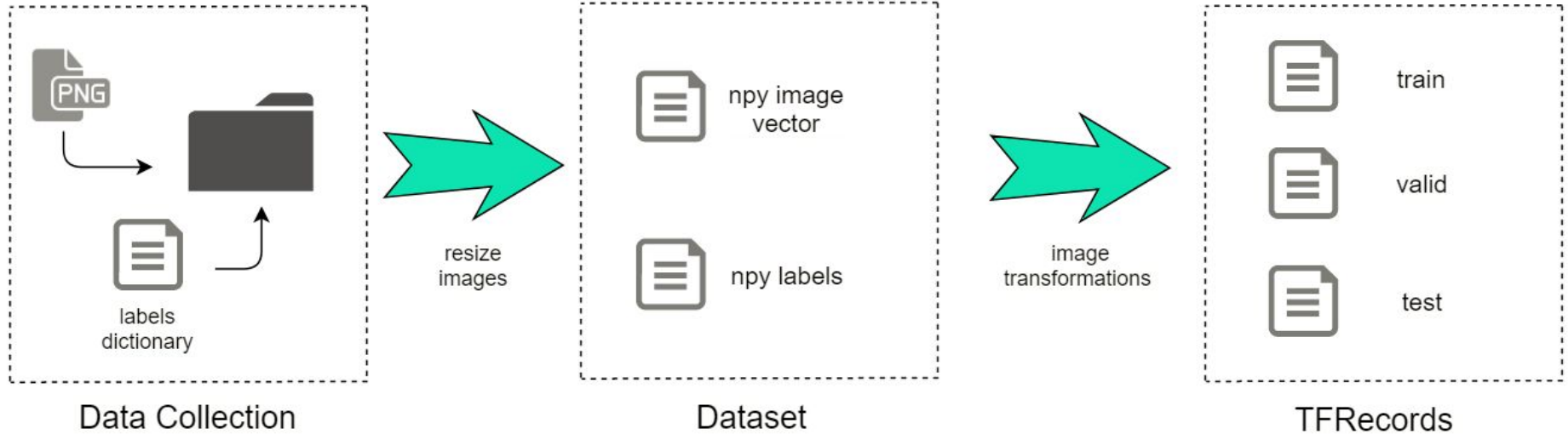


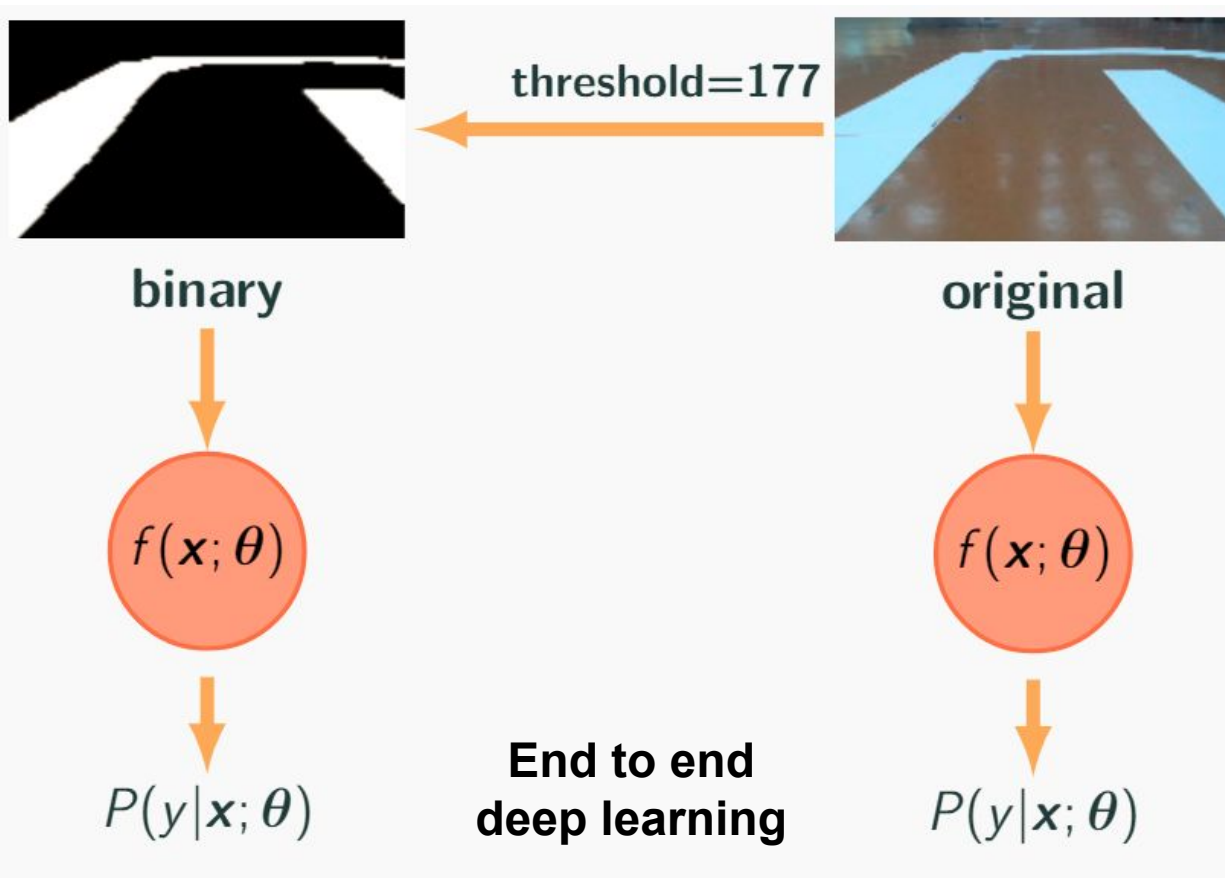
Grayscale



Gaussian Blur 5x5

# Data pipeline





## Resultados com DFN

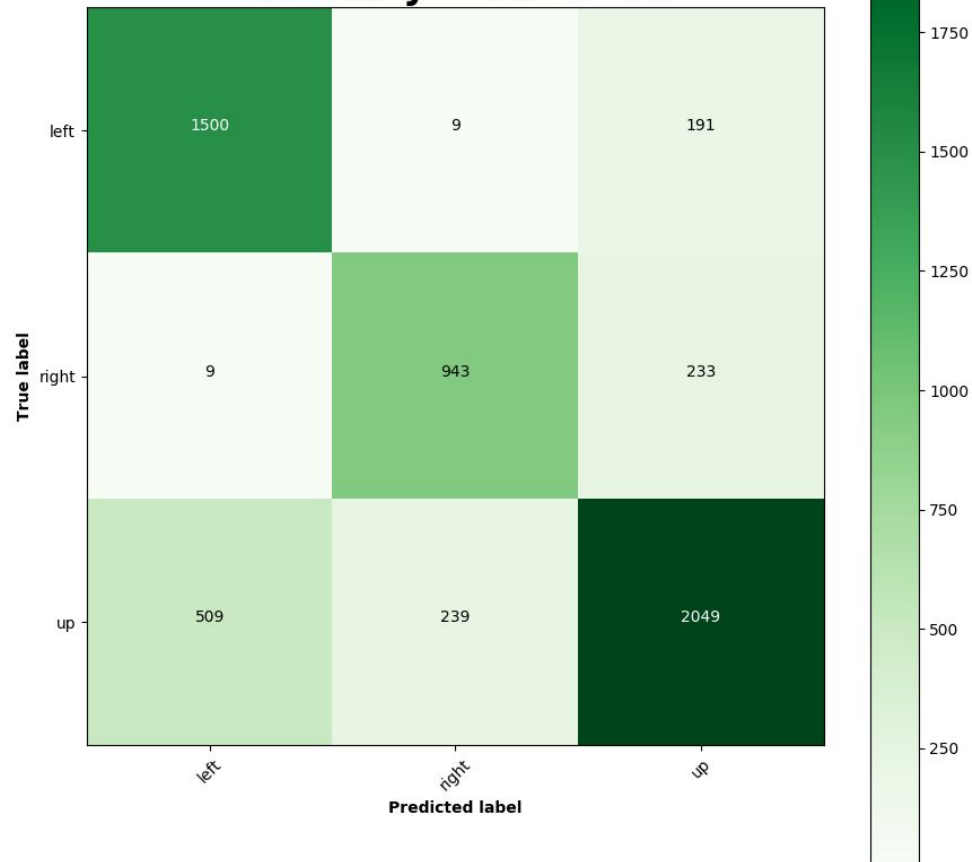
architecture	preprocessing	hit rate $\uparrow$	hit rate $\leftarrow$	hit rate $\rightarrow$
[3]	none	0.80	0.76	0.68
[2350, 3]	none	0.80	0.70	0.80
[1333, 200, 3]	none	0.79	0.82	0.67
[3]	binarization	0.75	0.87	0.64
[233, 3]	binarization	0.72	0.85	0.82
[1628, 47, 3]	binarization	0.71	0.90	0.84

# Resultados com CNN

architecture	preprocessing	hit rate $\uparrow$	hit rate $\leftarrow$	hit rate $\rightarrow$
$[(24, 5), 731, 3]$	none	0.80	0.71	0.73
$[(32, 5), (64, 5), 3]$	none	0.82	0.80	0.66
$[(24, 5), (36, 5), (64, 5), 200, 3]$	none	0.76	0.84	0.72
$[(24, 5), 456, 3]$	binarization	0.79	0.86	0.67
$[(32, 5), (64, 5), 3]$	binarization	0.78	0.80	0.73
$[(24, 5), (36, 5), (64, 5), 200, 3]$	binarization	0.79	0.83	0.73



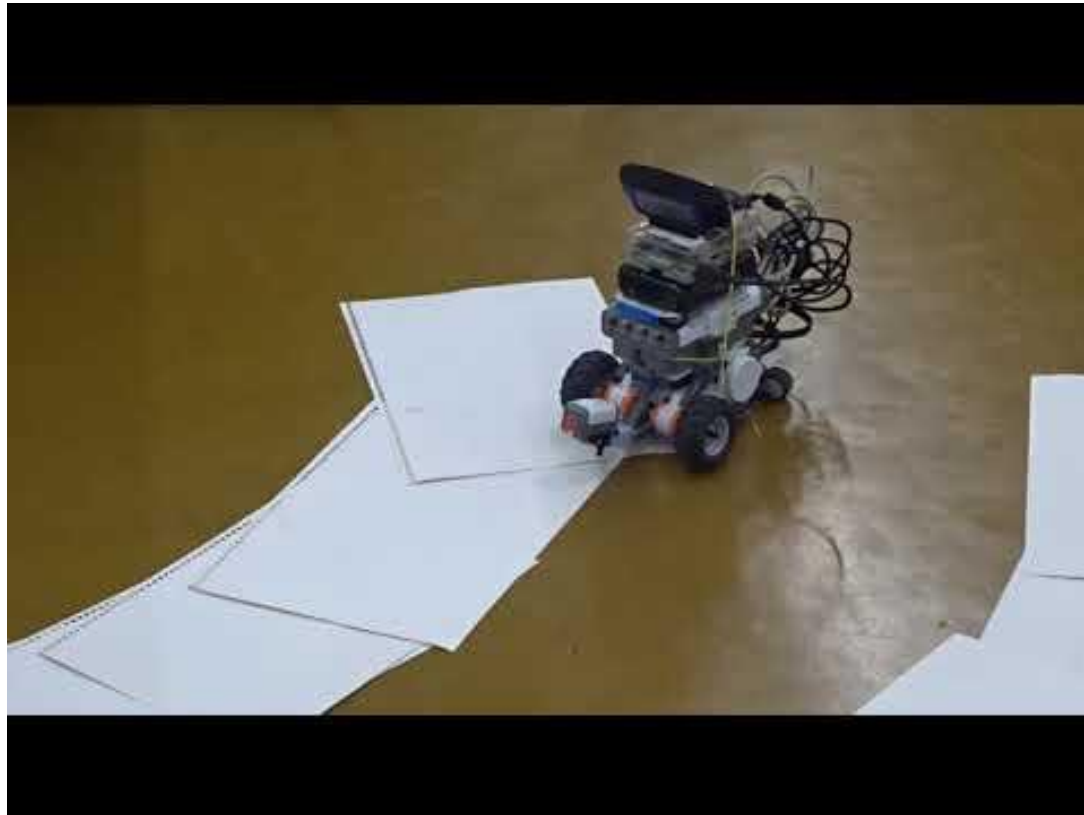
# Confusion matrix of 5682 examples accuracy = 0.790567



# Simulação



# Primeira Tentativa

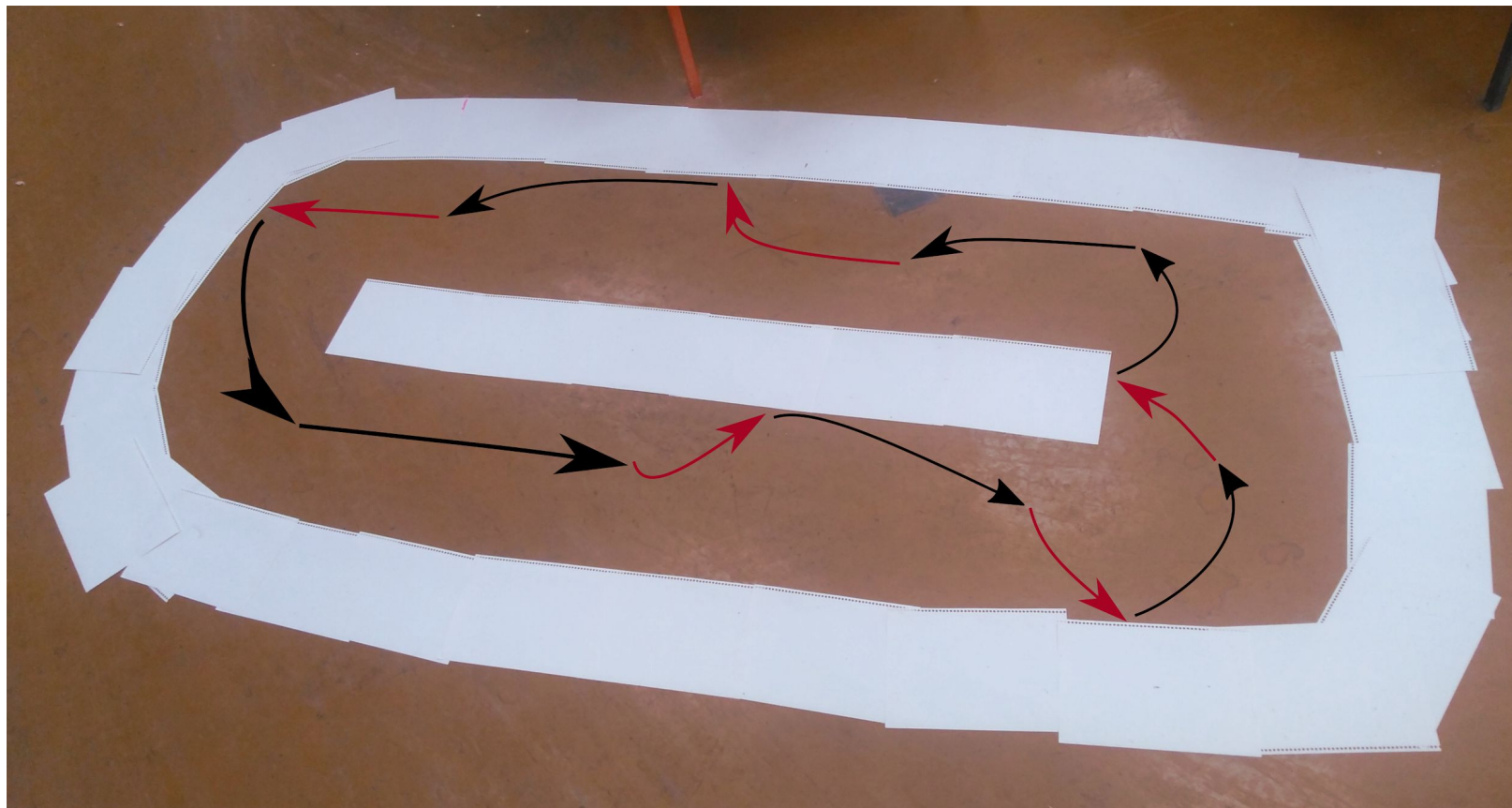


## **PROBLEMA:** dados pouco informativos

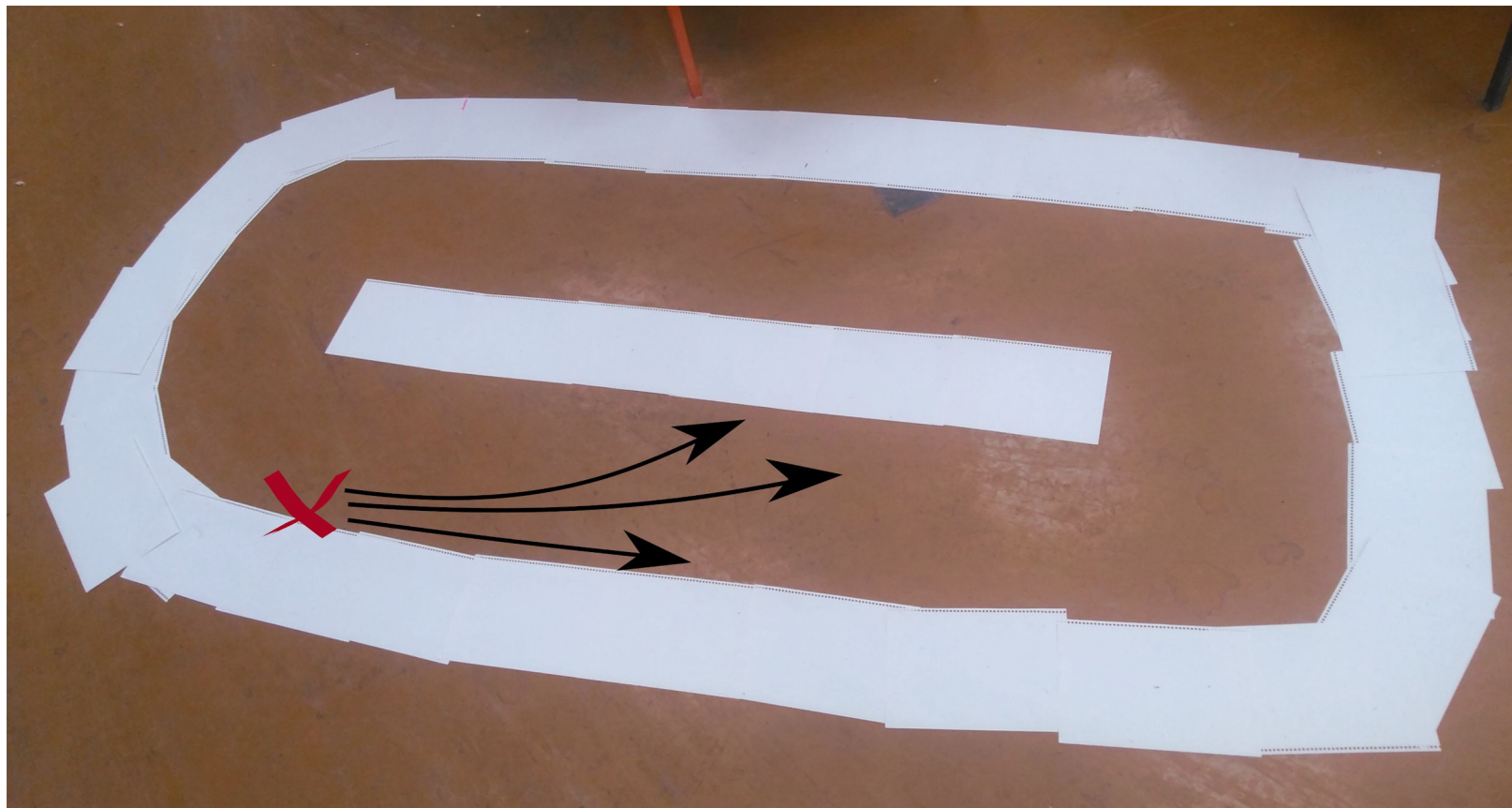
Comando “ir para frente” estava fortemente associado ao robô estar centralizado na pista



# Nova coleta de dados

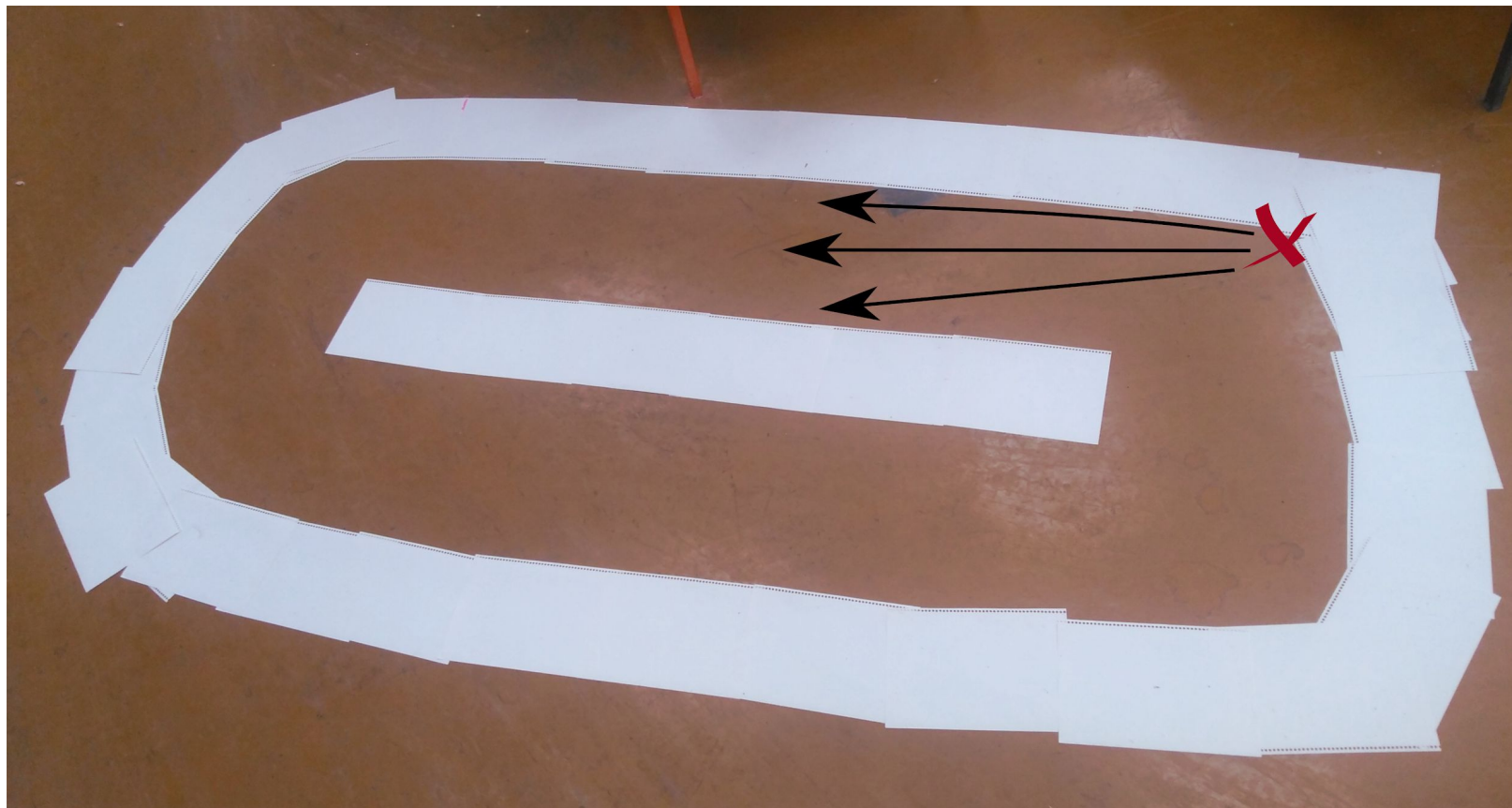


# Nova coleta de dados



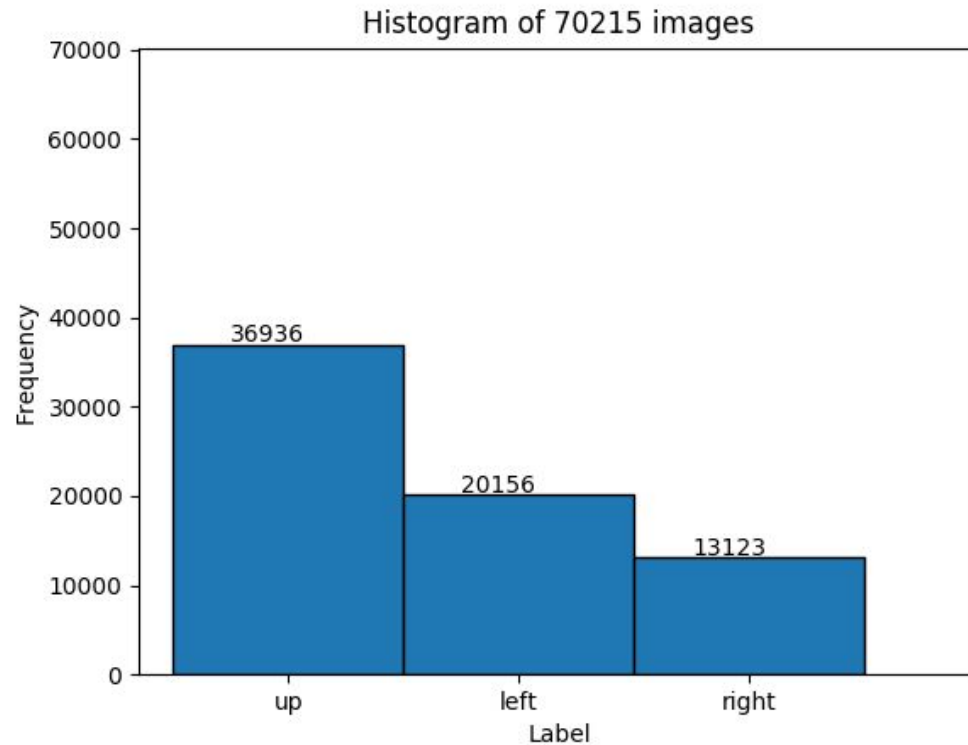


# Nova coleta de dados





# Nova coleta de dados: + 13403 imagens



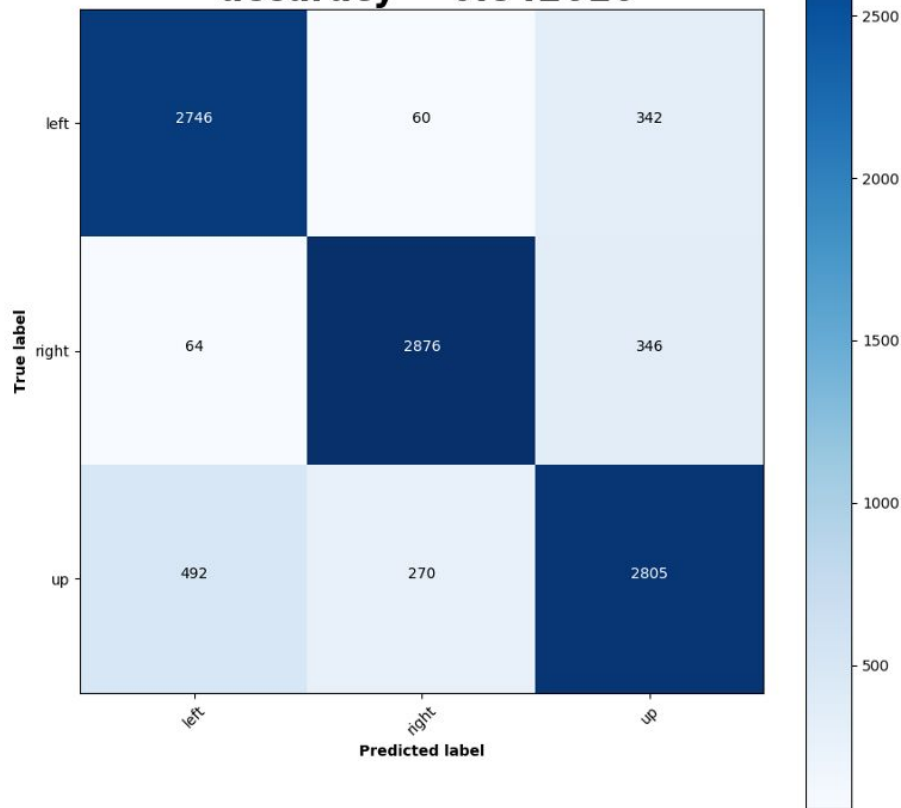
# PROBLEMA: predição x controle

**captura e processamento de imagem ~ 9 ms**

command	time
↑	0.06 s
←	0.29 s
→	0.29 s

architecture	preprocessing	inference time
[3]	none	0.43 s
[1333, 200, 3]	none	1.35 s
[(24, 5), 731, 3]	none	1.41 s
[3]	binarization	0.42 s
[233, 3]	binarization	0.59 s
[(32, 5), (64, 5), 3]	binarization	0.89 s
[(24, 5), (36, 5), (64, 5), 200, 3]	binarization	1.24 s

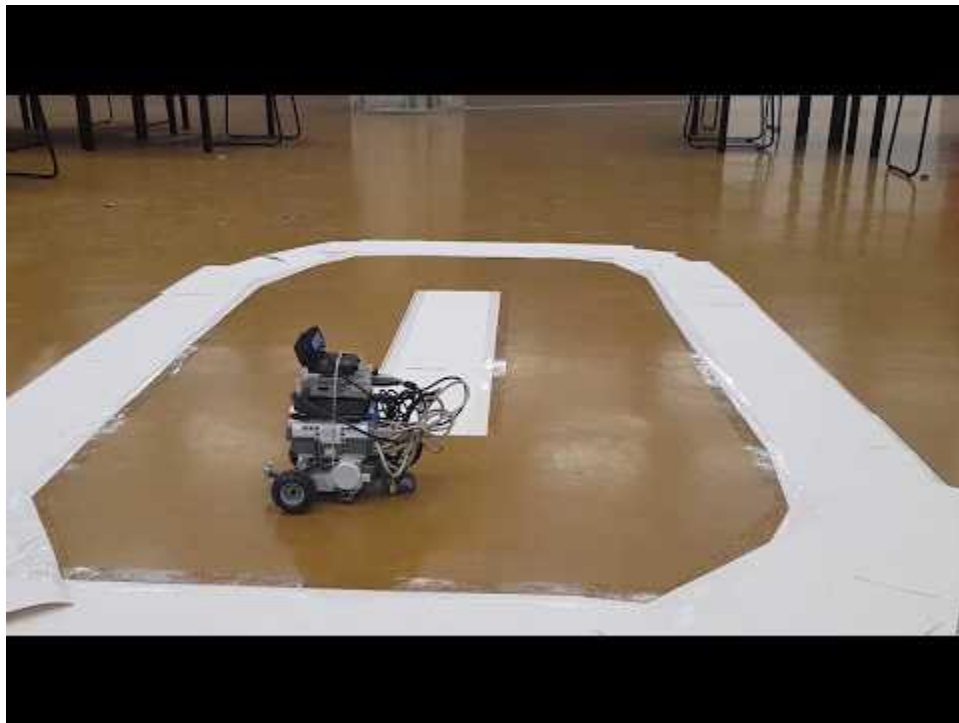
## Confusion matrix of 10001 examples accuracy = 0.842616



## Melhor modelo: [(36, 5), 3]

- imagens RGB
- uma camada de convolução:  
36 filtros 5x5
- uma camada de pooling 2x2
- sem camadas escondidas
- tempo de inferência: 0.69 s

## Modo autônomo - pista de treino



## Pista de teste



## Modo autônomo - pista de teste



# Próximos passos

- **Experimentar novos modelos de direção, e.g. modelo Ackerman**
- **Integrar o robô com outros sensores:**
  - GPS e Radar
- **Detecção de obstáculos**
- **Path planning**
  - Planejar trajetórias do ponto A ao ponto B



# Conclusão

- Machine learning em **aplicações reais** é mais complicada do que em ambientes simulados
- **Começar** com deep learning para carro autônomo é **fácil**
- É possível implementar técnicas avançadas com hardware de **baixo custo**
- Variabilidade na coleta de dados é **essencial**
- O protótipo apresentado pode ser uma solução viável a disciplinas de **inteligência artificial** que desejem ir além de *toy problems*

# Referências

- **Artigo no Medium (@project\_m)**
  - **Self drives me crazy: from 0 to autonomous car in 150 hours**
- **Código no GitHub**
  - **Self-Driving Pi Car**
- **Dataset**
  - **Self-Driving Data**
- **Curso do MIT:**
  - **Deep Learning for Self-Driving Cars**

# Agradecimentos



**Obrigado**