

# Development of Deep Learning-integrated Futuristic Biomedical Platforms for Translational Digital Healthcare

## Doctoral Candidate

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College of Information-Bio Convergence Engineering  
Ulsan National Institute of Science and Technology (UNIST)



**Dear committee, good day, this is a post-recorded PhD defense presentation of mine. It is done with the purpose to inform the committee members who could not participate, as well as our lab members.**

**Dear all, I am Sanzhar Askaruly, a PhD candidate in Biomedical Engineering at UNIST. The topic of my Ph.D thesis is called Development of Deep Learning-integrated Futuristic Biomedical Platforms for Translational Digital Healthcare. My research has been done under supervision by Professor Woonggyu Jung.**

**What?**



[1] "What is Digital Health?", U.S. Food and Drug Administration.



To begin with, I would like to introduce what is digital health. The broad scope of digital health includes categories such as wearable devices, mobile health, health IT, telehealth and personalized medicine. These digital tools give a more holistic view of human health through access to data and control.

**What?**



**Why?**


- 
-  Increase efficiency
  -  Improve access
  -  Reduce cost
  -  Increase quality
  -  Make medicine more personalized


[1] "What is Digital Health?", U.S. Food and Drug Administration.


**It offers real opportunities to improve medical outcomes and enhance efficiency. Providers and users of this tech have several benefits, including cost reduction, quality improvement, personalization and others.**


**Chapter 1. Introduction**


1.1. Digital healthcare	<b>1.2. Deep learning</b>	1.3. Motivation	1.4. Outline
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mHealth

  
health IT

  
wearables


  
telehealth

  
personalized  
medicine

**But generates large and complex data  
for human to analyze<sup>[1,2]</sup>**

[1] Shortliffe (2018), "Clinical decision support in the era of artificial intelligence."  
[2] Densen. (2011) "Challenges and opportunities facing medical education."

[3] Clinical Decision Support. [Agency for Healthcare Research and Quality](#)

  
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However, the extensive use of technologies within digital health creates a bottleneck of analysing large and complex amounts of medical data, where human is incapable.

## Chapter 1. Introduction

### 1.1. Digital healthcare

### 1.2. Deep learning

### 1.3. Motivation

### 1.4. Outline



mHealth



health IT



wearables

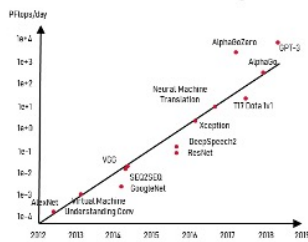


telehealth



personalized  
medicine

**But generates large and complex data  
for human to analyze<sup>[1,2]</sup>**



**also, AI capacity is expanding!**

[1] Shortliffe (2018), "Clinical decision support in the era of artificial intelligence."  
[2] Densen. (2011) "Challenges and opportunities facing medical education."


[3] Clinical Decision Support. [Agency for Healthcare Research and Quality](#)





**At the same time, the capacity of artificial intelligence keeps expanding.**


**Chapter 1. Introduction**


1.1. Digital healthcare
1.2. Deep learning
1.3. Motivation
1.4. Outline

  
mHealth

  
health IT

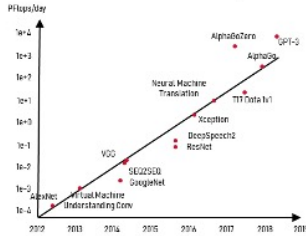
  
wearables

  
telehealth

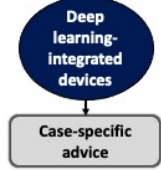
  
personalized  
medicine

**Therefore, a timely advice could be supported by AI<sup>[3]</sup>**



**But generates large and complex data for human to analyze<sup>[1,2]</sup>**



**also, AI capacity is expanding!**




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 [3] Clinical Decision Support. [Agency for Healthcare Research and Quality](#)



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**One of the opportunities for this challenge could be the suggestion of assistive intelligent devices. Their goal is to support the decision by giving a timely advice at the point of care.**

**Chapter 1. Introduction**


1.1. Digital healthcare
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mHealth




health IT



wearables

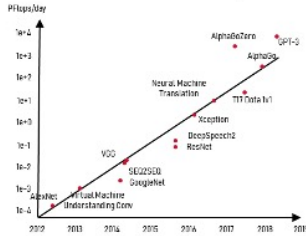


telehealth



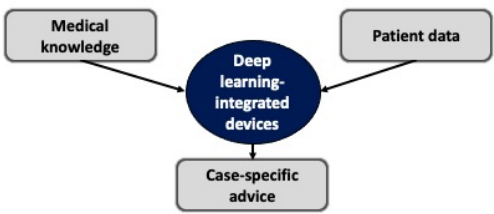
personalized  
medicine

**But generates large and complex data for human to analyze<sup>[1,2]</sup>**





**also, AI capacity is expanding!**

**Therefore, a timely advice could be supported by AI<sup>[3]</sup>**




[1] Shortliffe (2018), "Clinical decision support in the era of artificial intelligence."  
 [2] Densen. (2011) "Challenges and opportunities facing medical education."  
 [3] Clinical Decision Support. [Agency for Healthcare Research and Quality](#)


For this reason, they may need to utilize medical knowledge and patient data.

**Chapter 1. Introduction**


1.1. Digital healthcare      **1.2. Deep learning**      1.3. Motivation      1.4. Outline




mHealth




health IT



wearables

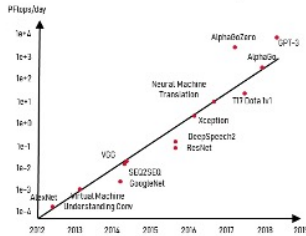


telehealth



personalized medicine

**But generates large and complex data for human to analyze<sup>[1,2]</sup>**

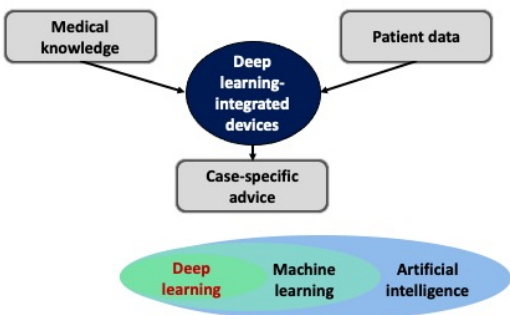


**also, AI capacity is expanding!**

[1] Shortliffe (2018), "Clinical decision support in the era of artificial intelligence."  
[2] Densen. (2011) "Challenges and opportunities facing medical education."

[3] Clinical Decision Support. [Agency for Healthcare Research and Quality](#)

**Therefore, a timely advice could be supported by AI<sup>[3]</sup>**



Deep learning is a computational technique, which is subset of a broader term of artificial intelligence. It was repeatedly reported to achieve success for various biomedical problems.



**Conventional** biomedical devices

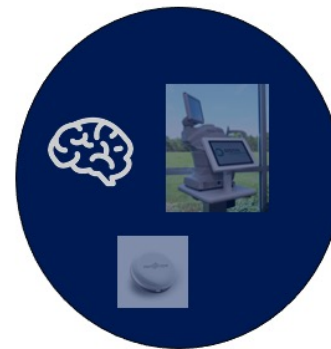


**Currently, conventional biomedical devices are developed with fixed requirements. They are often primitive, static, and are even analogue sometimes in their nature.**

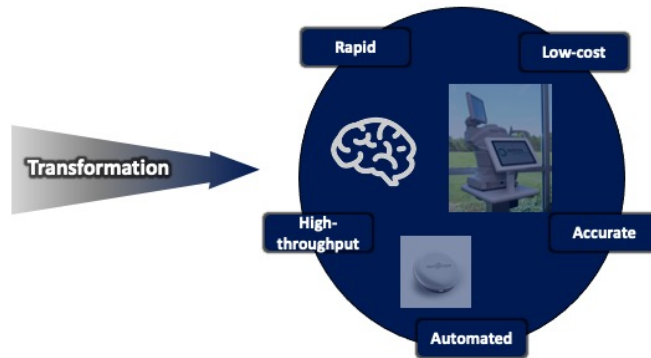
**Conventional** biomedical devices



**Smart** biomedical devices



**In contrast, smart biomedical devices possess built-in intelligence to support human decision. They exist, but rare, partly because they require multiple considerations. Also, their objective is not always obvious.**

**Conventional biomedical devices****Smart biomedical devices**

The transformation from one category to another is an open question. However, the exploration of opportunities within was my primary interest during the PhD program.

Chapter 1. Introduction

1.1. Digital healthcare	1.2. Deep learning	1.3. Motivation	1.4. Outline
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Chapter 2

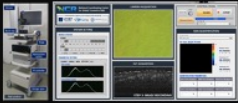
Deep learning

Faster Imaging

OCT volume inpainting

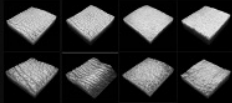
New biomedical device

Optical coherence tomography




Imaging

Human skin tissue



Translation

Cosmetical



\*OCT: Optical coherence tomography


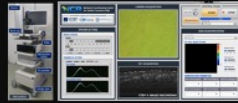
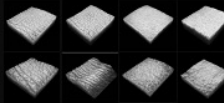


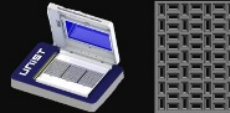


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In this slide, I present with the outline of research works. Initially, I will describe how deep learning could be integrated to accelerate OCT imaging of human skin for cosmetical fields.


**Chapter 1. Introduction**

1.1. Digital healthcare	1.2. Deep learning	1.3. Motivation	<b>1.4. Outline</b>
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	<b>Deep learning</b>	<b>New biomedical device</b>	<b>Imaging</b>	<b>Translation</b>
<b>Chapter 2</b>	<p><b>Faster Imaging</b></p>  <p>OCT volume inpainting</p>	<p>Optical coherence tomography</p> 	<p>Human skin tissue</p> 	<p>Cosmetical</p> 
<b>Chapter 3</b>	<p><b>Automated Analysis</b></p>  <p>Embryo segmentation</p>	<p>Scanner and PDMS microplate</p> 	<p><i>Xenopus laevis</i> model organism</p> 	<p>Pharmaceutical</p> 

\*OCT: Optical coherence tomography, \*PDMS: Polydimethylsiloxane

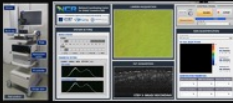
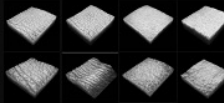

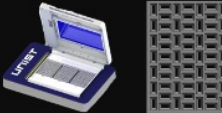





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Next, I demonstrate the results of leveraging deep learning for automated analysis of an aquatic animal model, *Xenopus*, having implications for pharmaceutical research.


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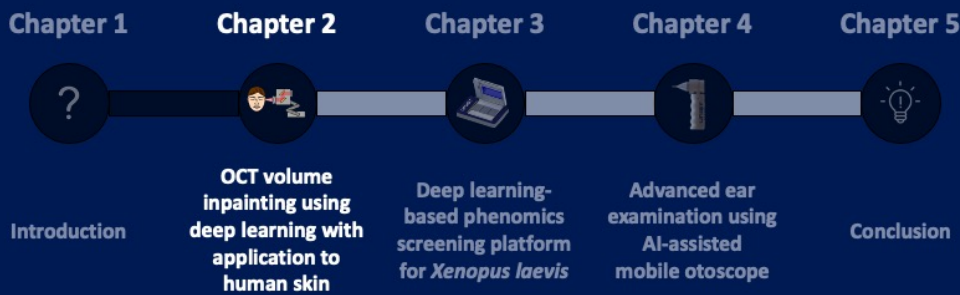
	<b>Deep learning</b>	<b>New biomedical device</b>	<b>Imaging</b>		<b>Translation</b>
<b>Chapter 2</b>	<b>Faster Imaging</b> OCT volume inpainting	<b>Optical coherence tomography</b> 	<b>Human skin tissue</b> 		<b>Cosmetical</b> 
<b>Chapter 3</b>	<b>Automated Analysis</b> Embryo segmentation	<b>Scanner and PDMS microplate</b> 	<b>Xenopus laevis model organism</b> 		<b>Pharmaceutical</b> 
<b>Chapter 4</b>	<b>Precise Diagnosis</b> TM detection	<b>Mobile and AR device</b> 	<b>Human tympanic membrane</b> 		<b>Clinical</b> 

\*OCT: Optical coherence tomography, \*PDMS: Polydimethylsiloxane, \*TM: Tympanic membrane

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Finally, in chapter 4, I will present the outcome of incorporating AI model to enhance ear examination procedure to support clinical diagnosis.

## Development of Deep Learning-integrated Futuristic Biomedical Platforms for Translational Digital Healthcare



### Joint work with:

Yujin Ahn<sup>1</sup>, Hyeongeun Kim<sup>2</sup>, Andrey Vavilin<sup>3</sup>, Sungbea Ban<sup>4</sup>,  
Pil Un Kim<sup>5</sup>, Seunghun Kim<sup>6</sup>, Haekwang Lee<sup>6</sup>, Jinhee Park<sup>7</sup>,  
Dongyoung Kim<sup>8</sup>, Gil-Jin Jang<sup>7</sup>, Woonggyu Jung<sup>1</sup>

<sup>1</sup>Ulsan National Institute of Science and Technology, South Korea

<sup>2</sup>Naver Research, South Korea

<sup>3</sup>ABBYY, Russia

<sup>4</sup>Samsung Research, South Korea

<sup>5</sup>LG Research, South Korea,

<sup>6</sup>Amore-Pacific Research and Development, South Korea

<sup>7</sup>Kyungpook National University, South Korea



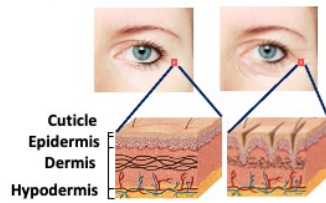
Department of Biomedical Engineering, PhD Thesis Presentation



Let me introduce the first project OCT volume inpainting using deep learning with application to human skin. This is a joint work with Professor Jang's laboratory from Kyungpook National University and several researchers.

## Evaluation of skin aging

Wrinkles as aging signal

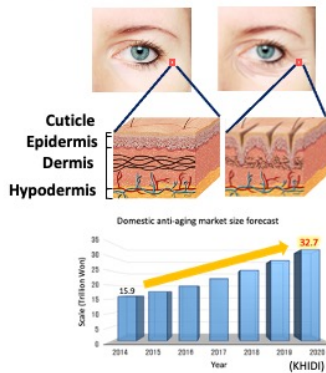


Wrinkle formation serves a representative signal of ageing in human skin.



## Evaluation of skin aging

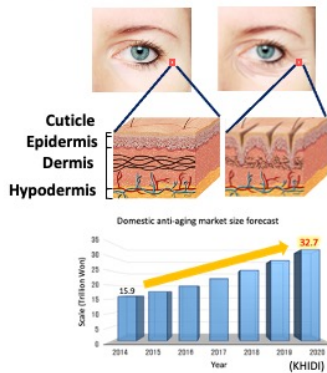
### Wrinkles as aging signal



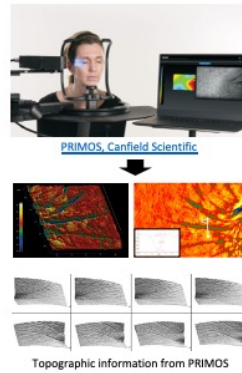
The anti-aging market is expanding, and the companies are driven to develop not only high-quality products, but also utilize high standard product assessment instruments. In particular, the *in vivo* and quantitative observation of skin is required for an accurate evaluation of the effectiveness of the product.

## Evaluation of skin aging

### Wrinkles as aging signal



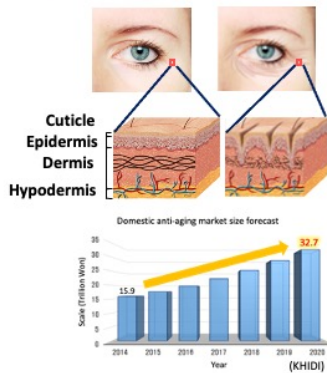
### A. Fringe projection (PRIMOS)



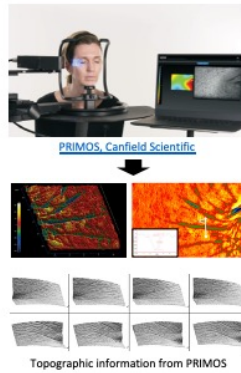
One of the most commonly used imaging systems for skin measurement, PRIMOS, was proposed as an objective tool in the cosmetics industry for studying skin topography and the volume of wrinkles. PRIMOS is a non-invasive, fast and direct measurement of the skin surface with high precision.

## Evaluation of skin aging

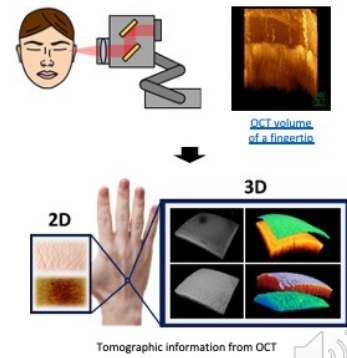
### Wrinkles as aging signal



### A. Fringe projection (PRIMOS)



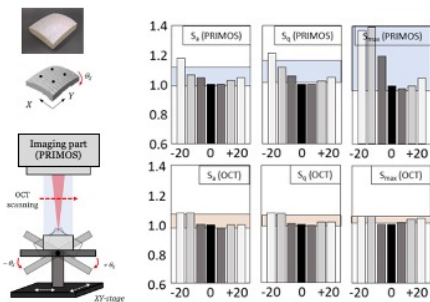
### B. Optical coherence tomography (OCT)



Another potential, but not so popular tool is OCT, which is a non-invasive, volumetric, real-time imaging modality providing a powerful tissue inspection. Detailed structural information is provided by OCT with high-resolution capability.

## The potential of OCT-AI for skin study

Robust to motion artifact



Normalized roughness values between PRIMOS and OCT at varied angular positions<sup>[1]</sup>

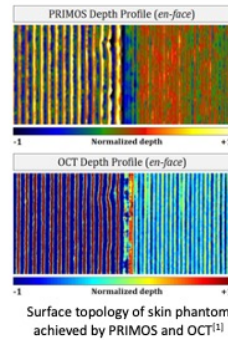
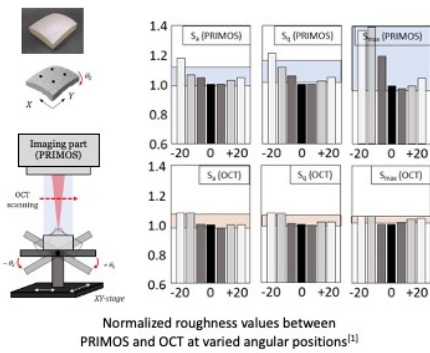
[1] Askaruly, et al (2018), "Quantitative evaluation of skin surface roughness using OCT in vivo." IEE

From our previously reported comparison study, it was identified PRIMOS has difficulty in providing accurate and reliable skin analysis because its results can vary according to orientation, motion artifacts, as well as back scattering of the subject.

## The potential of OCT-AI for skin study

Robust to motion artifact

Higher resolution



[1] Askaruly, et al (2018), "Quantitative evaluation of skin surface roughness using OCT in vivo." IEEE

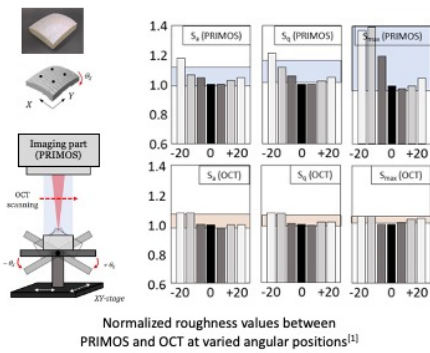
Moreover, in order to observe the compact and periodic structure of wrinkle, imaging device requires high resolution. Topologic image from OCT has well defined periodic structures and clear distinction of patterns compared to PRIMOS.

## The potential of OCT-AI for skin study

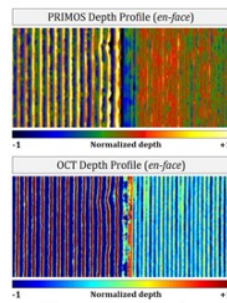
Robust to motion artifact

Higher resolution

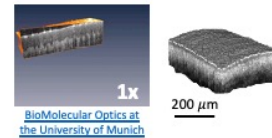
Slower scanning time



Normalized roughness values between PRIMOS and OCT at varied angular positions<sup>[1]</sup>



Surface topology of skin phantom achieved by PRIMOS and OCT<sup>[1]</sup>

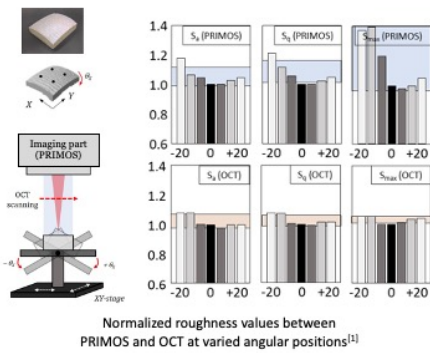


[1] Askaruly, et al (2018), "Quantitative evaluation of skin surface roughness using OCT in vivo." IEE

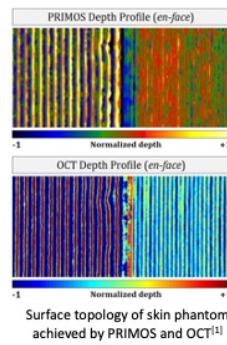
OCT inherently maintains essential advantages of in vivo skin imaging. However, OCT setups are often available in limited research environments. One obstacle is lengthy scanning procedure of the subject.

## The potential of OCT-AI for skin study

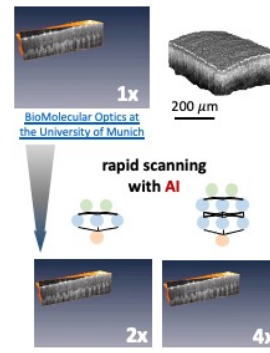
### Robust to motion artifact



### Higher resolution



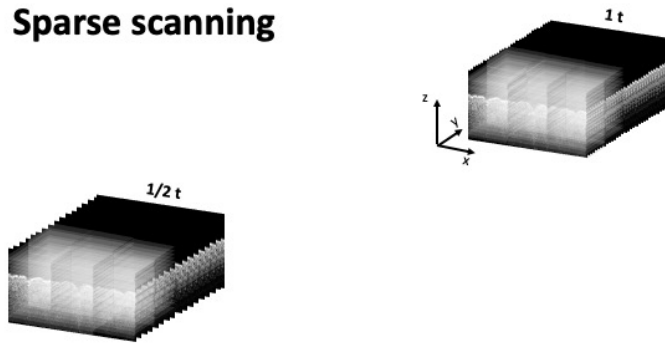
### Slower scanning time



[1] Askaruly, et al (2018), "Quantitative evaluation of skin surface roughness using OCT in vivo." IEE

Essentially, we can overcome this issue with the help of deep learning technique to reduce the time of imaging.

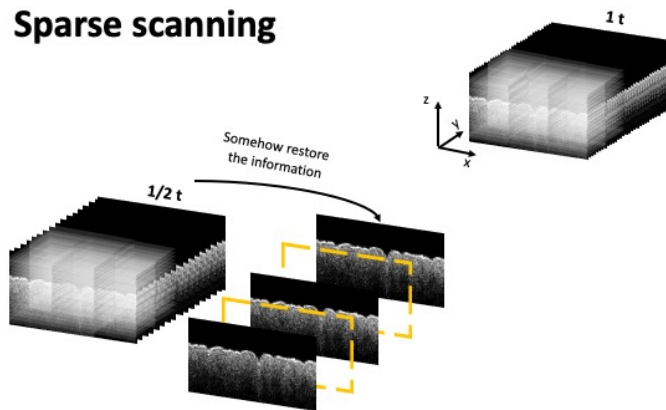
## Sparse scanning



In the principle of the suggested technique, we start by low-sample scanning to reduce time, in this case half.

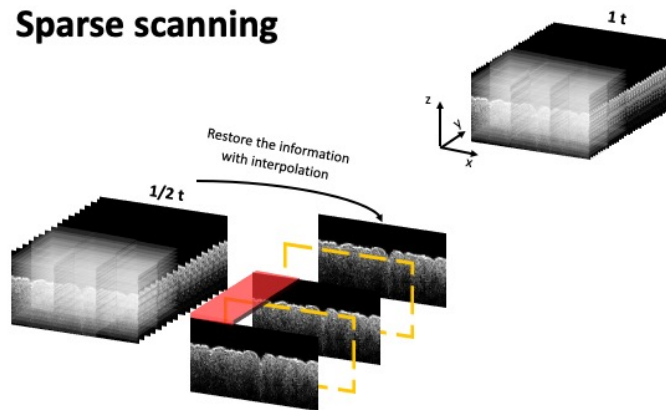


## Sparse scanning



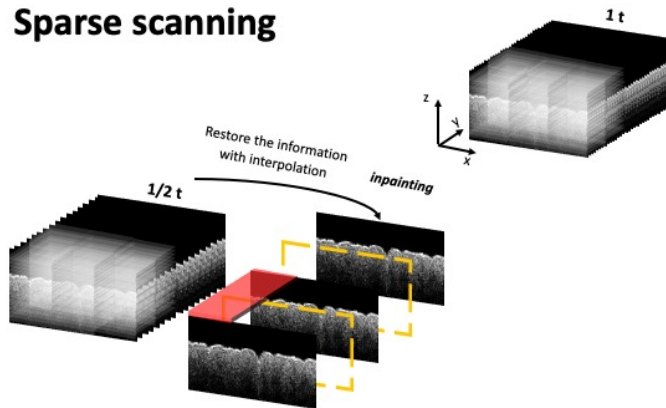
Further we somehow should restore the slices in between.

## Sparse scanning



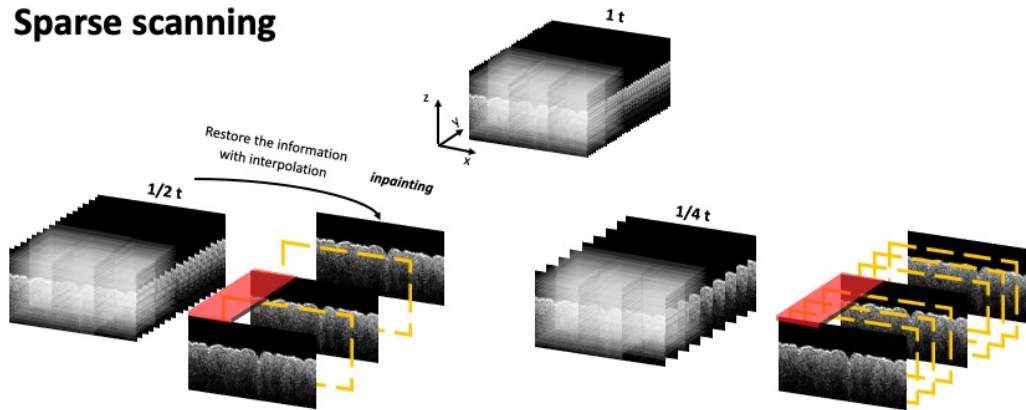
To do this, one straightforward way could be interpolation of so-called patches between two successive slices at each height and width. Basically, we can save half-time of full volume scanning at the cost of post-processing.

## Sparse scanning



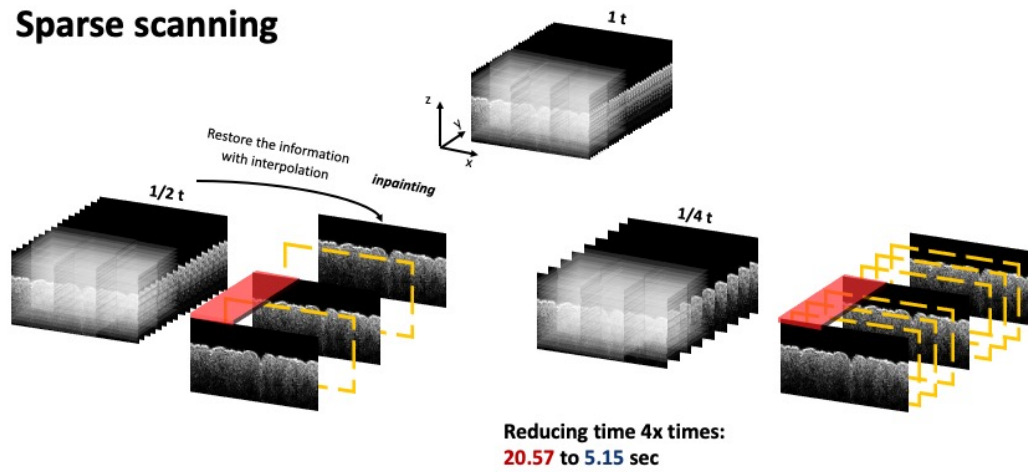
The common terminology for the information restoration represented here is called inpainting, and we will further refer to it this way.

## Sparse scanning



Similarly, we can go further and scan only every fourth slice to save even more.

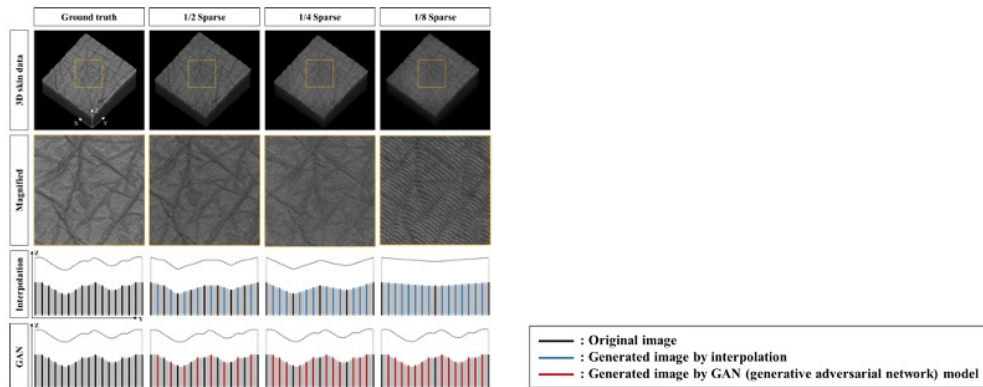
## Sparse scanning



In this case, the average scan time of typical 1cm<sup>2</sup> FOV would reduce from 20 seconds to 5 seconds.



## Volume inpainting using GAN



\*Result is presented with permission from



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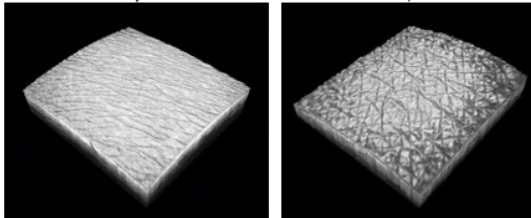
As we can expect, the described interpolation method could have adverse effect onto the accurate representation of structure, causing interrupted details, discontinuous surfaces, and other phenomena, reducing research and diagnostic significance. In this study, we present another, more precise approach based on deep learning technique.

## Dataset



정용규 (2018), 근적외선 3차원 광학영상기법을 이용한 피부 정량화 기술개발

Young (20s) ← Sample OCT volumes → Old (50s)



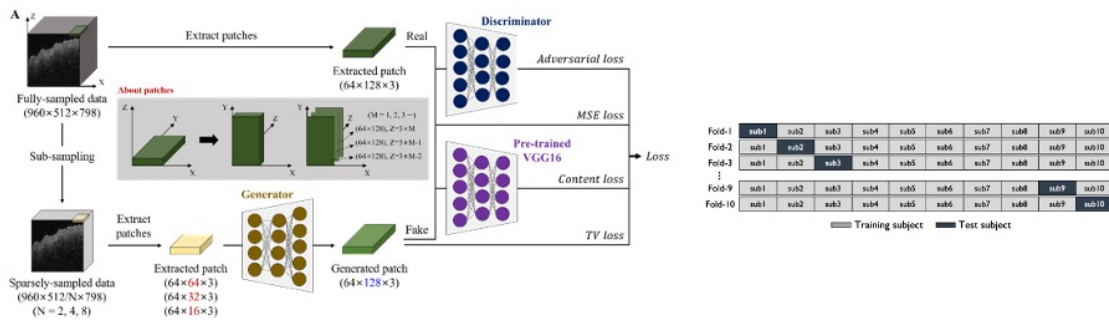
### Summary of skin dataset details

	Participant
Number of subjects	10
Patients' age (years)	$35.3 \pm 8.5$
Gender (% of female)	40
$S_a$	$2.23 \pm 0.57$
$S_l$	$2.84 \pm 0.71$
$S_{max}$	$14.36 \pm 2.66$



The collection of data was approved by the IRB protocol. A total of 10 people participated, average of 35 years and skin measurement using OCT conducted. Images on the bottom left visualize sample volumes of human skin.

## Overview of the OCT volume inpainting method<sup>[1]</sup>



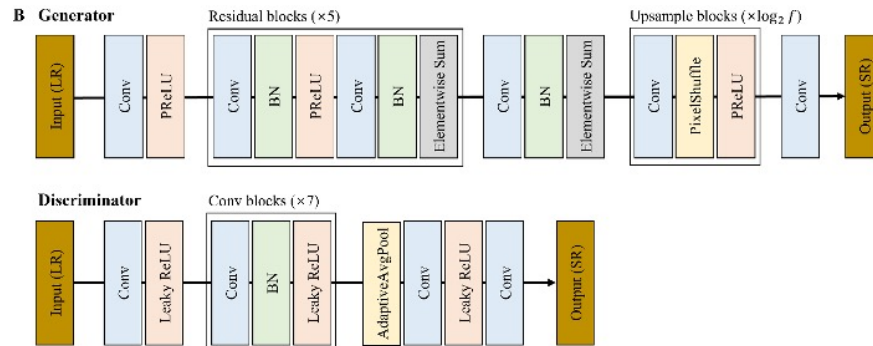
✓ The suggested network architecture was trained on the cropped patches from original and synthetically sparse data at several ratios

\*Result is presented with permission from [1]

Briefly speaking, we tried to restore the original dimension of the cropped patches of the intentionally dropped slices along C-mode scan axis. This patch is further utilized as input to the deep neural network. As for the model, we utilize generative adversarial network architecture. During training, we carried out 10-fold cross-validation to evaluate the performance. In each fold, a model is trained using 9-subjects data, and then tested using the other subject data not used for training.



## Model architecture

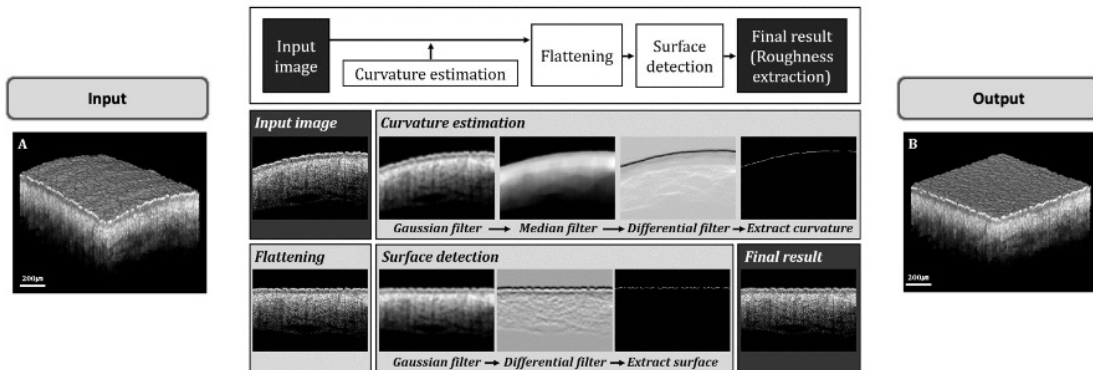


- ✓ We leverage super-resolution generative adversarial network as a technique for OCT scan inpainting



For deep neural network, we utilize SRGAN-like architecture. Its original purpose is the estimation of high-resolution images from its low-resolution images. Likewise, we can utilize the SRGAN for inpainting. Using the technique, we can obtain fully sampled OCT volume from sparsely sampled OCT scans.

## Flattening algorithm



One of the useful algorithms to know before the evaluation of surface is flattening. Its goal is to minimize the natural curvature of skin in order to perform correct measurements. Home-built combination of image processing steps produces the output as shown on the far right.

## Evaluation metrics

### A. Surface roughness

Average surface roughness:

$$S_a = \frac{1}{nx \times ny} \sum_{i=1}^{nx} \sum_{j=1}^{ny} |z(x_i, y_j)|$$

Root mean square roughness:

$$S_q = \sqrt{\frac{1}{nx \times ny} \sum_{i=1}^{nx} \sum_{j=1}^{ny} z(x_i, y_j)^2}$$

Maximal roughness:

$$S_{max} = \max(z) - \min(z)$$

### B. Image quality

The mean squared error:

$$MSE(x, y) = \frac{1}{N} \sum_{i=1}^N (x_i - y_i)^2$$

Peak signal-to-noise ratio:

$$PSNR = 20 \log_{10} \frac{(MAX_I)^2}{\sqrt{MSE}}$$

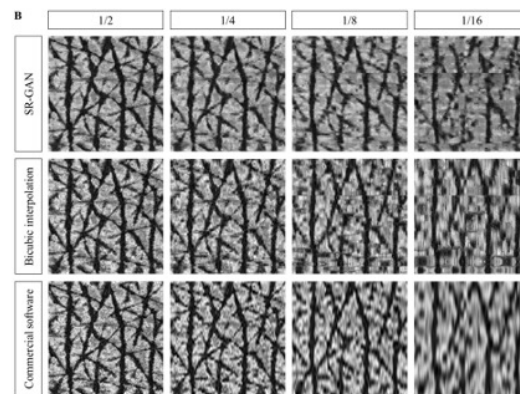
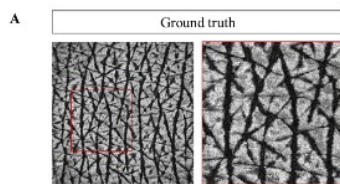
Multiscale structure similarity<sup>[1]</sup>:

$$SSIM_{MS} = [l_M(x, y)]^{\alpha_M} \cdot \prod_{j=1}^M [c_j(x, y)]^{\beta_j} [s_j(x, y)]^{\gamma_j}$$

[1] Wang, et al (2003) "Multiscale structural similarity for image quality assessment" ACSSC

We evaluated performance based on surface roughness and image quality. Roughness characterizes irregularities on surfaces, providing information on the geometry of structure. Additionally, image quality was assessed using MSE, multi-scale structural similarity index, and peak signal-to-noise ratio.

## Topography evaluation



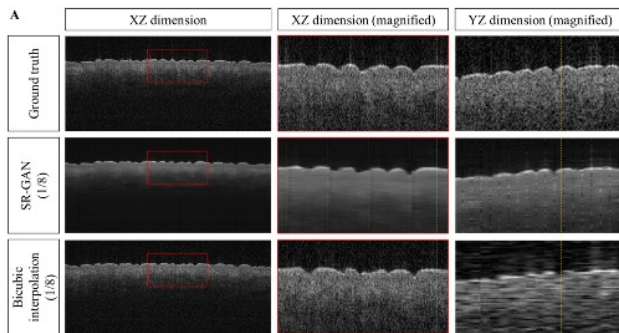
- ✓ In case of **interpolation**, **loss occurs** in the process of data restoration.
- ✓ Investigation of **wrinkle pattern** of the surface suggests that the 3D inpainting using **GAN** shows more **favorable results**.



One of the common applications of OCT imaging in skin is the observation of skin topography. It is useful for estimation of wrinkle width, wrinkle depth and overall geometric orientations.

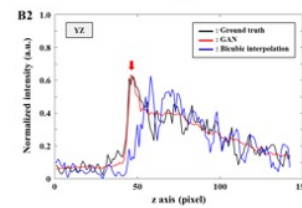
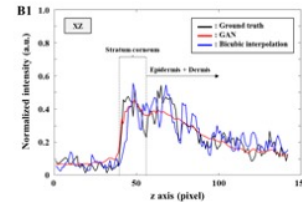
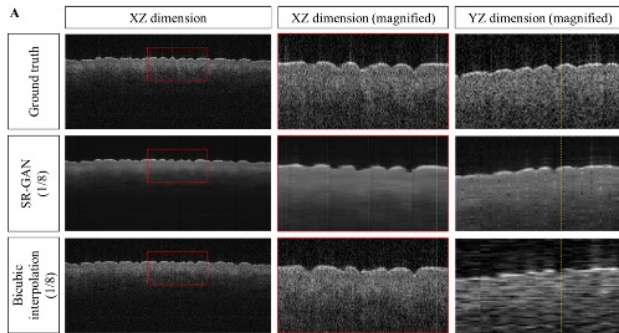
Here, we compared bicubic interpolation, commercial software and the suggested method at various sampling rates. Although better at half sampling rate, during interpolation, loss occurs in the process of data restoration for higher sampling. As a result of qualitative investigation of wrinkle pattern of the surface, we confirm that the 3D inpainting using GAN shows more favorable results.

## Surface evaluation



We investigated inpainting quality in cross-sectional dimensions. We can observe that interpolation could amplify artifact in the dimension, where it has less information. Although pixel information is blurred, the surface information is still restored with GAN.

## Surface evaluation



- ✓ As a result of inpainting using deep learning, it was confirmed the surface information of the ground truth was restored quite similarly
- ✓ In the case of inpainting using interpolation, irregular artifacts occur on the surface as the number of sampling decreases



If we plot the depth profile along the axis, we can observe that bicubic interpolation tends to have more deviation from the ground truth compared to the deep learning method.

## Survey

Mean opinion score (MOS) test by 14 subjects

Sampling	SR-GAN	Bicubic interpolation
1/2	4.25	3.96
1/4	3.68	3.50
1/8	3.18	2.36

Preference test by 14 subjects

Sampling	SR-GAN	Bicubic interpolation
1/2	8 (57.1%)	6 (42.9%)
1/4	12 (85.7%)	2 (14.3%)
1/8	13 (92.9%)	1 (7.1%)

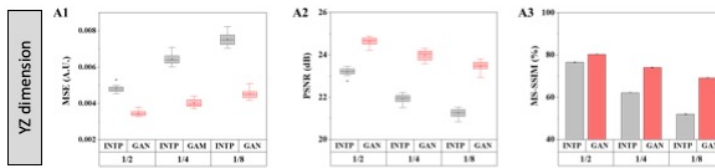


We evaluated the inpainting methods in terms of human opinion. To conduct survey, we provided the respondents the resultant images from interpolation and the deep learning approach. Table above reports mean opinion scores and table below describes the results of preference test. In both surveys, the deep learning-based method suggests prevalence over interpolation.

## Image quality

Comparison of OCT volume inpainting quality using deep learning method and bicubic interpolation

### Our findings



✓ We have produced our evaluation of two methods (deep learning / bicubic interpolation) inpainting quality with regards to the MSE, PSNR, and MS-SSIM parameters in YZ dimension



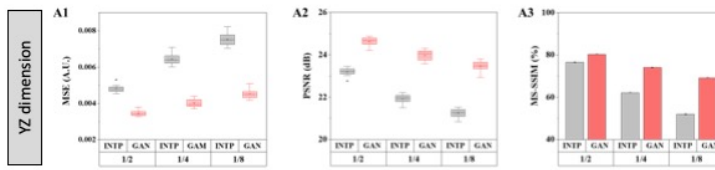
We investigated inpainting quality in cross-sectional dimension. In accordance with definitions, we compared MSE, PSNR and MS-SSIM parameters for bicubic interpolation and generative adversarial network.



## Image quality

Comparison of OCT volume inpainting quality using deep learning method and bicubic interpolation

### Our findings



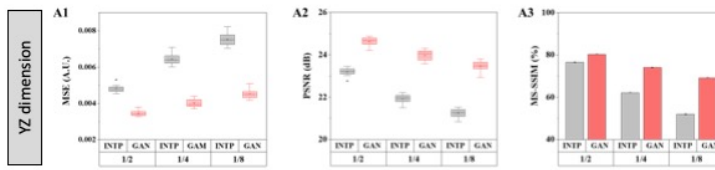
- ✓ We have produced our evaluation of two methods (deep learning / bicubic interpolation) inpainting quality with regards to the MSE, PSNR, and MS-SSIM parameters in YZ dimension
- ✓ MSE error of **interpolation** grows more sharply with more sparse sampling from 1/2 to 1/8 suggesting it is **more prone to inaccurate representation** of ground truth



Here, MSE error of interpolation grows more sharply compared to the GAN with more sparse sampling from half to one-eighth suggesting it is more prone to inaccurate representation of ground truth

## Image quality

Comparison of OCT volume inpainting quality using deep learning method and bicubic interpolation



### Our findings

- ✓ We have produced our evaluation of two methods (deep learning / bicubic interpolation) inpainting quality with regards to the MSE, PSNR, and MS-SSIM parameters in YZ dimension
- ✓ MSE error of interpolation grows more sharply with more sparse sampling from 1/2 to 1/8 suggesting it is **more prone to inaccurate representation** of ground truth
- ✓ **Analogous conclusion** could be drawn from PSNR metrics, performed on the logarithmic scale and in inverse nature

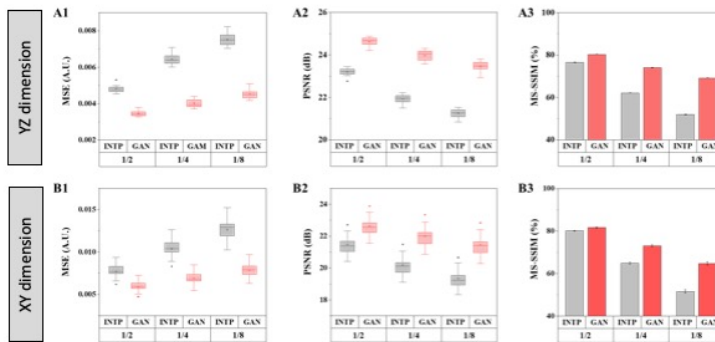


Analogous conclusion could be drawn from PSNR metrics, performed on the logarithmic scale and in inverse nature

## Image quality

Comparison of OCT volume inpainting quality using deep learning method and bicubic interpolation

### Our findings



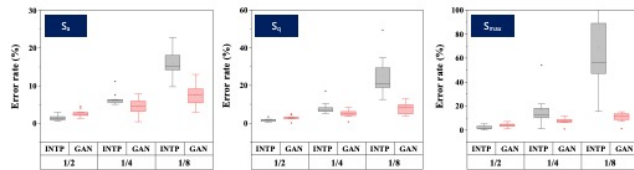
- ✓ We have produced our evaluation of two methods (deep learning / bicubic interpolation) inpainting quality with regards to the MSE, PSNR, and MS-SSIM parameters in YZ dimension
- ✓ MSE error of interpolation grows more sharply with more sparse sampling from 1/2 to 1/8 suggesting it is **more prone to inaccurate representation** of ground truth
- ✓ Analogous conclusion could be drawn from PSNR metrics, performed on the logarithmic scale and in inverse nature
- ✓ XY dimension repeats the tendency of YZ



As for the top-view XY dimension, MSE and PSNR have analogous tendency and similar deviation ranges. SSIM measurements drop less abruptly for GAN.

## Skin roughness

Comparison of skin roughness deviation from ground truth after OCT volume inpainting using deep learning method and bicubic interpolation



### Our findings

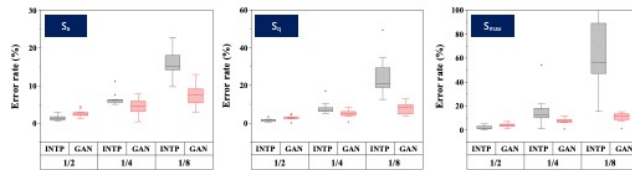
- ✓ In case of data reconstructed by **interpolation**, with increase of sparse ratio, a **large error occurs** compared to the roughness values of ground truth.



Another valuable perspective to inspect inpainting quality is the examination of roughness data with the increase of sampling ratio. In particular, here we present error rates for the measured roughness parameters. A large error occurs compared to the roughness values for interpolation cases.

## Skin roughness

Comparison of skin roughness deviation from ground truth after OCT volume inpainting using deep learning method and bicubic interpolation



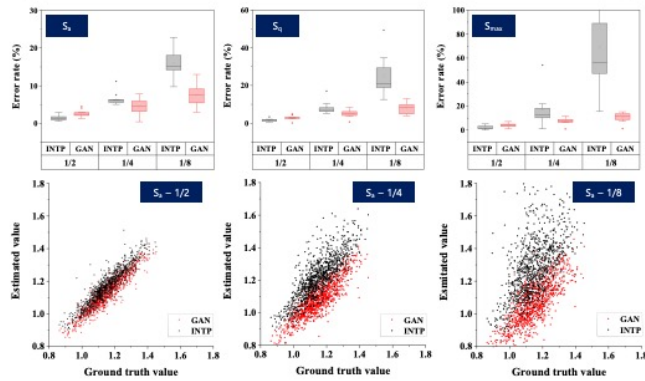
### Our findings

- ✓ In case of data reconstructed by **interpolation**, with increase of sparse ratio, a **large error occurs** compared to the roughness values of ground truth.
- ✓ In case of data reconstructed by **GAN**, it was confirmed that the **error rate** was significantly **suppressed** despite the increase of the sparse ratio.

On contrast, in case of data reconstructed by GAN, it was confirmed that the error rate was significantly suppressed despite the increase of the sparse ratio.

## Skin roughness

Comparison of skin roughness deviation from ground truth after OCT volume inpainting using deep learning method and bicubic interpolation



### Our findings

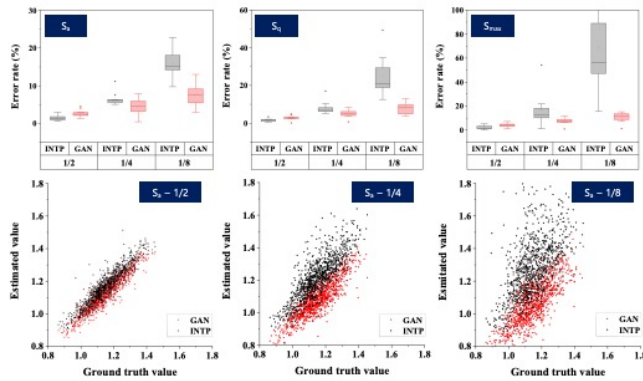
- ✓ In case of data reconstructed by **interpolation**, with increase of sparse ratio, a **large error occurs** compared to the roughness values of ground truth.
- ✓ In case of data reconstructed by **GAN**, it was confirmed that the **error rate** was significantly **suppressed** despite the increase of the sparse ratio
- ✓ From the results, it can be stated that **GAN** is a more **robust technique** to maintain the **surface measurements** close to the ground truth.



From the results, it can be stated that GAN is a more robust technique to maintain the surface measurements close to the ground truth.

## Skin roughness

Comparison of skin roughness deviation from ground truth after OCT volume inpainting using deep learning method and bicubic interpolation



### Our findings

- ✓ In case of data reconstructed by **interpolation**, with increase of sparse ratio, a **large error occurs** compared to the roughness values of ground truth.
- ✓ In case of data reconstructed by **GAN**, it was confirmed that the **error rate** was significantly **suppressed** despite the increase of the sparse ratio
- ✓ From the results, it can be stated that **GAN** is a **more robust technique** to **maintain the surface measurements** close to the ground truth.
- ✓ This **new type** of optical volume inpainting using deep learning has high effectiveness, which has **potential** be **applied to other optical imaging technologies** beyond OCT technology



This new type of optical volume inpainting using deep learning has high effectiveness, which has potential be applied to other optical imaging technologies beyond OCT technology.

## Conclusion

- ✓ **OCT technology is advantageous for skin wrinkle analysis compared to existing PRIMOS, however lacks scanning speed**



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## Conclusion

- ✓ OCT technology is advantageous for skin wrinkle analysis compared to existing PRIMOS, however lacks scanning speed
- ✓ To overcome, we suggest deep learning technique for rapid scanning



To overcome this issue, we suggest deep learning technique for rapid scanning.

## Conclusion

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- ✓ To overcome, we suggest deep learning technique for rapid scanning
- ✓ We investigated volume inpainting method using GAN (generative adversarial network) technique



We investigated volume inpainting method using GAN (generative adversarial network) technique.

## Conclusion

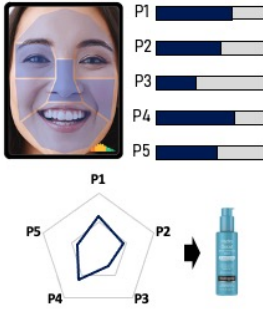
- ✓ **OCT technology is advantageous for skin wrinkle analysis compared to existing PRIMOS, however lacks scanning speed**
- ✓ **To overcome, we suggest deep learning technique for rapid scanning**
- ✓ **We investigated volume inpainting method using GAN (generative adversarial network) technique**
- ✓ **Our results demonstrated accurate restoration performance and has a potential to be applied beyond OCT technology**



**Our results demonstrated accurate restoration performance and has a potential to be applied beyond OCT technology.**

Potential applications

- ❖ Skin aging monitoring
- ❖ Personalized skin care



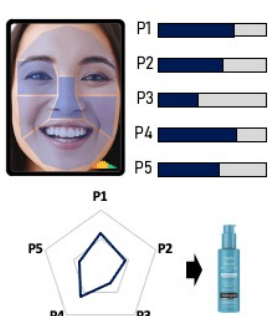
This project could potentially be useful for skin aging monitoring or personalized skin care.

**Chapter 2. OCT volume inpainting using deep learning with application to human skin**

2.1. Motivation	2.2. Research approach	2.3. Validation	<b>2.4. Conclusion</b>
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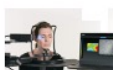
**Potential applications**

❖ Skin aging monitoring  
 ❖ Personalized skin care



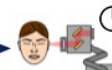
**Relevance to thesis**

**Before**





➔

**After**



Transformation

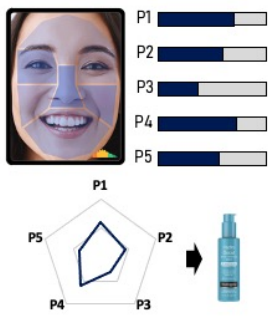






53

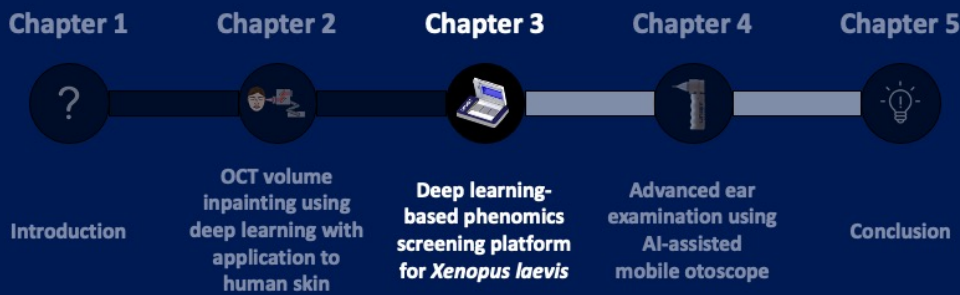
**Within bounds of my thesis, I have explored the transformation of traditional skin assessment towards novel deep learning-integrated smart device. It could in perspective contribute towards the telehealth, or personalized medicine directions of digital healthcare technology.**

**Chapter 2. OCT volume inpainting using deep learning with application to human skin**

2.1. Motivation	2.2. Research approach	2.3. Validation	2.4. Conclusion
<p><b>Potential applications</b></p> <ul style="list-style-type: none"> <li>❖ Skin aging monitoring</li> <li>❖ Personalized skin care</li> </ul> 	<p><b>Relevance to thesis</b></p> <p style="text-align: center;">Before <span style="margin-left: 150px;">After</span></p>  <div style="text-align: center;">  </div>	<p><b>Main contributions</b></p> <div style="border: 1px solid black; padding: 5px; margin-bottom: 5px;"> <p><b>Imaging system (OCT)</b></p> <ul style="list-style-type: none"> <li>• Surface analysis UI</li> </ul> </div> <div style="border: 1px solid black; padding: 5px; margin-bottom: 5px;"> <p><b>Image analysis (Image processing)</b></p> <ul style="list-style-type: none"> <li>• Surface segmentation</li> <li>• Flattening algorithm</li> <li>• Roughness metrics</li> </ul> </div> <div style="border: 1px solid black; padding: 5px;"> <p><b>Deep learning (Inpainting)</b></p> <ul style="list-style-type: none"> <li>• Data preparation</li> <li>• Model validation</li> </ul> </div> <p style="text-align: center; margin-top: 10px;">End-to-end engineering</p>	

Although my experience with hardware was limited in this project and supported by my senior, here I outlined my personal contributions inside the research work towards end-to-end engineering.

## Development of Deep Learning-integrated Futuristic Biomedical Platforms for Translational Digital Healthcare



**Joint work with:**

Seongmin Yun<sup>1</sup>, Hyunmo Yang<sup>1</sup>, Geoseong Na<sup>1</sup>,  
Jungkweon Bae<sup>2</sup>, Taejoon Kwon<sup>1</sup>, Woongyu Jung<sup>1</sup>

<sup>1</sup>Ulsan National Institute of Science and Technology, South Korea

<sup>2</sup>Samsung Research, South Korea



Department of Biomedical Engineering, Ph.D. Thesis Presentation



In the third chapter, I will present about the development of deep learning-based phenomics screening platform for *xenopus laevis*. This is a joint work with Professor Kwon's laboratory from UNIST and several researchers.

## Existing challenges in aquatic model screening



*Xenopus laevis* is emerging model to study human disease and to investigate pharmaceutical effects *in vivo* due to smaller size and faster developmental rates. It is also an effective organism to observe drug effects on phenotypic characteristics because it can provide many biological systems in a short time and remain optically accessible at the early stages of development. However, traditional screening of massive *Xenopus* data requires expensive equipment and labor-intensive inspection under an optical microscope.





## Flatbed scanner for screening



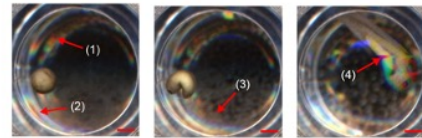
[1] Yun, et al. (2021) "Development of deep-learning-based high-throughput phenotype screening platform of aquatic model organism embryos," International Xenopus Soci-

Alternatively, the flatbed scanner was considered to obtain quantitative images for large-scale phenotype assay. Its large field-of-view and low cost are advantageous. We could observe the phenotypic characteristics with a reasonable resolution as time-lapse images.

## Flatbed scanner for screening



### Image artifacts during imaging<sup>[1]</sup>

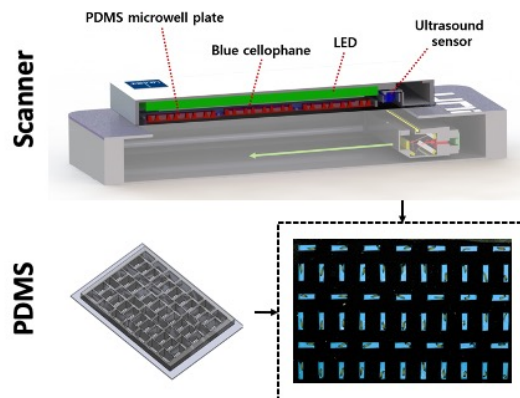


- (1) Light scattering
- (2) Wall observation
- (3) Evaporation and condensation
- (4) Movement of embryo

[1] Yun, et al. (2021) "Development of deep-learning-based high-throughput phenotype screening platform of aquatic model organism embryos," *International Xenopus Soci-*

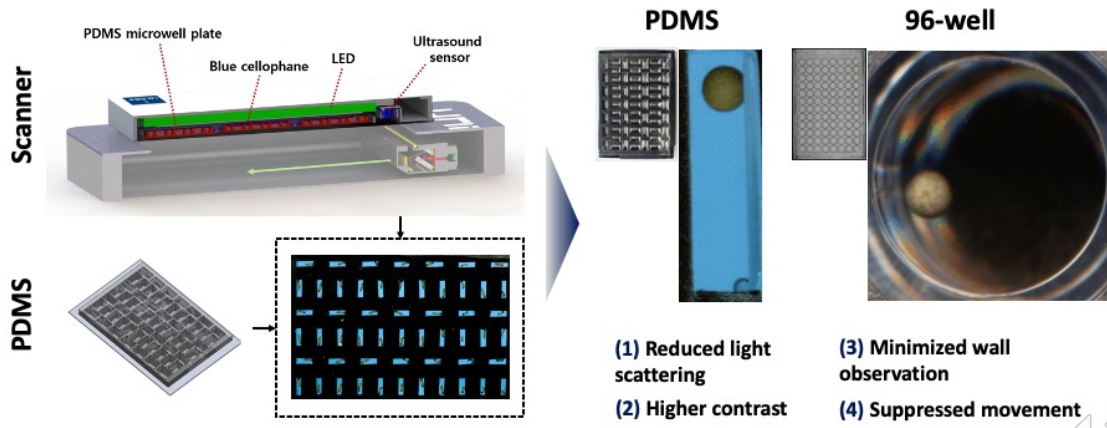
However, it was found that there were issues with the downstream image analysis, such as light scattering, wall observation and other artifacts.

## Modification of imaging conditions



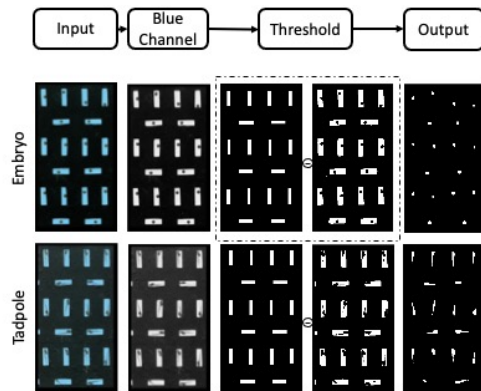
To overcome these issues, we have suggested modifications to the commercial scanner, converting it into a custom imaging device. We also fabricated the customized PDMS plate for efficient and stress-free imaging of living *Xenopus* samples in normal and drug environments.

### Modification of imaging conditions



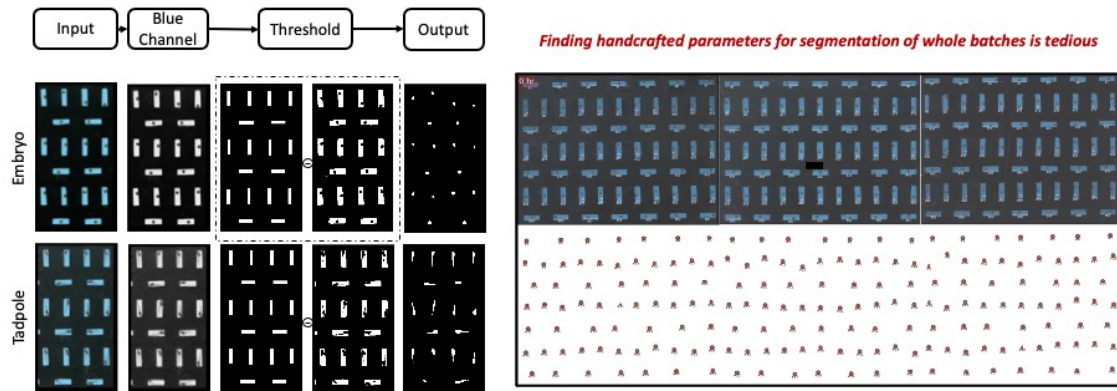
Our goal is to achieve reduced light scattering, higher contrast, and minimize wall observation.

## Generalization of image processing



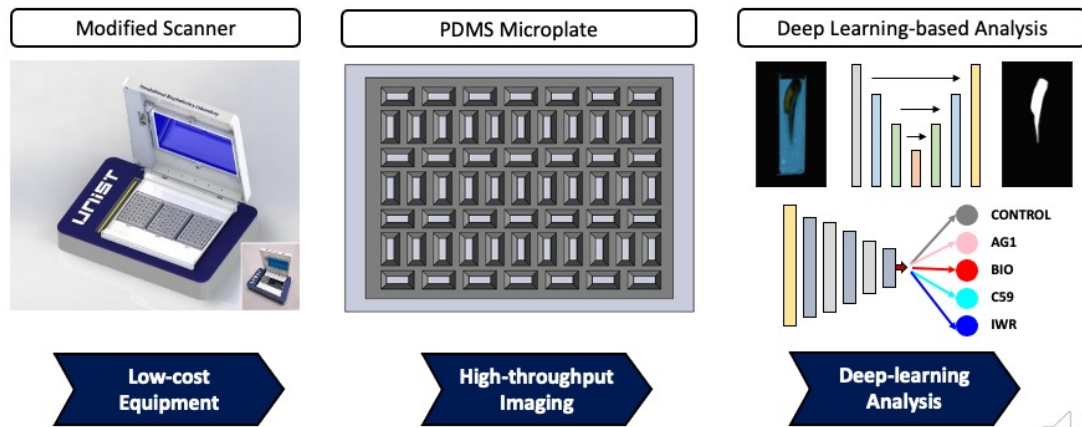
Our preliminary approach of analyzing embryos consisted of image processing pipeline for identification of the regions of interest with a few simple steps.

## Generalization of image processing



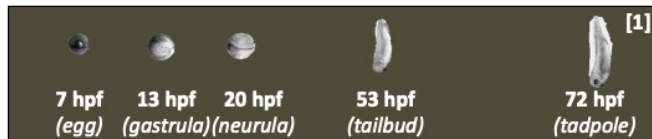
But as we expanded the technique to large-scale, we had to look for handcrafted parameters, which was necessary for better segmentation. We realized this computational approach quickly became manual task.

## Screening platform



Therefore, in this work we suggest a screening platform consisting of modified flatbed office scanner, PDMS plate and utilize deep learning technique for automated phenotypic analysis. Our suggested system is low-cost and high-throughput, with automated analysis.

## Animal model and drug phenotypes



Drug-specific phenotypes<sup>[1]</sup> at 72 \*hpf



### Drug related information used in experimental study

Drug	Signaling Pathway	Concentration	Phenotype
BIO	Wnt activator	10 $\mu$ M	Burst at gastrulation
AG1	Wnt activator	5 $\mu$ M	Head deformation, short body
C59	Wnt inhibitor	30 $\mu$ M	Short tail, tail bending
IWR	Wnt inhibitor	150 $\mu$ M	Edema, waist bending

\*hpf: hours post fertilization

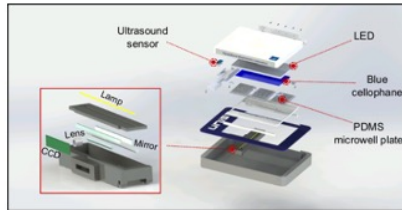
[1] Bowes, Jeff B., et al. "Xenbase: a *Xenopus* biology and genomics resource." *Nucleic acids research* 36.suppl\_1 (2007): D761-D767.

\*Result is presented with permission from Springer

For drug screening, four different types were used under specific concentrations to cause noticeable phenotypes under 72 hours post fertilization, affecting physical changes in body and tails of embryos. Figure shows the deformations visually and table summarizes the concentrations of each drug.



## Imaging technique

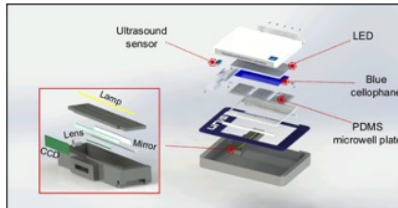


\*Result is presented with permission from Geor



The figure demonstrates modified elements of the scanner. LED and blue cellophane was required to enhance contrast, while ultrasound was put to achieve automation.

## Imaging technique



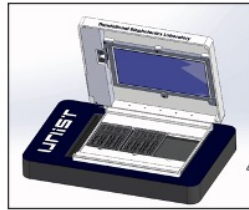
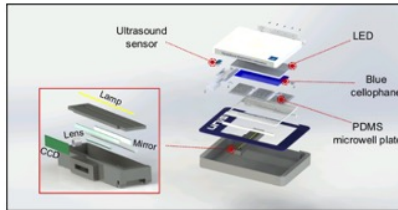
- Scanning | 25 min / 1 scan
- Resolution | 2400 dpi
- Horizontally: 39.40 micron
- Vertically: 44.19 micron

\*Result is presented with permission from Geor

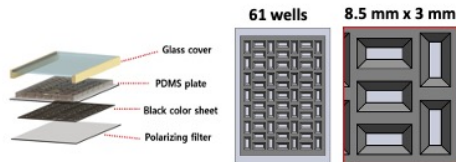


In this way, we performed imaging within 4 days by modified scanner taking 25 minutes per scan. The acquired image resolution is enough to resolve phenotypes. The temperature was below 25°C.

## Imaging technique



- Scanning | 25 min / 1 scan
- Resolution | 2400 dpi
- Horizontally: 39.40 micron
- Vertically: 44.19 micron

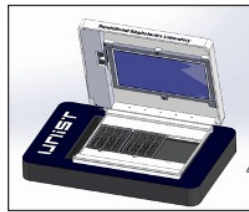
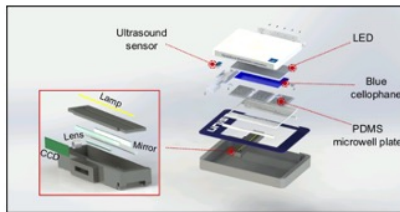


\*Result is presented with permission from Geor

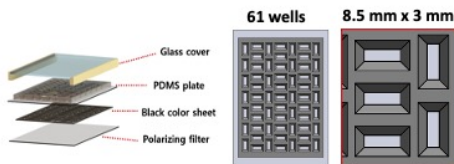


The suggested PDMS plate contains 61 wells and its design primarily targets for embryo studies.

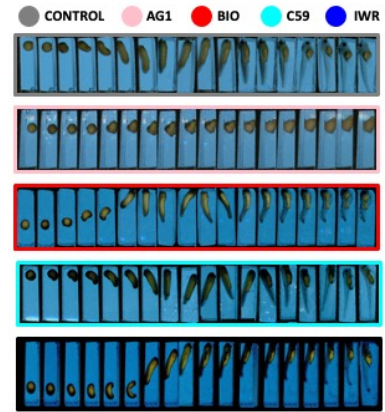
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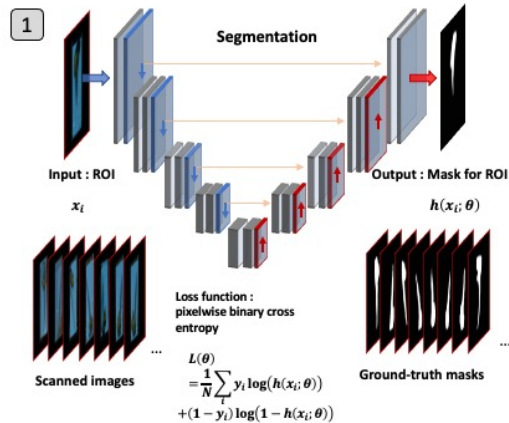
### Sample output



\*Result is presented with permission from Geor...

Sample output demonstrates the reduced effect of imaging artifacts in the figure.

## Deep learning



For analysis using deep learning technique, we acquired large number of corresponding manual masks. We utilized U-Net architecture for segmentation to locate embryo ROIs. At the input of our architecture, each individual well was cropped for the size of 900 by 600 pixels.

**Chapter 3. Deep Learning-based Phenomics Screening Platform for *Xenopus Laevis***

3.1. Motivation
3.2. Research approach
3.3. Validation
3.4. Conclusion

## Deep learning

**1** Segmentation

Input : ROI  $x_i$

Output : Mask for ROI  $h(x_i; \theta)$

Loss function : pixelwise binary cross entropy

$$L(\theta) = \frac{1}{N} \sum_T y_i \log(h(x_i; \theta)) + (1 - y_i) \log(1 - h(x_i; \theta))$$

Scanned images ...

Ground-truth masks ...

**2** Classification

- CONTROL
- AG1
- BIO
- C59
- IWR

UNIST 70

The segmented output was then further processed to the input of another CNN for the definition of drug related phenotypes.

**Chapter 3. Deep Learning-based Phenomics Screening Platform for *Xenopus Laevis***

3.1. Motivation
3.2. Research approach
3.3. Validation
3.4. Conclusion

## Deep learning

**1**

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Scanned images

Loss function: pixelwise binary cross entropy

$$L(\theta) = \frac{1}{N} \sum_T y_i \log(h(x_i; \theta)) + (1 - y_i) \log(1 - h(x_i; \theta))$$

Ground-truth masks

Output: Mask for ROI  $h(x_i; \theta)$

Segmentation

**2**

Classification

- 
 CONTROL
- 
 AG1
- 
 BIO
- 
 C59
- 
 IWR

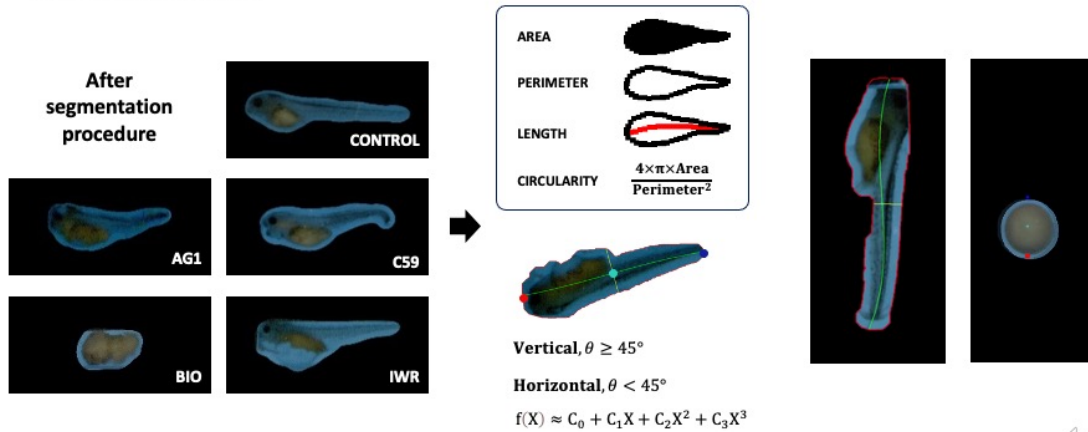
Augmentation

- Random Contrast
- Random Brightness
- Random Rotation
- Random CLAHE

\*CLAHE: Contrast Limited Adaptive Histogram Equalization

We applied augmentation strategy focusing on the generalization of the model towards color information.

## Quantification

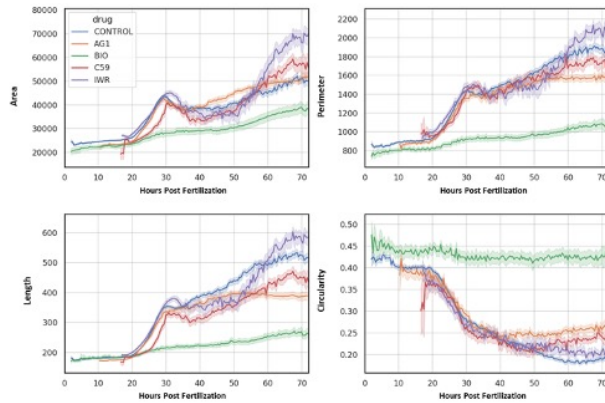


Acquired segmentation is basis for further quantitative analysis. In this outcome, we investigated four geometrical parameters: area, perimeter, length, and circularity. Our suggested evaluation could contribute to the observation of variant development dynamics as well as assist to early differentiation of signals.



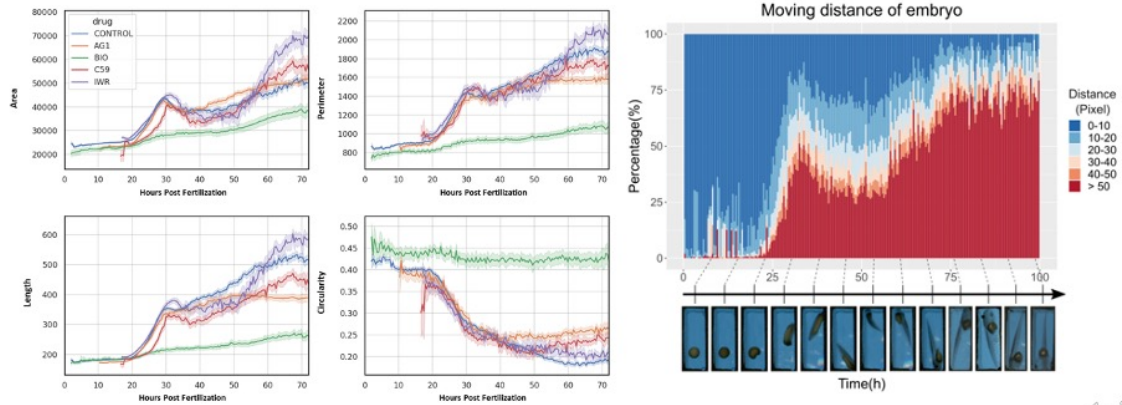


## Phenotype quantification



In this result, I will describe the quantitative evaluation of embryo's phenotypic changes from morphological perspective. We could observe various development dynamics under different drugs. Specifically, tracking the beginning of hatching stage or alterations in growth of tail at ~30 hpf and corresponding >60 hours post fertilization could provide meaningful insights for discovery of drugs, designed to target certain pathways.

## Phenotype quantification



Another characterization could possibly be the tracking of embryo activities with time by determination of the moving distance. For later stages of control cases, as expected, it is increased.





In this video, we present the results of quantification of segmented regions with deep learning. Control group and four drug cases are presented. Although, the work has been carried in post-processing mode, in the perspective, this results could contribute to building real-time, large-scale monitoring platforms for small aquatic animal models.

## Phenotype screening



Model 1 → Stage 1  
2h-20h Early egg



Model 2 → Stage 2  
20h-28h Hatching



Model 3 → Stage 3  
28h-55h Tail development



Model 4 → Stage 4  
55h~ Grown after tail

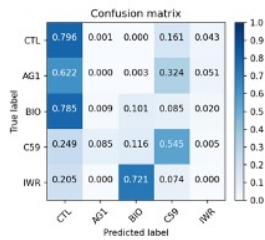


Although quantitative variations are provided, they are not sufficient to differentiate clearly which type of drug were treated before dramatic morphological changes. Therefore, we further developed CNN model for embryo images. We trained separate CNN classifiers for 4 developmental stages of *Xenopus laevis*: early egg, hatching, tail development, and grown tail.

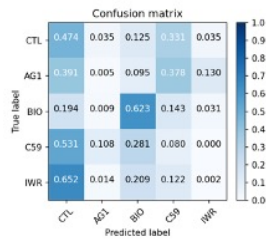
## Phenotype screening



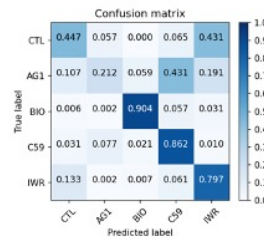
Model 1 → Stage 1  
2h-20h Early egg



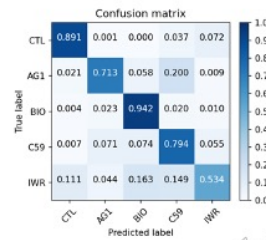
Model 2 → Stage 2  
20h-28h Hatching



Model 3 → Stage 3  
28h-55h Tail development

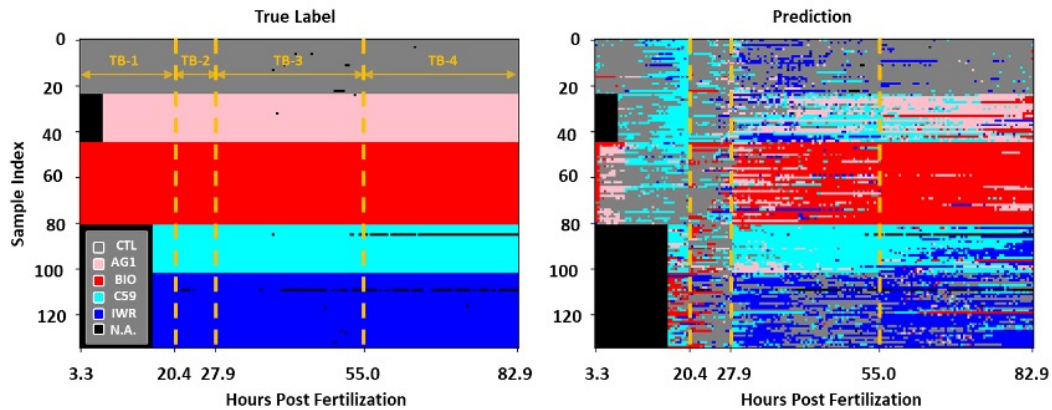


Model 4 → Stage 4  
55h~ Grown after tail



The acquired confusion matrix suggests the screening functionality can be confirmed at each developmental period, showing higher capability at later stages.

## Phenotype screening



\*Result is presented with permission from Yang

Below figure on the right shows classification results as heatmap of predicted labels compare to true labels from the validation dataset. In the egg and hatching stages classification accuracy is not sufficient for all drug types, however, along the tail development stage, drug treated samples resulted in higher classification accuracy levels.

## Conclusion

- ✓ **Aquatic model screening involves laborious procedure and expensive equipment**



**To conclude, *Xenopus* screening involves laborious procedure and expensive equipment.**

## Conclusion

- ✓ **Aquatic model screening involves laborious procedure and expensive equipment**
- ✓ **To overcome, we suggest modified flatbed scanner supported high-throughput, time-lapse imaging**



**Therefore, in this study, we developed the high-throughput screening platform with modifying flatbed office scanner.**



## Conclusion

- ✓ Aquatic model screening involves laborious procedure and expensive equipment
- ✓ To overcome, we suggest modified flatbed scanner supported high-throughput, time-lapse imaging
- ✓ We integrated deep learning technique for automated segmentation and investigated phenotype changes quantitatively



**Based on the power of massive data acquisition and the deep learning-based technique, quantitative phenotype analysis, and automated screening capability.**

## Conclusion

- ✓ **Aquatic model screening involves laborious procedure and expensive equipment**
- ✓ **To overcome, we suggest modified flatbed scanner supported high-throughput, time-lapse imaging**
- ✓ **We integrated deep learning technique for automated segmentation and investigated phenotype changes quantitatively**
- ✓ **Our results suggest proposed platform has potential to become a promising tool for massive and dynamic observation, and could be applied to developmental studies, drug testing, and phenotype-genotype assays**



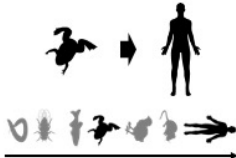
**The proposed platform could become a promising tool in massive and dynamic observation based biological studies, such as developmental studies, drug testing, and phenotype-genotype assays.**

Potential applications

- ❖ Drug screening
- ❖ Precision medicine



from [Translational Biophotonics Lab](#) website



This project could potentially be useful for drug screening or precision medicine applications.

### Chapter 3. Deep Learning-based Phenomics Screening Platform for *Xenopus Laevis*

3.1. Motivation

3.2. Research approach

3.3. Validation

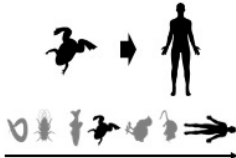
3.4. Conclusion

#### Potential applications

- ❖ Drug screening
- ❖ Precision medicine



from [Translational Biophotonics Lab](#) website


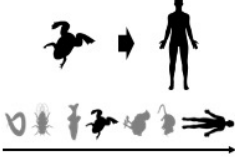






#### Relevance to thesis



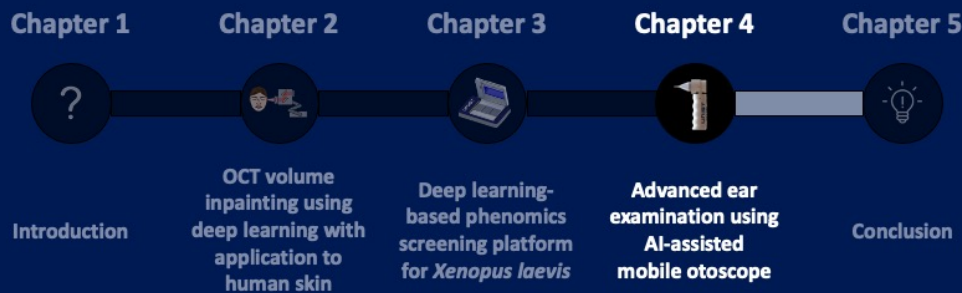
Within bounds of my thesis, I have explored the transformation of aquatic model screening towards novel deep learning-integrated smart device. It could in perspective contribute towards the personalized medicine, or health IT directions of digital healthcare technology.

**Chapter 3. Deep Learning-based Phenomics Screening Platform for *Xenopus Laevis***

3.1. Motivation	3.2. Research approach	3.3. Validation	3.4. Conclusion
<p style="text-align: center; background-color: #1a3d54; color: white; padding: 5px;"><b>Potential applications</b></p> <div style="border: 1px solid #ccc; padding: 5px; margin-bottom: 10px;"> <p>❖ Drug screening</p> <p>❖ Precision medicine</p> </div>  <p style="font-size: small;">from <a href="#">Translational Biophotonics Lab</a> website</p> 	<p style="text-align: center; background-color: #1a3d54; color: white; padding: 5px;"><b>Relevance to thesis</b></p> <div style="display: flex; justify-content: space-around; align-items: center;"> <div style="text-align: center;"> <p><b>Before</b></p>  </div> <div style="font-size: 2em; font-weight: bold; color: #1a3d54;">➔</div> <div style="text-align: center;"> <p><b>After</b></p>  </div> </div> <p style="text-align: center; font-weight: bold; color: #1a3d54;">Transformation</p> <div style="text-align: center; margin-top: 20px;">  <p style="font-weight: bold; color: #1a3d54;">Digital Healthcare</p> </div>	<p style="text-align: center; background-color: #1a3d54; color: white; padding: 5px;"><b>Main contributions</b></p> <div style="border: 1px solid #ccc; padding: 5px; margin-bottom: 10px;"> <p style="background-color: #1a3d54; color: white; padding: 2px;"><b>Imaging system (Scanner &amp; PDMS)</b></p> <ul style="list-style-type: none"> <li>• Designing</li> <li>• Hardware prototype</li> </ul> </div> <div style="border: 1px solid #ccc; padding: 5px; margin-bottom: 10px;"> <p style="background-color: #1a3d54; color: white; padding: 2px;"><b>Image analysis (Image processing)</b></p> <ul style="list-style-type: none"> <li>• Segmentation</li> <li>• Quantification</li> </ul> </div> <div style="border: 1px solid #ccc; padding: 5px;"> <p style="background-color: #1a3d54; color: white; padding: 2px;"><b>Deep learning (Segmentation)</b></p> <ul style="list-style-type: none"> <li>• Data preparation</li> <li>• Model validation</li> </ul> </div> <div style="text-align: center; margin-top: 10px;"> <p style="writing-mode: vertical-rl; transform: rotate(180deg); font-size: small;">End-to-end engineering</p>  </div>	

Finally, here I outlined my personal contributions inside the research work towards end-to-end engineering.

## Development of Deep Learning-integrated Futuristic Biomedical Platforms for Translational Digital Healthcare



### Joint work with:

Hyunmo Yang<sup>1</sup>, Nurbolat Aimakov<sup>1</sup>, Geoseong Na<sup>1</sup>, Yujin Ahn<sup>1</sup>, Joon S Yoo<sup>2</sup>, Gil-Jin Jang<sup>3</sup>, Jeong Hun Jang<sup>4</sup>, Woonggyu Jung<sup>1</sup>

<sup>1</sup>Ulsan National Institute of Science and Technology, South Korea

<sup>2</sup>Inciplan LLC, CA, The United States

<sup>3</sup>Kyungpook National University, South Korea

<sup>4</sup>Ajou University Hospital, South Korea



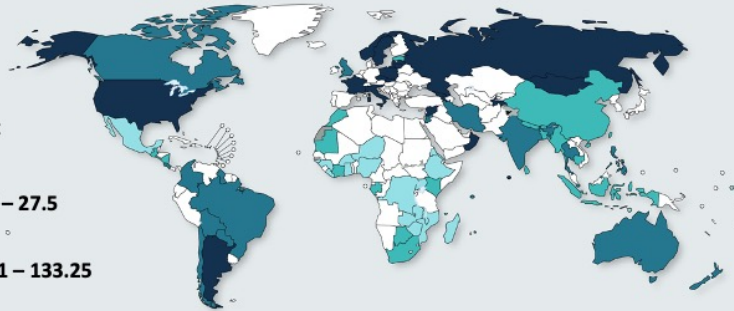
Department of Biomedical Engineering, Ph.D. Thesis Presentation



In the last chapter, I will present about the development of “Advanced ear examination using AI-assisted mobile otoscope”. This is a joint work with Professor Jang from Ajou university hospital and several researchers.

## Number of ENT specialists per million population, worldwide in 2013<sup>[1]</sup>

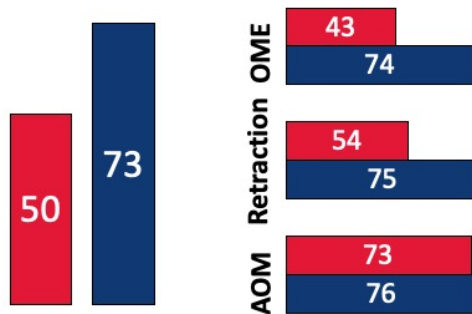
\*ENT: Otolaryngologist.  
Short for ear, nose and throat specialist



[1] World Health Organization. "Multi-country assessment of national capacity to provide hearing care." (2013)

In 2013 multi-country assessment of hearing care capacity held by World Healthcare Organization, there was a statistics regarding the number of ENT specialists' availability across various countries. Just to clarify, ENT specialist is an otolaryngology doctor equivalent and stands short for ear, nose and throat. A critical finding to pay attention in this report is that there is a considerable number of countries which lacks ENT doctors in low and lower-middle income segment.

**Comparison of diagnostic accuracy between pediatrician and ENT specialist<sup>[2]</sup>**



\***OME:** Otitis media with effusion, **AOM:** Acute otitis media

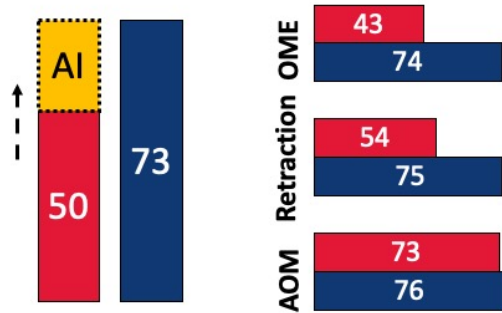
[2] Pichichero, Michael E., and Michael D. Poole. "Assessing diagnostic accuracy and tympanocentesis skills in the management of otitis media." Archives of pediatrics & adolescent medicine 155.10 (2001): 1137-1142.



Essentially, such an absence of expertise knowledge in this domain could negatively affect in proper medical treatment decisions. For instance, studies have indicated a 23% distinction in technical competence between pediatricians and specialists to correctly diagnose possible a condition.



**Comparison of diagnostic accuracy between pediatrician and ENT specialist<sup>[2]</sup>**



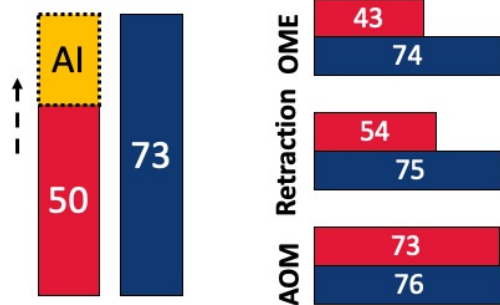
\***OME:** Otitis media with effusion, **AOM:** Acute otitis media

[2] Pichichero, Michael E., and Michael D. Poole. "Assessing diagnostic accuracy and tympanocentesis skills in the management of otitis media." Archives of pediatrics & adolescent medicine 155.10 (2001): 1137-1142.



However, the recent advancement of the deep learning opens a possibility to compensate the current limitation of physician knowledge to reach ENT level diagnosis.

**Comparison of diagnostic accuracy between pediatrician and ENT specialist<sup>[2]</sup>**



\*OME: Otitis media with effusion, AOM: Acute otitis media

[2] Pichichero, Michael E., and Michael D. Poole. "Assessing diagnostic accuracy and tympanocentesis skills in the management of otitis media." Archives of pediatrics & adolescent medicine 155.10 (2001): 1137-1142.



**We suggest development of non-specialist and affordable ear examination tool**



Therefore, we believe equipping non-specialists with an assistive technology in an affordable manner could support a more accurate diagnosis, thereby improving the ear examination situation within low resource settings.

## Deep learning for otolaryngology

Study	Application	Accuracy
Basaran (2020) <sup>[3]</sup>	Diagnosis of middle ear inflammation	<b>90.48%</b>
Cha (2019) <sup>[4]</sup>	Detection of ear and mastoid disease	<b>93.67%</b>
Livingstone (2019) <sup>[5]</sup>	Otologic disease screening	<b>84.4%</b>

✓ **Convolutional neural networks** are reported **strong** performance

[3] Cha, et al, (2019), "Automated diagnosis of ear disease using ensemble deep learning with a big otoendoscopy image database." EBioMedicine

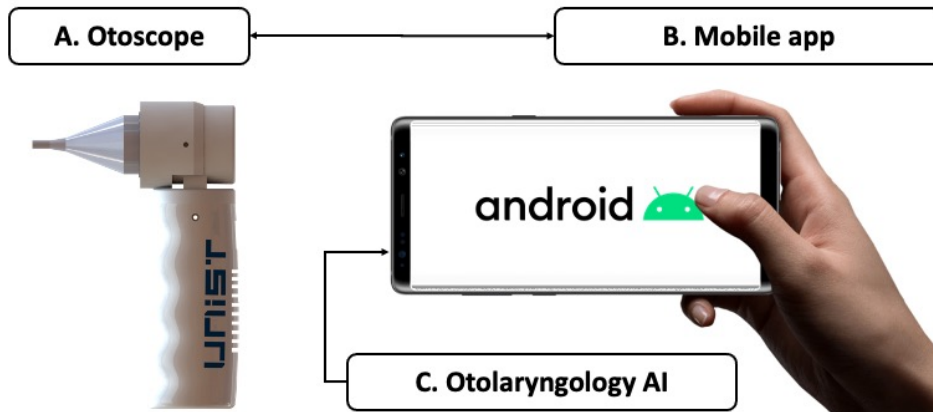
[4] Livingstone, et al, (2019), "Building an Otoscopic screening prototype tool using deep learning." *Journal of Otolaryngology-Head & Neck Surgery*

[5] Basaran, et al, (2020) "Convolutional neural network approach for automatic tympanic membrane detection and classification." *Biomedical Signal Processing and Control*



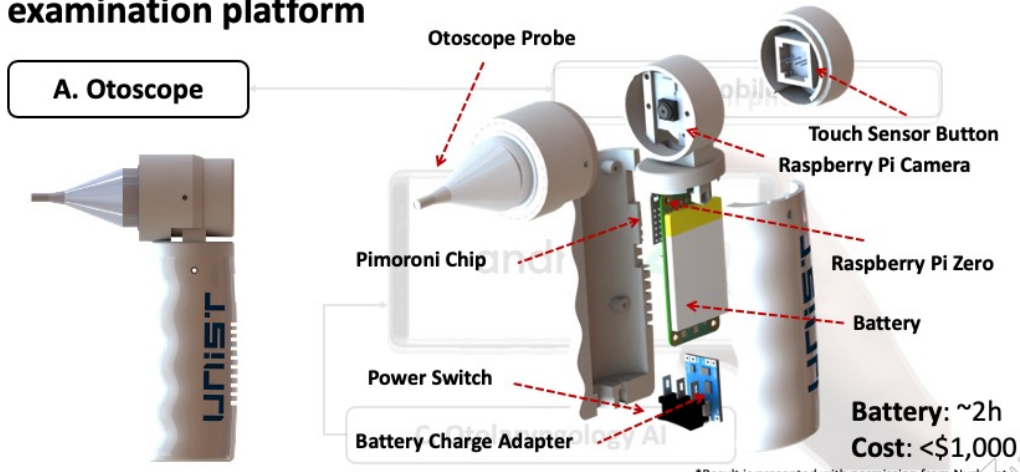
A survey of previously reported research efforts has demonstrated on the potential of AI in otolaryngology. These consider different applications, including diagnosis of middle ear inflammation and otologic screening purposes. More specifically, they unite convolutional neural networks as dominant machine learning technique with high performance.

## Ear examination platform



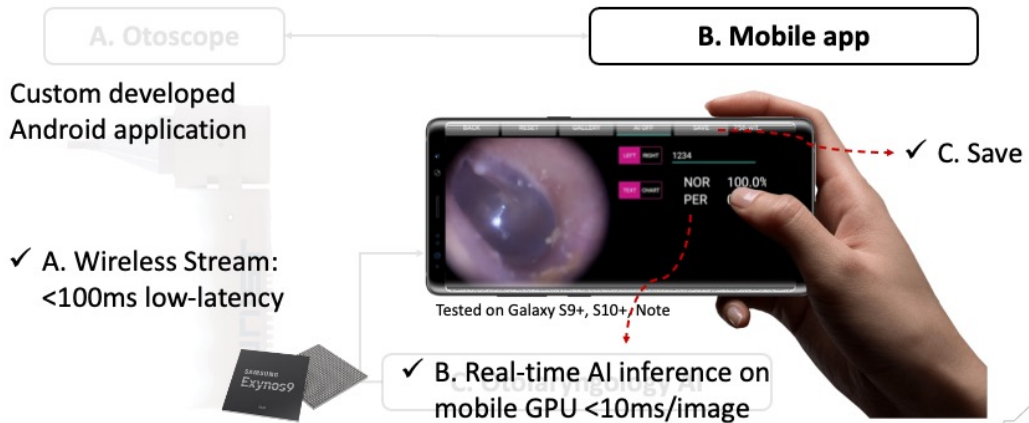
However, to tackle the real-world problem a holistic approach in the form of targeting platform is required. Therefore here, we suggest a custom otoscope and mobile phone application with on-device AI an accessible platform to enhance traditional ear examination with minimal training. A physical component was determined from the perspective of the end user, who is potentially a general physician residing without superior infrastructure.

### Ear examination platform



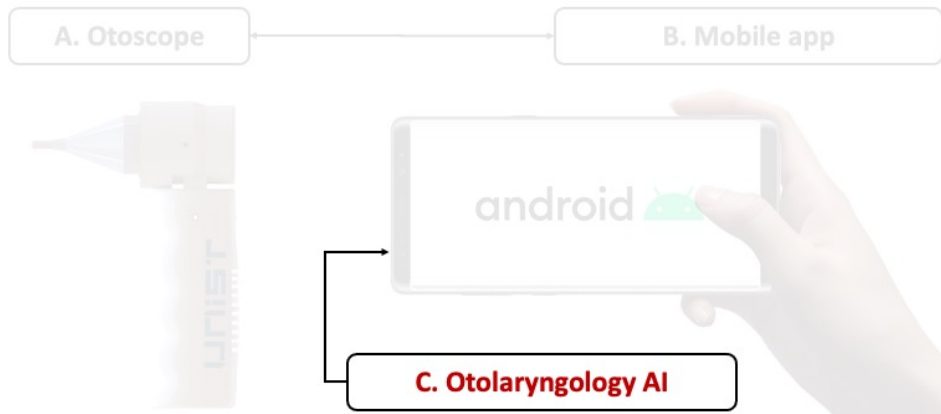
Our suggested otoscope is minimalist and effectively adapted for the ear inspection purpose. Empirically, it withstands 2 hours of continuous operation and lies under \$1000 price range.

## Ear examination platform

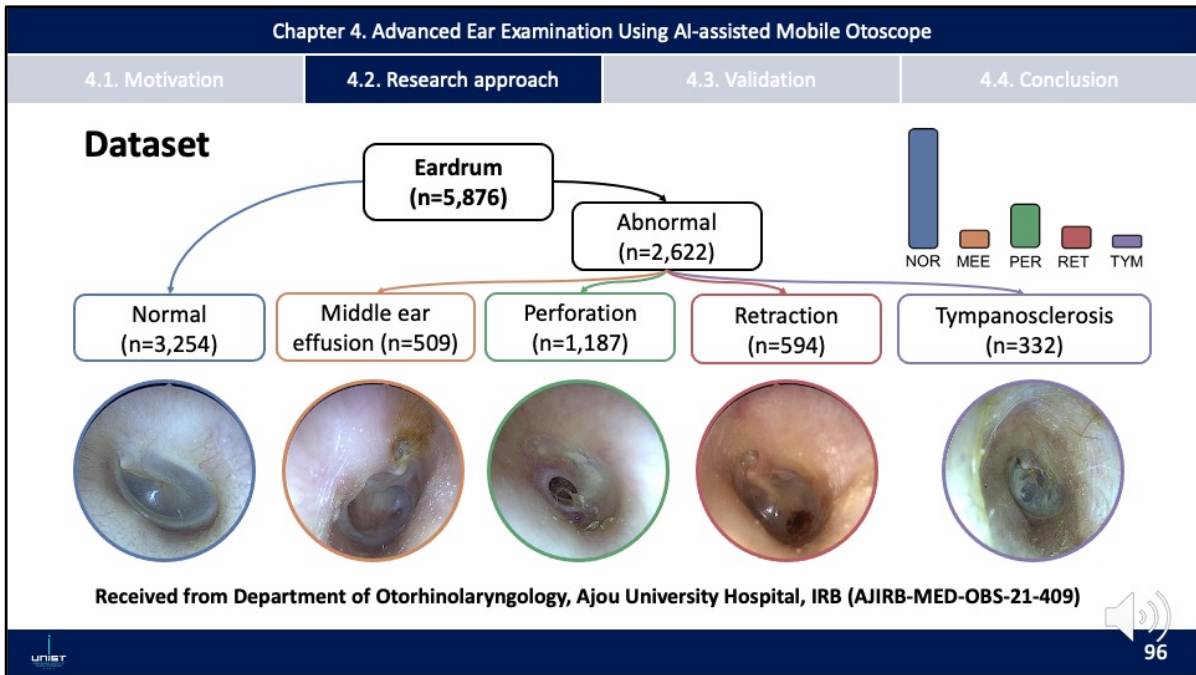


As of the mobile application side, it is based on the customly developed Android software merging several functionality, such as low-latency video streaming, saving image for later review, and real-time on-device AI inference

## Ear examination platform



Further, let me focus your attention on our deep learning approach used for this study.



The integral part of the deep learning technique is data acquisition. Following the IRB protocol, our collaborators from the Department of Otolaryngology of Ajou University Hospital in South Korea provided us with 5 commonly represented ear conditions accumulated within a clinical setup, resulting in over 5,800 unique patient cases.



**Chapter 4. Advanced Ear Examination Using AI-assisted Mobile Otoscope**

4.1. Motivation
4.2. Research approach
4.3. Validation
4.4. Conclusion

### Dataset

Epoch: 1, Acc: 0.269

**Training entire model**

Epoch: 1, Acc: 0.494

**Transfer learning**

**Revealing classification using Grad-CAM<sup>[7]</sup>**

$$L_{Grad-CAM}^c = ReLU \left( \frac{1}{Z} \sum_k \sum_i \sum_j A^k \frac{\partial y^c}{\partial A_{i,j}^k} \right)$$

*\*Linear combination; Global average pooling; Backprop gradients*

**NORMAL**

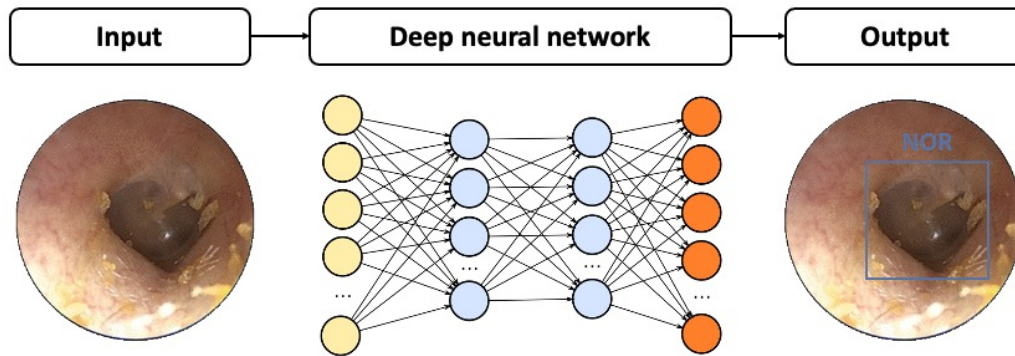
[6] Selvaraju, et al, (2017), "Grad-cam: Visual explanations from deep networks via gradient-based localization," *Proceedings of the IEEE international conference on computer vision*

[7] He, et al, (2016), "Deep residual learning for image recognition," *Proceedings of the IEEE conference on computer vision and pattern recognition*.

Based on acquired data, with the help of existing explainable AI techniques, we were curious to identify which patterns and meaningful regions contribute to the discrimination of ear diseases. Our observation led to constitute that region inside the actual tympanic membrane is more important to successfully classify diseases.



## Model

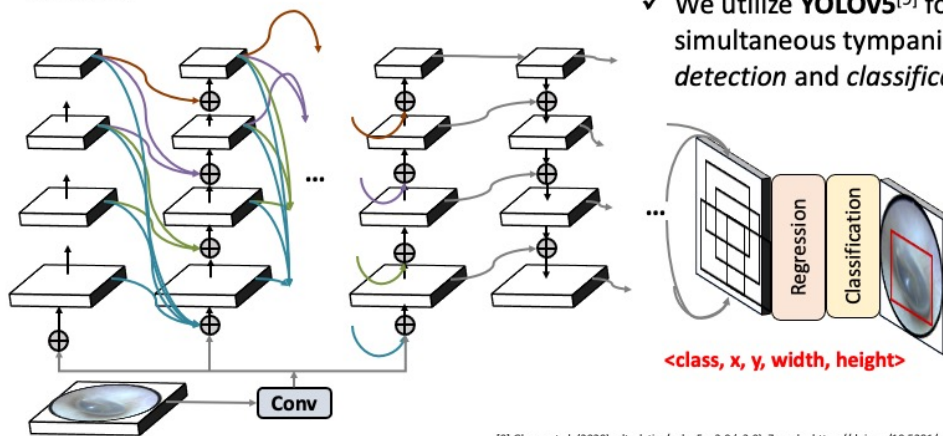


✓ We want to model tympanic membrane ROI and its class as output



Our previous observations suggest that AI is in favor to focus on the tympanic membrane region and could cluster clearly. Therefore, it led us to impose a requirement in the development of deep neural network component with object detection-oriented task.

## Model



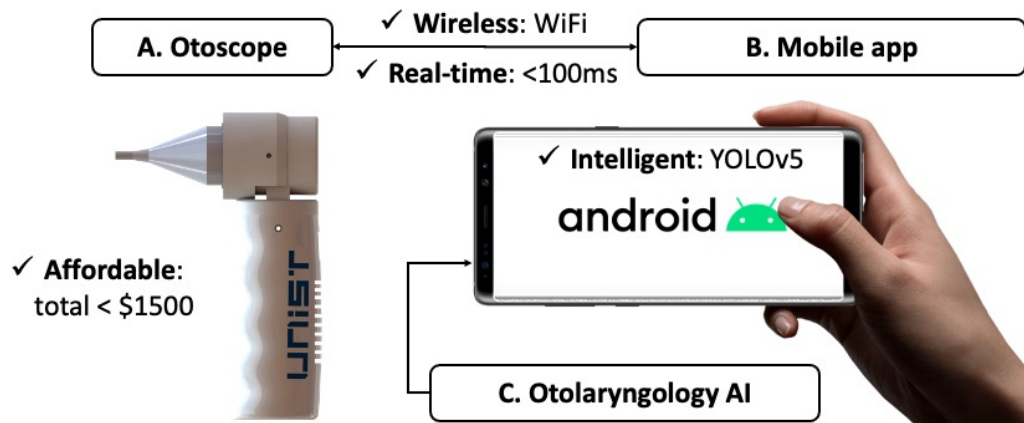
[9] Glenn, et al, (2020). ultralytics/yolov5: v3.0 (v3.0). Zenodo. <https://doi.org/10.5281/zenodo.3983579>



100

When we addressed our attention to the computer vision field, YOLOv5 has been a prominent method combining robust performance and quick response. Although at architectural complexity, the efforts of open-source community made this model significant and well-engineered, which influenced our decision to utilize it for tympanic membrane data.

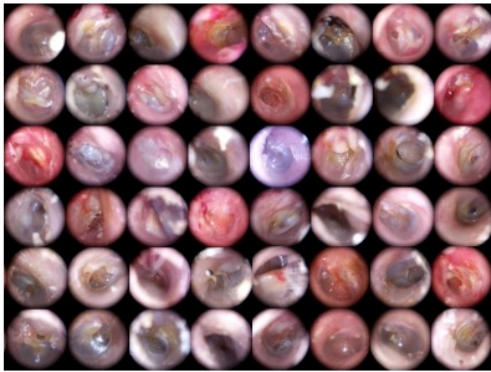
## Ear examination platform



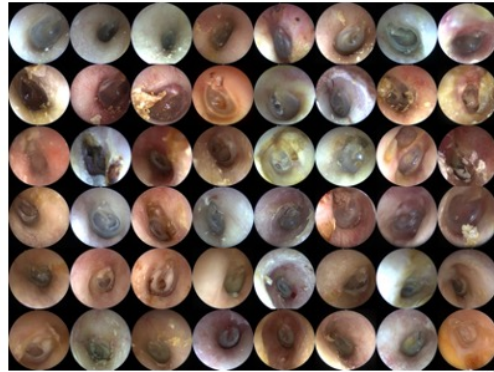
Let me reiterate on our suggested ear examination platform one more time. It consists of the custom otoscope, mobile application, and on-device AI model to support the real-time diagnosis.

### Image quality

Ours

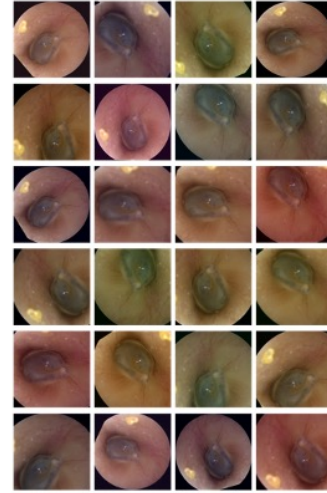
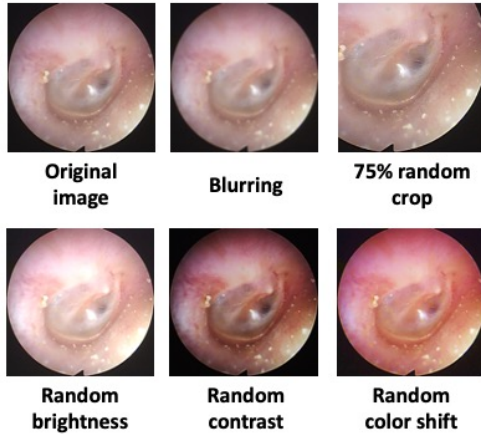


Clinical



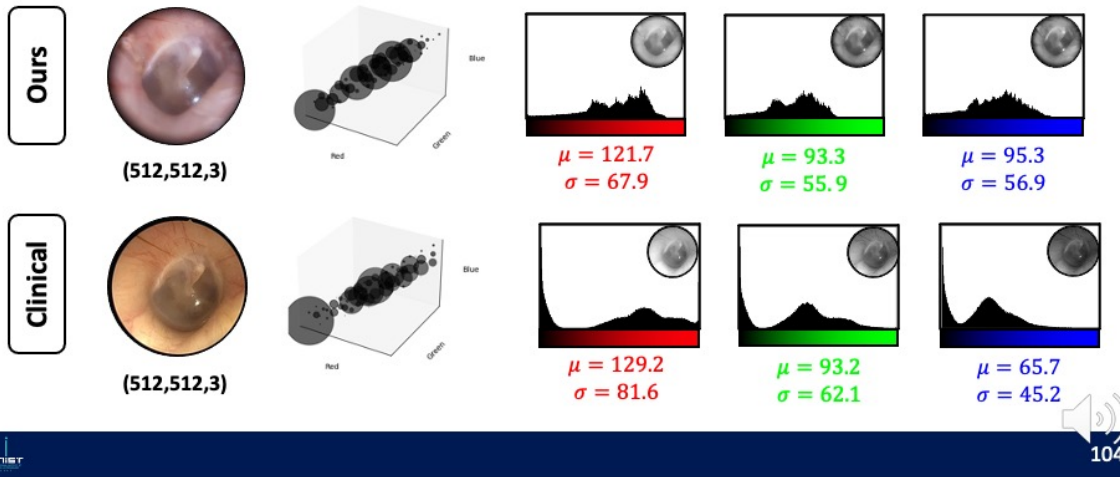
We were interested to visually compare images acquired from our developed otoscope and the clinical setup. Therefore, in this slide, we summarize the results of 48 randomly picked samples after the conducted field test examinations in Ajou University Hospital.

### Image augmentation



To minimize the effect of inherent distinctions present between clinical setup and our platform in image color and image quality, we additionally introduced blurring and random color shift operations during dataset augmentation to increase the overall accuracy of the deep learning model.

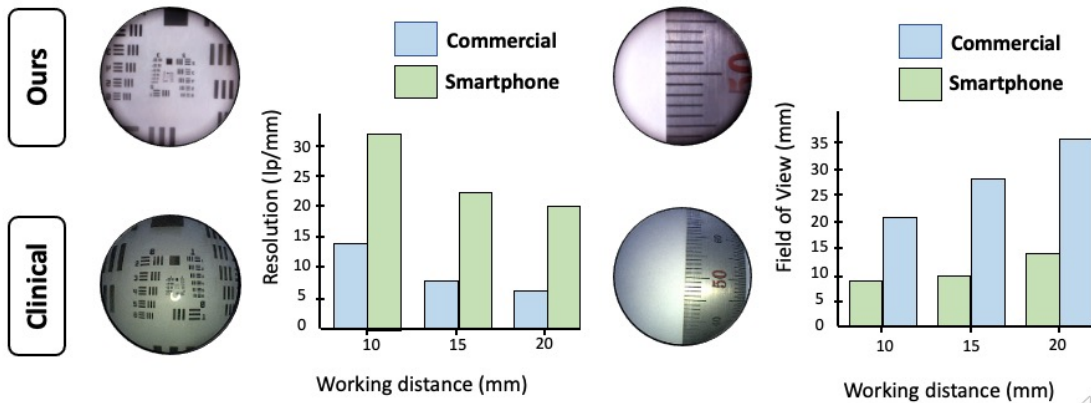
### Image color



For instance, in this slide, you can see a summary of color variance investigation between our device and clinical setup.



### Image quality

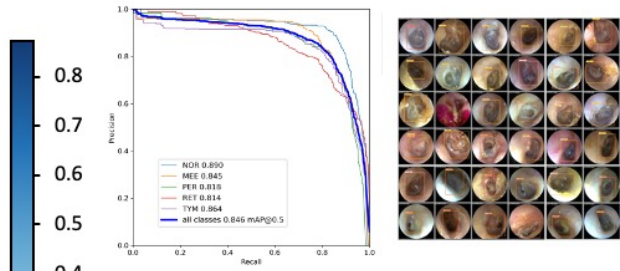


Let's also take a closer look at both images in terms of the quality, characterized by resolution and field of view parameters. At the smaller field of view, our suggested setup provides a superior resolution at working distances of 10, 15, and 20 mm, within which tympanic membrane distance is typically represented.



### AI performance

Predicted	NOR	<b>0.86</b>	0.02	0.01	0.01	0.06
	MEE	0.04	<b>0.80</b>		0.06	0.03
	PER	0.01	0.02	<b>0.79</b>	0.07	0.02
	RET	0.03	0.08	0.06	<b>0.75</b>	0.04
	TYM	0.03	0.03	0.05	0.04	<b>0.79</b>
		NOR	MEE	PER	RET	TYM
		True				



Evaluation

Metrics	Value
Epochs	300
Precision	<b>0.834</b>
Recall	<b>0.808</b>
mAP <sub>0.5</sub>	<b>0.87</b>
mAP <sub>0.5:0.95</sub>	0.568

Configuration

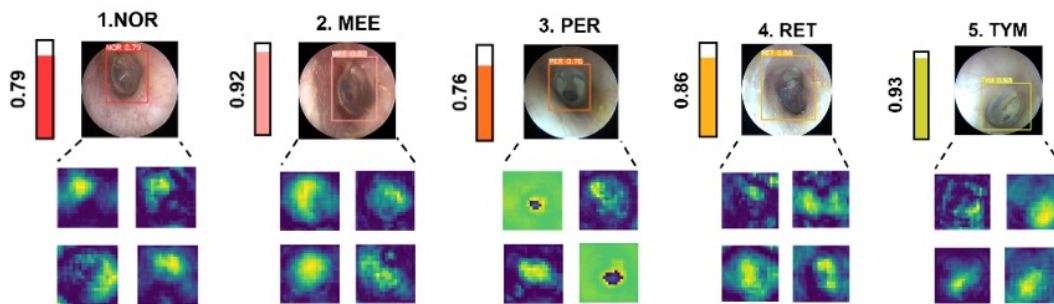
Parameter	Description
Layers	224
Hyperparams	7,064,698
GFLOPs	16.4
Size (MB)	14.4
Fp16 (MB)	<b>6.9</b>

Our inspection of the AI model performance suggested on the accurate results for tympanic membrane detection and classification, with overall of over 83% precision and 80% recall. Interestingly, the compressed trained model produced only 7MB of size, which states on the practicability to process inference on the mobile devices in real-time.



## AI performance

### Class probability identification in validation set

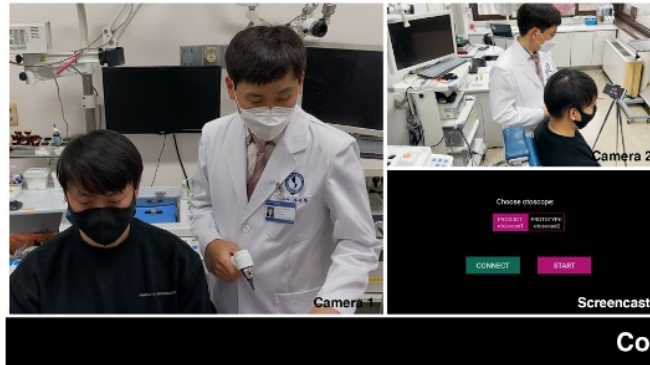


### Reasoning results with class activation maps



One can further analyze the reasoning behind the deep learning model performance and find important regions contributing inference through the investigation of activation maps at certain levels. This research direction is another central topic of the deep learning community and is under active exploration.

## Demo



(In collaboration with otologist, professor (JHJ) from Aju University Hospital, Suwon, South Korea, 2021)



We finally demonstrate the actual protocol of user application in this video. First, the doctor connects the device, enters relevant patient information and does the necessary setup. After that he can start the ear inspection procedure. He is supported with real-time AI diagnosis and can capture images for later review.

## Conclusion

- ✓ **Specialist ear examination remains common issue in low-income countries**



**Specialist ear examination remains common issue in low-income countries.**

## Conclusion

- ✓ **Specialist ear examination remains common issue in low-income countries**
- ✓ **To overcome, procedure needs assistive and affordable technology**

**To overcome this problem, we believe procedure needs a supportive and affordable technology.**

## Conclusion

- ✓ **Specialist ear examination remains common issue in low-income countries**
- ✓ **To overcome, procedure needs assistive and affordable technology**
- ✓ **Here, we propose a mobile, deep learning-assisted otoscope**



**In this study, we propose a mobile, deep learning-assisted otoscope for this role.**

## Conclusion

- ✓ **Specialist ear examination remains common issue in low-income countries**
- ✓ **To overcome, procedure needs assistive and affordable technology**
- ✓ **Here, we propose a mobile, deep learning-assisted otoscope**
- ✓ **Our results demonstrated high diagnostic accuracy indicating potential to become a viable screening solution in low-resource, non-specialist settings.**



**Our results demonstrated high diagnostic accuracy indicating potential to become a viable screening solution in low-resource, non-specialist settings.**



## Chapter 4. Advanced Ear Examination Using AI-assisted Mobile Otoscope

4.1. Motivation

4.2. Research approach

4.3. Validation

4.4. Conclusion

### Potential applications

- ❖ Telemedicine
- ❖ Point-of-care diagnostics

### Setup 1.



from [Translational Biophotonics Lab](#) website



**This project could potentially be useful for telemedicine or point-of-care diagnostics.**


**Chapter 4. Advanced Ear Examination Using AI-assisted Mobile Otoscope**

4.1. Motivation	4.2. Research approach	4.3. Validation	<b>4.4. Conclusion</b>
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**Potential applications**

- ❖ Telemedicine
- ❖ Point-of-care diagnostics

**Setup 1.**




Google Glass      Otoscope




from [Translational Biophotonics Lab](#) website

**Relevance to thesis**

**Before**      **After**




**Transformation**



**Digital Healthcare**

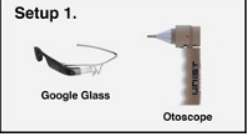
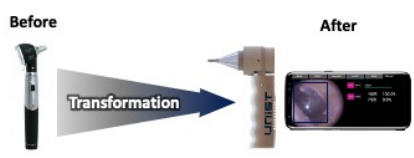

wearables      personalized medicine  
mHealth      telehealth  
health IT



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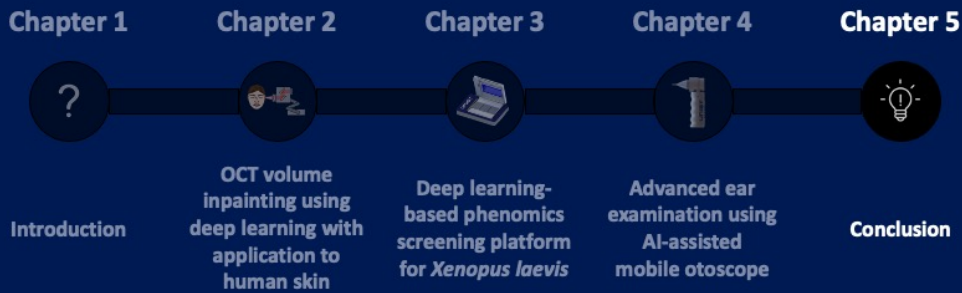
**Within bounds of my thesis, I have explored the transformation of traditional ear examination tool towards novel deep learning-integrated smart device. It could in perspective contribute towards the mobile health, or telehealth directions of digital healthcare technology.**

**Chapter 4. Advanced Ear Examination Using AI-assisted Mobile Otoscope**

4.1. Motivation	4.2. Research approach	4.3. Validation	4.4. Conclusion
<p><b>Potential applications</b></p> <ul style="list-style-type: none"> <li>❖ Telemedicine</li> <li>❖ Point-of-care diagnostics</li> </ul> <p><b>Setup 1.</b></p>  <p>from <a href="#">Translational Biophotonics Lab website</a></p>	<p><b>Relevance to thesis</b></p> <p><b>Before</b> → <b>Transformation</b> → <b>After</b></p>  <p style="text-align: center;"><b>Digital Healthcare</b></p> 	<p><b>Main contributions</b></p> <p style="writing-mode: vertical-rl; transform: rotate(180deg);"><b>End-to-end engineering</b></p> <ul style="list-style-type: none"> <li><b>Imaging system (Otoscope)</b> <ul style="list-style-type: none"> <li>• Designing</li> <li>• Hardware prototype</li> </ul> </li> <li><b>Integration (Android app)</b> <ul style="list-style-type: none"> <li>• Functionality</li> <li>• Interface</li> </ul> </li> <li><b>Deep learning (Detection)</b> <ul style="list-style-type: none"> <li>• Data preparation</li> <li>• Model deployment</li> </ul> </li> </ul>	

Finally, here I outlined my personal contributions inside the research work towards end-to-end engineering.

## Development of Deep Learning-integrated Futuristic Biomedical Platforms for Translational Digital Healthcare



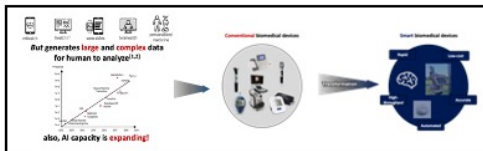
Department of Biomedical Engineering, Ph.D. Thesis Presentation



Let me finally conclude today's presentation.

## Development of Deep Learning-integrated Futuristic Biomedical Platforms for Translational Digital Healthcare

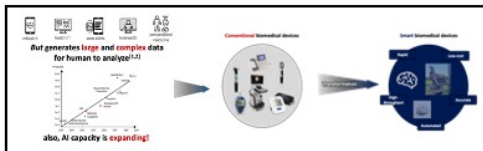
## 1. Motivation



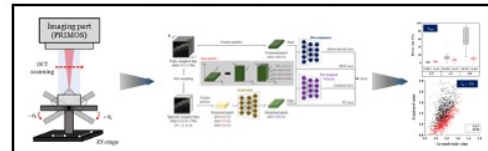
The extensive use of digital health technologies creates challenge of analysing large and complex data, where human is incapable. At the same time, the capacity of artificial intelligence keeps expanding. One of the opportunities could be the suggestion of assistive smart devices. Currently, conventional biomedical devices are developed with fixed requirements. They are often primitive and static. In contrast, smart biomedical devices possess built-in intelligence to support human decision. The transformation from one category to another is an open question. And the exploration of such opportunities was my primary interest during the PhD program.

## Development of Deep Learning-integrated Futuristic Biomedical Platforms for Translational Digital Healthcare

## 1. Motivation



## 2. OCT volume inpainting using deep learning with application to human skin

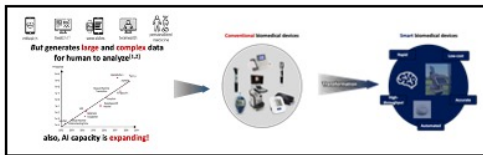


In chapter 2, I presented advantages of OCT for human skin study and how deep learning technique could be integrated for volume inpainting in order to make OCT scanning more efficient. Our results are promising, showing little deviation of image quality restoration parameters as well as roughness compared to the conventional interpolation method.

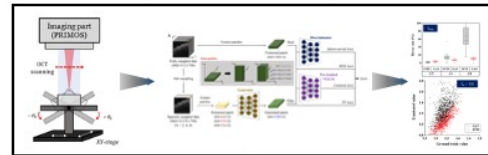
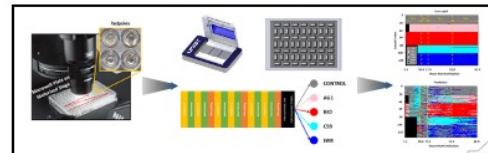


## Development of Deep Learning-integrated Futuristic Biomedical Platforms for Translational Digital Healthcare

## 1. Motivation



## 2. OCT volume inpainting using deep learning with application to human skin

3. Deep learning-based phenomics screening platform for *Xenopus laevis*

In chapter 3, we addressed challenges of phenotype screening problem by the development of the high-throughput, modified scanning platform. Here, deep learning technique was utilized for further automated phenotypic analysis and screening of massive embryo timelapse images. The proposed platform could become a promising tool in dynamic observation based developmental studies or drug testing applications.

## Chapter 5. Conclusion

### 5.1. Summary

### 5.2. Perspectives

### 5.3. Acknowledgements

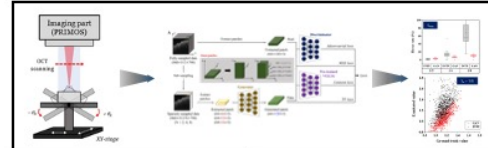
### 5.4. Achievements

#### Development of Deep Learning-integrated Futuristic Biomedical Platforms for Translational Digital Healthcare

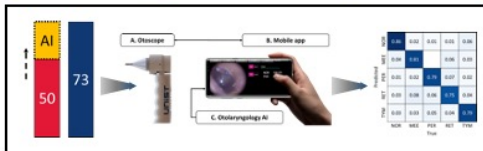
##### 1. Motivation



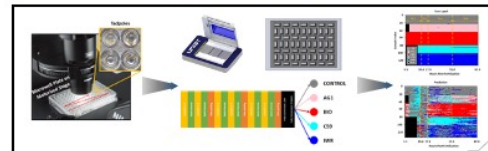
##### 2. OCT volume inpainting using deep learning with application to human skin



##### 4. Advanced ear examination using AI-assisted mobile otoscope



##### 3. Deep learning-based phenomics screening platform for *Xenopus laevis*



Finally, in chapter 4, we target the shortage of ENT doctors in low-income countries. For that reason, we suggest mobile otoscope platform with on-device AI to equip non-specialists with assistive technology in an affordable manner. Our results suggest it could support a more accurate diagnosis, thereby improving the ear examination situation within low resource settings.



**Chapter 5. Conclusion**

5.1. Summary	<b>5.2. Perspectives</b>	5.3. Acknowledgements	5.4. Achievements
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**What's next?**

Novel biomedical platforms to support decision!

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In this work, I focused on the development of novel biomedical platforms for digital healthcare, integrating deep learning techniques. In the perspective, I believe there are two interesting ways for my research and professional trajectory.

**Chapter 5. Conclusion**

5.1. Summary    **5.2. Perspectives**    5.3. Acknowledgements    5.4. Achievements

**What's next?**

Novel biomedical platforms to support decision!

1. Better ways to visualize

3D    AR/VR

Meta    Interviewing with Meta AI Research

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One could possibly be exploring better ways of visualization and making more the overall experience of delivery more convenient. These could include extension for three-dimensional technologies, as well as adaptation of AR/VR technology.

Chapter 5. Conclusion

5.1. Summary	<b>5.2. Perspectives</b>	5.3. Acknowledgements	5.4. Achievements
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**What's next?**

UNIST

Another direction is investigating additional ways to interpret information by understanding the richness and diversity from various source signals. For this reason, I believe multimodal AI techniques could assist this task.

## Chapter 5. Conclusion

### 5.1. Summary

### 5.2. Perspectives

### 5.3. Acknowledgements

### 5.4. Achievements



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SCIENCE AND TECHNOLOGY



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#### Advisor

Woonggyu Jung, Ph.D.

I would like to thank my advisor; all the contributors participating in the projects, acknowledge research fundings supporting projects and you, committee members for feedbacks.

## Chapter 5. Conclusion

### 5.1. Summary

### 5.2. Perspectives

### 5.3. Acknowledgements

### 5.4. Achievements

#### Journal Publications

- S Yun\*, H Yang\*, S Askaruly\*, G Na, J Bae, W Jung, T Kwon, "XenoScan: Deep learning-based phenomics screening platform for aquatic model organism development," *In preparation to SCI*
- Y Ahn\*, J Park\*, S Askaruly\*, D Kim, G Jang, W Jung, "OCT volumetric inpainting using deep learning network with application to human skin", *In preparation to SCI*
- S Askaruly\*, H Yang\*, N Aimakov\*, G Na, Y Ahn, JS You, G Jang, JH Jang, W Jung, "Advanced ear examination using deep learning-assisted mobile otoscope", *In preparation to SCI*
- JK Bae, H Roh, JS You, K Kim, Y Ahn, S Askaruly, K Park, H Yang, G Jang, K Moon, W Jung (2020). "Quantitative screening of cervical cancers for low-resource settings: Pilot study of smartphone-based endoscopic visual inspection after acetic acid using machine learning techniques," *JMIR mHealth and uHealth* 8 (3), e16467
- S Askaruly, Y Ahn, H Kim, A Vavilin, S Ban, PU Kim, S Kim, H Lee, W Jung (2018). "Quantitative evaluation of skin surface roughness using optical coherence tomography in vivo," *IEEE Journal of Selected Topics in Quantum Electronics* 25 (1), 1-8
- S Kim, Yujin Ahn, S Askaruly, P Kim, W Jung, H Lee (2017). "Evaluation of skin texture and wrinkle using optical coherence tomography (Pilot study)," *Journal of the Society of Cosmetic Scientists of Korea* 43 (3), 247-254

#### Oral Presentations

- S Askaruly, H Yang, N Aimakov, G Na, Y Ahn, JS You, G Jang, JH Jang, W Jung (2022) "Advanced ear examination using deep learning-assisted mobile otoscope", *SPIE Photonics West*
- G Na, H Yang, U Shin, Y Kim, S Askaruly, T Kwon, Y Lee, W Jung (2022) "High-throughput screening with deep learning for quantitative phenotype analysis of zebrafish", *SPIE Photonics West*
- H Yang, S Askaruly, S Yun, G Na, T Kwon, W Jung (2021), "High-throughput screening platform for quantitative phenotype analysis of *Xenopus laevis* with deep learning," *SPIE Advanced Biophotonics Conference*
- S Yun, H Yang, S Askaruly, TJ Park, W Jung, T Kwon (2021), "Development of deep-learning-based high-throughput phenotype screening platform of aquatic model organism embryos," *International Xenopus Society*
- S Askaruly, Y Ahn, J Bak, A Vavilin, G Jang, P Kim, H Lee, W Jung (2018), "Quantitative classification of OCT skin images with deep learning," *SPIE Photonics West*

#### Poster Presentations

- S Askaruly, N Aimakov, A Iskakov, H Cho, Y Ahn, MH Choi, H Yang, W Jung, "Farbio: Deep learning for biomedical imaging," *PyTorch Developer Day 2021*
- S Askaruly, Y Ahn, H Kim, A Vavilin, PU Kim, H Lee, W Jung (2017), "Evaluation of age-related effects on human skin surface roughness using optical coherence tomography," *The optical society of Korea*

#### Registered Patents

- W Jung, Y Ahn, S Askaruly, "A method and apparatus for detecting wrinkle of skin using optical coherence tomography," *Korean Registered Patent*, 10-2306486, (2021.09.23)

#### Teaching Activities

- Mobile AI - Focus on BME Applications, Summer 2021, <https://tbl-unist.github.io/mobile-ai-21/>
- Mobile development, Summer 2020, <https://tbl-unist.github.io/tbl-edge/>

Here I have listed research activities during the period of my Ph.D. program. I am currently working on final preparations of manuscripts for submission.



## Closing remarks



Dear committee members,

Before we go to the Q&A session, I would like to say a few words of closing remarks.

I would like to thank you for the valuable feedbacks which helped me to grow not only from our last meeting, but also for the continuous support during the whole period of my PhD program.

When I look back, I feel to have grown a lot. I widened my outlook and deepened expertise. Also, I acquired many skills, which hopefully will serve well in my later career. But more importantly, I believe I became more patient and humble.

Although this journey was challenging, quite often I was lost in the curiosity of research and passion for engineering. My acknowledgement here primarily goes to my family, friends, labmates. The role of my supervisor, professor Woonggyu Jung is doubtlessly huge. He always kept advising, supporting and cheering up for whom I am grateful, especially I admire his endless enthusiasm :)

Further, I hope to wrap up the works within the soonest period and concentrate on the next stage of life, building professional career. Given the time and resources, I am now confident to explore opportunities in the development end-to-end solutions for biomedical fields and not only, thanks to obtained research training. I am also grateful to UNIST, and hope I can contribute to its international reputation

**later in my career as its alumni.**

**That said, I am ready for your comments and expert opinions, to evaluate the qualification of the presented thesis.**



**Thank you for your attention!**

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**Q&A**

Correspondence:  
s.askaruly@gmail.com 

**Finally, thank you for your time and attention. If you have any questions regarding the defense presentation, I would be glad to answer them now.**