

# ISTANBUL TECHNICAL UNIVERSITY FACULTY OF COMPUTER AND INFORMATICS

Computer Engineering Graduation Project Presentation



## PERFORMANCE ANALYSIS OF DEEPPFAKE DETECTION USING DIFFERENT FACIAL REGIONS

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# Introduction

## What is deepfake?

- Deepfake is visual data that created using the deep learning to replace human faces inside the video or image with another face within the video or image. The name deepfake comes from the combination of the terms “deep learning” and “fake”.

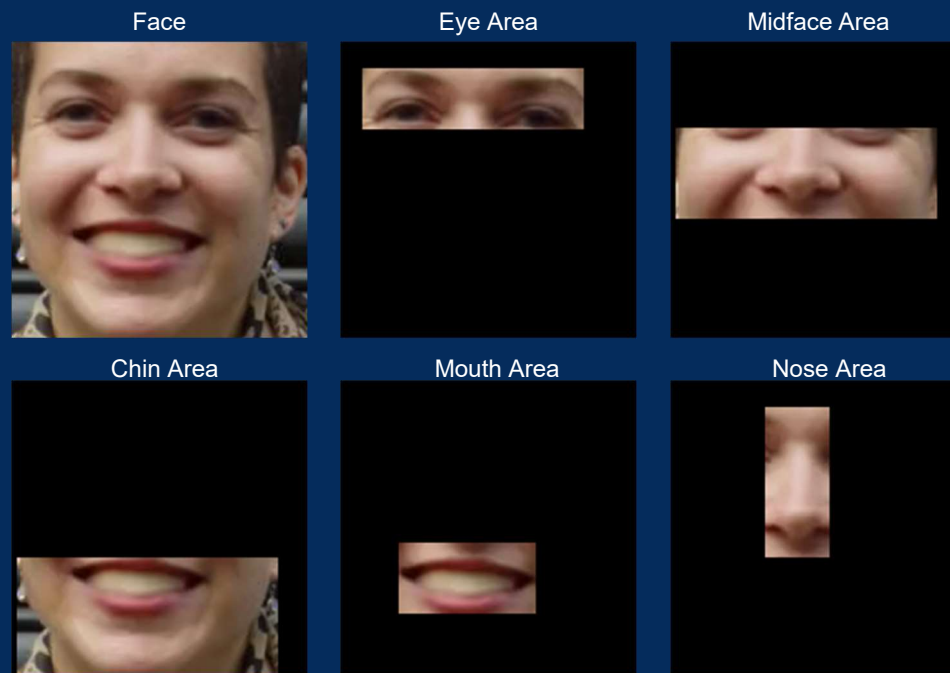


Example deepfake images from Celeb-DF [1] Dataset. Left image is the original image and others are Deepfakes generated different donor subjects.

[1] Y. Li, P. Sun, H. Qi and S. Lyu, "Celeb-DF: A Large-scale Challenging Dataset for DeepFake Forensics," in IEEE Conference on Computer Vision and Patten Recognition (CVPR), Seattle, WA, United States, 2020.

# Problem Statement

Comparing deepfake detection performances of models by using different facial regions.



Images: A. Rössler, D. Cozzolino, L. Verdoliva, C. Riess, J. Thies and M. Nießner, "FaceForensics++: Learning to Detect Manipulated Facial Images," in ICCV, 2019.

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# Dataset

	Image Count			
	planned		actual	
	manipulated	original	manipulated	original
<b>Train</b>	12544	14410	12048	13732
<b>Validation</b>	3150	3610	3061	3447
<b>Test</b>	3934	4510	3746	4283

Dataset of train, validation and test splits

Dataset	Type	Count
FaceForensics++ [1]	Deepfake Detection	767
	Deepfakes	260
	Face2Face	264
	FaceShifter	263
	FaceSwap	263
	Neural Textures	258
	Original	2542
Celeb-DF [2]	Fake	1580
	Original	1741
DeepfakeTIMIT [3]	Fake	91

Detailed data distribution of test set

[1] A. Rössler, D. Cozzolino, L. Verdoliva, C. Riess, J. Thies and M. Nießner, "FaceForensics++: Learning to Detect Manipulated Facial Images," in ICCV, 2019.

[2] Y. Li, P. Sun, H. Qi and S. Lyu, "Celeb-DF: A Large-scale Challenging Dataset for DeepFake Forensics," in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Seattle, WA, United States, 2020.

[3] P. Korshunov and S. Marcel, "DeepFakes: a New Threat to Face Recognition? Assessment and Detection," 2018.

```

Input-224,224,3
conv3-64
conv3-64
maxpool
conv3-128
conv3-128
maxpool
conv3-256
conv3-256
conv3-256
conv3-256
maxpool
conv3-512
conv3-512
conv3-512
conv3-512
maxpool
conv3-512
conv3-512
conv3-512
conv3-512
maxpool
FC-4096
FC-4096
FC-1

```

Diagram illustrating the AlexNet architecture, showing the flow of data through two parallel processing paths. The input is a 224x224x3 image, which is processed by five convolutional layers (Conv 64, 128, 128, 256, 256) and three fully connected layers (FC 2048, FC 2048, FC 1000) to produce the final output.

**Input:** 224 224 3

**Path 1 (Left):**

- Conv 64 7x7 stride=2x2
- Maxpool 3x3 stride=2x2
- Conv 64 1x1
- Conv 64 3x3
- Conv 256 1x1
- Conv 64 1x1
- Conv 64 3x3
- Conv 256 1x1
- Conv 64 1x1
- Conv 64 3x3
- Conv 256 1x1
- Conv 128 1x1 stride=2x2
- Conv 128 3x3
- Conv 512 1x1
- Conv 128 1x1
- Conv 128 3x3
- Conv 512 1x1
- Conv 128 1x1
- Conv 128 3x3
- Conv 512 1x1

**Path 2 (Right):**

- Conv 256 1x1 stride=2x2
- Conv 256 3x3
- Conv 1024 1x1
- Conv 256 1x1
- Conv 256 3x3
- Conv 1024 1x1
- Conv 256 1x1
- Conv 256 3x3
- Conv 1024 1x1
- Conv 256 1x1
- Conv 256 3x3
- Conv 1024 1x1
- Conv 512 1x1 stride=2x2
- Conv 512 3x3
- Conv 2048 1x1
- Conv 512 1x1
- Conv 512 3x3
- Conv 2048 1x1
- Conv 512 1x1
- Conv 512 3x3
- Conv 2048 1x1

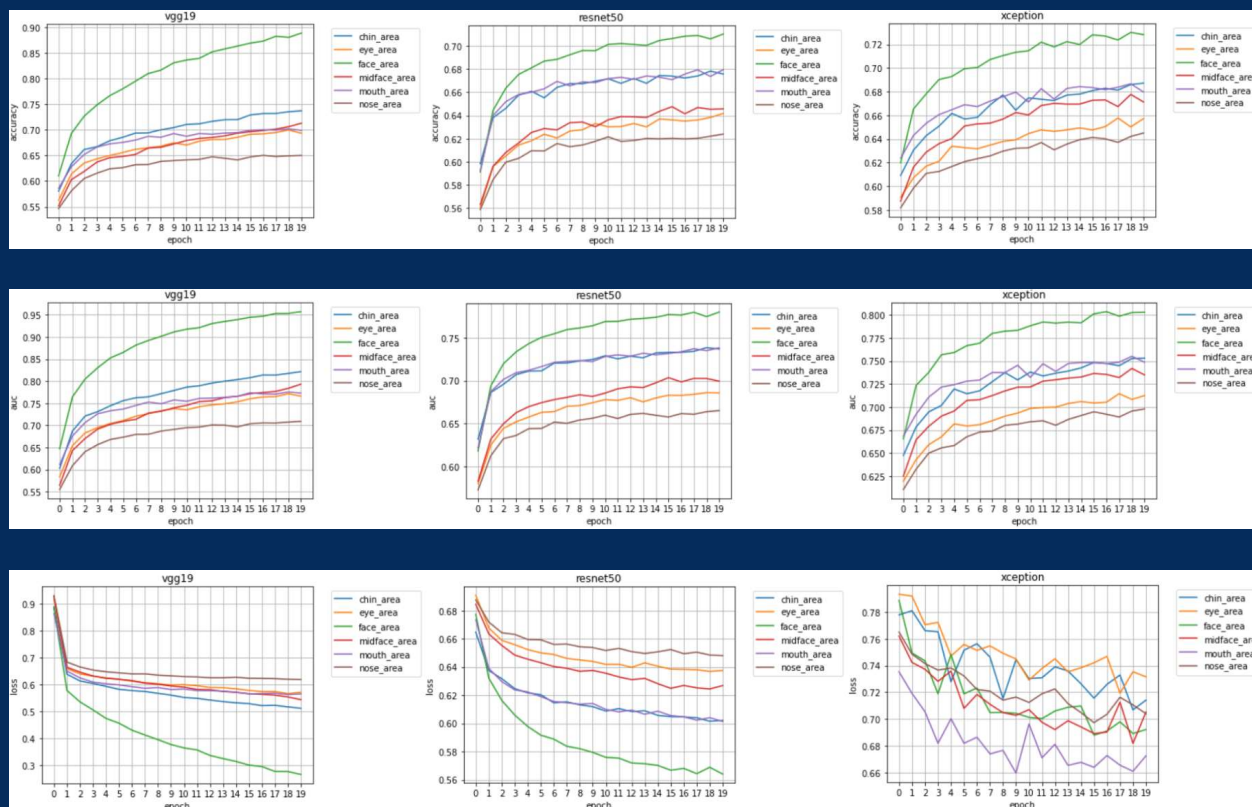
**Final Processing:**

- Average Pooling
- Sigmoid

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# Results

## Train Results



Accuracy

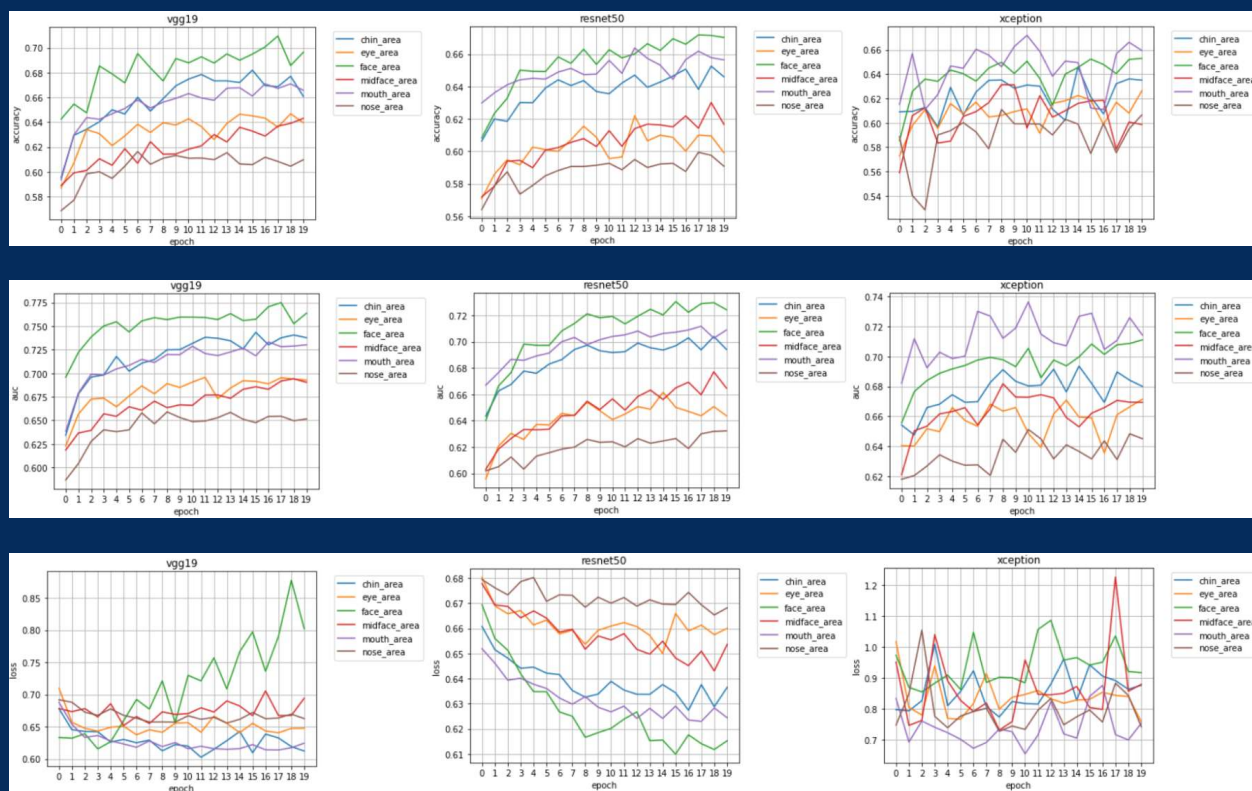
AUC

Loss

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# Results

## Validation Results



Accuracy

AUC

Loss



# Results

## Test Results

region	VGG19 [1]	ResNet50 [2]	Xception [3]
chin_area	0.66185081	0.65250963	0.645534933
eye_area	0.635446489	0.616639674	0.628347218
face_area	0.679412127	0.674305618	0.613899589
midface_area	0.620874345	0.631211877	0.642172098
mouth_area	0.676422954	0.663594484	0.666832745
nose_area	0.610536814	0.607049465	0.602192044

Accuracies of models and facial regions.

region	VGG19 [1]	ResNet50 [2]	Xception [3]
chin_area	0.720196605	0.704772115	0.697542071
eye_area	0.687221289	0.667445362	0.677461565
face_area	0.74442941	0.736271441	0.642947078
midface_area	0.664794207	0.685279429	0.691203296
mouth_area	0.731904447	0.722529709	0.728539944
nose_area	0.649096489	0.642353654	0.639755368

AUC scores of models and facial regions.

[1] K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," 2015.

[2] K. He, X. Zhang, S. Ren and J. Sun, "Deep Residual Learning for Image Recognition," in CVPR, 2016.

[3] F. Chollet, "Xception: Deep Learning with Depthwise Separable Convolutions," in IEEE/CVF Conference on Computer Vision and Pattern, 2017.

# Results

## Test Results Contd.

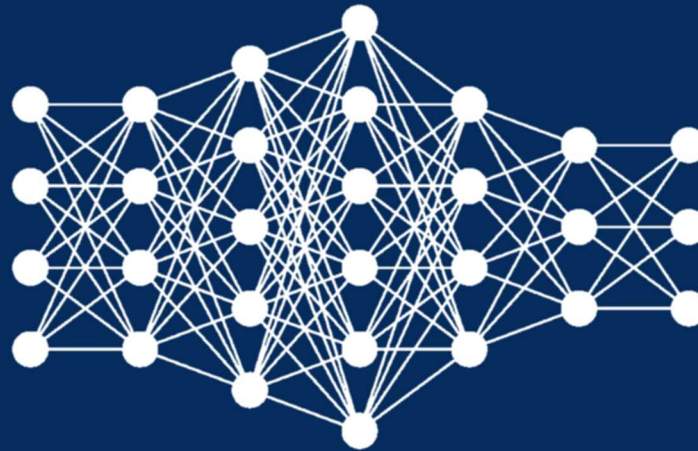
Dataset	Category	chin_area			eye_area			face_area			midface_area			mouth_area			nose_area		
		Resnet50	VGG19	Xception	Resnet50	VGG19	Xception	Resnet50	VGG19	Xception	Resnet50	VGG19	Xception	Resnet50	VGG19	Xception	Resnet50	VGG19	Xception
Celeb-DF [1]	Real	0.51	0.53	0.73	0.46	0.53	0.57	0.62	0.70	0.68	0.73	0.66	0.36	0.59	0.51	0.68	0.66	0.52	0.56
	Fake	0.79	0.79	0.53	0.79	0.81	0.69	0.75	0.79	0.68	0.56	0.64	0.85	0.77	0.83	0.64	0.54	0.74	0.70
	Youtube	0.65	0.70	0.82	0.54	0.58	0.66	0.75	0.85	0.76	0.75	0.73	0.42	0.66	0.60	0.72	0.73	0.63	0.60
DeepfakeTIMIT [2]	Fake	0.78	0.80	0.65	0.65	0.84	0.70	0.75	0.73	0.69	0.42	0.74	0.91	0.56	0.75	0.59	0.57	0.80	0.89
Faceforensics++ [3]	DeepfakeDetection	0.61	0.76	0.67	0.56	0.76	0.61	0.69	0.58	0.68	0.41	0.56	0.84	0.69	0.75	0.64	0.36	0.53	0.58
	Face2Face	0.53	0.45	0.55	0.41	0.36	0.38	0.47	0.38	0.49	0.45	0.38	0.79	0.43	0.56	0.44	0.27	0.35	0.61
	FaceShifter	0.28	0.38	0.43	0.49	0.43	0.44	0.33	0.23	0.34	0.30	0.28	0.65	0.27	0.33	0.27	0.29	0.44	0.51
	FaceSwap	0.20	0.27	0.30	0.22	0.41	0.34	0.18	0.33	0.32	0.25	0.26	0.65	0.12	0.24	0.20	0.16	0.23	0.41
	NeuralTextures	0.62	0.52	0.58	0.39	0.35	0.31	0.37	0.22	0.42	0.51	0.32	0.73	0.52	0.60	0.47	0.31	0.38	0.51
	Original	0.74	0.70	0.68	0.76	0.69	0.71	0.80	0.81	0.73	0.83	0.78	0.47	0.80	0.74	0.81	0.83	0.70	0.63
	Deepfakes	0.60	0.68	0.65	0.57	0.50	0.58	0.57	0.48	0.61	0.39	0.47	0.78	0.67	0.71	0.65	0.39	0.53	0.60

Accuracies of each sub dataset for each region and model (VGG19 [4], Resnet50 [5], Xception [6])

- [1] Y. Li, P. Sun, H. Qi and S. Lyu, "Celeb-DF: A Large-scale Challenging Dataset for DeepFake Forensics," in IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Seattle, WA, United States, 2020.
- [2] P. Korshunov and S. Marcel, "DeepFakes: a New Threat to Face Recognition? Assessment and Detection," 2018.
- [3] A. Rössler, D. Cozzolino, L. Verdoliva, C. Riess, J. Thies and M. Nießner, "FaceForensics++: Learning to Detect Manipulated Facial Images," in ICCV, 2019.
- [4] K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," 2015.
- [5] K. He, X. Zhang, S. Ren and J. Sun, "Deep Residual Learning for Image Recognition," in CVPR, 2016.
- [6] F. Chollet, "Xception: Deep Learning with Depthwise Separable Convolutions," in IEEE/CVF Conference on Computer Vision and Pattern, 2017.

# Future Work

- More balanced distributed dataset
- Complex ANNs
- RNN based deepfake detector
- Different face detectors





# THANK YOU FOR LISTENING!

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