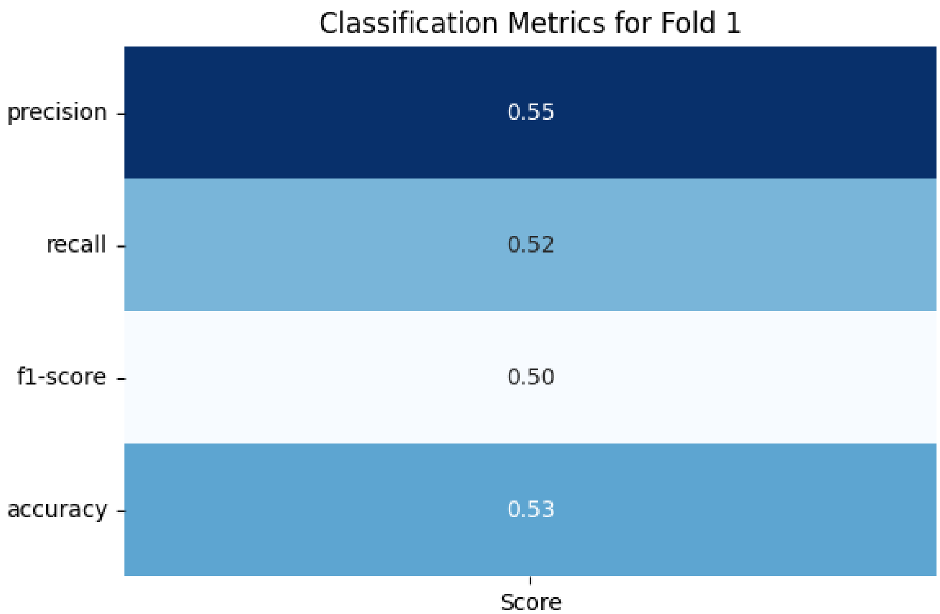
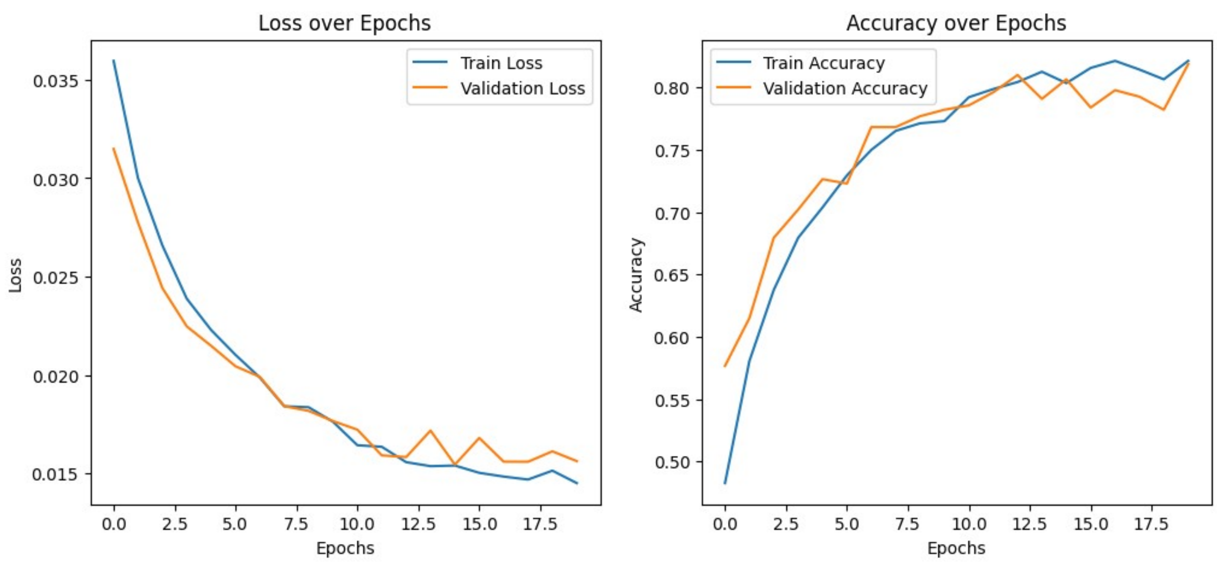
Raport etapa2

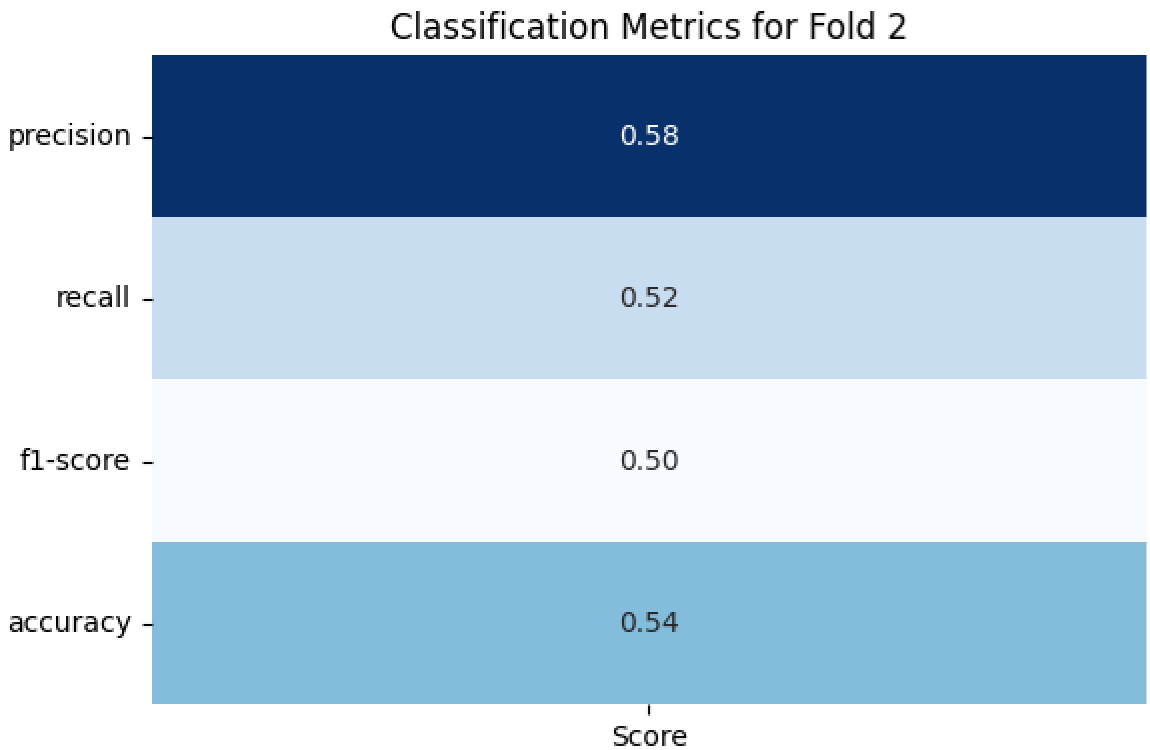
Cerinta 1 - raport clasificare folduri

Fold 1

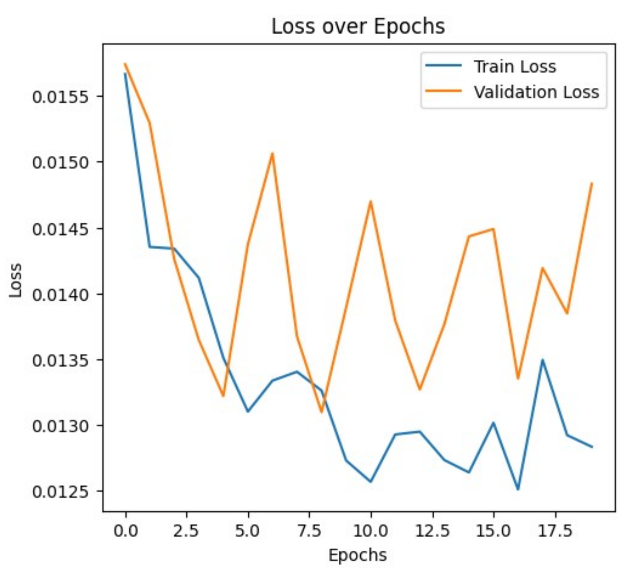




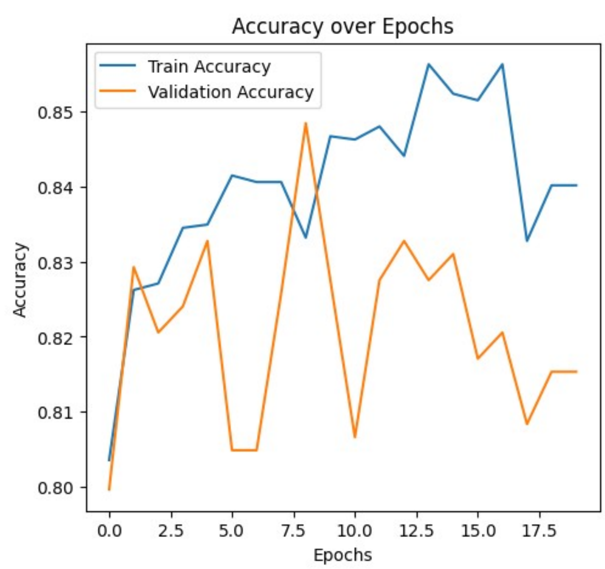
Fold 2



Classification Metrics for Fold 2
precision
recall
f1-score
accuracy
0.58
0.52
0.50
0.54
Score

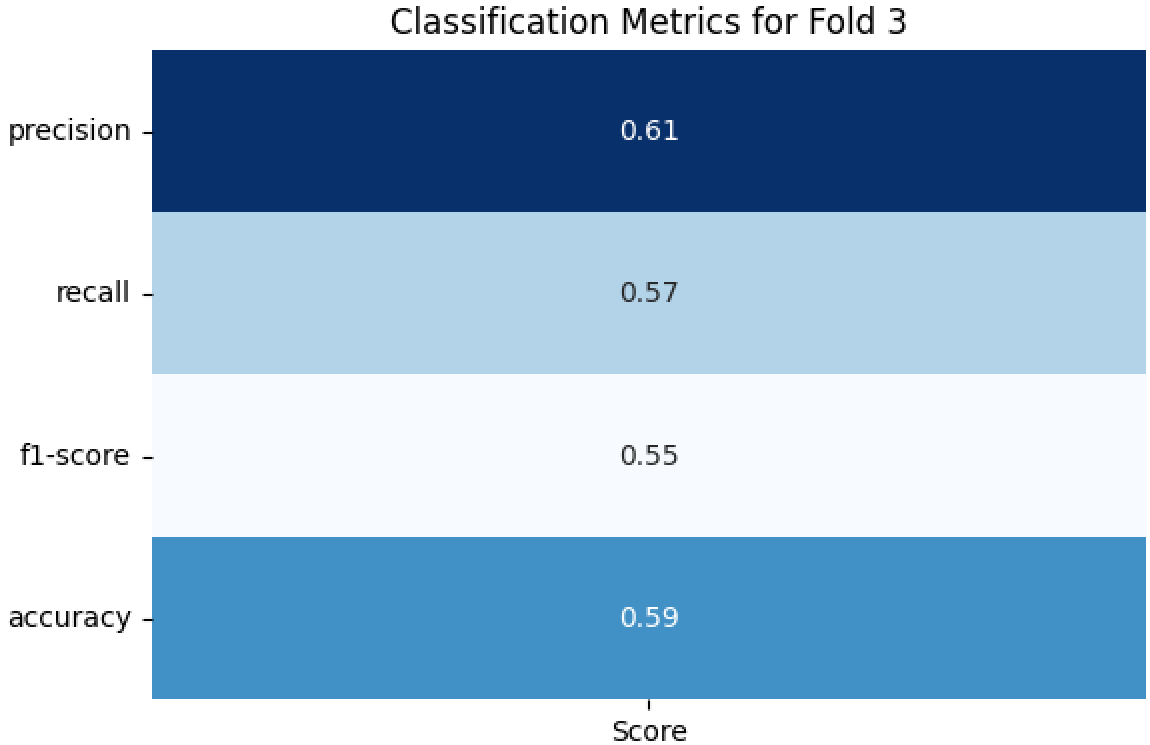


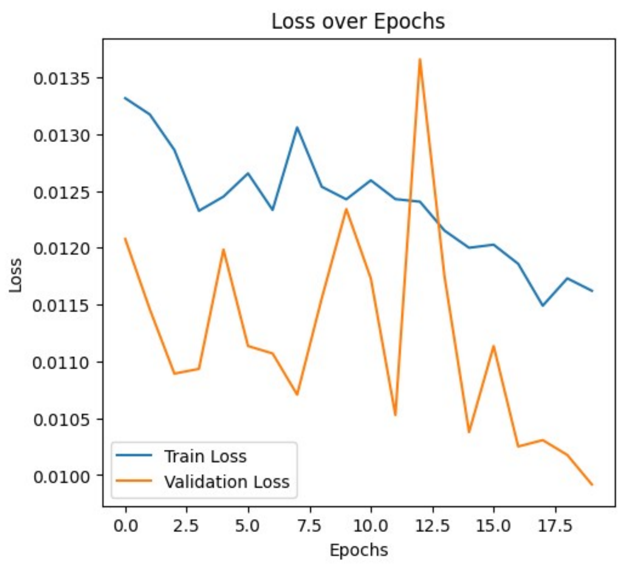
Loss over Epochs
Train Loss
Validation Loss
Loss
Epochs

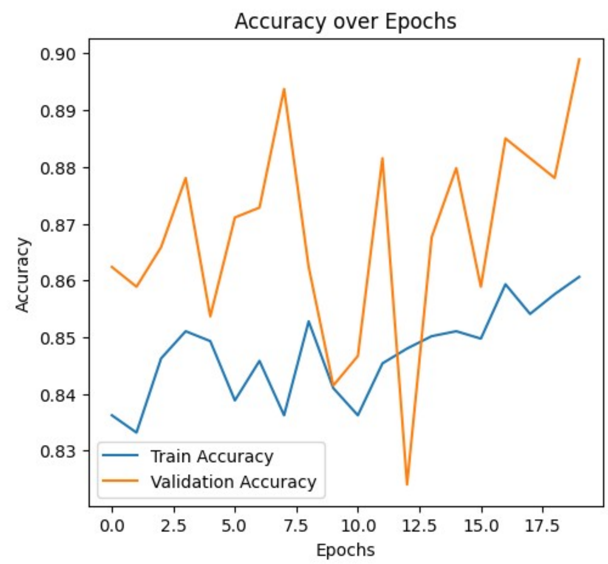


Accuracy over Epochs
Train Accuracy
Validation Accuracy
Accuracy
Epochs

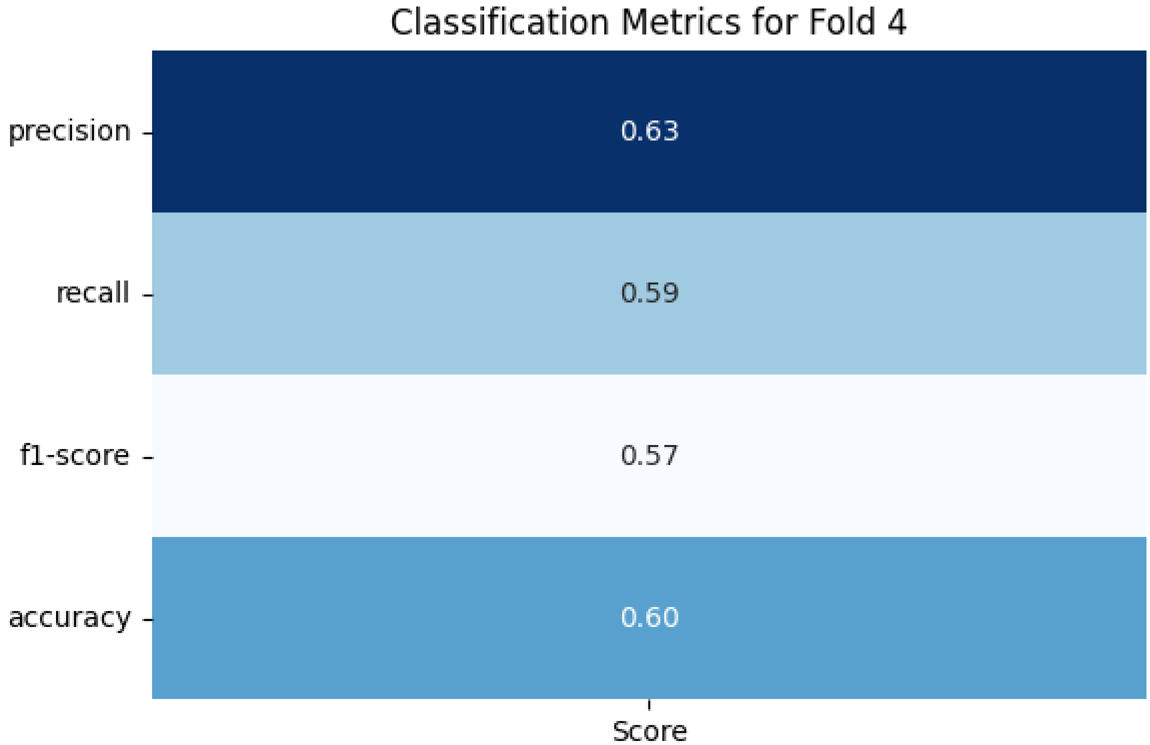
Fold 3

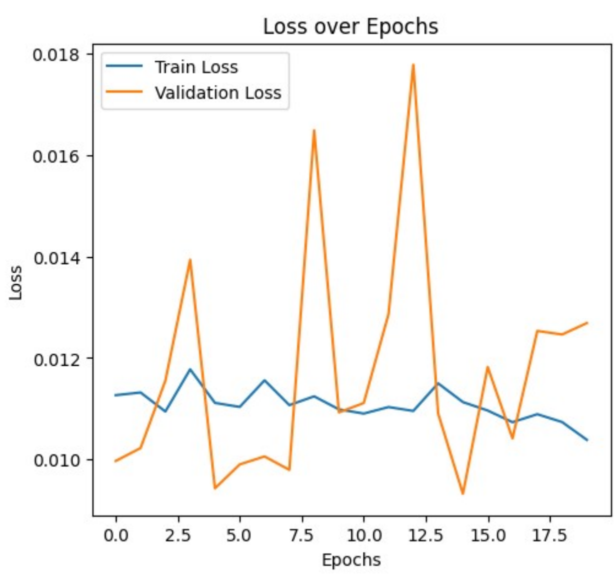

Classification Metrics for Fold 3
precision
0.61
recall
0.57
f1-score
0.55
accuracy
0.59
Score

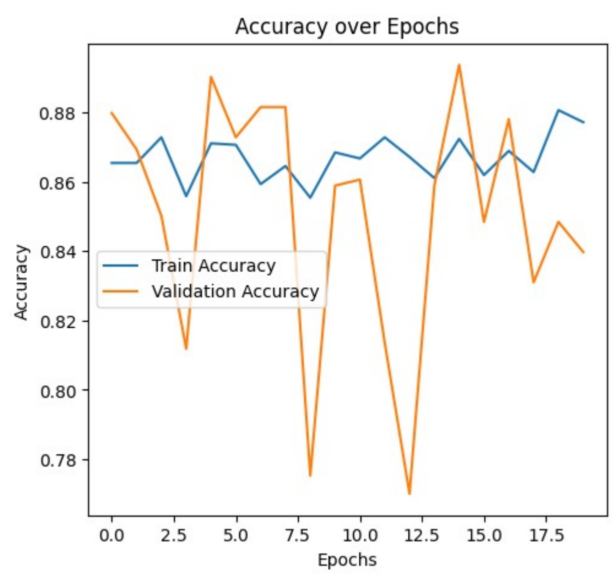

Loss over Epochs
Loss
Epochs
Train Loss
Validation Loss


Accuracy over Epochs
Accuracy
Epochs
Train Accuracy
Validation Accuracy

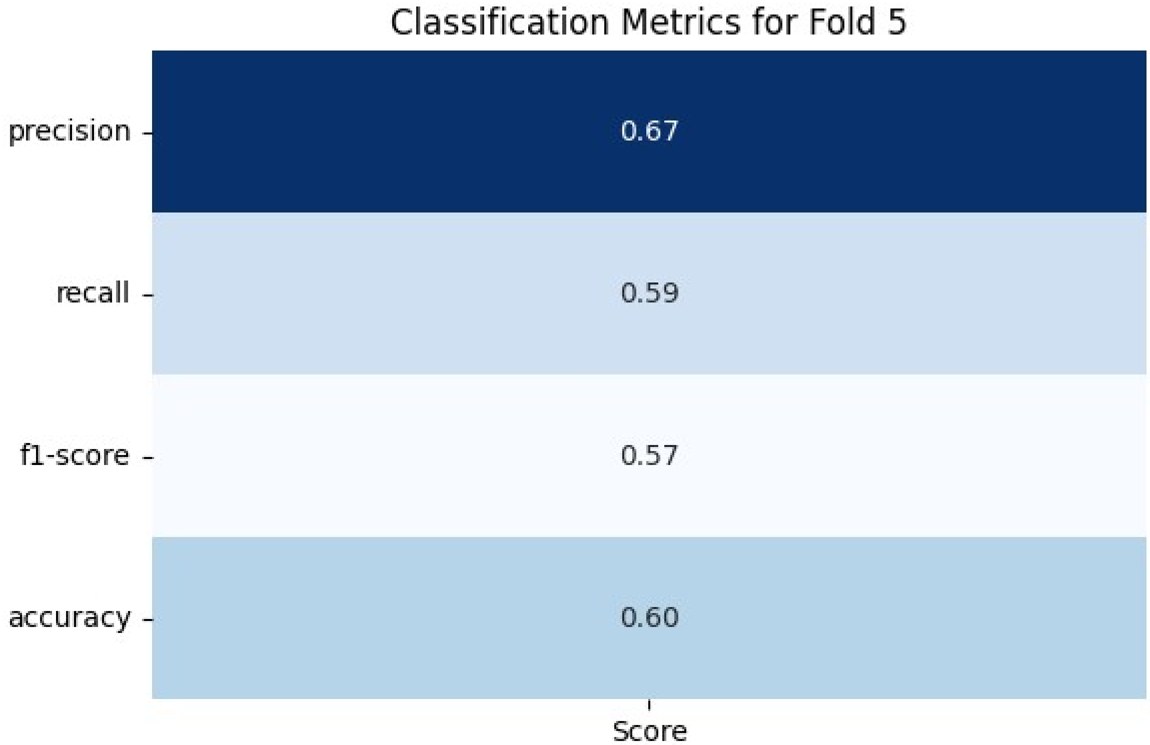
Fold 4

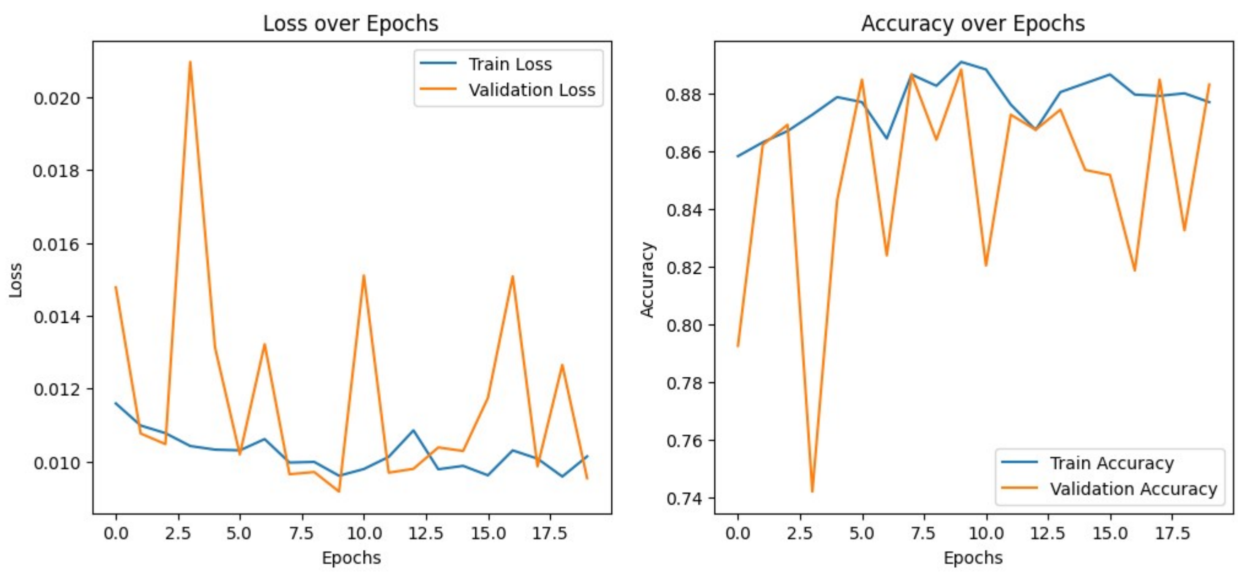

Classification Metrics for Fold 4
precision
0.63
recall
0.59
f1-score
0.57
accuracy
0.60
Score


Loss over Epochs
Train Loss
Validation Loss
Loss
Epochs


Accuracy over Epochs
Train Accuracy
Validation Accuracy
Accuracy
Epochs

Fold 5


Classification Metrics for Fold 5
precision
0.67
recall
0.59
f1-score
0.57
accuracy
0.60
Score


Loss over Epochs
Train Loss
Validation Loss
Loss
0.020
0.018
0.016
0.014
0.012
0.010
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Epochs
Accuracy over Epochs
Accuracy
0.88
0.86
0.84
0.82
0.80
0.78
0.76
0.74
Train Accuracy
Validation Accuracy
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Epochs

Metrici per folduri

Rezultate Fold-uri (Validare si Testare):

Validare

Fold	Precision	Recall	F1-Score	Accuracy
1	0.874031	0.888884	0.880398	0.876307
2	0.882727	0.893305	0.887382	0.883275
3	0.881768	0.894802	0.887363	0.885017
4	0.885691	0.893198	0.889002	0.885017
5	0.899832	0.908368	0.903546	0.902439

Testare

Fold	Precision	Recall	F1-Score	Accuracy
1	0.550163	0.521420	0.496295	0.525381
2	0.582197	0.518297	0.546046	0.535533
3	0.614475	0.567236	0.887363	0.588832
4	0.627048	0.591060	0.569705	0.601523
5	0.668920	0.589545	0.568413	0.598985

Medii si Deviatii Standard pentru Validare:

	Precision	Recall	F1-Score	Accuracy
mean	0.884810	0.895711	0.889538	0.886411
std	0.009437	0.007412	0.008506	0.009653

Medii si Deviatii Standard pentru Testare:

	Precision	Recall	F1-Score	Accuracy
mean	0.608561	0.557512	0.535838	0.570051
std	0.045070	0.035660	0.036238	0.036631

Concluzii si Observatii

Documentarea si Compararea Rezultatelor

- **Validare**:
  - Performanta medie pe validare este consistenta, cu **Precision** (0.8848), **Recall** (0.8957), **F1-Score** (0.8895), si **Accuracy** (0.8864).
  - Devierea standard este foarte mica (sub 0.01), indicand stabilitatea modelului pe diferite fold-uri si o buna generalizare in timpul validarii.
- **Testare**:
  - Metricile pe testare arata o variabilitate mai mare comparativ cu validarea, cu o medie a **Precision** de 0.6086 si a **Accuracy** de 0.5701.
  - Devierea standard semnificativ mai mare (aproximativ 0.04) evidentiaza sensibilitatea modelului la seturi de date diferite in testare.

Evaluarea Stabilitatii si Generalizarii

- **Stabilitate**:
  - Metricile consistente pe validare confirma ca modelul invata eficient din seturile de date de antrenare si validare, fara fluctuatii mari intre fold-uri.
  - Rezultatele sugereaza ca proportiile claselor au fost mentinute corect intre fold-uri.
- **Generalizare**:
  - Performantele mai scazute si variabile pe testare indica faptul ca modelul intampina dificultati in a generaliza pe date noi.
  - Fold-ul 1 are cele mai slabe performante pe testare (Accuracy: 0.5254), ceea ce evidentiaza sensibilitatea modelului la seturile de testare mai dificile.

Concluzie Generala

K-fold cross-validation ofera o evaluare robusta si reduce influenta particularitatilor seturilor de date. Modelul demonstreaza stabilitate pe validare, dar exista potential de imbunatatire pentru generalizare, indicand necesitatea unor tehnici suplimentare precum augmentari mai eficiente sau balansarea claselor.

Cerinta 2 - Balansare

Fold 1

Scenariu	Precision	Recall	F1-Score	Accuracy
No Balancing	0.6675	0.6087	0.5831	0.6168
Weighted Loss	0.6947	0.588	0.5670	0.6091
Oversampling with Augmentation	0.6876	0.6326	0.6168	0.6472
Oversampling without Augmentation	0.2186	0.3348	0.2397	0.3807

Fold 2

Scenariu	Precision	Recall	F1-Score	Accuracy
No Balancing	0.6932	0.6283	0.6041	0.6447
Weighted Loss	0.6785	0.5956	0.5699	0.6091
Oversampling with Augmentation	0.2045	0.3653	0.2622	0.4086
Oversampling without Augmentation	0.2110	0.3447	0.2469	0.3909

Fold 3

Scenariu	Precision	Recall	F1-Score	Accuracy
No Balancing	0.6510	0.6082	0.5871	0.6193
Weighted Loss	0.7162	0.6336	0.6122	0.6447
Oversampling with Augmentation	0.2182	0.3925	0.2801	0.4365
Oversampling without Augmentation	0.2299	0.3272	0.2334	0.3731

Fold 4

Scenariu	Precision	Recall	F1-Score	Accuracy
No Balancing	0.7121	0.6651	0.6363	0.6751
Weighted Loss	0.7204	0.6460	0.6137	0.6574
Oversampling with Augmentation	0.2201	0.3694	0.2681	0.4162
Oversampling without Augmentation	0.2162	0.3748	0.2646	0.4137

Fold 5

Scenariu	Precision	Recall	F1-Score	Accuracy
No Balancing	0.2086	0.3756	0.2661	0.4162
Weighted Loss	0.2253	0.3743	0.2734	0.4213
Oversampling with Augmentation	0.2155	0.3790	0.2737	0.4239
Oversampling without Augmentation	0.2359	0.3300	0.2393	0.3756

Fold 1:

- **No Balancing**: A obtinut un F1-Score de **0.5831** si o acuratete de **0.6168**, fiind cea mai buna metoda pe acest fold.
- **Weighted Loss**: Performante similare cu metoda fara balansare, F1-Score de **0.5670** si o acuratete de **0.6091**, sugerand un impact limitat al ponderilor.
- **Oversampling cu Augmentare**: F1-Score de **0.6168** si o acuratete de **0.6472**, aratand o usoara imbunatatire datorita augmentarii.
- **Oversampling fara Augmentare**: F1-Score scazut de **0.2397**, indicand ca simpla duplicare nu este eficienta.

Concluzie: Oversampling cu Augmentare ofera cel mai bun rezultat pe acest fold.

Fold 2:

- **No Balancing**: F1-Score de **0.6041** si o acuratete de **0.6447**, aratand performante bune.
- **Weighted Loss**: Performante aproape identice, F1-Score de **0.5699** si o acuratete de **0.6091**.
- **Oversampling cu Augmentare**: Performante scazute, F1-Score de **0.2622** si o acuratete de **0.4086**, indicand ineficienta.
- **Oversampling fara Augmentare**: F1-Score de **0.2469** si o acuratete de **0.3909**, confirmand ineficienta duplicarii fara augmentare.

Concluzie: No Balancing si Weighted Loss ofera rezultate comparabile pe acest fold.

Fold 3:

- **No Balancing**: F1-Score de **0.5871** si o acuratete de **0.6193**, fiind cea mai consistenta metoda.
- **Weighted Loss**: Cea mai buna metoda pe acest fold, cu F1-Score de **0.6122** si o acuratete de **0.6447**.
- **Oversampling cu Augmentare**: Performante scazute, F1-Score de **0.2801** si o acuratete de **0.4365**.
- **Oversampling fara Augmentare**: F1-Score de **0.2334** si o acuratete de **0.3731**, aratand ca metoda nu ajuta.

Concluzie: Weighted Loss este cea mai eficienta metoda pe acest fold.

Fold 4:

- **No Balancing**: Performanta ridicata, F1-Score de **0.6363** si o acuratete de **0.6751**.
- **Weighted Loss**: Cea mai buna metoda pe acest fold, cu F1-Score de **0.6137** si o acuratete de **0.6574**.
- **Oversampling cu Augmentare**: F1-Score de **0.2681** si o acuratete de **0.4162**, aratand performante slabe.
- **Oversampling fara Augmentare**: F1-Score de **0.2646** si o acuratete de **0.4137**, confirmand limitarile metodei.

Concluzie: No Balancing ofera cele mai bune rezultate generale pe acest fold.

Fold 5:

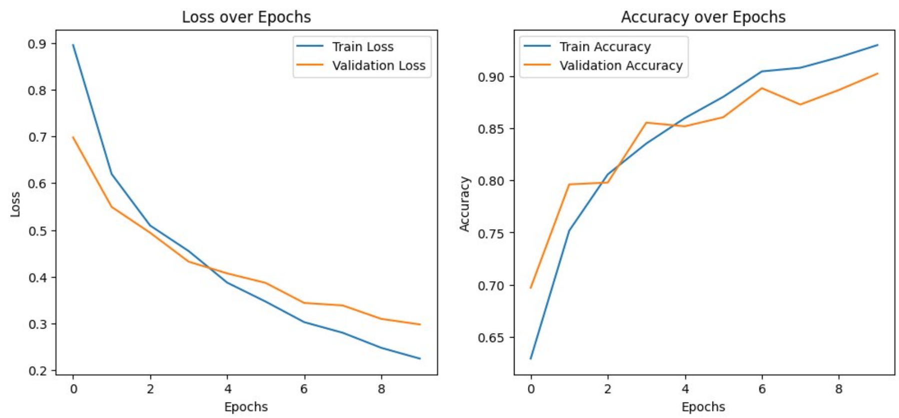
- **No Balancing**: Performanta scazuta, F1-Score de **0.2661** si o acuratete de **0.4162**.
- **Weighted Loss**: O mica imbunatatire, F1-Score de **0.2734** si o acuratete de **0.4213**.
- **Oversampling cu Augmentare**: Performante similare cu Weighted Loss, F1-Score de **0.2737** si o acuratete de **0.4239**.
- **Oversampling fara Augmentare**: Cea mai slaba metoda, F1-Score de **0.2393** si o acuratete de **0.3756**.

Concluzie: Weighted Loss si Oversampling cu Augmentare ofera performante marginal mai bune pe acest fold.

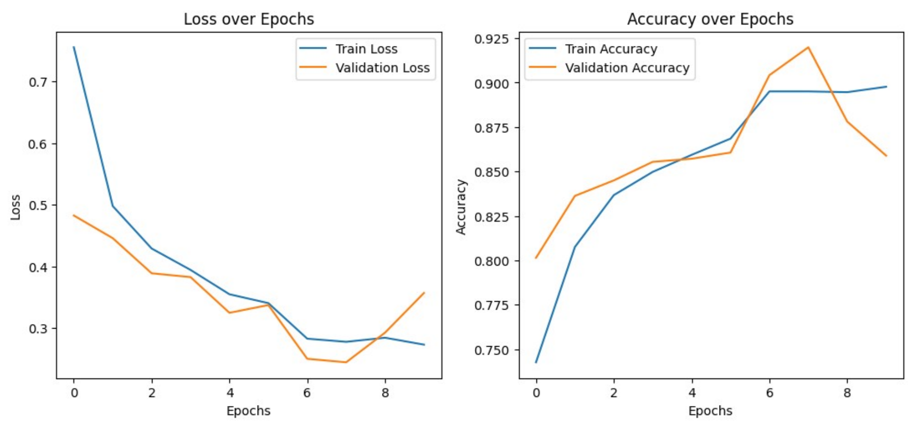
Cerinta 3 - impact augmentari

Fold 1

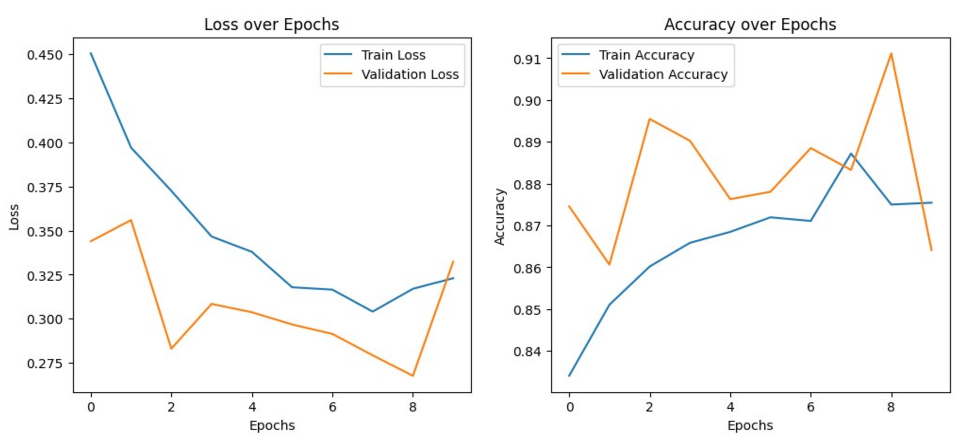
Basic augmentation



Flip and Noise augmentation

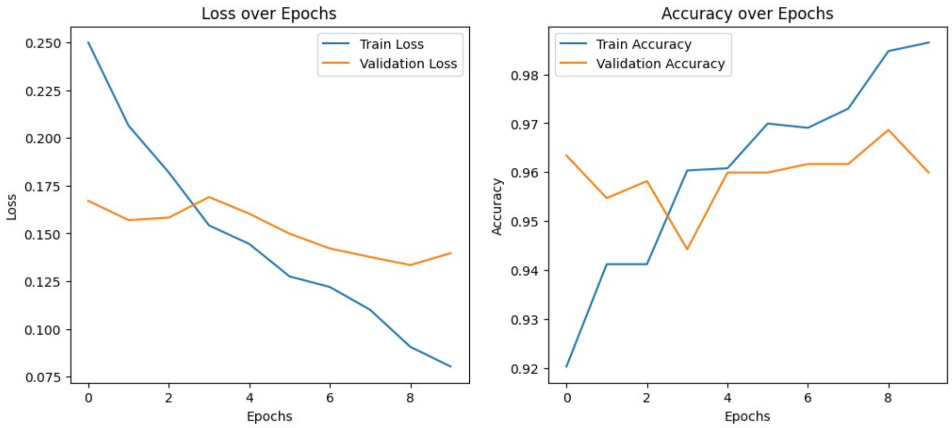


Rotation and Elastic augmentation

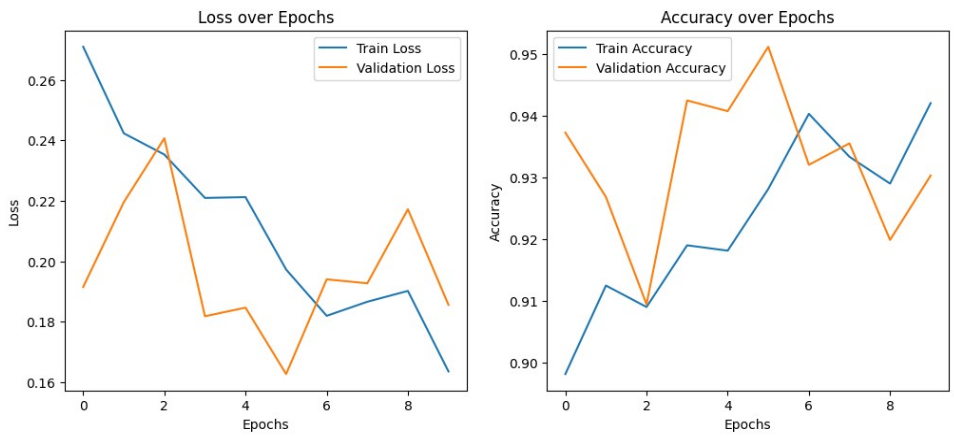


Fold 2

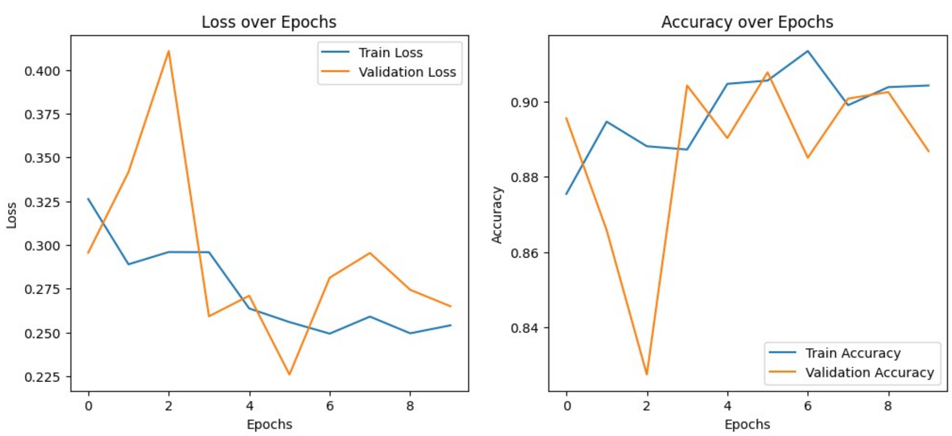
Basic augmentation



Flip and Noise augmentation

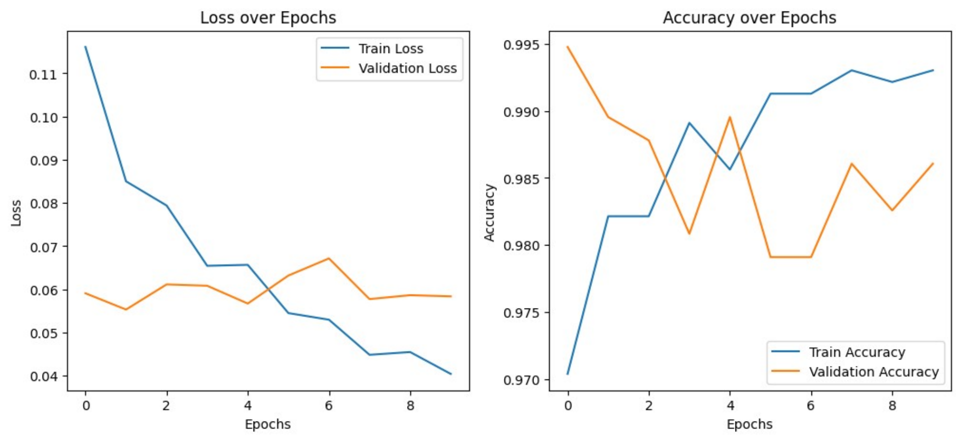


Rotation and Elastic augmentation

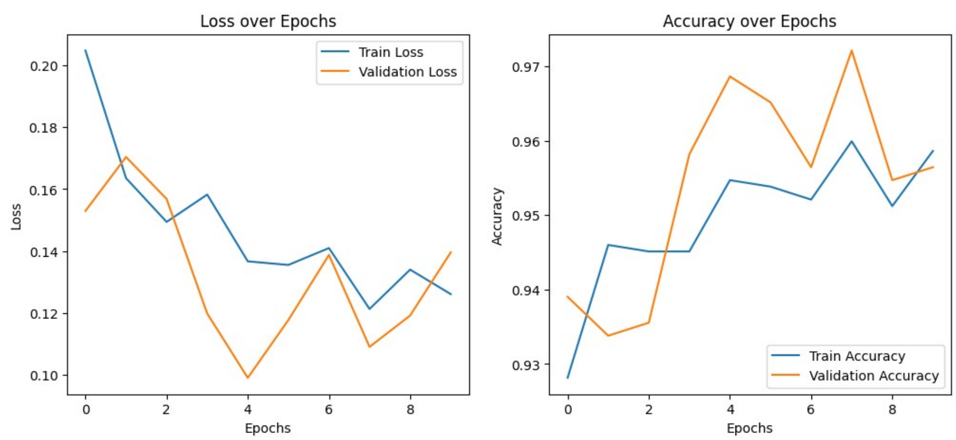


Fold 3

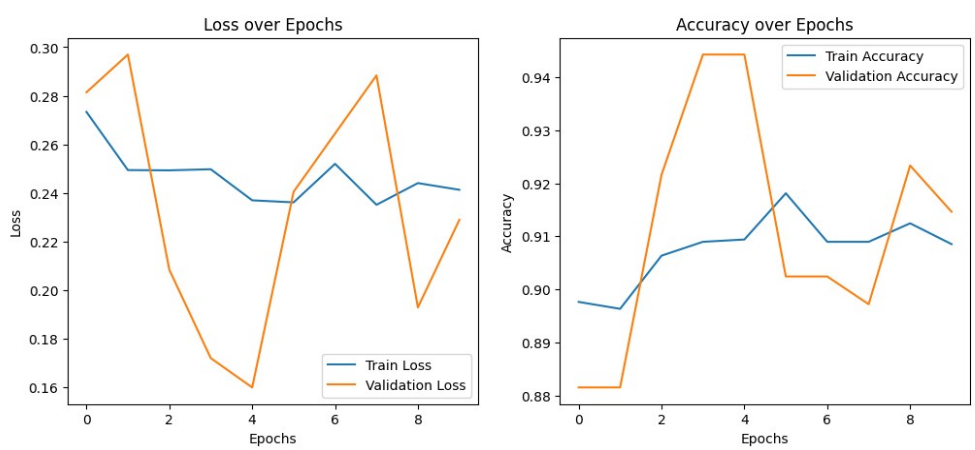
Basic augmentation



Flip and Noise augmentation

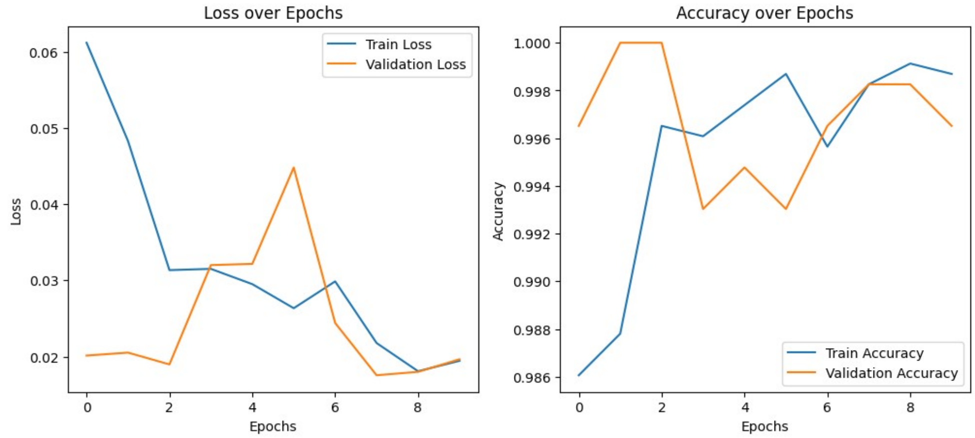


Rotation and Elastic augmentation

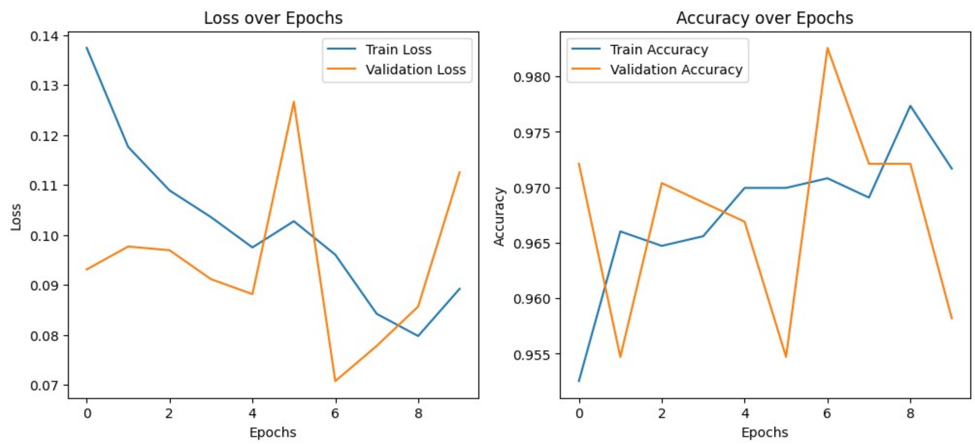


Fold 4

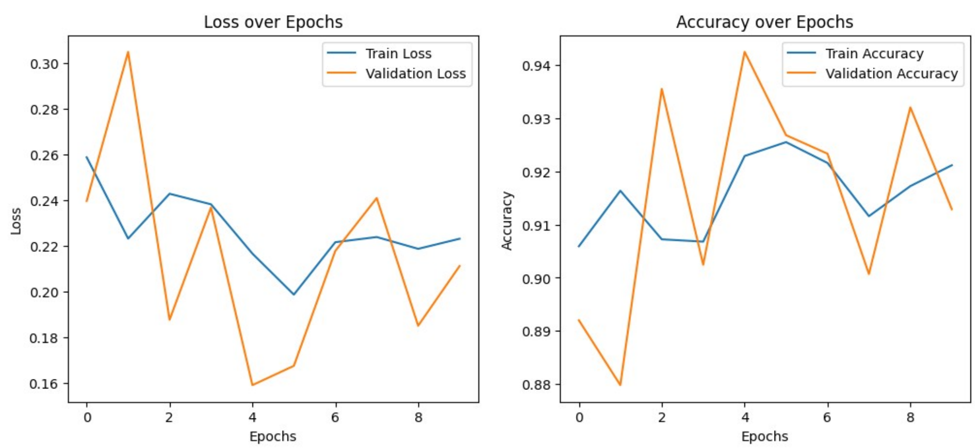
Basic augmentation



Flip and Noise augmentation

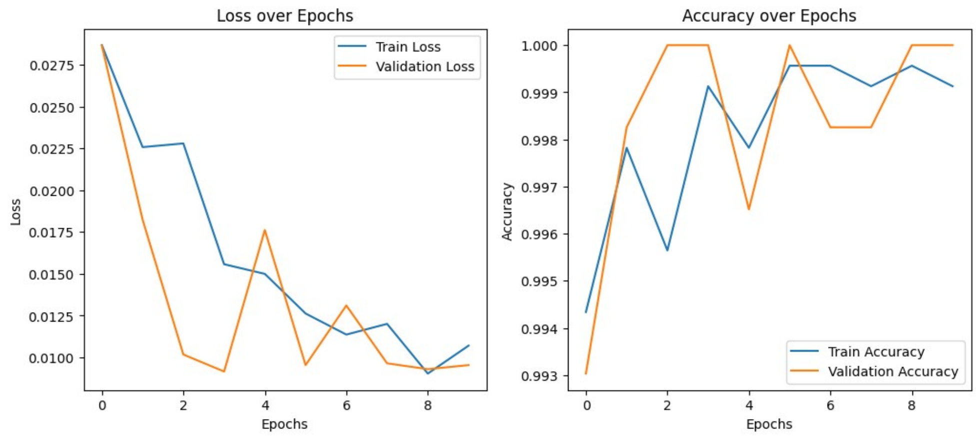


Rotation and Elastic augmentation

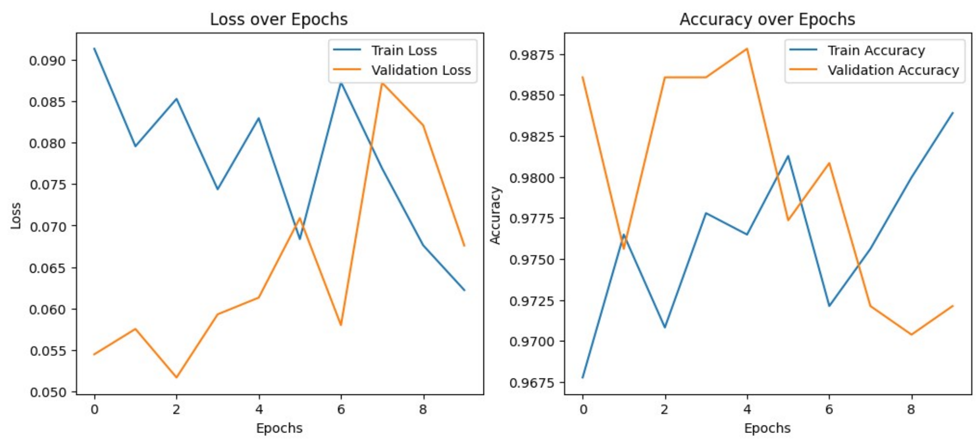


Fold 5

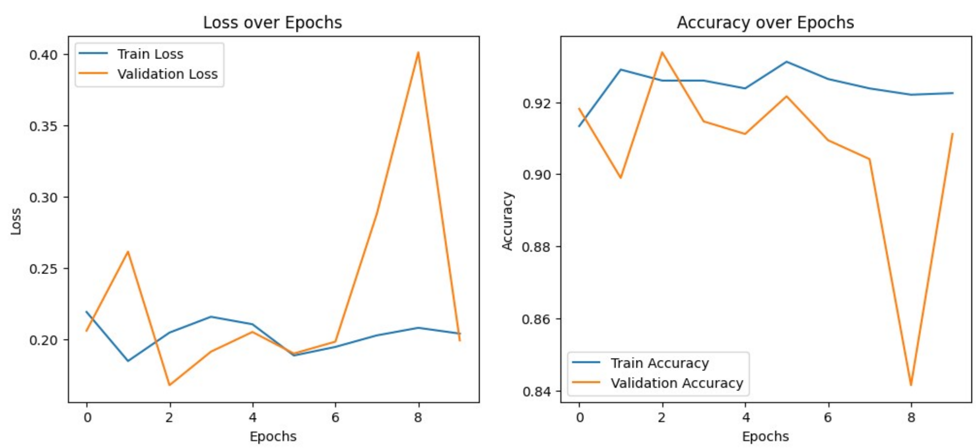
Basic augmentation



Flip and Noise augmentation



Rotation and Elastic augmentation



Valorile medii pentru metricile obtinute dupa augmentari

Fold	Augmentare	Accuracy	Precision	Recall	F1 Score	AUC
1	Basic	0.631980	0.666673	0.623716	0.590665	0.821928
2	Basic	0.677665	0.785396	0.662037	0.634149	0.845256
3	Basic	0.758883	0.836015	0.755021	0.714365	0.868223
4	Basic	0.743655	0.838669	0.733220	0.697269	0.869406
5	Basic	0.761421	0.845065	0.756868	0.716226	0.879722
1	Flip & Noise	0.604061	0.671337	0.605719	0.579027	0.806592
2	Flip & Noise	0.685279	0.768979	0.670554	0.636822	0.831608
3	Flip & Noise	0.675127	0.726225	0.665591	0.634926	0.837746
4	Flip & Noise	0.710660	0.781394	0.699106	0.664969	0.847113
5	Flip & Noise	0.728426	0.784838	0.716889	0.681696	0.852022
1	Rotation & Elastic	0.576142	0.664741	0.570225	0.552934	0.795327
2	Rotation & Elastic	0.647208	0.694309	0.634858	0.613236	0.818103
3	Rotation & Elastic	0.649746	0.707853	0.641800	0.602052	0.827673
4	Rotation & Elastic	0.649746	0.727903	0.636280	0.615207	0.822713
5	Rotation & Elastic	0.654822	0.742055	0.642070	0.626639	0.828136

```
Metricile medii pentru fiecare augmentare:
```

augmentation	accuracy	precision	recall	f1_score	auc
Basic	0.714721	0.794364	0.706173	0.670535	0.856907
Flip & Noise	0.680711	0.746555	0.671572	0.639488	0.835016
Rotation & Elastic	0.635533	0.707372	0.625047	0.602014	0.818391

Cele mai bune performante au fost obtinute cu augmentarea Basic:

```
accuracy        0.714721
precision       0.794364
recall          0.706173
f1_score        0.670535
auc             0.856907
```

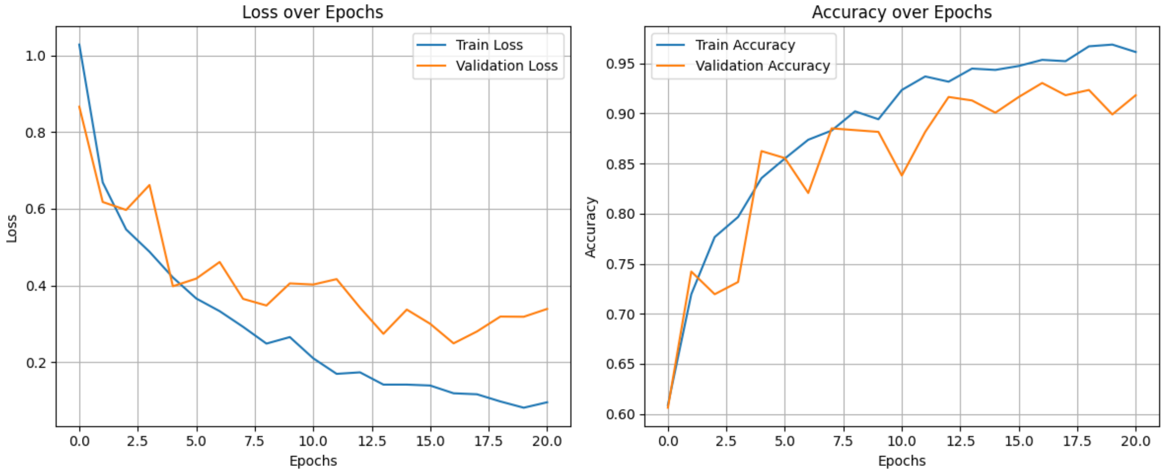
Concluzie si justificare

- **Concluzie**:
  - Setul de augmentare **Basic** a oferit cele mai bune performante globale, cu **cea mai mare acuratete (0.714721)**, **precizie (0.794364)**, si **AUC (0.856907)**. Acesta a demonstrat un echilibru optim intre toate metricile, indicand generalizare buna si capacitatea de a diferentia corect clasele.
- **Justificare**:
  - **Echilibru intre metrici**: Spre deosebire de celelalte augmentari, **Basic** a mentinut un echilibru consistent intre **Precision**, **Recall** si **F1-Score**, ceea ce sugereaza ca modelul a fost capabil sa invete atat exemplele usor de clasificat, cat si cele mai dificile.
  - **AUC ridicat**: AUC-ul ridicat indica faptul ca augmentarea Basic a imbunatatit capacitatea modelului de a separa clasele, ceea ce este esential pentru clasificarea multi-clasa.
  - **Performante scazute pentru alte augmentari**:
    - **Flip & Noise** a oferit rezultate rezonabile, dar mai slabe decat Basic, probabil din cauza adaugarii de zgomot care poate introduce variatii ce nu reflecta distributia reala a datelor.
    - **Rotation & Elastic** a avut cele mai slabe performante, sugerand ca aceste transformari pot fi excesiv de complexe pentru acest set de date, ducand la o pierdere a informatiei relevante.

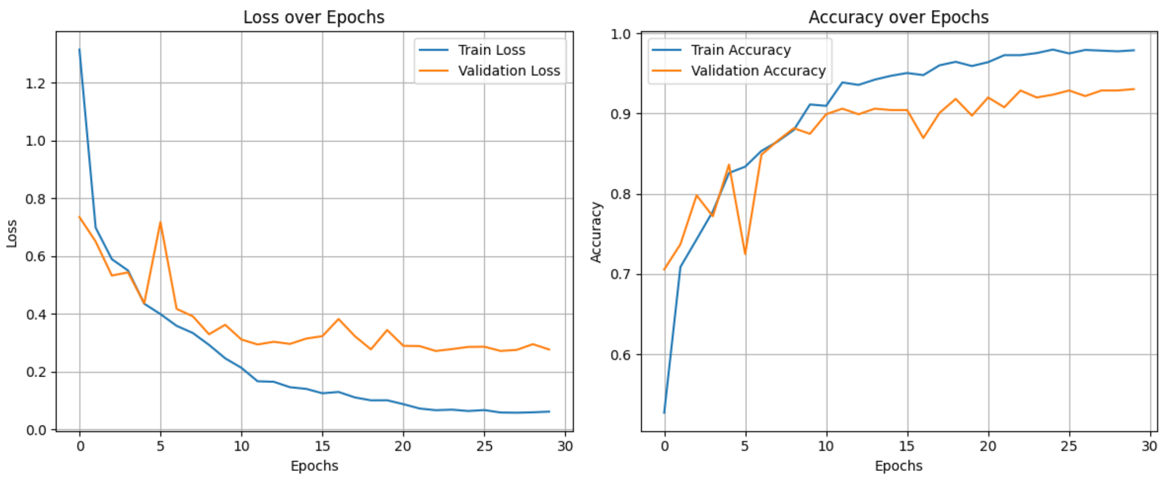
Se recomanda utilizarea setului de augmentare **Basic** pentru imbunatatirea performantei generale a modelului si evitarea augmentarilor complexe care reduc semnificativ metricile de performanta.

Cerinta 4 - prevenire overfitting

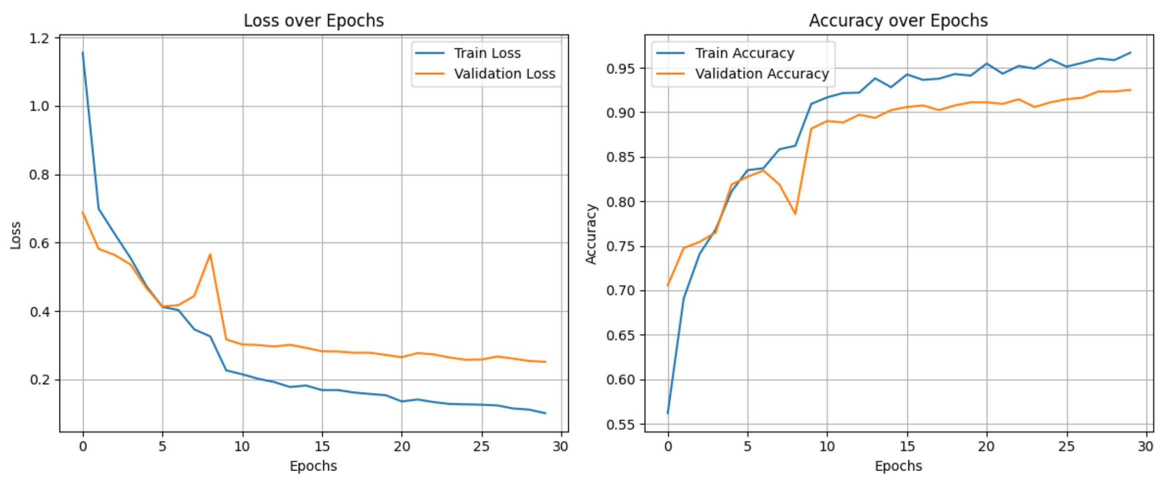
Early Stopping



StepLR



PlateauLR



Tehnica	Train Time(s)	Precision	Recall	F1-Score	Accuracy
early_stopping	159.946	0.7485	0.6396	0.6211	0.6599
step_lr	223.017	0.7844	0.7065	0.6708	0.7157
plateau_lr	213.827	0.7892	0.6944	0.6661	0.7081

Analiza si justificare pentru tehnicile implementate

1. Early Stopping

- **Performanta**: Early Stopping a imbunatatit usor **acuratetea** pe validare si test (**Accuracy: 0.6599**), prevenind overfitting-ul prin oprirea antrenarii inainte ca modelul sa inceapa sa suprainvete zgomotul din datele de antrenament.
- **Avantaj**: Economiseste resurse computationale, reducand timpul de antrenare (**Train Time: 159.946s**) comparativ cu alte tehnici.
- **Limitare**: Imbunatatirile in **Precision** si **F1-Score** sunt moderate, indicand ca performanta poate fi mai sensibila la alte tehnici de ajustare.

2. StepLR

- **Performanta**: StepLR a oferit cea mai mare **Accuracy** pe validare si test (**Accuracy: 0.7157**), cu un echilibru intre metrici (**Precision: 0.7844, F1-Score: 0.6708**). Reducerea treptata a ratei de invatare a permis modelului sa exploreze si sa ajusteze in mod stabil parametrii.
- **Avantaj**: Ideal pentru modele complexe care necesita ajustari treptate ale ratei de invatare pentru a convergenta mai bine.
- **Limitare**: A necesitat cel mai mult timp de antrenare (**Train Time: 223.017s**), ceea ce poate fi costisitor pentru date mai mari.

3. ReduceLROnPlateau

- **Performanta**: ReduceLROnPlateau a obtinut rezultate apropiate de StepLR, cu un **F1-Score** usor inferior (**0.6661**) si **Accuracy** marginal mai mica (**0.7081**).
- **Avantaj**: Eficient pentru a ajusta rata de invatare in mod adaptiv atunci cand performanta pe validare stagneaza, ceea ce ajuta la evitarea overfitting-ului.
- **Limitare**: Timpul de antrenare (**Train Time: 213.827s**) este aproape comparabil cu StepLR, fara a oferi imbunatatiri semnificative in metrici.

Justificarea utilizarii tehnicilor

- **Early Stopping** este recomandat pentru economisirea resurselor atunci cand performanta pe validare este acceptabila si imbunatatirile suplimentare sunt marginale.
- **StepLR** este potrivit pentru maximizarea performantei, mai ales in problemele cu modele complexe, unde este necesara o reducere treptata a ratei de invatare.
- **ReduceLROnPlateau** ofera o abordare echilibrata, fiind util pentru ajustari dinamice, dar poate fi redundant daca StepLR obtine performante similare.

Concluzie

StepLR este cea mai eficienta tehnica pentru acest context, obtinand cele mai bune rezultate la costul unui timp de antrenare crescut. Early Stopping este o alternativa practica pentru economisirea resurselor, iar ReduceLROnPlateau poate fi util pentru optimizari automate in probleme complexe.

Cerinta 5

Evaluarea rezultatelor

1. AUGMENTATION

Type	Train Time (s)	Validation Accuracy	Test Accuracy	Precision	Recall	F1-Score
Minimal	90.16	0.9146	0.7056	0.7829	0.6954	0.6622
Advanced	172.63	0.8415	0.5406	0.6143	0.5464	0.5184
Complex	86.18	0.3084	0.2157	0.1983	0.2091	0.1529

AUC per class

Class	Minimal	Advanced	Complex
Normal	0.6395	0.6101	0.5031
Pituitary	0.9420	0.7625	0.5542
Glioma	0.9325	0.8104	0.4979
Meningioma	0.9286	0.9197	0.3331

Metrics per class

Minimal

Class	Precision	Recall	F1-Score
Normal	0.9000	0.1800	0.3000
Pituitary	0.7482	0.9043	0.8189
Glioma	0.5852	0.9810	0.7331
Meningioma	0.8983	0.7162	0.7970
Macro Avg	0.7829	0.6954	0.6622
Weighted Avg	0.7715	0.7056	0.6602

Advanced

Class	Precision	Recall	F1-Score
Normal	0.6522	0.1500	0.2439
Pituitary	0.6044	0.4783	0.5340
Glioma	0.4352	0.8952	0.5857
Meningioma	0.7656	0.6622	0.7101
Macro Avg	0.6143	0.5464	0.5184
Weighted Avg	0.6017	0.5406	0.5072

Complex

Class	Precision	Recall	F1-Score
Normal	0.2454	0.6600	0.3577
Pituitary	0.3659	0.1304	0.1923
Glioma	0.1538	0.0190	0.0339
Meningioma	0.0282	0.0270	0.0276
Macro Avg	0.1983	0.2091	0.1529
Weighted Avg	0.2153	0.2157	0.1611

2. LOSS FUNCTION

Type	Train Time (s)	Validation Accuracy	Test Accuracy	Precision	Recall	F1-Score
CrossEntropyLoss	89.62	0.3136	0.2411	0.2379	0.2357	0.1900
BCEWithLogitsLoss	83.75	0.3293	0.1904	0.2479	0.1876	0.1604
FocalLoss (α=0.25, γ=2.0)	84.74	0.3014	0.2893	0.2976	0.2803	0.1968

AUC per class

Class	CrossEntropyLoss	BCEWithLogitsLoss	FocalLoss (α=0.25, γ=2.0)
Normal	0.4697	0.4974	0.4845
Pituitary	0.4856	0.4884	0.5164
Glioma	0.4580	0.3684	0.5299
Meningioma	0.4011	0.3945	0.2402

Metrics per class

CrossEntropyLoss

Class	Precision	Recall	F1-Score
Normal	0.2510	0.6600	0.3636
Pituitary	0.3902	0.1391	0.2051
Glioma	0.2162	0.0762	0.1127
Meningioma	0.0943	0.0676	0.0787
Macro Avg	0.2379	0.2357	0.1900
Weighted Avg	0.2529	0.2411	0.1970

BCEWithLogitsLoss

Class	Precision	Recall	F1-Score
Normal	0.2146	0.5000	0.3003
Pituitary	0.6087	0.1217	0.2029
Glioma	0.1000	0.0476	0.0645
Meningioma	0.0682	0.0811	0.0741
Macro Avg	0.2479	0.1876	0.1604
Weighted Avg	0.2716	0.1904	0.1665

FocalLoss (α=0.25, γ=2.0)

Class	Precision	Recall	F1-Score
Normal	0.2843	0.8900	0.4310
Pituitary	0.4500	0.1565	0.2323
Glioma	0.3846	0.0476	0.0847
Meningioma	0.0714	0.0270	0.0392
Macro Avg	0.2976	0.2803	0.1968
Weighted Avg	0.3194	0.2893	0.2071

3. Optimizer

Type	Train Time (s)	Validation Accuracy	Test Accuracy	Precision	Recall	F1-Score
Adam	85.51	0.3206	0.2335	0.1986	0.2277	0.1741
SGD	101.92	0.3902	0.2056	0.1978	0.2289	0.1752
RMSprop	86.14	0.1551	0.2563	0.1395	0.2357	0.1527

AUC per class

Class	Adam	SGD	RMSprop
Normal	0.4874	0.4683	0.5818
Pituitary	0.4177	0.3484	0.5336
Glioma	0.5300	0.3139	0.4609
Meningioma	0.3507	0.4484	0.2293

Metrics per class

Adam

Class	Precision	Recall	F1-Score
Normal	0.2370	0.5900	0.3381
Pituitary	0.2000	0.0174	0.0320
Glioma	0.3085	0.2762	0.2915
Meningioma	0.0488	0.0270	0.0348
Macro Avg	0.1986	0.2277	0.1741
Weighted Avg	0.2099	0.2335	0.1794

SGD

Class	Precision	Recall	F1-Score
Normal	0.2229	0.3500	0.2724
Pituitary	0.2564	0.0870	0.1299
Glioma	0.1250	0.0190	0.0331
Meningioma	0.1868	0.4595	0.2656
Macro Avg	0.1978	0.2289	0.1752
Weighted Avg	0.1998	0.2056	0.1657

RMSprop

Class	Precision	Recall	F1-Score
Normal	0.0000	0.0000	0.0000
Pituitary	0.3151	0.2000	0.2447
Glioma	0.2430	0.7429	0.3662
Meningioma	0.0000	0.0000	0.0000
Macro Avg	0.1395	0.2357	0.1527
Weighted Avg	0.1567	0.2563	0.1690

Interpretarea Rezultatelor

1. Comparatia intre versiuni ale modelului

- **Augmentari**:
  - Minimal Augmentation a depasit modelul de baza pe setul de validare (**Accuracy: 0.914 vs. 0.876**) si pe testare (**Accuracy: 0.706 vs. 0.525**), sugerand o generalizare mai buna fara overfitting.
  - Complex Augmentation a redus drastic performantele (**Validation Accuracy: 0.308, Test Accuracy: 0.216**), ceea ce indica introducerea de zgomot excesiv.
- **Functii de pierdere**:
  - FocalLoss a crescut **Recall** si **AUC** pentru clasele minoritare, dar a obtinut o **Validation Accuracy** inferioara modelului de baza (**0.301 vs. 0.876**).
  - CrossEntropyLoss, desi stabila, nu a imbunatatit rezultatele in comparatie cu modelul de baza.
- **Optimizatori**:
  - Adam a oferit rezultate apropiate de modelul de baza, dar **SGD** a avut o performanta mai slaba pe testare (**Accuracy: 0.206**) din cauza convergentei mai lente.
  - RMSprop a fost inconsistent, obtinand un **AUC** ridicat pe clasa "Normal" (**0.582**), dar performante generale scazute (**Accuracy: 0.256**).

2. Impactul modificarilor hiperparametrilor

- **Functii de pierdere**:
  - FocalLoss a prioritizat exemplele dificil de clasificat, imbunatatind performanta pe clasele minoritare (ex. clasa "Glioma", **AUC: 0.530**), dar a sacrificat acuratetea globala.
- **Optimizatori**:
  - Adam a fost cel mai stabil, mentinand o **Validation Accuracy** aproape de modelul de baza (**0.321 vs. 0.876**).
  - SGD si RMSprop au fost mai putin eficiente, indicand sensibilitatea la hiperparametrii specifici (de ex. rata de invatare).

3. Performanta pe clasele minoritare

- **Modelul de baza**:
  - Clasa "Meningioma" a avut cele mai scazute metrici pe testare (**F1-Score: 0.078**), indicand dificultati majore in invatarea acestei clase.
- **FocalLoss**:
  - A imbunatatit usor metricile pentru clasele minoritare, in special pentru "Glioma" (**F1-Score: 0.084, Recall: 0.048**), dar nu a corectat complet dezechilibrul.
- **Augmentari complexe**:
  - Au diminuat drastic performantele pe toate clasele, afectand in special "Meningioma" (**F1-Score: 0.027**), sugerand sensibilitatea modelului la date augmentate excesiv.

4. Impactul augmentarii si regularizarii

- Minimal Augmentation a obtinut cel mai bun echilibru intre generalizare si acuratete, depasind modelul de baza.
- Augmentarile complexe au introdus zgomot si au afectat negativ toate metricile, ceea ce indica o sensibilitate ridicata a modelului la regularizari excesive.

5. Comparatia metricilor

- F1-Score-ul pentru Minimal Augmentation (**0.662**) a fost semnificativ mai mare decat cel al modelului de baza (**0.496**), ceea ce sugereaza ca aceasta tehnica este mai potrivita pentru acest set de date.
- Performantele FocalLoss pe testare au fost mai bune pentru "Pituitary" si "Glioma", ceea ce indica eficienta sa in tratarea dezechilibrului de clasa.