



DIPLOMSKI RAD BR. 2016


Klasifikacija histopatoloških snimaka dijelova limfnih čvorova pomoću strojnog učenja


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Sadržaj

- 
- Histopatološke slike
 - Skup podataka
 - Korišteni modeli

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- Usporedba načina učenja
 - Usporedba transformacija za proširivanje skupa podataka

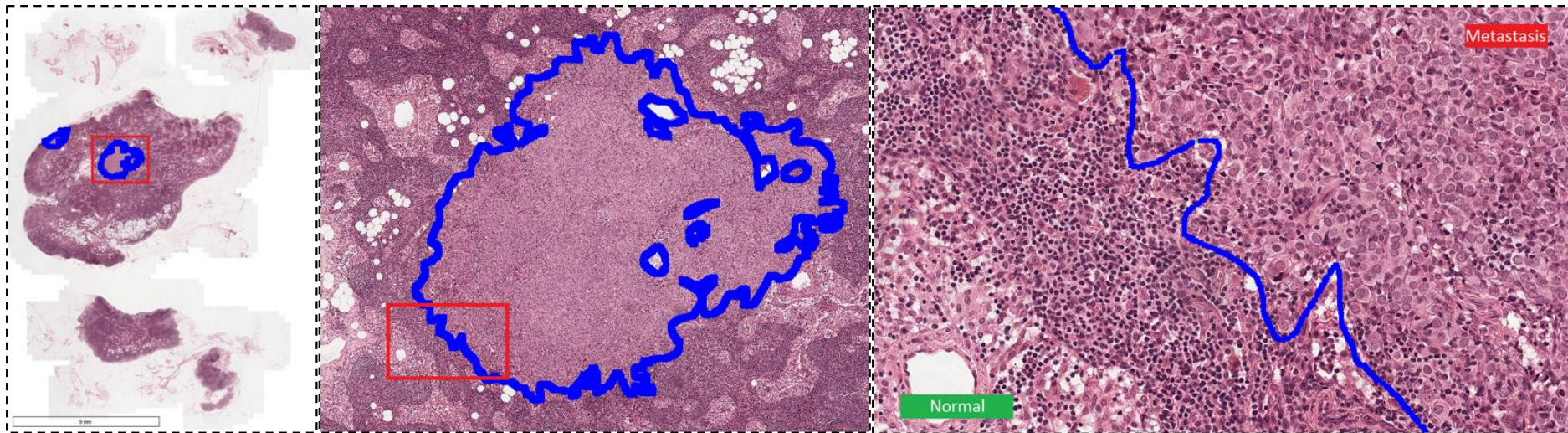
- 
- Rezultati
 - Zaključak

Histopatološke slike

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



Primjer

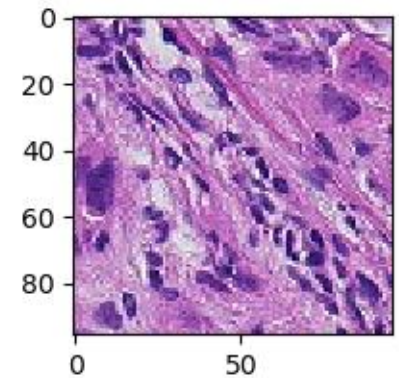


- Izvor: Camelyon 16 natjecanje
- Veličina: $200,000 \times 100,000$ slikovnih elemenata

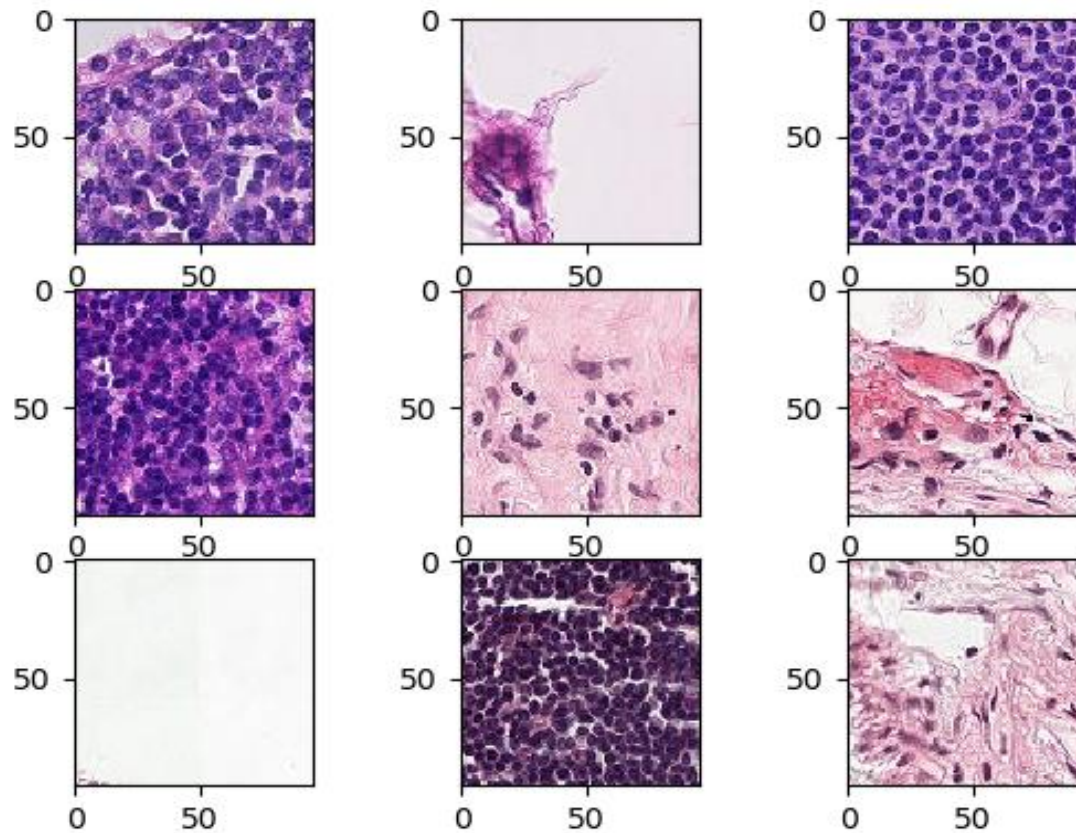


Skup podataka - PatchCamelyon

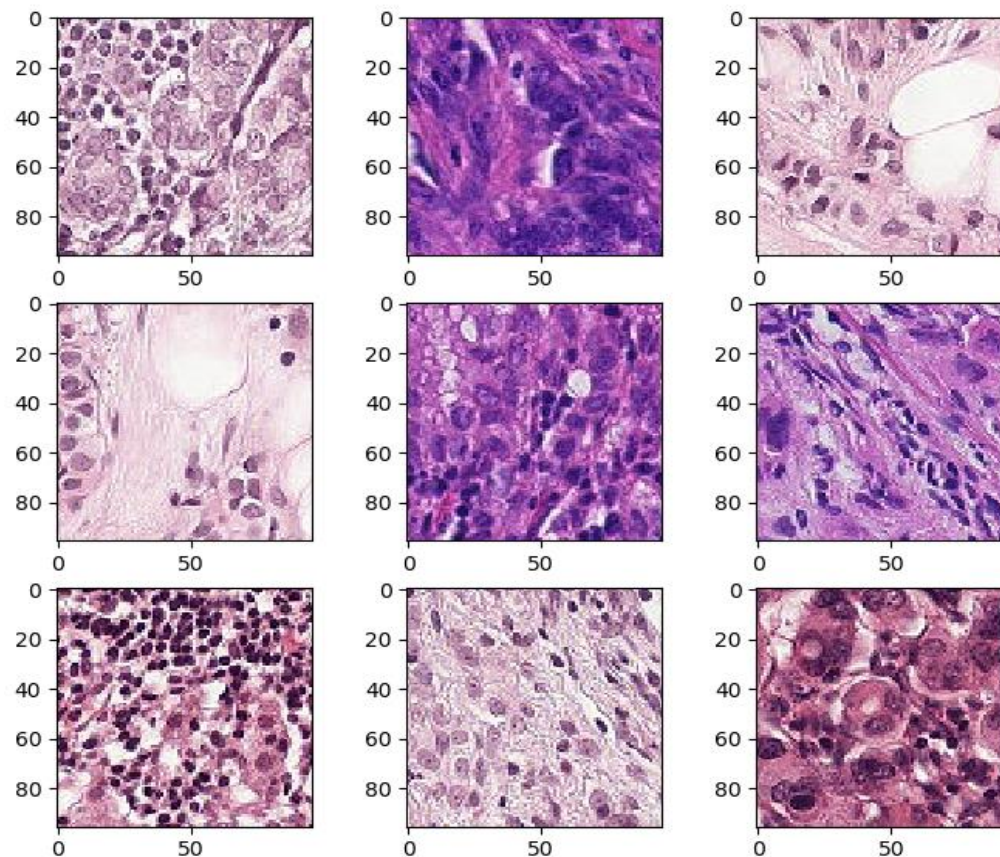
- 96 × 96 slikovna elementa
- **Binarne oznake**
 - 0 – ne sadrži tumor
 - 1 – sadrži tumor
- Veličina – **327,680 slika**
 - Skup za **učenje 80%**
 - Skup za **validaciju 10%**
 - Skup za **testiranje 10%**
- **Jednaki omjer** pozitivnih i negativnih primjera



PCam - negativni primjeri



PCam - pozitivni primjeri



Zadatak klasifikacije

- **Binarna klasifikacija**
 - Slika $\rightarrow \{0, 1\}$
- Odabir pristupa \rightarrow **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

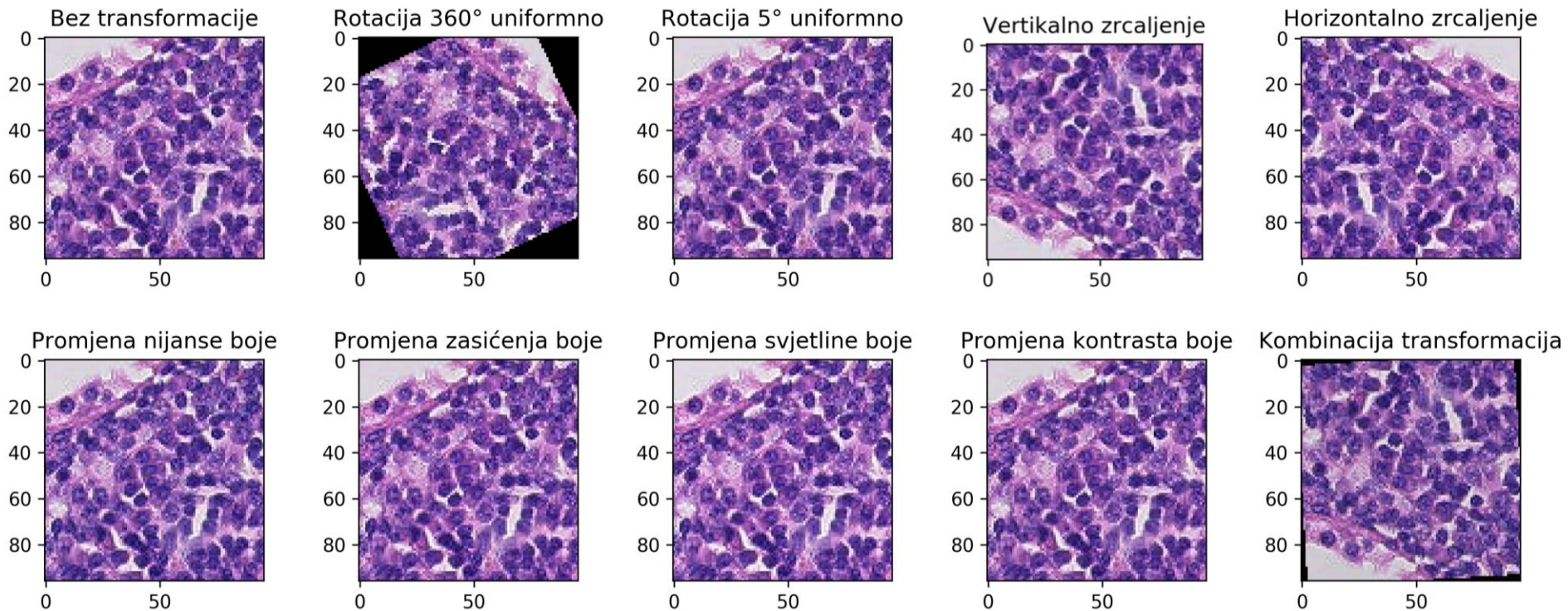


Eksperimenti 2/2

- **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

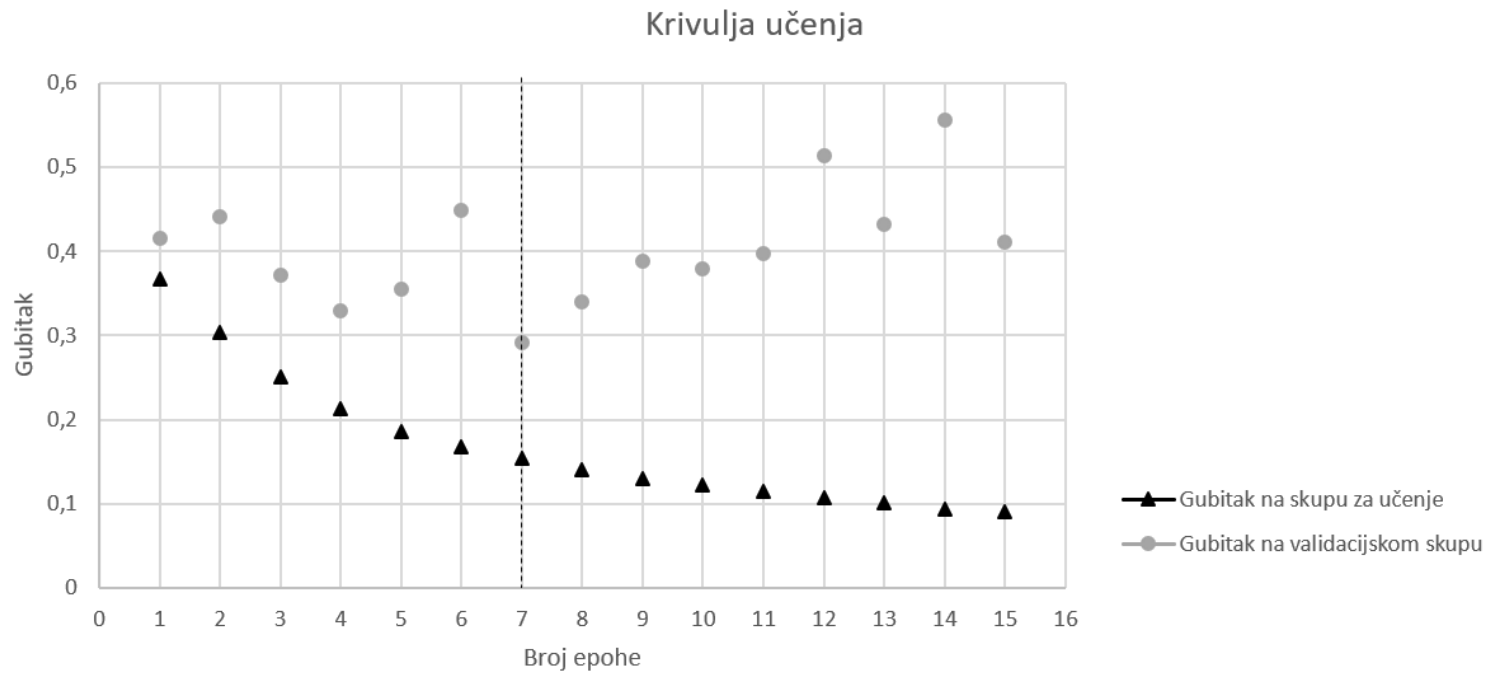
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Krivulja učenja



Rezultati modela učenih ispočetka s različitom stopom učenja

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

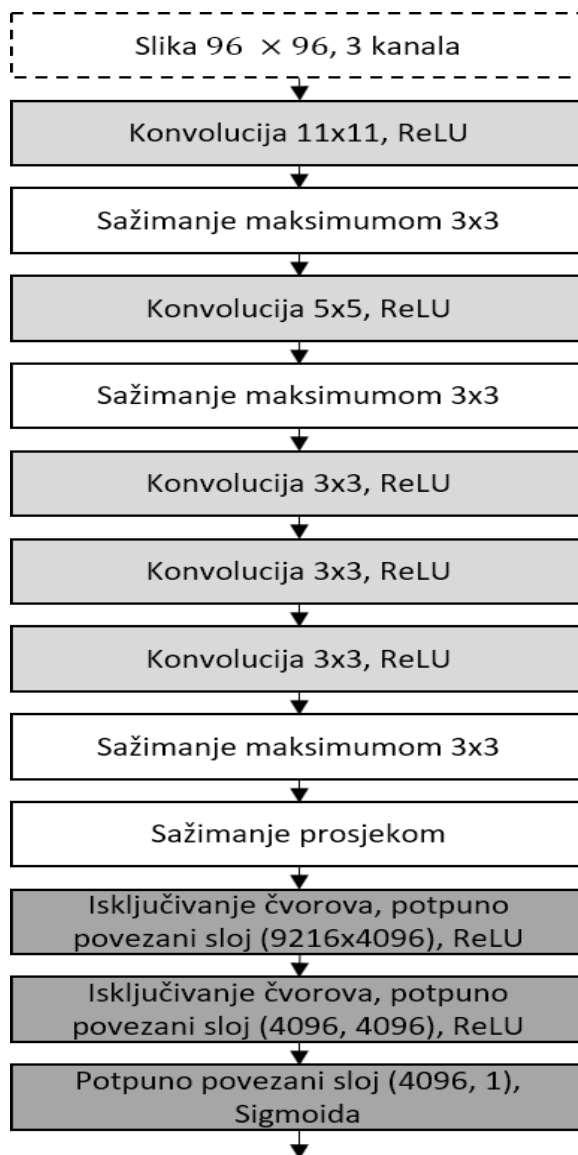
Rezultati modela inicijaliziranih prijenosom značajki sa skupa podataka ImageNet. Prilikom učenja svi parametri su prilagođavani.

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

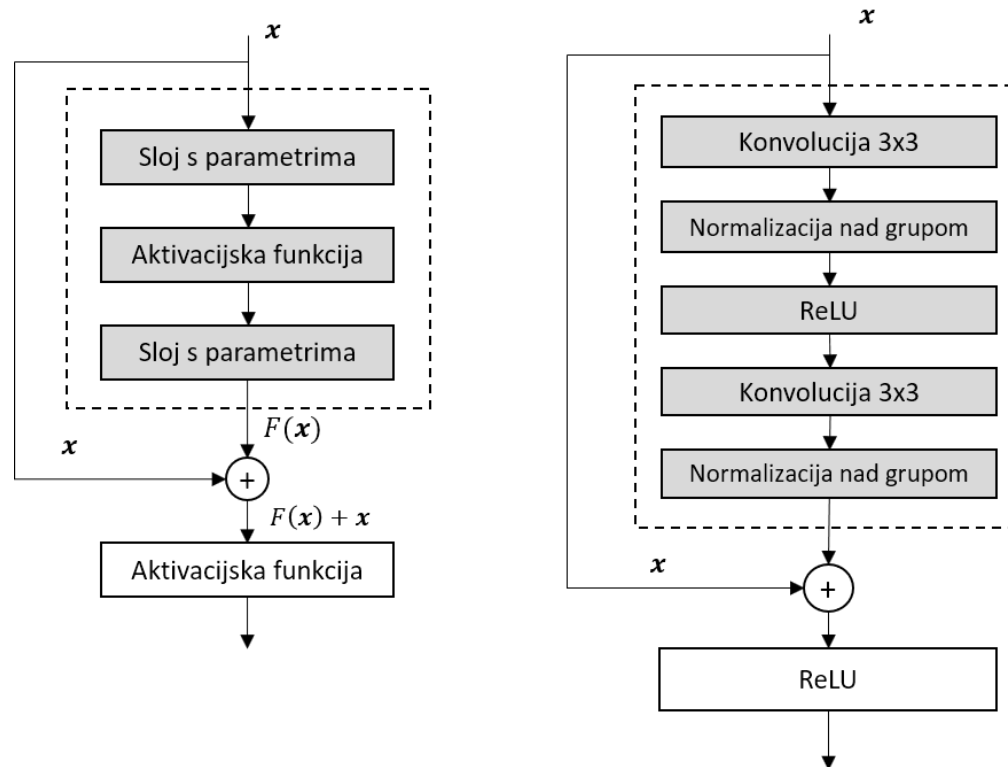
Rezultati modela inicijaliziranih prijenosom značajki sa skupa podataka ImageNet. Prilikom učenja samo zadnji potpuno povezani slojevi su prilagođavani.

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

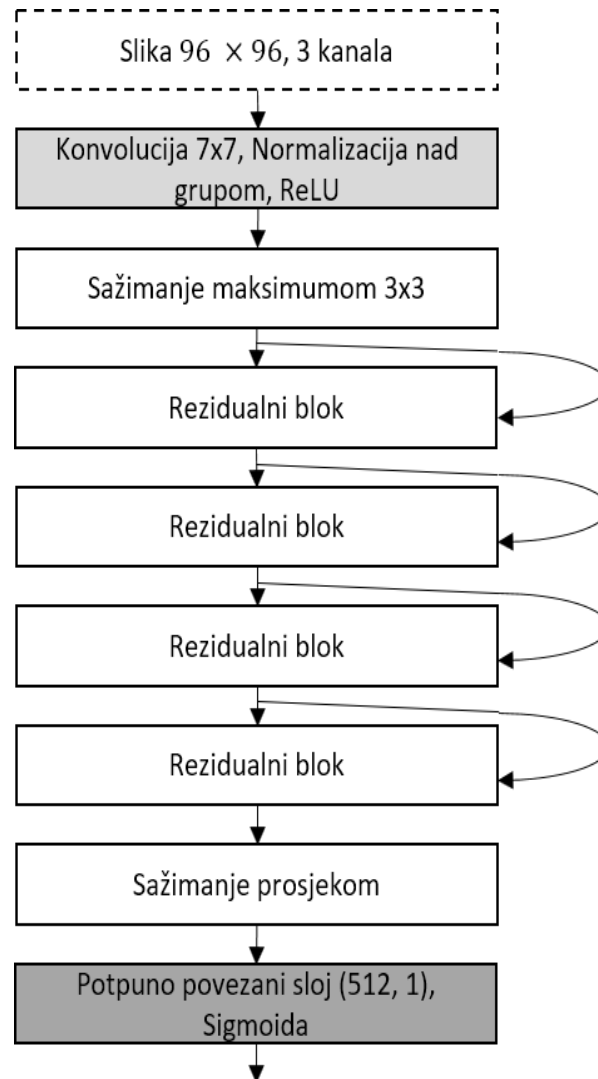
AlexNet



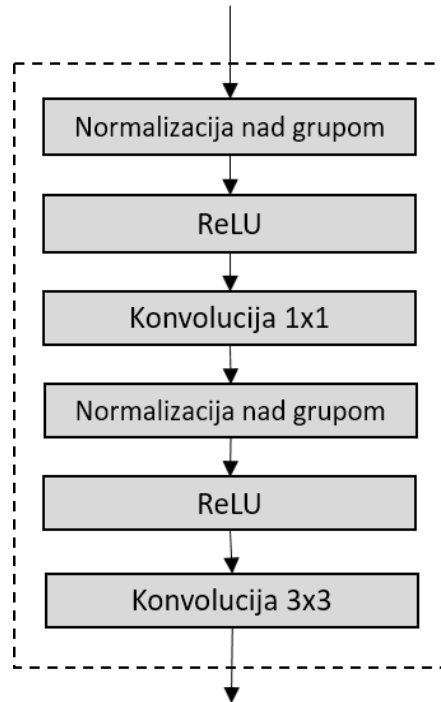
ResNet – rezidualni blok



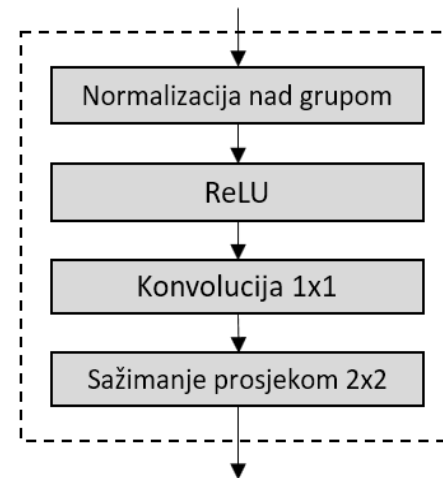
ResNet



DenseNet - slojevi

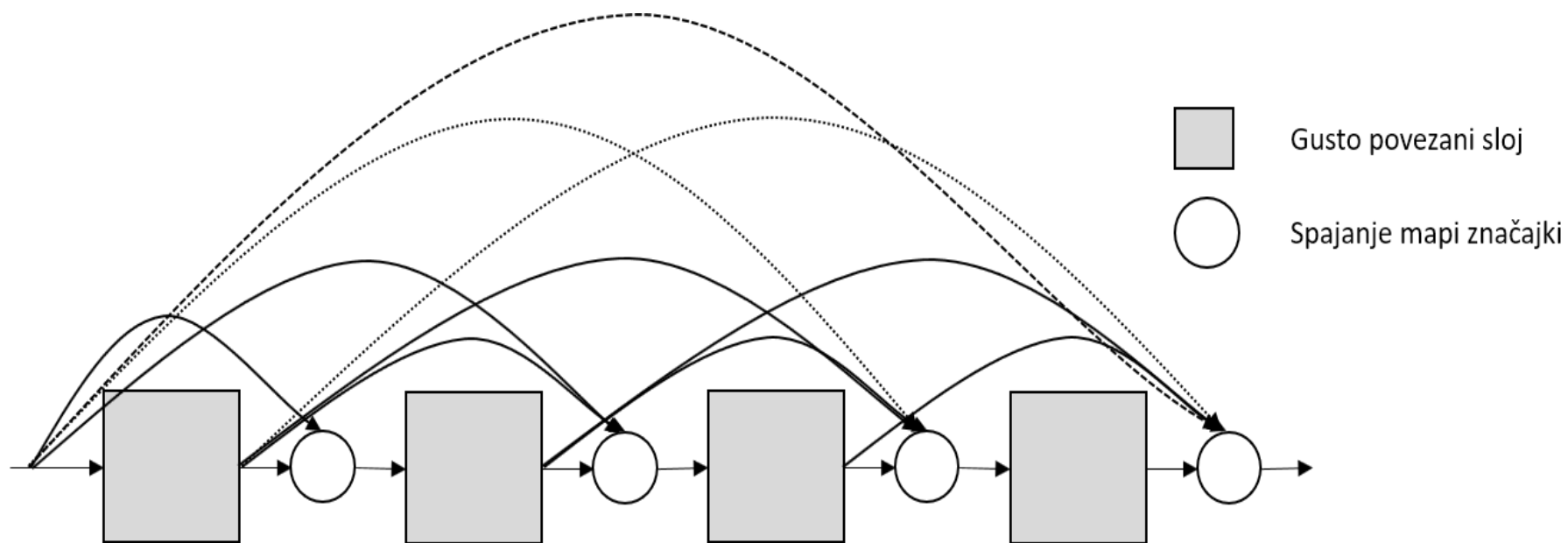


Gusto povezani sloj

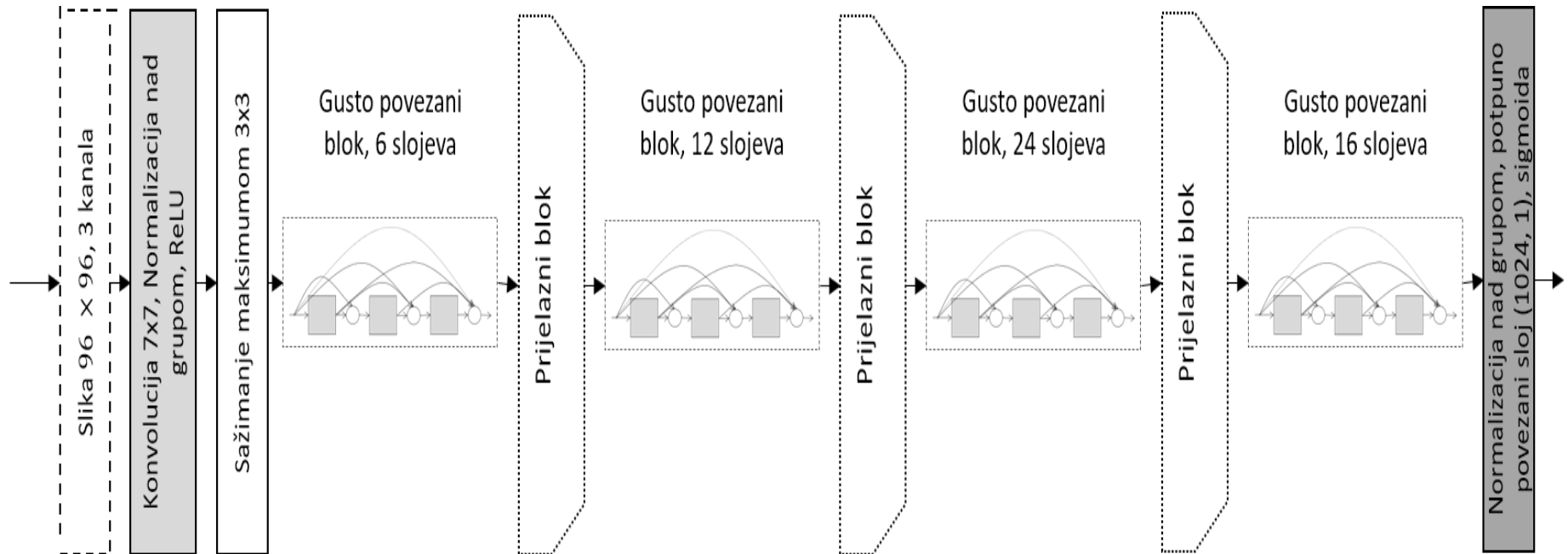


Prijelazni sloj

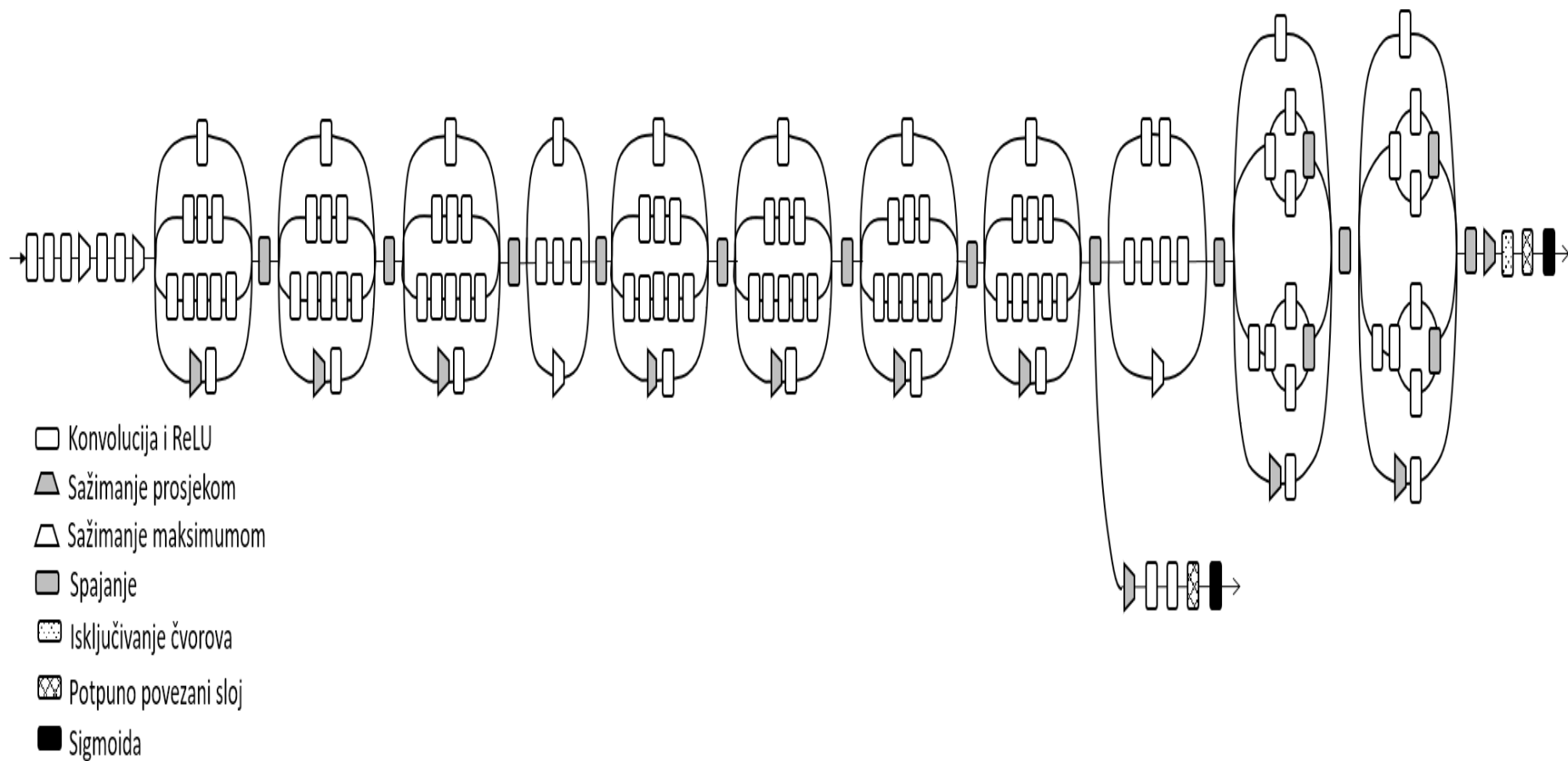
DenseNet - blokovi



DenseNet



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 θ

Initialize 1st and 2nd moment variables $\mathbf{s} = \mathbf{0}$, $\mathbf{r} = \mathbf{0}$

Initialize time step $t = 0$

while stopping criterion not met **do**

 Sample a minibatch of m examples from the training set $\{\mathbf{x}^{(1)}, \dots, \mathbf{x}^{(m)}\}$ with corresponding targets $\mathbf{y}^{(i)}$.

 Compute gradient: $\mathbf{g} \leftarrow \frac{1}{m} \nabla_{\theta} \sum_i L(f(\mathbf{x}^{(i)}; \theta), \mathbf{y}^{(i)})$

$t \leftarrow t + 1$

 Update biased first moment estimate: $\mathbf{s} \leftarrow \rho_1 \mathbf{s} + (1 - \rho_1) \mathbf{g}$

 Update biased second moment estimate: $\mathbf{r} \leftarrow \rho_2 \mathbf{r} + (1 - \rho_2) \mathbf{g} \odot \mathbf{g}$

 Correct bias in first moment: $\hat{\mathbf{s}} \leftarrow \frac{\mathbf{s}}{1 - \rho_1^t}$

 Correct bias in second moment: $\hat{\mathbf{r}} \leftarrow \frac{\mathbf{r}}{1 - \rho_2^t}$

 Compute update: $\Delta \theta = -\epsilon \frac{\hat{\mathbf{s}}}{\sqrt{\hat{\mathbf{r}} + \delta}}$ (operations applied element-wise)

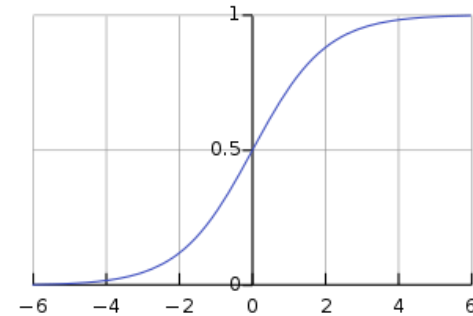
 Apply update: $\theta \leftarrow \theta + \Delta \theta$

end while

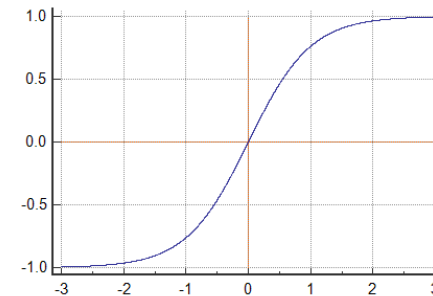
Predmet Duboko učenje, FER

Aktivacijske funkcije

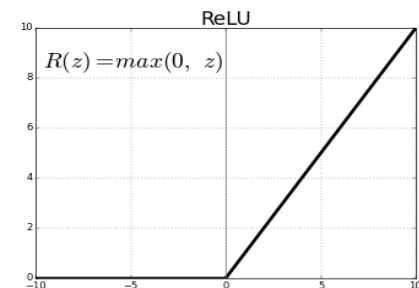
- $\sigma(x) = \frac{1}{1+e^{-x}}$



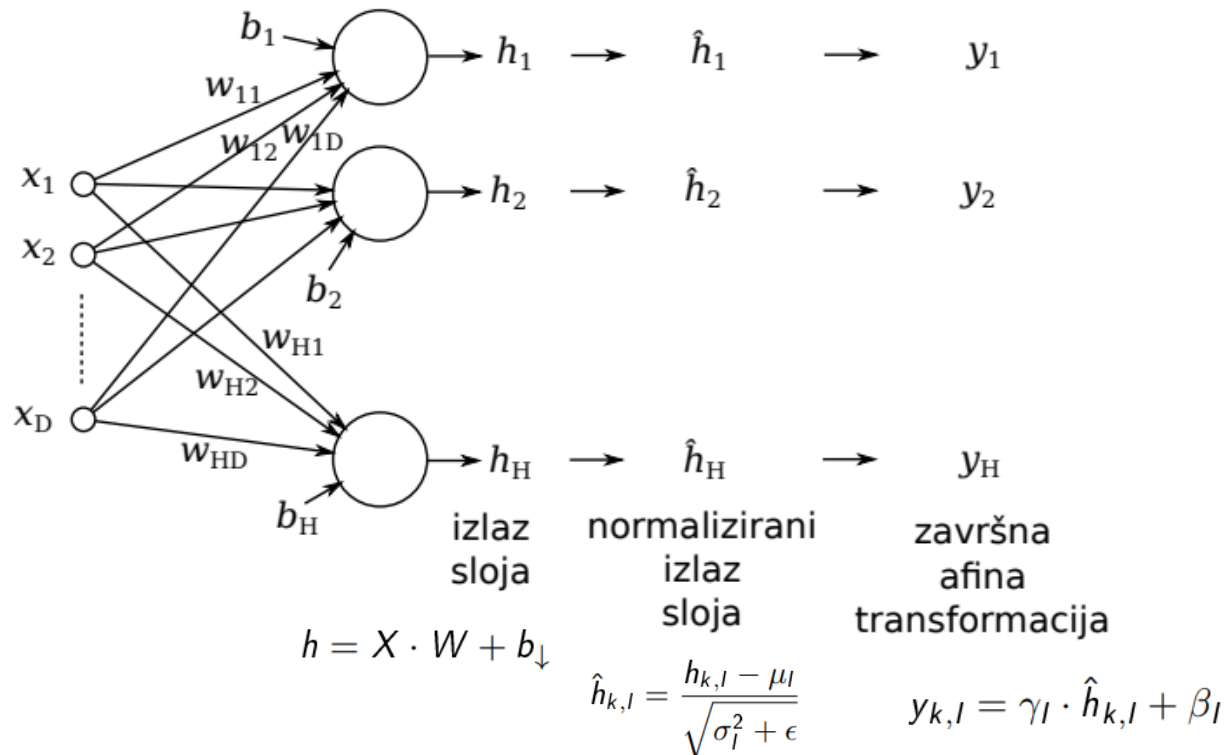
- $f(x) = \tanh(x)$



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



Normalizacija nad grupom



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

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

He inicijalizacija

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

$$W^{[l]} = \text{np.random.randn}(\text{size_l}, \text{size_l-1}) * \text{np.sqrt}(2 / (\text{size_l-1} + \text{size_l}))$$