DIPLOMSKI RAD BR. 2016

Klasifikacija histopatoloških snimaka dijelova limfnih čvorova pomoću strojnog učenja

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ZAGREB, 3.7.2019.

Sadržaj

- Histopatološke slike
- Skup podataka
- Korišteni modeli

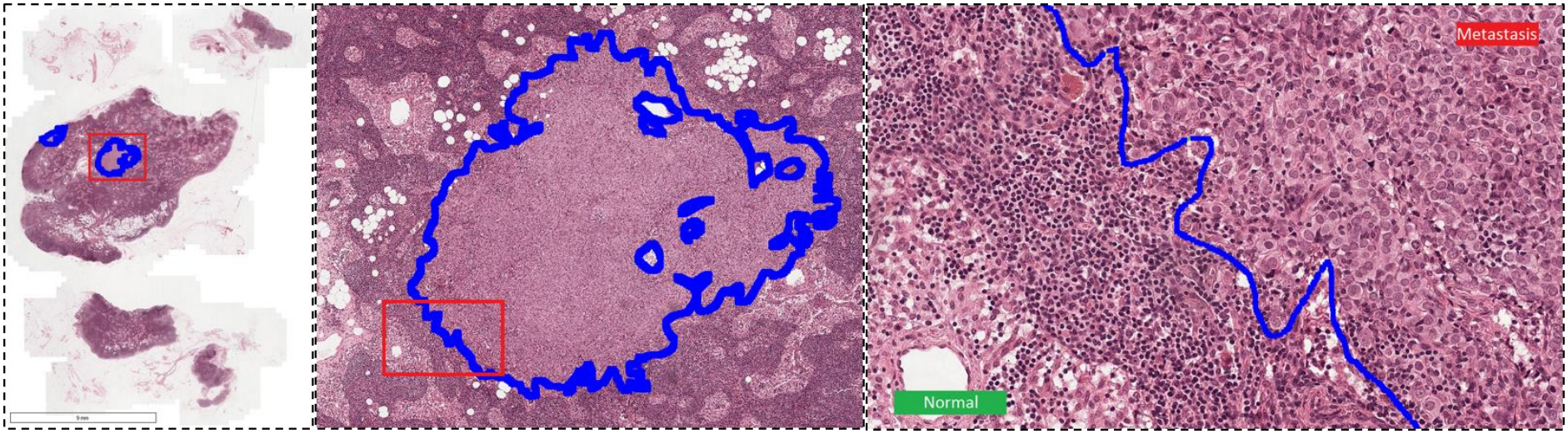
- Usporedba načina učenja
- Usporedba transformacija za proširivanje skupa podataka

- Rezultati
- Zaključak

Histopatološke slike

- **Histopatologija**
- Tehnika **snimanja čitavog preparata** (WSI)
- Camelyon16 natjecanje

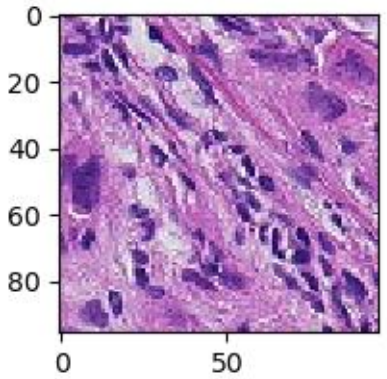
Primjer



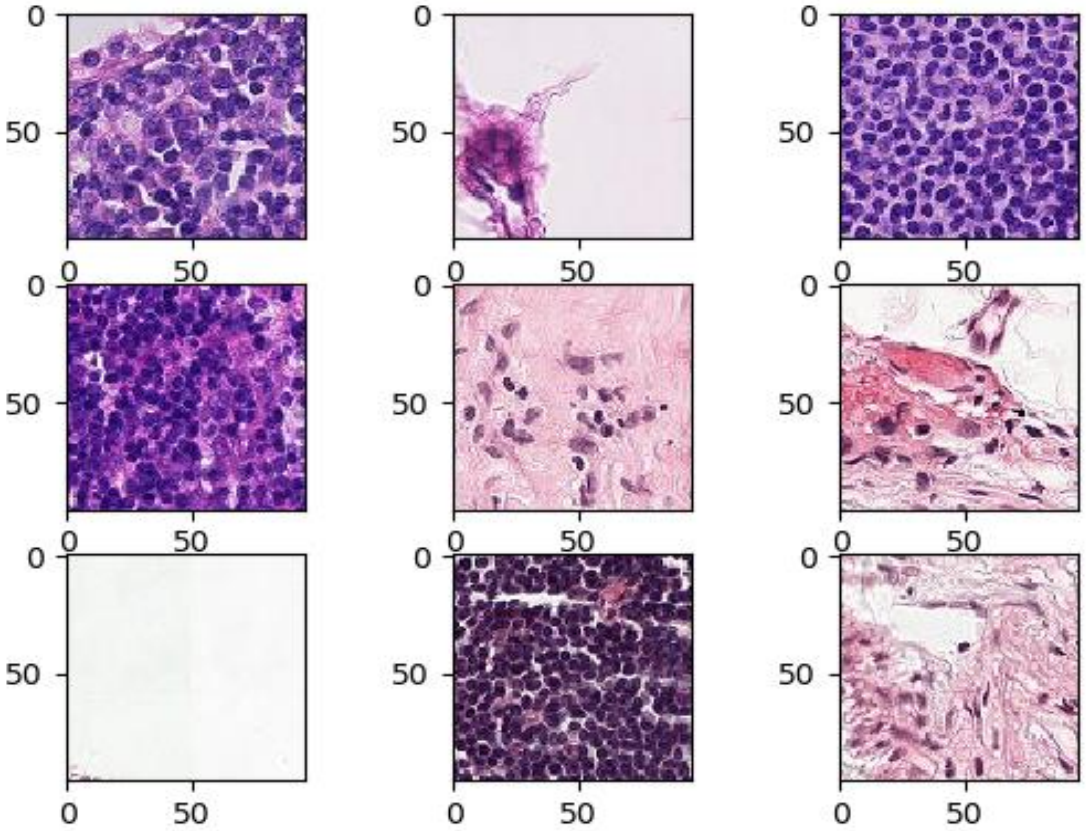
- Izvor: Camelyon 16 natjecanje
- Veličina: $200{,}000 \times 100{,}000$ slikovnh elemenata

Skup podataka - PatchCamelyon

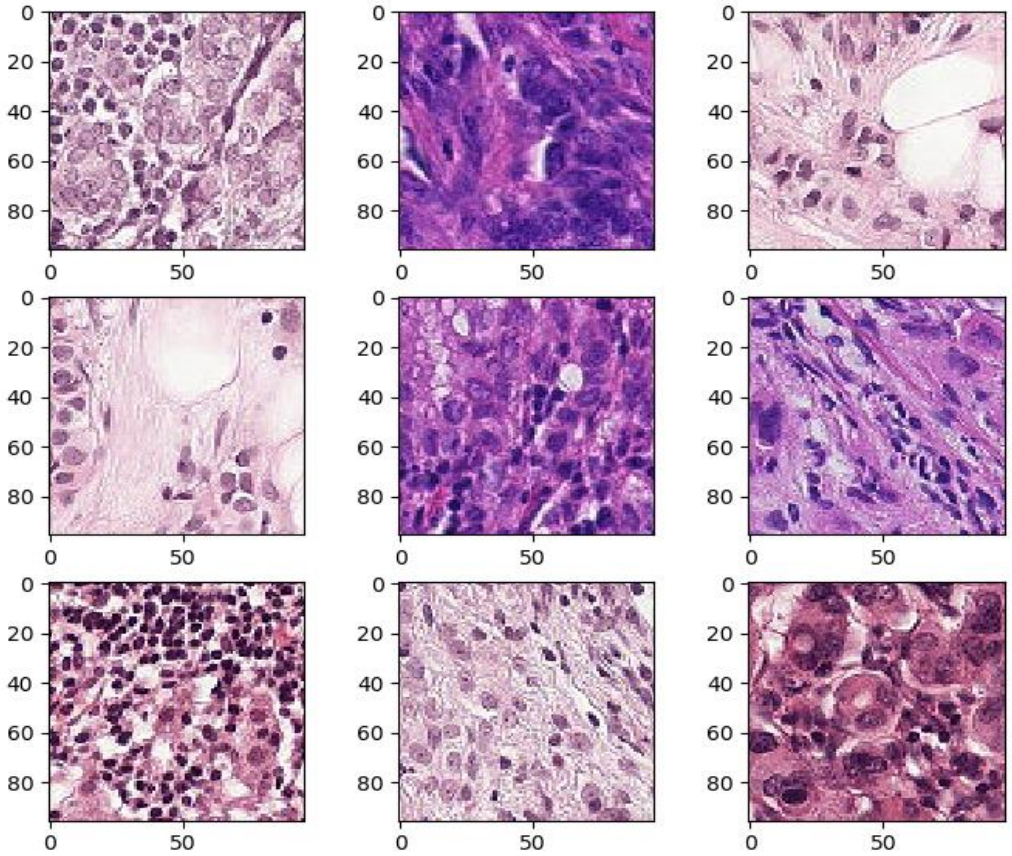
- 96×96 slikovna elementa
- **Binarne oznake**
  - 0 – ne sadrži tumor
  - 1 – sadrži tumor
- Veličina – **327,680 slika**
  - Skup za **učenje 80%**
  - Skup za **validaciju 10%**
  - Skup za **testiranje 10%**
- **Jednaki omjer** pozitivnih i negativnih primjera



PCam - negativni primjeri



PCam - pozitivni primjeri



Zadatak klasifikacije

- **Binarna klasifikacija**
  - Slika -> {0, 1}
- Odabir pristupa → **modeli dubokog učenja**

Korišteni modeli

Naziv modela	Broj parametara	Broj slojeva s aktivacijskom funkcijom
AlexNet	57,877,824	8
ResNet18	11,186,645	18
DenseNet121	6,954,881	121
Inception-v3	27,161,264	98

Eksperimenti 1/2

- **Usporedba** korištenih **modela**
- Korištenje **različitih stopa učenja**
- Analiza utjecaja **učenja prijenosom značajki**
  - Učenje **ispočetka**
  - Učenje **prijenosom značajki** i mijenjanje **svih slojeva**
  - Učenje **prijenosom značajki** i mijenjanje **zadnjeg sloja**

➢ Prijenos značajki sa skupa podataka *ImageNet*

Dodatne napomene

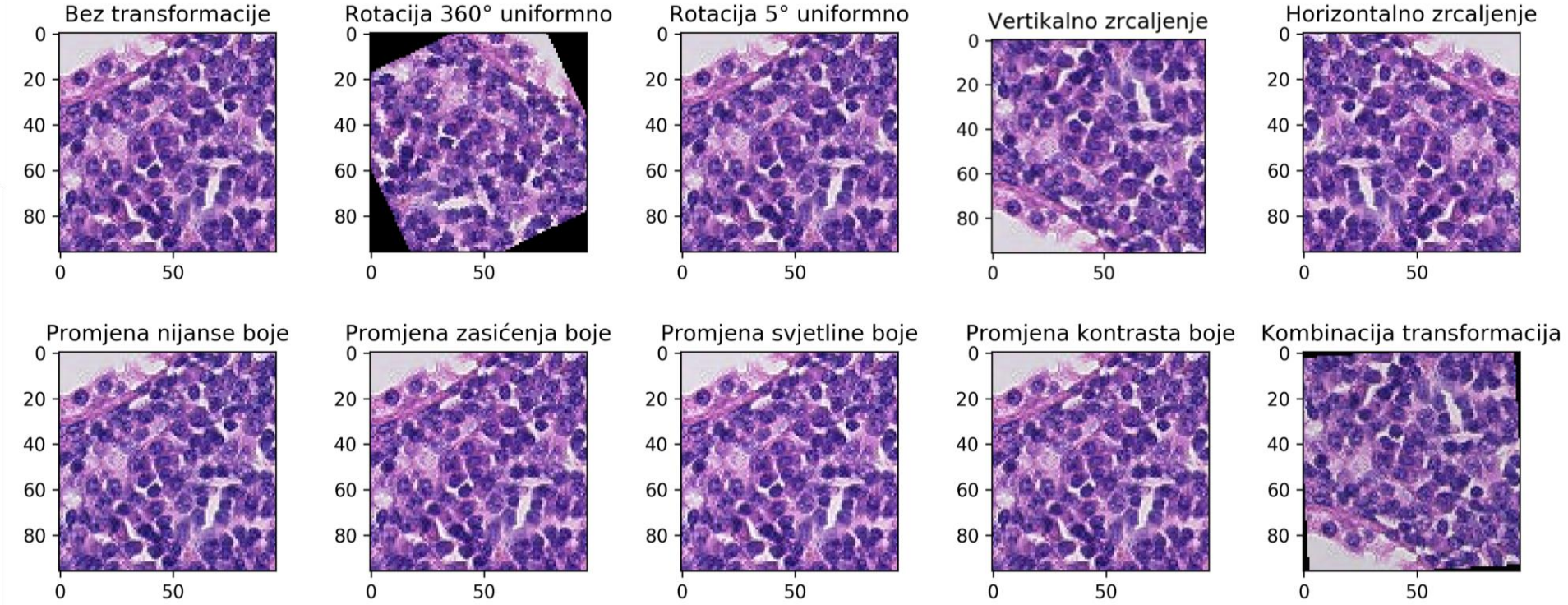
- Algoritam za učenje ADAM
- Veličina mini-grupe: 32
- Rano zaustavljanje
- Stopa učenja: $\{10^{-3}, 10^{-4}, 10^{-5}, 10^{-6}\}$
- Gubitak unakrsne entropije
- Mjere usporedbe: točnost, F1, površina ispod krivulje ROC

Eksperimenti 2/2

- **Analiza utjecaja transformacija** za proširivanje skupa podataka

- Model DenseNet
  - Prijenos značajki sa skupa podataka ImageNet
  - Stopa učenja: 10^{-4}

Transformacije



Rezultati – učenje ispočetka (1)

Naziv	Stopa učenja	Točnost	Mjera F1	AUC ROC
AlexNet	10^{-5}	0.7847	0.7763	0.8662
ResNet	10^{-3}	0.8123	0.7898	0.9042
DenseNet	10^{-3}	0.8125	0.7862	0.8788

Rezultati – učenje prijenosom značajki – svi slojevi (2)

Naziv	Stopa učenja	Točnost	Mjera F1	AUC ROC
AlexNet	10^{-4}	0.7991	0.7720	0.9048
ResNet	10^{-4}	0.8518	0.8334	0.9295
DenseNet	10^{-4}	0.8670	0.8522	0.9409
Inception-v3	10^{-3}	0.8884	0.8872	0.9489

Rezultati – učenje prijenosom značajki – zadnji sloj (3)

Naziv	Stopa učenja	Točnost	Mjera F1	AUC ROC
AlexNet	10^{-6}	0.7592	0.7301	0.8496
ResNet	10^{-4}	0.7822	0.7676	0.8637
DenseNet	10^{-3}	0.8065	0.8009	0.8874
Inception-v3	10^{-4}	0.8210	0.8149	0.9022

Rezultati – usporedba načina učenja

Naziv modela	AUC ROC (1)	AUC ROC (2)	AUC ROC (3)
AlexNet	0.8662	0.9048	0.8496
ResNet	0.9042	0.9295	0.8637
DenseNet	0.8788	0.9409	0.8874
Inception-v3	-	0.9489	0.9022

(1) učenje ispočetka
(2) prijenos značajki - svi slojevi
(3) prijenos značajki - zadnji sloj

Rezultati - transformacije

Transformacija	Točnost	Mjera F1	AUC ROC
Bez transformacija	0.8670	0.8522	0.9409
Rotacija slike 360°	0.8447	0.8266	0.9110
Rotacija slike 5°	0.8719	0.8619	0.9407
Vertikalno zrcaljenje	**0.8881**	**0.8816**	**0.9563**
Horizontalno zrcaljenje	0.8766	0.8701	0.9419
Promjena nijanse	0.8704	0.8577	0.9473
Promjena zasićenja	0.8566	0.8425	0.9271
Promjena svjetline	0.8669	0.8549	0.9346
Promjena kontrasta	0.8714	0.8637	0.9425
Kombinacija	**0.8867**	**0.8798**	**0.9589**

Zaključak 1/2

- Uspoređeni su različiti modeli za klasifikaciju histopatoloških snimaka limfnih čvorova
  - AlexNet, ResNet, DenseNet, Inception-v3
- **Učenje prijenosom značajki** sa skupa podataka ImageNet i **učenje čitavog modela** se pokazalo najbolje
- Model s najboljim rezultatima **Inception-v3**
- Ispitan je utjecaj transformacija za proširivanje skupa podataka
  - **Najbolji** rezultat: **vertikalno zrcaljenje**, **kombinacija** transformacija
  - **Negativan** rezultat: promjena **zasićenja**, **velika rotacija**

Zaključak 2/2

- Nastavak rada
  - Vrednovanje modela na snimkama snimanim metodom WSI
  - Istraživanje primjene metoda interpretabilnosti

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Hvala

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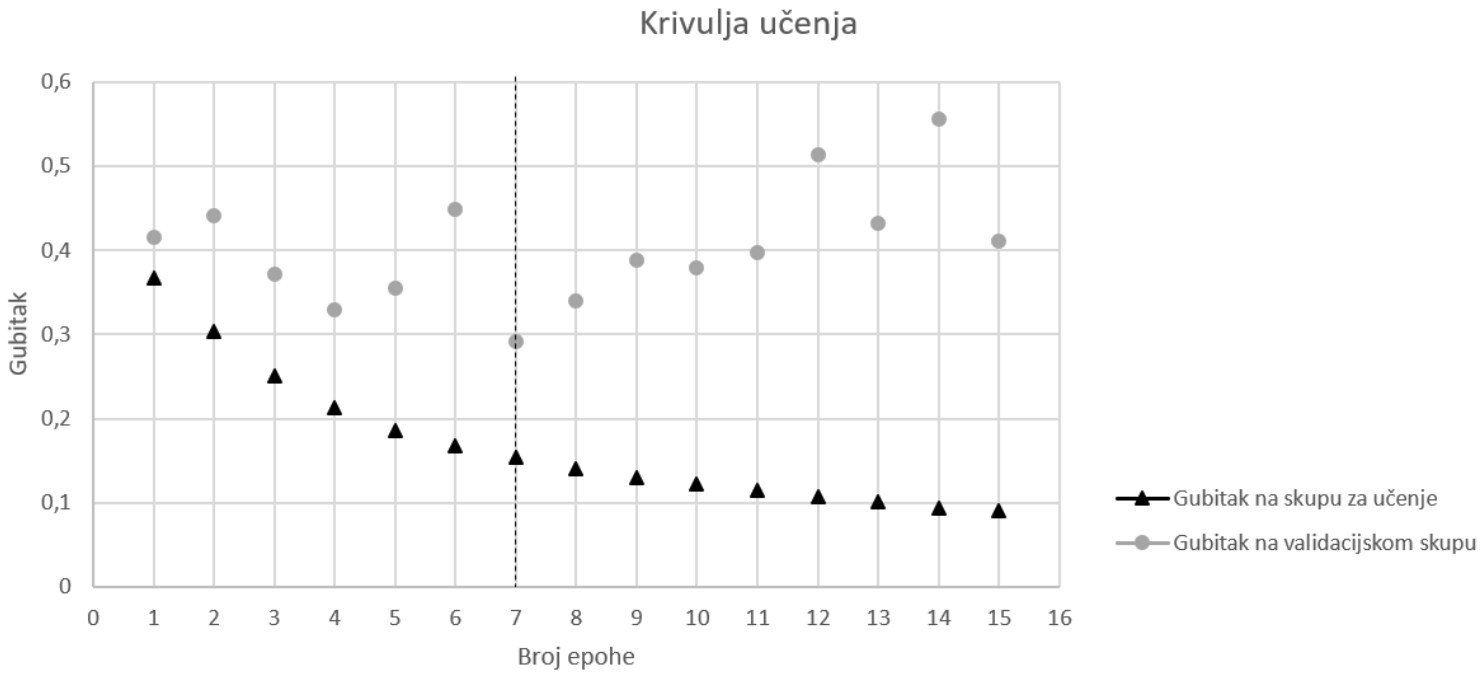
Krivulja učenja



Rezultati modela učenih ispočetka s različitom stopom učenja

Naziv modela	Stopa učenja	Točnost	Mjera *F1*	*AUC ROC*
AlexNet	10^{-3}	0.4998	0.6665	0.5000
AlexNet	10^{-4}	0.7838	0.7697	0.8711
AlexNet	$\mathbf{10^{-5}}$	**0.7847**	**0.7763**	**0.8662**
AlexNet	10^{-6}	0.7688	0.7694	0.8479
ResNet	$\mathbf{10^{-3}}$	**0.8123**	**0.7898**	**0.9042**
ResNet	10^{-4}	0.7853	0.7827	0.8743
ResNet	10^{-5}	0.7892	0.7857	0.8720
ResNet	10^{-6}	0.7613	0.7492	0.8382
DenseNet	$\mathbf{10^{-3}}$	**0.8125**	**0.7862**	**0.8788**
DenseNet	10^{-4}	0.7910	0.7583	0.8999
DenseNet	10^{-5}	0.7872	0.7690	0.8714
DenseNet	10^{-6}	0.7752	0.7684	0.8581

Rezultati modela inicijaliziranih prijenosom značajki sa skupa podataka ImageNet. Prilikom učenja svi parametri su prilagođavani.

Naziv modela	Stopa učenja	Točnost	Mjera *F1*	*AUC ROC*
AlexNet	10^{-3}	0.4997	0.6664	0.4999
AlexNet	$\mathbf{10^{-4}}$	**0.7991**	**0.7720**	**0.9048**
AlexNet	10^{-5}	0.7812	0.75336	0.8815
AlexNet	10^{-6}	0.7800	0.7477	0.8764
ResNet	10^{-3}	0.8297	0.8144	0.9184
ResNet	$\mathbf{10^{-4}}$	**0.8518**	**0.8334**	**0.9295**
ResNet	10^{-5}	0.8485	0.8386	0.9266
ResNet	10^{-6}	0.8200	0.7978	0.9164
DenseNet	10^{-3}	0.8150	0.7858	0.9088
DenseNet	$\mathbf{10^{-4}}$	**0.8670**	**0.8522**	**0.9409**
DenseNet	10^{-5}	0.8555	0.8408	0.9354
DenseNet	10^{-6}	0.8201	0.7920	0.9271
Inception-v3	$\mathbf{10^{-3}}$	**0.8884**	**0.8872**	**0.9489**
Inception-v3	10^{-4}	0.8741	0.8661	0.9430
Inception-v3	10^{-5}	0.8501	0.8327	0.9483
Inception-v3	10^{-6}	0.8587	0.8436	0.9459

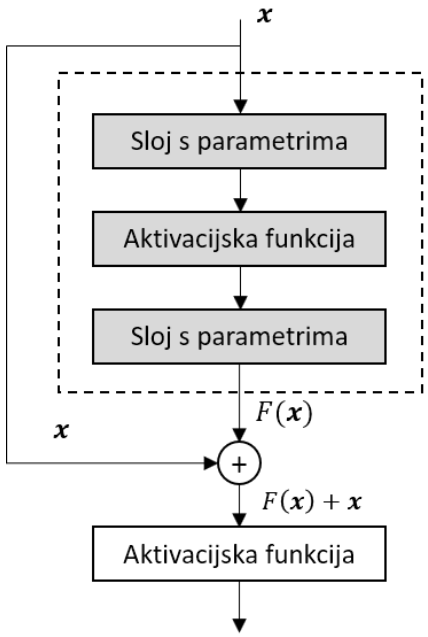
Rezultati modela inicijaliziranih prijenosom značajki sa skupa podataka ImageNet. Prilikom učenja samo zadnji potpuno povezani slojevi su prilagođavani.

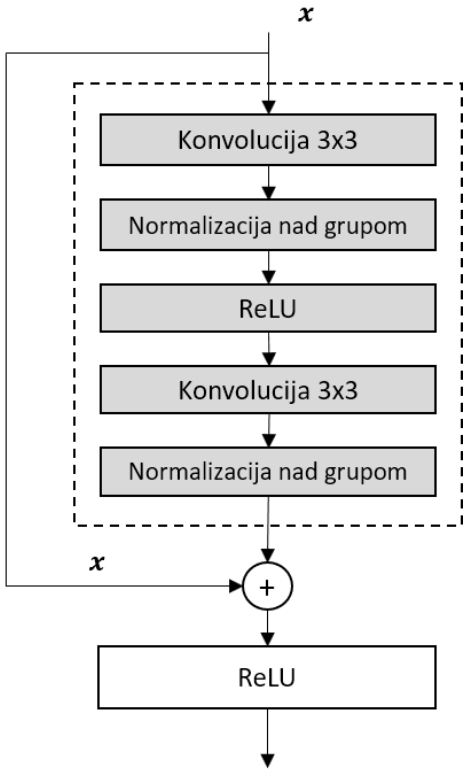
Naziv modela	Stopa učenja	Točnost	Mjera *F1*	*AUC ROC*
AlexNet	10^{-3}	0.7569	0.7398	0.8308
AlexNet	10^{-4}	0.7453	0.7061	0.8287
AlexNet	10^{-5}	0.7589	0.7359	0.8395
AlexNet	10^{-6}	**0.7592**	**0.7301**	**0.8496**
ResNet	10^{-3}	0.7760	0.7767	0.8547
ResNet	10^{-4}	**0.7822**	**0.7676**	**0.8637**
ResNet	10^{-5}	0.7795	0.7685	0.8599
ResNet	10^{-6}	0.7492	0.7447	0.8156
DenseNet	10^{-3}	**0.8065**	**0.8009**	**0.8874**
DenseNet	10^{-4}	0.7988	0.7906	0.8818
DenseNet	10^{-5}	0.7904	0.7783	0.8766
DenseNet	10^{-6}	0.7630	0.7546	0.8406
Inception-v3	10^{-3}	0.8270	0.8204	0.9018
Inception-v3	$\mathbf{10^{-4}}$	**0.8210**	**0.8149**	**0.9022**
Inception-v3	10^{-5}	0.8121	0.8059	0.8948
Inception-v3	10^{-6}	0.7728	0.7704	0.8536

AlexNet

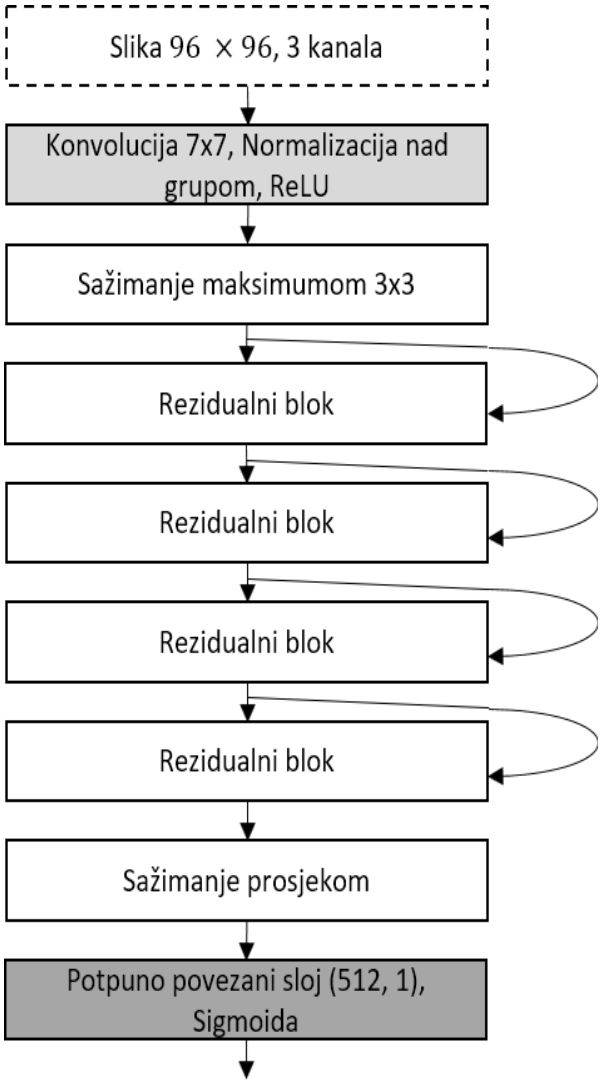

Slika 96 × 96, 3 kanala
Konvolucija 11x11, ReLU
Sažimanje maksimumom 3x3
Konvolucija 5x5, ReLU
Sažimanje maksimumom 3x3
Konvolucija 3x3, ReLU
Konvolucija 3x3, ReLU
Konvolucija 3x3, ReLU
Sažimanje maksimumom 3x3
Sažimanje prosjekom
Isključivanje čvorova, potpuno povezani sloj (9216x4096), ReLU
Isključivanje čvorova, potpuno povezani sloj (4096, 4096), ReLU
Potpuno povezani sloj (4096, 1), Sigmoida

ResNet – rezidualni blok

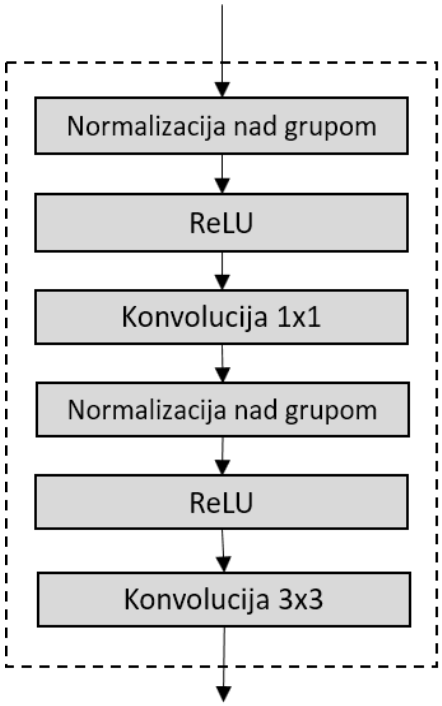




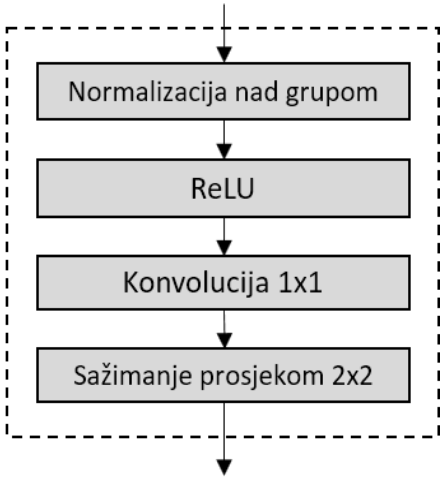
ResNet


Slika 96 × 96, 3 kanala
Konvolucija 7x7, Normalizacija nad grupom, ReLU
Sažimanje maksimumom 3x3
Rezidualni blok
Rezidualni blok
Rezidualni blok
Rezidualni blok
Sažimanje prosjekom
Potpuno povezani sloj (512, 1), Sigmoida

DenseNet - slojevi

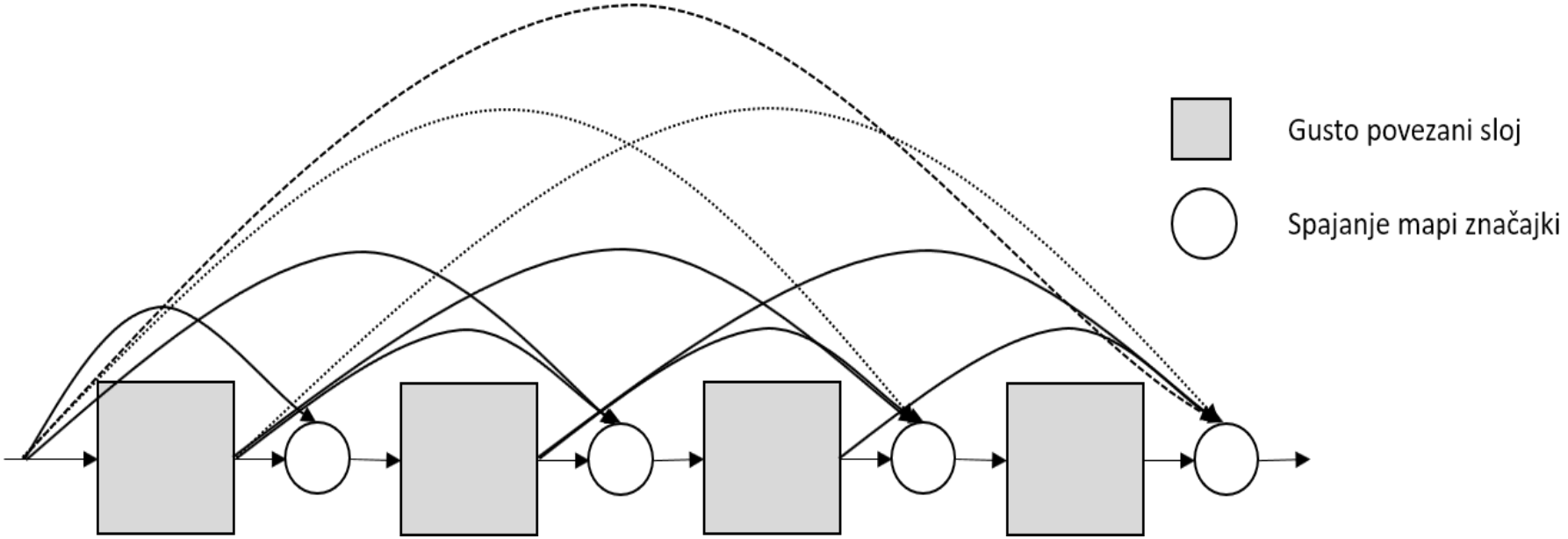


Gusto povezani sloj

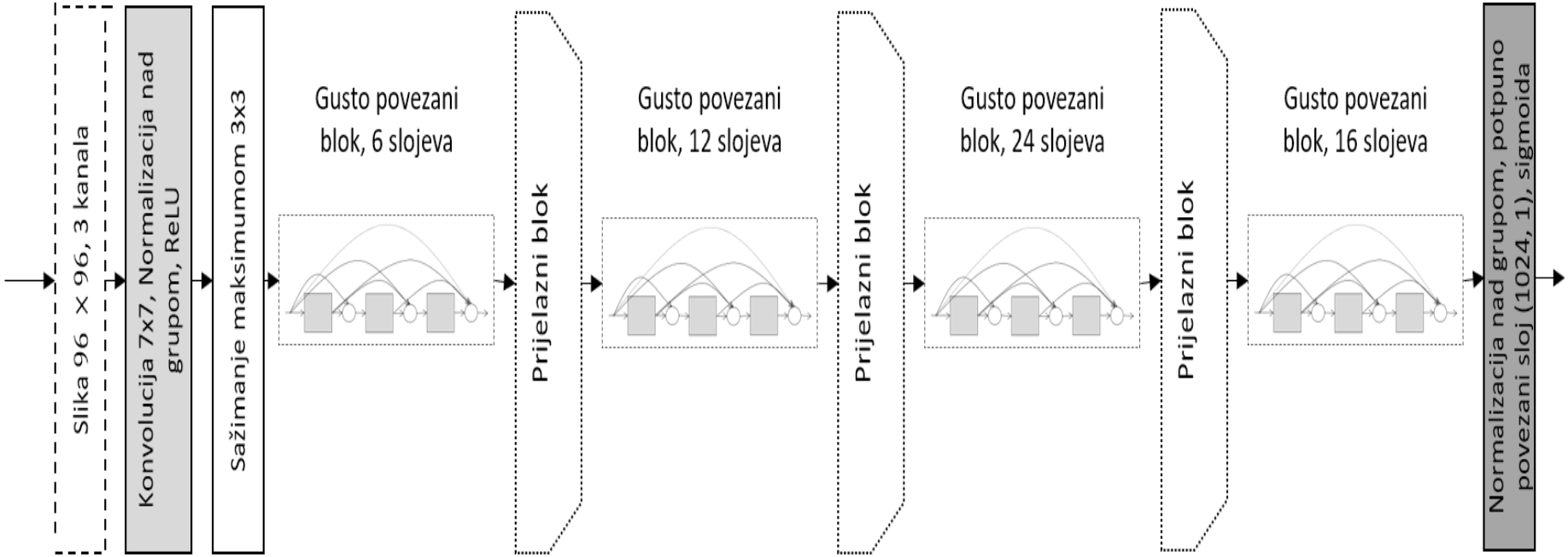


Prijelazni sloj

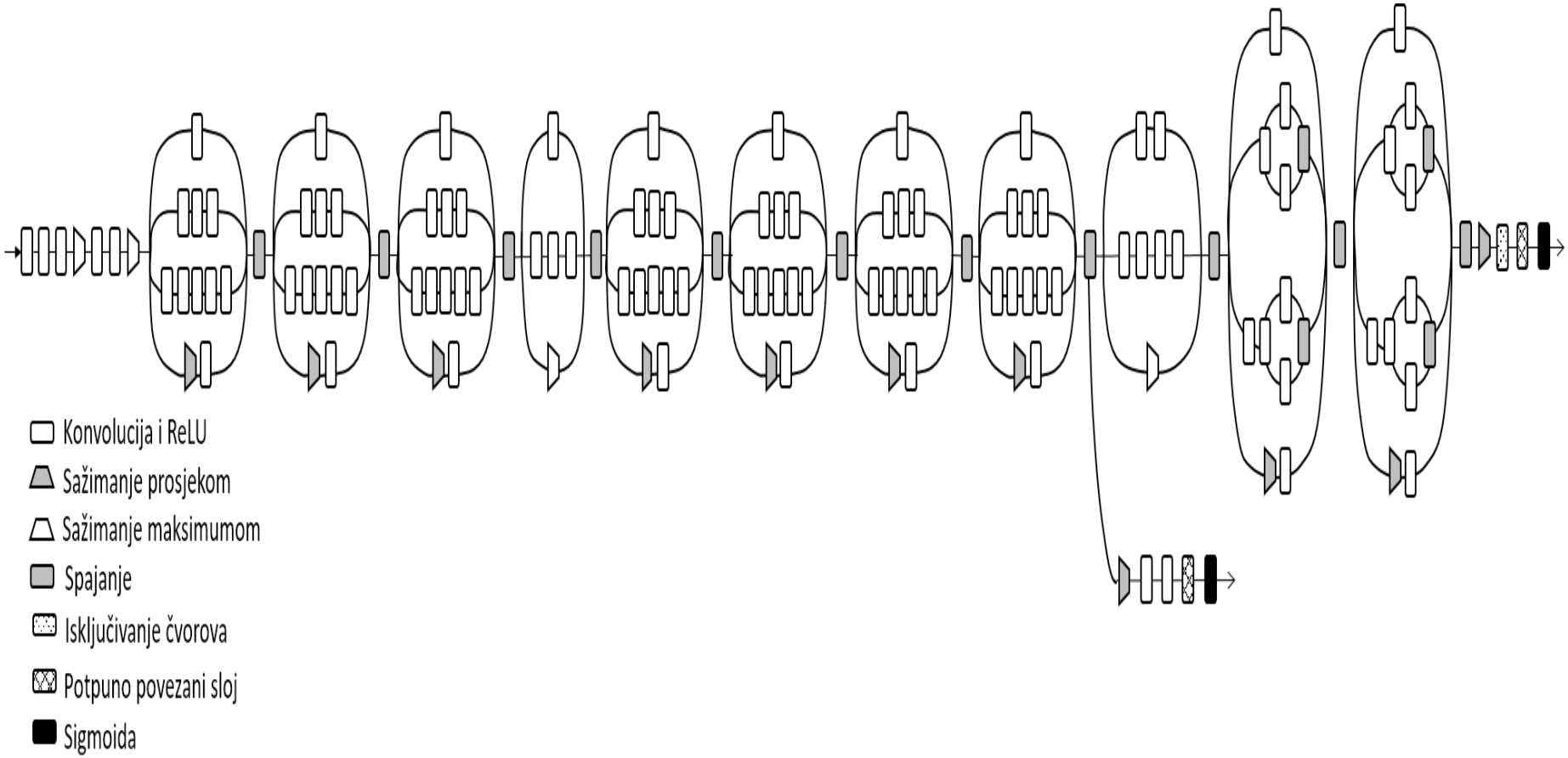
DenseNet - blokovi



DenseNet


Slika 96 × 96, 3 kanala
Konvolucija 7x7, Normalizacija nad grupom, ReLU
Sažimanje maksimumom 3x3
Gusto povezani blok, 6 slojeva
Prijelazni blok
Gusto povezani blok, 12 slojeva
Prijelazni blok
Gusto povezani blok, 24 slojeva
Prijelazni blok
Gusto povezani blok, 16 slojeva
Normalizacija nad grupom, potpuno povezani sloj (1024, 1), sigmoida

Inception-v3



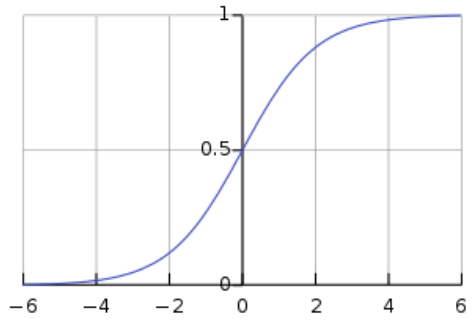
Algoritam Adam

Algorithm 8.7 The Adam algorithm

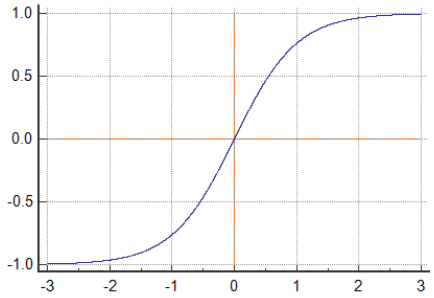
Require: Step size ϵ (Suggested default: 0.001)
Require: Exponential decay rates for moment estimates, ρ_1 and ρ_2 in $[0, 1)$. (Suggested defaults: 0.9 and 0.999 respectively)
Require: Small constant δ used for numerical stabilization. (Suggested default: 10^{-8})
Require: Initial parameters $\boldsymbol{\theta}$
  Initialize 1st and 2nd moment variables $\boldsymbol{s} = \mathbf{0}$, $\boldsymbol{r} = \mathbf{0}$
  Initialize time step $t = 0$
  while stopping criterion not met **do**
    Sample a minibatch of m examples from the training set $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ with corresponding targets $\boldsymbol{y}^{(i)}$.
    Compute gradient: $\boldsymbol{g} \leftarrow \frac{1}{m} \nabla_{\boldsymbol{\theta}} \sum_i L(f(\boldsymbol{x}^{(i)}; \boldsymbol{\theta}), \boldsymbol{y}^{(i)})$
    $t \leftarrow t + 1$
    Update biased first moment estimate: $\boldsymbol{s} \leftarrow \rho_1 \boldsymbol{s} + (1 - \rho_1)\boldsymbol{g}$
    Update biased second moment estimate: $\boldsymbol{r} \leftarrow \rho_2 \boldsymbol{r} + (1 - \rho_2)\boldsymbol{g} \odot \boldsymbol{g}$
    Correct bias in first moment: $\hat{\boldsymbol{s}} \leftarrow \frac{\boldsymbol{s}}{1 - \rho_1^t}$
    Correct bias in second moment: $\hat{\boldsymbol{r}} \leftarrow \frac{\boldsymbol{r}}{1 - \rho_2^t}$
    Compute update: $\Delta\boldsymbol{\theta} = -\epsilon \frac{\hat{\boldsymbol{s}}}{\sqrt{\hat{\boldsymbol{r}}} + \delta}$ (operations applied element-wise)
    Apply update: $\boldsymbol{\theta} \leftarrow \boldsymbol{\theta} + \Delta\boldsymbol{\theta}$
  end while

Aktivacijske funkcije

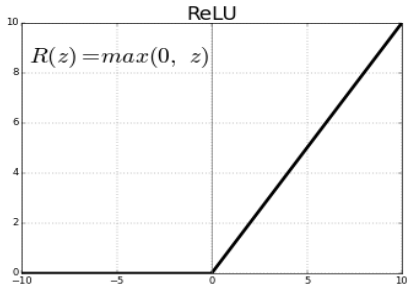
- $\sigma(x) = \frac{1}{1+e^{-x}}$



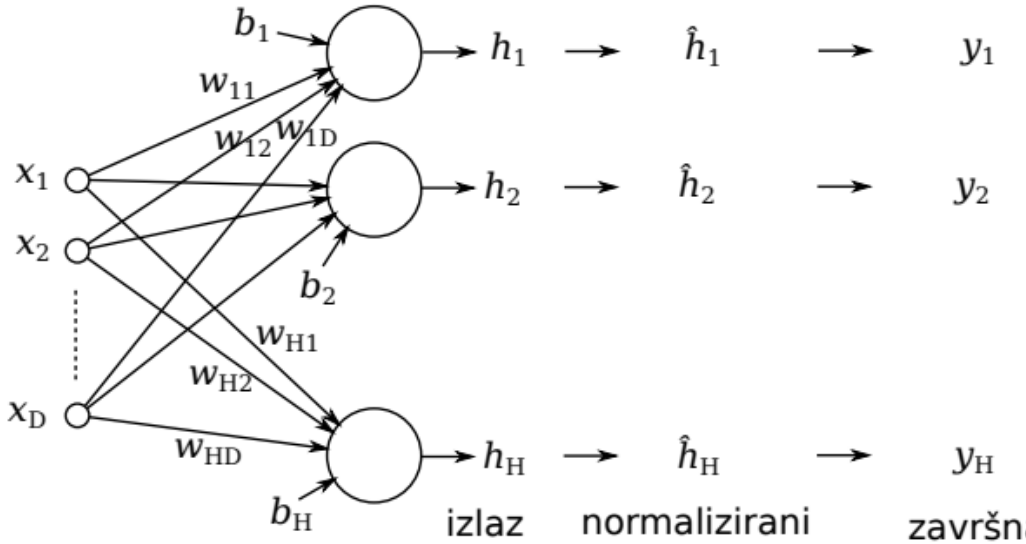
- $f(x) = tanh(x)$



- $ReLU(x) = \max(0, x)$



Normalizacija nad grupom



izlaz sloja

normalizirani izlaz sloja

završna afina transformacija

$$h = X \cdot W + b_{\downarrow}$$

$$\hat{h}_{k,l} = \frac{h_{k,l} - \mu_l}{\sqrt{\sigma_l^2 + \epsilon}}$$

$$y_{k,l} = \gamma_l \cdot \hat{h}_{k,l} + \beta_l$$

$$\mu_l = \frac{1}{N} \sum_{p=1}^{N} h_{p,l}$$

$$\sigma_l^2 = \frac{1}{N} \sum_{p=1}^{N} (h_{p,l} - \mu_l)^2$$

He inicijalizacija

- He et al, 2015
- Srednja vrijednost $\mu = 0$
- Varijanca $\sigma = \sqrt{\frac{2}{layersize[l-1]+layersize[l]}}$
- Težine u l-tom sloju

```
W[l] = np.random.randn(size_l, size_l-1) * np.sqrt(2 / (size_l-1 + size_l) )
```