

1.

, , . , (computer-aided diagnosis) (image segmentation)(image registration)(image fusion)(image-guided therapy)(image annotation)(image database retrieval), , . : [?], [?], [?], .

, , [?]. . , CT. :

2.

2.1.

(neurons) . , . 6, x_i , (bias). (1). w_i , b , $f(.)$ (nonlinear activation function).

$$output = f\left(\sum_{i=1}^3 w_i x_i + b\right) \quad (1)$$

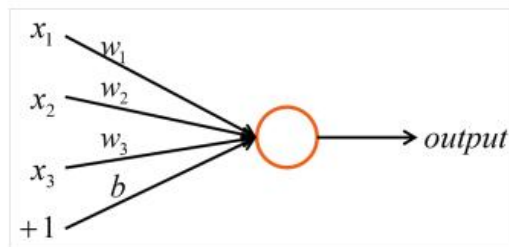


Figura 1.

, x_i w_i . b_i . $f(.)$: S(Logistic Sigmoid Function), (Hyperbolic Tangent Function), (Rectified Linear Unit, ReLU)(Leaky ReLU). 2.

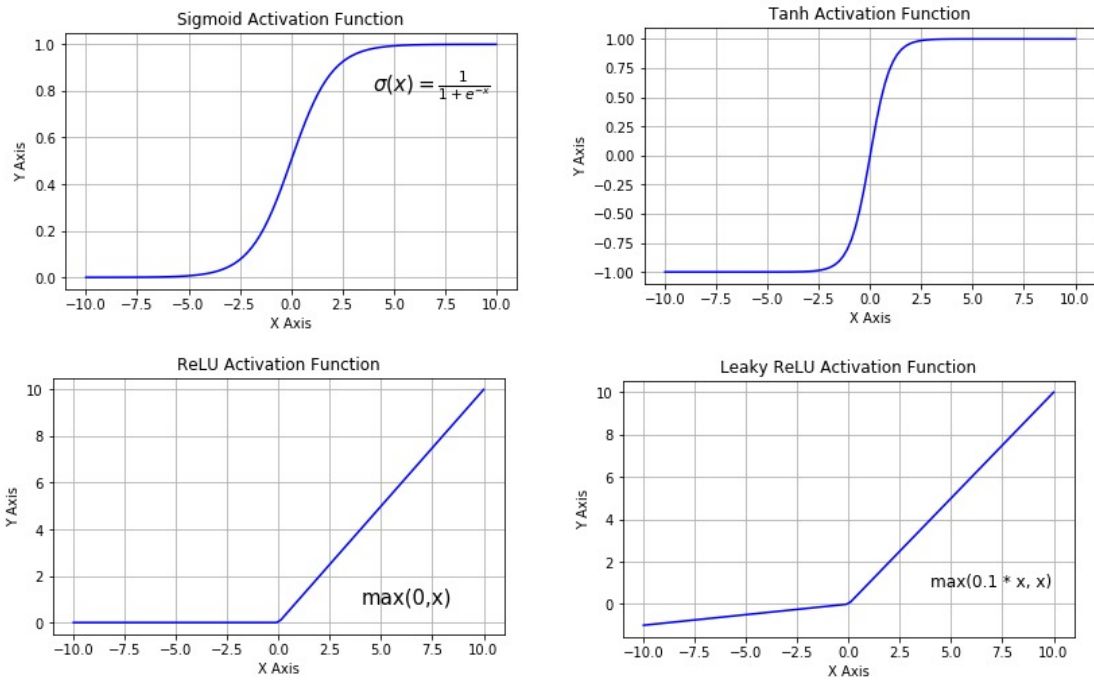


Figure 2. : S(Logistic Sigmoid Function), (Hyperbolic Tangent Function), (Rectified Linear Unit, ReLU)(Leaky ReLU)

(2) - (5)

S(Logistic Sigmoid Function):

(2)

(Hyperbolic Tangent Function):

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (3)$$

(Rectified Linear Unit, ReLU)

$$f(x) = \max(0, x) \quad (4)$$

(Leaky ReLU)

$$f(x) = \begin{cases} x & \text{if } x > 0 \\ 0.01x & \text{otherwise} \end{cases} \quad (5)$$

2.2.

(1) +1+1(unit)

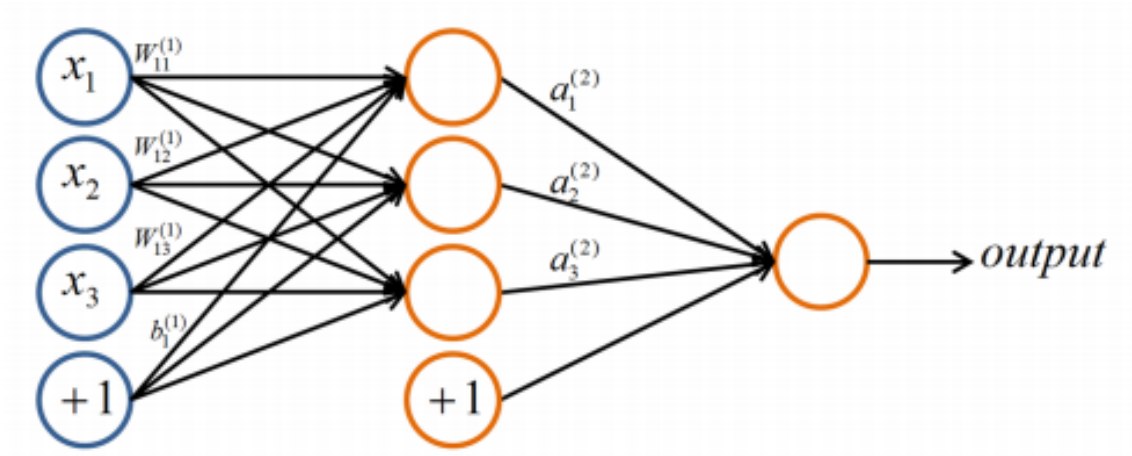


Figura 3. (bias)+1 $a_i^{(l)}$ il

$iL_i, n_L = 3. L_1 L_2, L_3, (W, B) = (W^{(1)}, b^{(1)}, W^{(2)}, b^{(2)}), b_i^{(l)} iW_{ij}^{(l)} lil + 1jW^{(1)} \in \mathbb{R}^{3 \times 3}, W^{(2)} \in \mathbb{R}^{1 \times 3}, b^{(1)} \in \mathbb{R}^3$ and $b^{(2)} \in \mathbb{R}^1$.

$$a_1^{(2)} = f(W_{11}^{(1)} x_1 + W_{12}^{(1)} x_2 + W_{13}^{(1)} x_3 + b_1^{(1)}) \quad (6)$$

$$a_2^{(2)} = f(W_{21}^{(1)} x_1 + W_{22}^{(1)} x_2 + W_{23}^{(1)} x_3 + b_2^{(1)}) \quad (7)$$

$$a_3^{(2)} = f(W_{31}^{(1)} x_1 + W_{32}^{(1)} x_2 + W_{33}^{(1)} x_3 + b_3^{(1)}) \quad (8)$$

$$a_i^{(l)} 1f(.)ll+1$$

$$output = a_1^{(3)} = \sigma(W_{11}^{(2)} a_1^{(2)} + W_{12}^{(2)} a_2^{(2)} + W_{13}^{(2)} a_3^{(2)} + b_1^{(2)}) \quad (9)$$

σ S(Logistic Sigmoid Function), Sigmoid (forward propagation) . $y\{0, 1\}n0, 1, \dots, n$

2.3.

(Back Propagation Gradient Decent) $O_k, \sigma^i(k), i = 1, 2, \dots, n.W$:

$$W(k+1) = W(k) - \lambda \frac{\partial E}{\partial w} \quad (10)$$

:

$$E = \frac{1}{2} \sum_{k=1}^n (t_k - O_k)^2 \quad (11)$$

$t_k k.$

:

:

$$\frac{\partial E}{\partial w_{jk}} = - \sum_k (t_k - O_k) \frac{O_k}{\partial w_{jk}} \quad (12)$$

:

$$\frac{\partial E}{\partial w_{ij}} = - \sum_k (t_k - O_k) \frac{O_k}{\partial w_{ij}} \quad (13)$$

:

$$\frac{\partial E}{\partial w_l} = - \sum_k (t_k - O_k) \frac{O_k}{\partial w_l} = - \sum_k (t_k - O_k) \frac{O_k}{\partial \sigma_k} \frac{\partial \sigma_k}{\partial w_l} \quad (14)$$

1. .

Algorithm 1:

```

1 :
2   (x,y),w, (V, E), V, E
3    $\sigma : \mathbb{R} \rightarrow \mathbb{R}$ 
4 :
5   V0, ..., VT, Vt = {vt,1, ..., vt,kt}
6   tt+1((vt,j, vt+1,i)) Wt,i,j, (vt,j, vt+1,i ∉ E), Wt,i,j = 0
7 :
8   O0 = x
9   for t = 1, ..., T do
10    for i = 1, ..., kt do
11       $a_{t,i} = \sum_{j=1}^{k_{t-1}} W_{t-1,i,j} O_{t-1,j}$ 
12       $O_{t,i} = \sigma(a_{t,i})$ 
13    end
14  end
15 :
16   $\delta_T = \mathbf{O}_T - \mathbf{y}$ 
17  for t = T − 1, T − 2, ..., 1 do
18    for i = 1, ..., kt do
19       $\delta_{t,i} = \sum_{j=1}^{k_{t+1}} W_{t,i,j} \delta_{t+1,j} \sigma'(a_{t+1,j})$ 
20    end
21  end
22 :
23  (vt-1,j, vt,i) ∈ E
24   $\delta_{t,i} \sigma'(a_{t,i}) O_{t-1,j}$ 

```

3. CT

3.1.

, CTCTCTCT

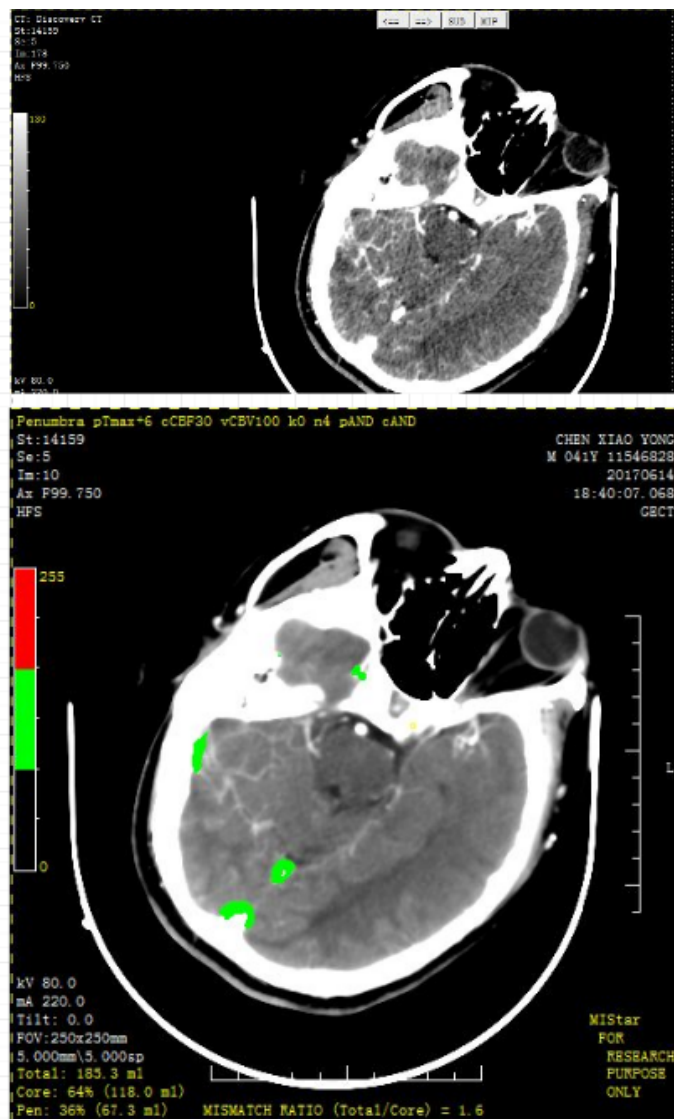


Figura 4. CTCT

(CNN): (Convolutions) , (Subsampling)(fully connected). , , 5,,1, , , 0, . 6, , ()..

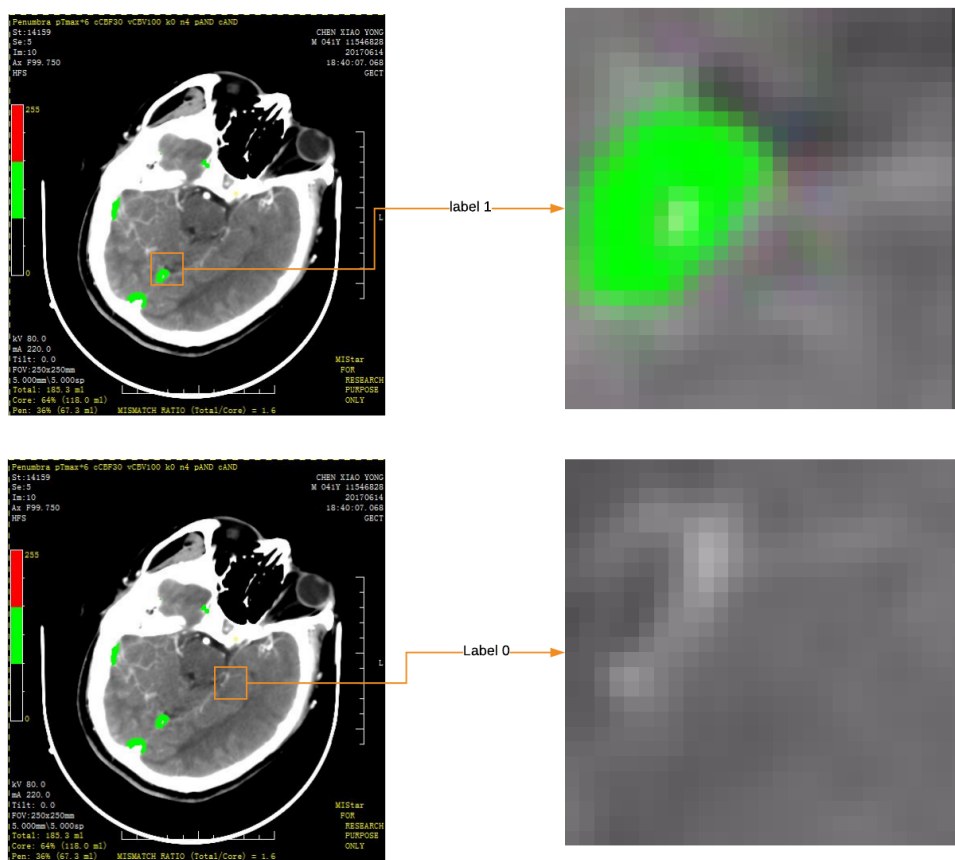


Figure 5. CT: $CT_{422} \times 733, \dots, 1, \dots, 0, \dots$

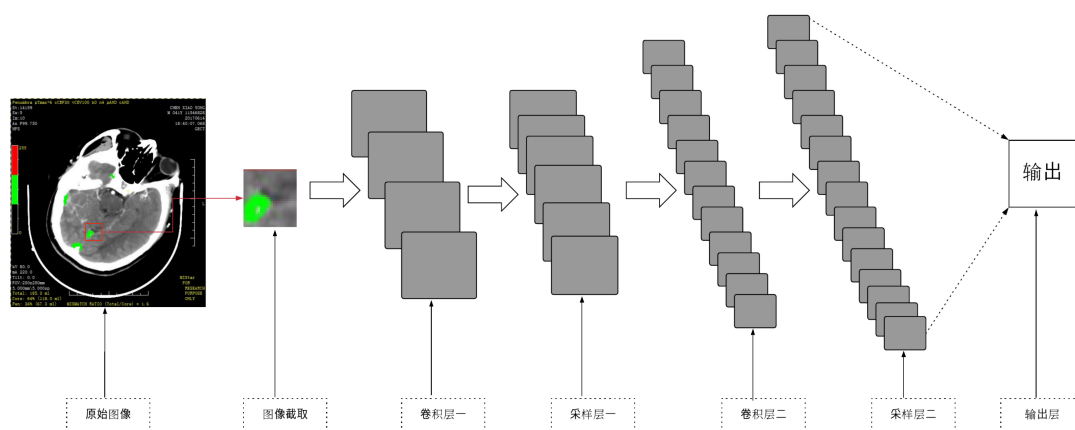


Figure 6. : , ()

3.2.

, Google Tensorflow, KerasOpenCV. KerasTheanoTensorflowPython, . Python 2.73.5KerasGPU/CPU.Keras, :

- .
- keras,
- Keras

KerasPython .

Listing 1. Keras example

```
def getModel():
    model=Sequential()

    # CNN 1
    model.add(Conv2D(64, kernel_size=(3, 3), activation='relu', input_shape=(28, 28, 1)))
    model.add(MaxPooling2D(pool_size=(3, 3), strides=(2, 2)))
    model.add(Dropout(0.2))

    # CNN 2
    model.add(Conv2D(128, kernel_size=(3, 3), activation='relu' ))
    model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
    model.add(Dropout(0.2))

    # CNN 3
    model.add(Conv2D(128, kernel_size=(3, 3), activation='relu' ))
    model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
    model.add(Dropout(0.2))

    #CNN 4
    model.add(Conv2D(64, kernel_size=(3, 3), activation='relu' ))
    model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
    model.add(Dropout(0.2))

    model.add(Flatten())

    #Dense 1
    model.add(Dense(512, activation='relu' ))
    model.add(Dropout(0.2))

    #Dense 2
    model.add(Dense(256, activation='relu' ))
    model.add(Dropout(0.2))

    # Output
    model.add(Dense(1, activation="sigmoid"))

    optimizer = Adam(lr=0.001, decay=0.0)
    model.compile(loss='binary_crossentropy', optimizer=optimizer, metrics=['accuracy'])

    return model
```

3.3.

, , , , : , , .7, ,, 100, . : (Rotation), (transportation), (Shear) (Brightness).



Figura 7.

4.

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<https://ani.stat.fsu.edu/jinfeng/>

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:<https://jianwang2018.github.io/jianwang.github.io/>