### Solving CAPTCHAs using Optical Character Recognition

## ES654 Machine Learning Project Presentation



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#### Chars74K Dataset



#### Datasets

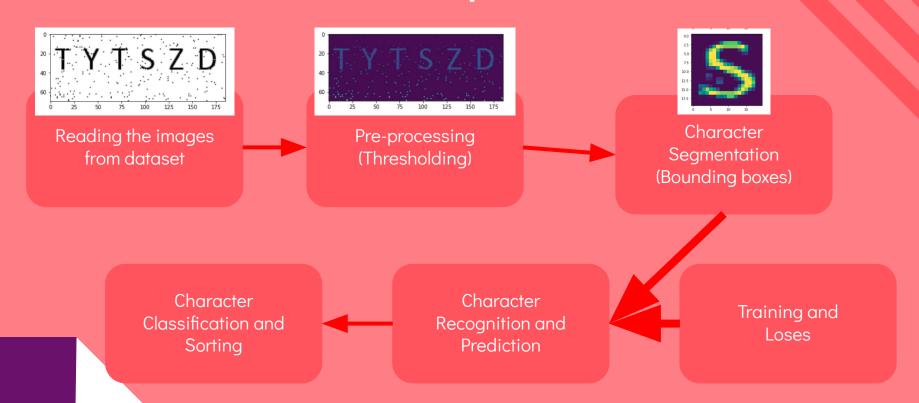
1. Single character dataset



#### 2. Salt and pepper dataset

CACINU PPXXXXQ VNTKTI B WV D C K OHYUGKTI MJ DW QQI FKC Y ET L WD URQKMN SQJKEP EAJWKWZZSBXA GXUZI G DRARRF F P Y N T H Y R R C K X PKJ QDG LKYXTM OLPAPC CJVMTO TXQZTT FAVQOH X HSS WI B N B U V T AI ORFL C MQDYY FPHJYO L WK VYR

#### Basic Pipeline



#### **SVM** Implementation

- ★ We have generated characters for inputs from captcha's.
- ★ We have currently used scikit learn to classify our model.
- ★ Implementation uses one to one coding design.
- ★ We will make two hyperplanes which will separate positive points with negative points and the Hinge loss between the planes will be
  - Hingeloss =  $\max(0,(1 y_i^* (w^T * x_i + b))/2$
- ★ Then we will compute the gradient of cost function.

$$\nabla_{w} J(\mathbf{w}) = \frac{1}{N} \sum_{i}^{n} \begin{cases} \mathbf{w} & \text{if max } (0, 1 - y_{i} * (\mathbf{w} \cdot x_{i})) = 0 \\ \mathbf{w} - Cy_{i} x_{i} & \text{otherwise} \end{cases}$$

- ★ We will then find the weights and bias for the given input images and target images.
- ★ We have also tried to implement SVM from scratch.

#### Fully-Connected NN Implementation

Model: "sequential"		
Layer (type)	Output Shape	Param #
flatten (Flatten)	(None, 400)	Θ
dense (Dense)	(None, 100)	40100
dense_1 (Dense)	(None, 100)	10100
dense_2 (Dense)	(None, 100)	10100
dense_3 (Dense)	(None, 26)	2626

Total params: 62,926 Trainable params: 62,926 Non-trainable params: 0

#### **CNN** Implementation

Layer (type)	Output	Shape	Param #
conv2d_54 (Conv2D)	(None,	32, 32, 1)	26
max_pooling2d_18 (MaxPooling	(None,	16, 16, 1)	0
conv2d_55 (Conv2D)	(None,	16, 16, 1)	2
up_sampling2d_18 (UpSampling	(None,	32, 32, 1)	0
conv2d_56 (Conv2D)	(None,	32, 32, 1)	2
flatten_18 (Flatten)	(None,	1024)	0
dense_108 (Dense)	(None,	1024)	1049600
dropout_90 (Dropout)	(None,	1024)	0
dense_109 (Dense)	(None,	512)	524800
dropout_91 (Dropout)	(None,	512)	0
dense_110 (Dense)	(None,	256)	131328
dropout_92 (Dropout)	(None,	256)	0
dense_111 (Dense)	(None,	128)	32896
dropout_93 (Dropout)	(None,	128)	0
dense_112 (Dense)	(None,	64)	8256
dropout_94 (Dropout)	(None,	64)	0
dense_113 (Dense)	(None,	26)	1690

Total params: 1,748,600 Trainable params: 1,748,600 Non-trainable params: 0

#### Results: SVM sklearn model

Salt-n-pepper

Without noise

Total images processed: 10000

Accuracy: 60.08

WCITEB : WCTEB : False

Total images processed: 10000

Accuracy: 73.99

PRQVTU : PRQVTU : True

#### Results: Fully-connected

Chars74k

Coloured & Noisy

	Pos	Neg	Acc
Char	43548	13407	76.460363
Captcha	3152	6848	31.520000
Current FXYQIR:		10000	

	Pos	Neg	Acc
Char	48972	8368	85.406348
Captcha	6383	3617	63.830000
Current file: 10000 ZJPVCH : ZJPVCH			

#### Results: CNN

	Pos	Neg	Acc
Char	4869	855	85.062893

Captcha 576 424 57.600000

Current file: 1000

RJDFMI : RJDFMI

	Pos	Neg	Acc
Char	48459	8881	84.511685
Captcha	5849	4151	58.490000
Current f	ile: 1	0000	

REWBDL : REWBDL

#### Insights & Inferences

- CNN requires more dissimilar Input data and computational power.
- Our simple dataset (without any noise) had poor performance efficiency as it is reaches its accuracy very quickly. Hence, we added colour and noise.
- Training dataset has variating:
  - Text & background color, rotation, transformation
  - o Blur, noise, font
- Bias-Variance trade off helped us decide the variations required for generating our dataset.

#### Limitations & Future Prospects

- ★ Using our boxed segmentation method we could not recognize the anti-segmented captchas (captcha with connected characters) with good accuracy.
- ★ An End-to-end CNN based model could be developed to give better results.
  - Con: Computationally heavy

# Thank you