Handwritten letter recognition using multi-layer perceptron

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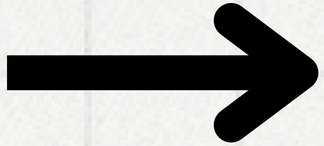

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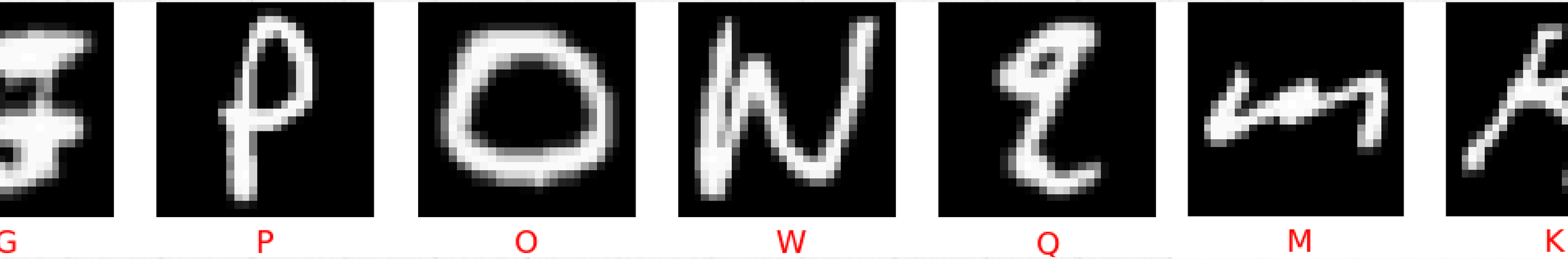
The goal

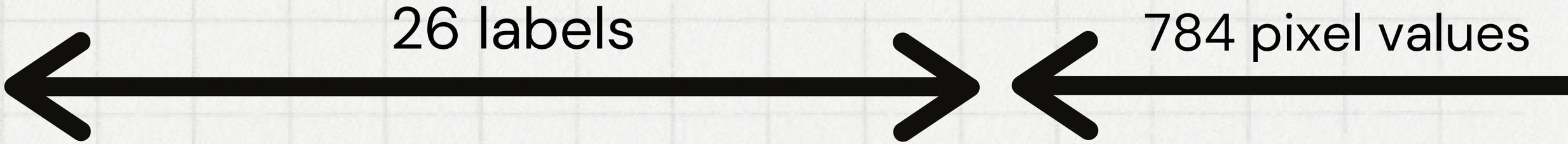
The goal is to develop a feed forward neural network that can accurately classify handwritten letters based on their visual representations.



The dataset for handwritten letters we chose is **Extended MNIST**.
The **EMNIST** Letters dataset merges a balanced set of the uppercase and lowercase letters into a single 26-class task.

Data pre-processing

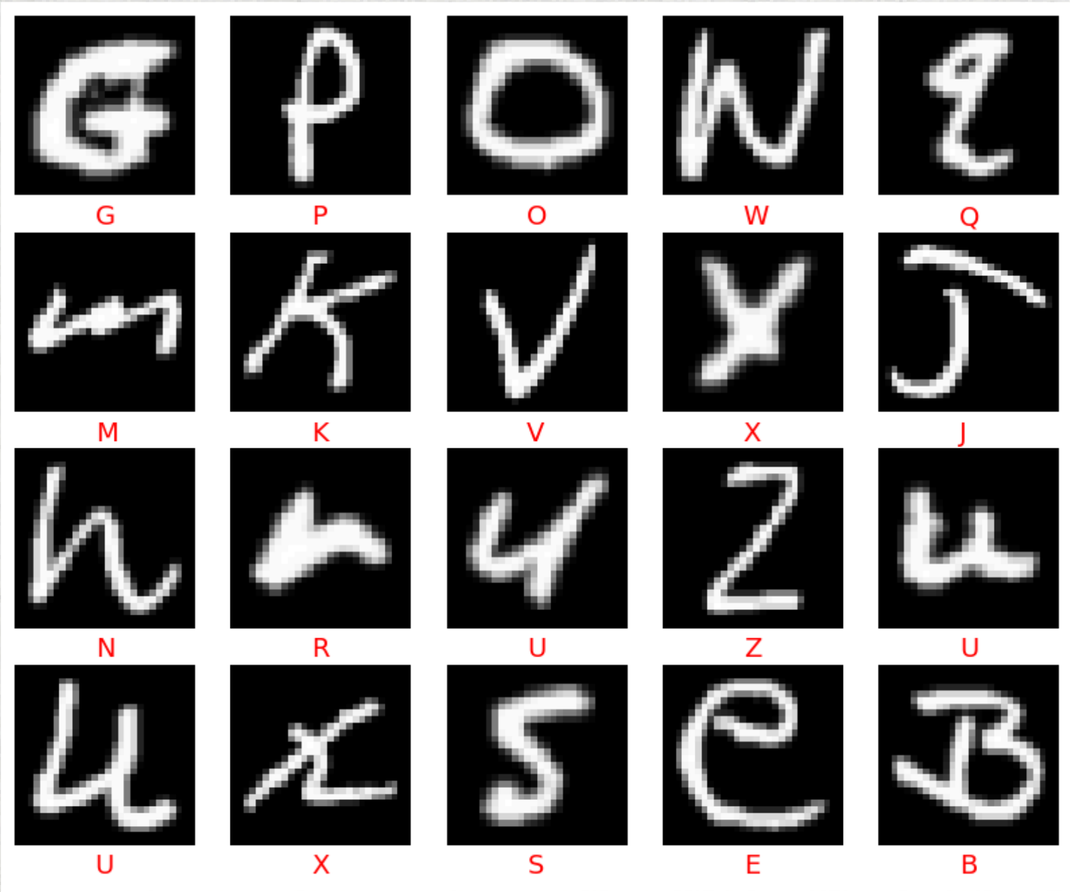
- We split the training dataset into train and test sets (71039 train images, 17760 test images) due to readily available test data not fitting our goals.
- The first column of the datasets were the labels
- Labels were then one-hot encoded.
- The pixels have been normalized

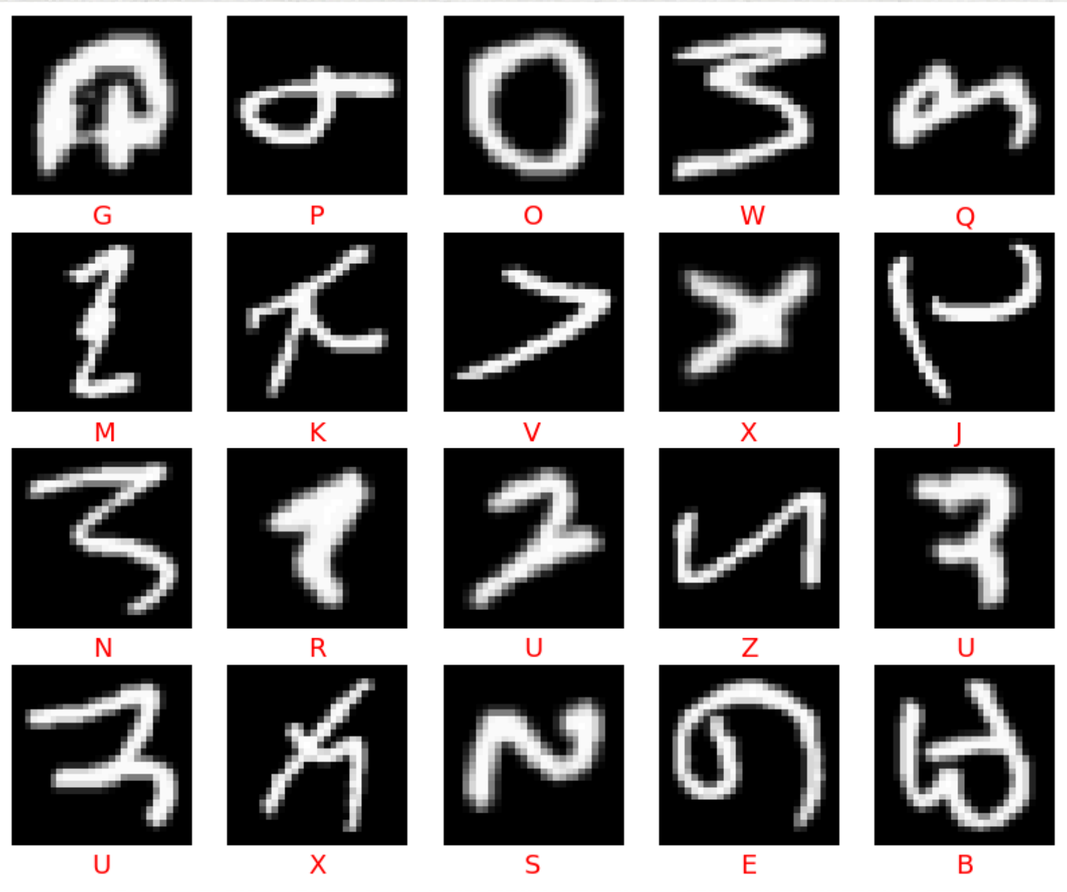


A	B	C	D	E	F	G	.	.	.	Z						
0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1
1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0

working with pixel data

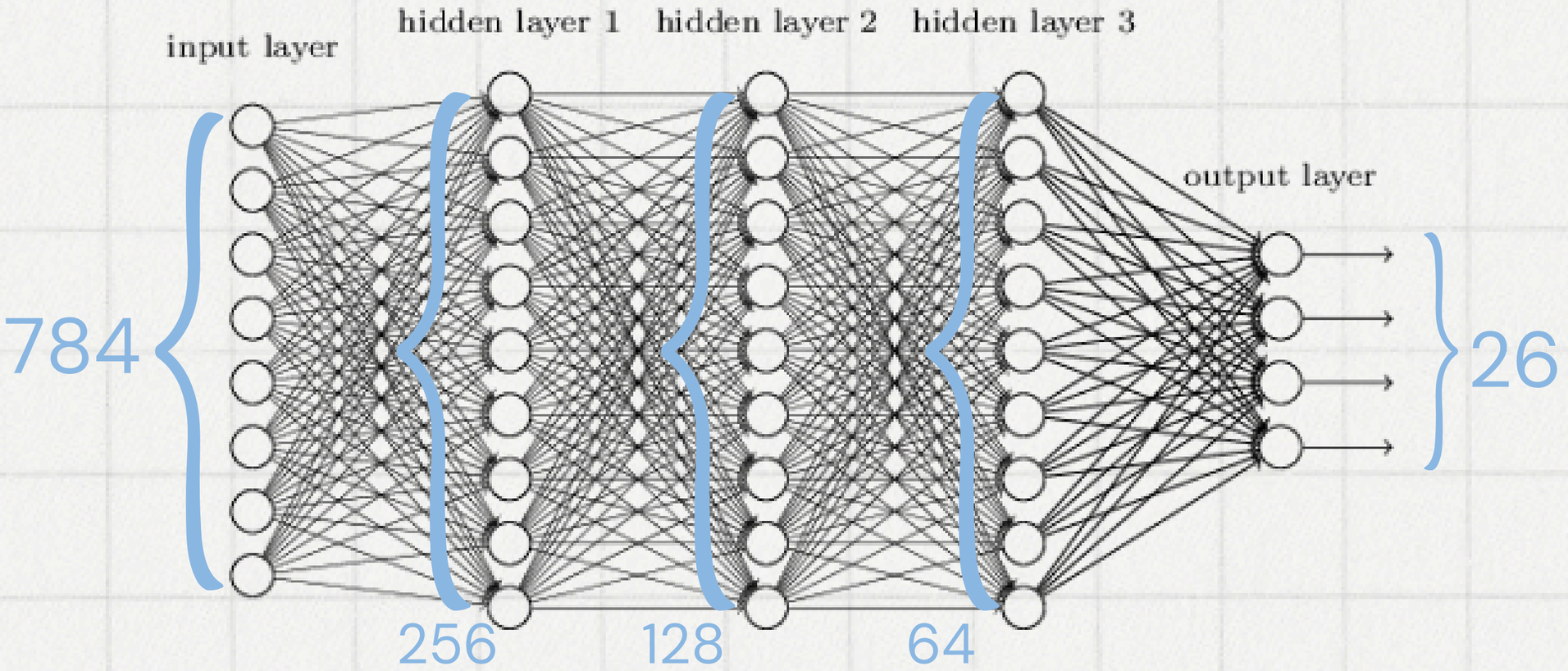
we experimented with the right angle and horizontal flip for the pixel data provided in dataset





Neural Network Architecture

The architecture is composed of linear layers with activations after each



Neurons of those layers are connected through weights, which are initialized from a random uniform distribution in range -0.5, 0.5

$$f(x) = \ln(1 + e^x)$$

In forward propagation each layer has then been activated by Softplus activations. Softplus is a smooth approximation to the ReLU activation function. Through Softplus we dealt with the ”vanishing” gradient problem in the back propagation.

$$f'(x) = \frac{d}{dx} \ln(1 + e^x) = \frac{1}{1 + e^x} \cdot e^x$$

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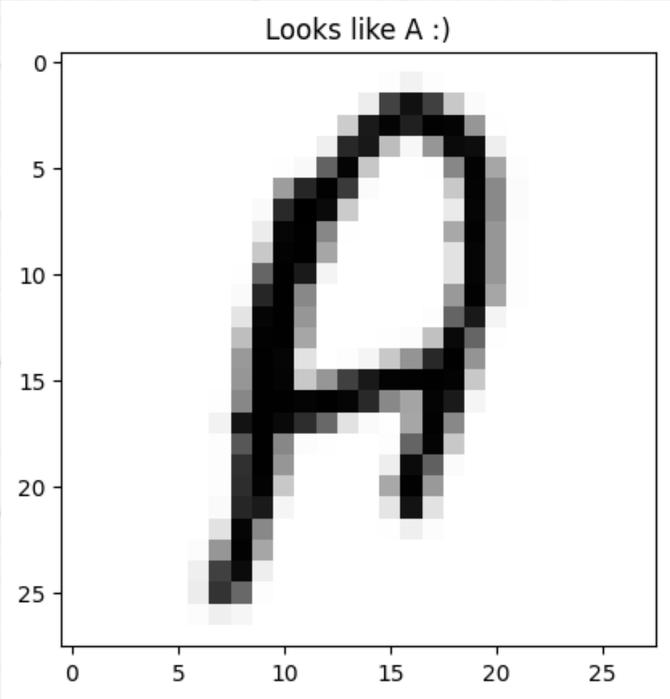
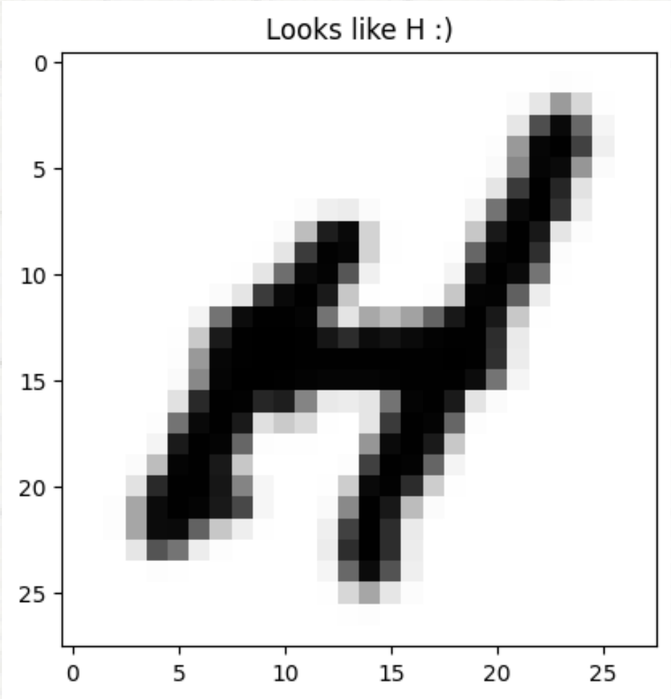
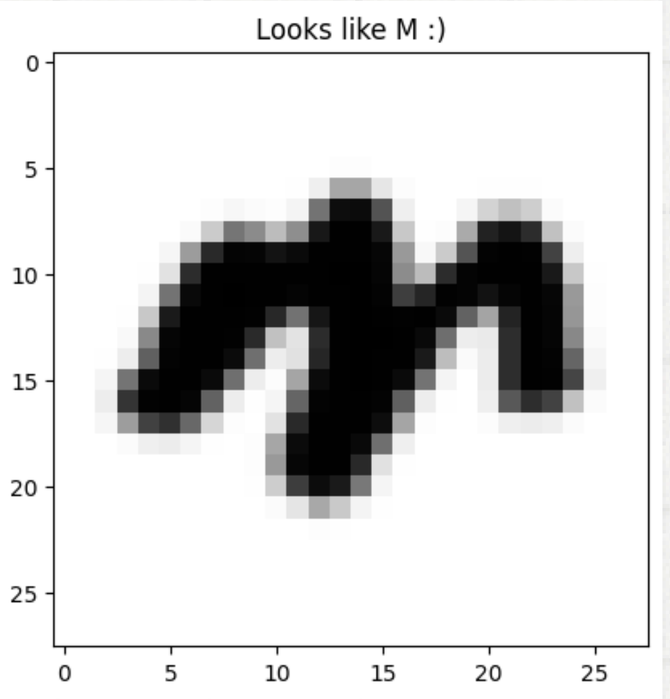
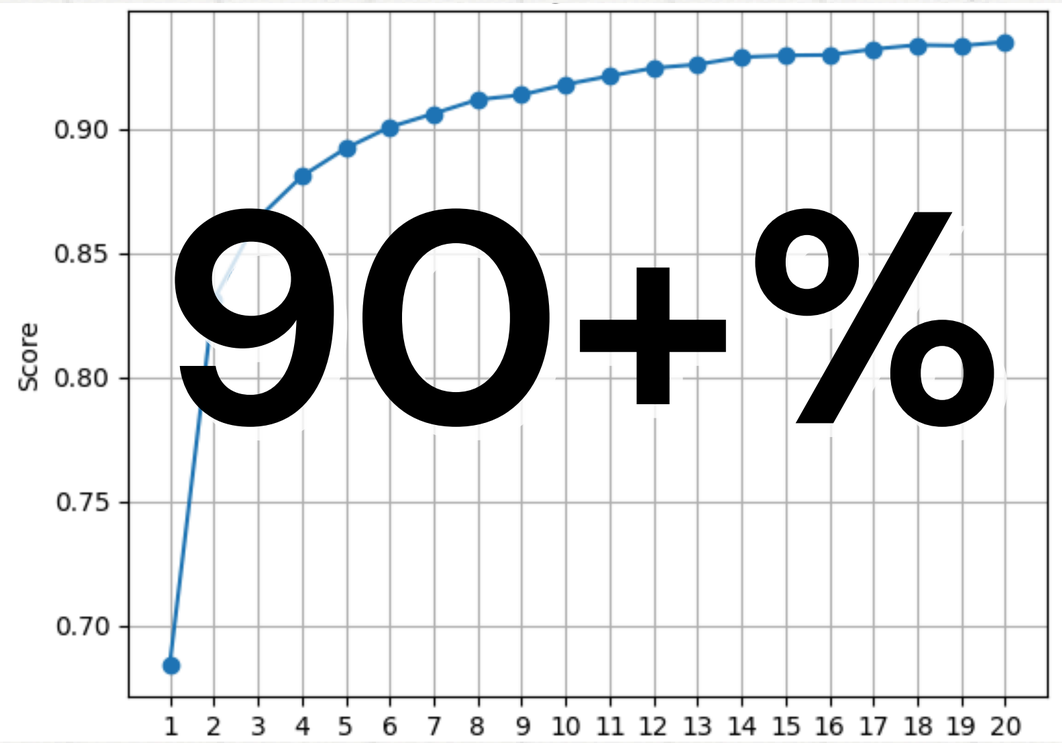
Experiments and Results

Our experiments were aimed at increasing the rate of accuracy during training and giving correct classifications during testing.









accuracy
on training

87+%

accuracy
on test set

Thank you very much!