IT2805 Major Project

De-blurring X-ray Radiographs by enhancing image resolution using Deep Learning

Project Guide	Group No	Group Members
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Agenda

- Motivation
- Scope
- Objectives
- Literature Survey
- Implementation
- Results
- Conclusion
- Future Scope

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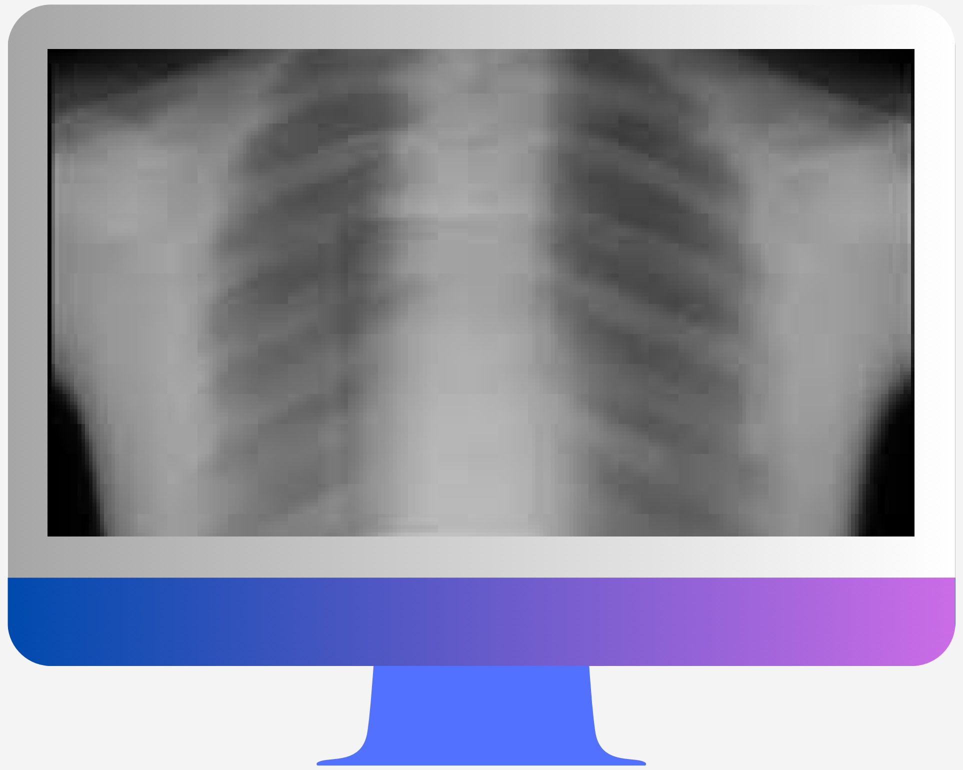
Motivation

Decreased diagnostic accuracy

Delayed or improper treatment



Biological effect of radiation exposure

Impaired communication and collaboration

Scope

1

Improved diagnosis Quality

Improved quality of image leads to accurate diagnosis

2

Surgical planning and intervention

Clearer visualization of anatomical structures, fractures, or implant placements, aiding in surgical planning and decision-making

3

Save Cost

Reduced cost of using x-ray imaging

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OBJECTIVES

Extend support for multiple scanning Techniques

Comparing results of Traditional Algorithms and Deep Learning Approach

Eliminate redundant X-Ray Retakes

Mitigating Health risk factors

Literature Survey

Sr No	Title	Methodology	Advantages	Limitations
1	Deblurring X-Ray Digital Image Using LRA Algorithm (2019)	Lucy Richardson algorithm (LRA)	Improve image contrast and reduce noise in microscope images	Iterative algorithm hence results may depend on the number of iterations employed
2	Deep learning-based image processing approaches for image deblurring (2020)	Enhanced Deformable Convolutional, Networks (EDVR) for Multi-frame deblurring	Outcomes obtained by the EDVR algorithm are visually more appealing	Suitable for images taken from smartphone camera by burst mode

Sr No	Title	Methodology	Advantages	Limitations
3	A machine learning approach for non-blind image deconvolution	Space-invariant non-blind deconvolution i.e., PSF is constant	Can handle different types of noise and artifacts	Each MLP has to be trained on only one blur kernel
4	Blind Deblurring of Spiral CT Images (July 2003)	Expectation Maximization (EM) deblurring algorithm for Gaussian blur	Reduces CT scan image blurring by about 24%	The EM algorithm assumes nonnegative valued images CT numbers in Hounsfield units (HU) can be negative.
5	Blind Image Blur Estimation via Deep Learning (2016)	Deep Neural Network (DNN) General Regression Neural Network (GRNN)	Estimates the blur type and kernel parameters	Useful to estimate blur type but this introduces complexity in main problem statement

Sr No	Title	Methodology	Advantages	Limitations
6	Deblurring Low-Resolution X-ray Images Using CNN (2022)	Two network models based on the U-Net architecture	Deblur the low-resolution PCB images	Predicted images may suffer from unexpected artifacts when the edge-knife images, which have a much simpler structure, are input to the networks
7	Image Deblurring via Enhanced Low-Rank Prior (2016)	Low-Rank Prior and weighted nuclear norm minimization method	Used for blind image deblurring Can effectively recover latent images	Method will fail if a blurred image contains rich textures, because most of textures will be removed
8	Enhancement of X-ray images using various Image Processing Approaches (2021)	Logarithmic image processing, Edge detection method	Improves image quality by boosting contrast, brightness, removing noise	Introduce artifacts or distortions in the image

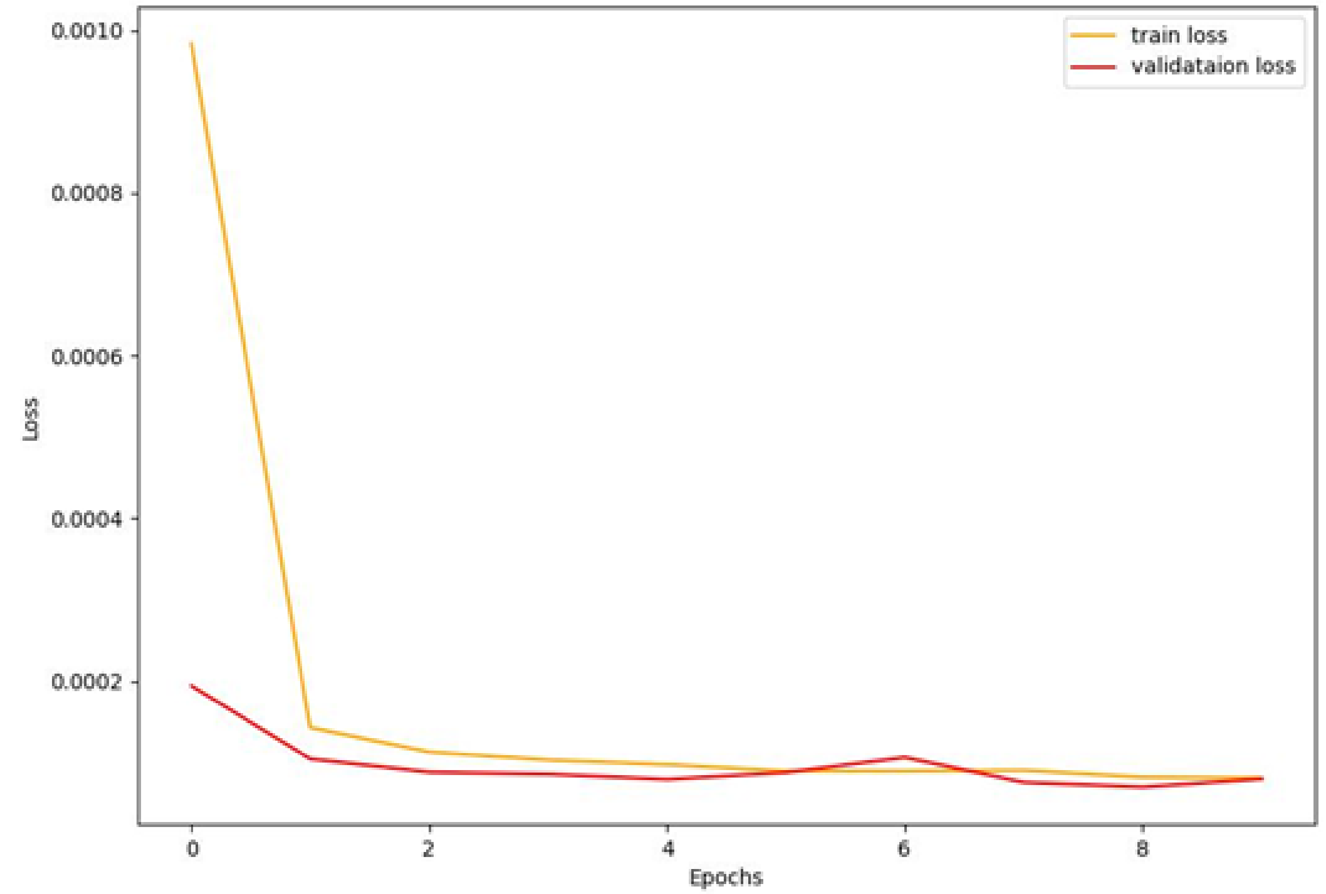
Sr No	Title	Methodology	Advantages	Limitations
9	Angular super-resolution in X-ray projection radiography using deep neural network: Implementation on rotational angiography. (2022)	Ten models were trained for different levels of angular super-resolution (ASR), denoted as ASRN, where for every Nþ2 frames, the first and the last frames were submitted as inputs to super-resolve the intermediate N frames.	ASR technique is capable of super-resolving rotational angiographic frames at intermediate projection angles	Dataset only consisted of carotid and vertebral rotational angiograms, and the generalizability to other anatomical regions may be limited. Additionally, the study did not evaluate the clinical impact of the ASR technique on diagnostic accuracy or patient outcomes
10	Medical Image Enhancement using Deep Learning (2022)	Deep learning algorithms (particularly Convolutional Neural Networks)	speckle noise reduction Improved image quality	The effectiveness of the system depends on the quality of input images. Low-quality images with severe artifacts may not be improved significantly by the proposed system.

Model Training

Comparison of Trained Models

Model	Epochs	PSNR	SSIM	Validation Loss
UNET	25	33.25303	0.988993	0.00047
DAE	50	16.396184	0.4653409	0.0041
SRCNN	30	40.12646	0.98896	0.00006

Loss curve for SRCNN



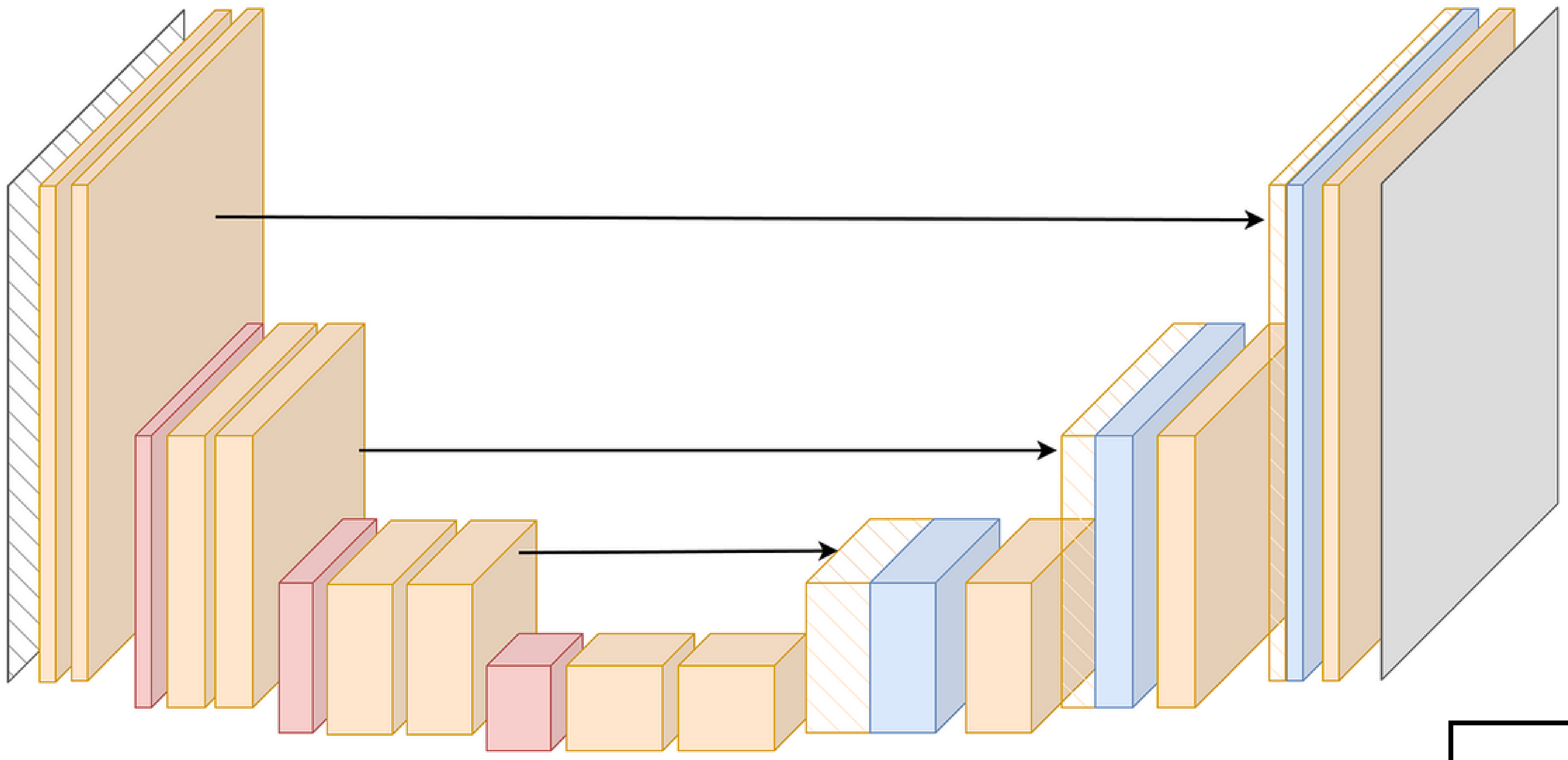
Model Training

DAE

```
Model: "encoder"
_________________________________________________________________
 Layer (type)                Output Shape
=================================================================
 encoder_input (InputLayer)  [(None, 224, 224, 3)]

 conv2d (Conv2D)             (None, 112, 112, 128)

 conv2d_1 (Conv2D)           (None, 56, 56, 64)

 conv2d_2 (Conv2D)           (None, 28, 28, 128)

 conv2d_3 (Conv2D)           (None, 14, 14, 64)

 conv2d_4 (Conv2D)           (None, 7, 7, 32)

 flatten (Flatten)           (None, 1568)

 latent_vector (Dense)       (None, 256)
```

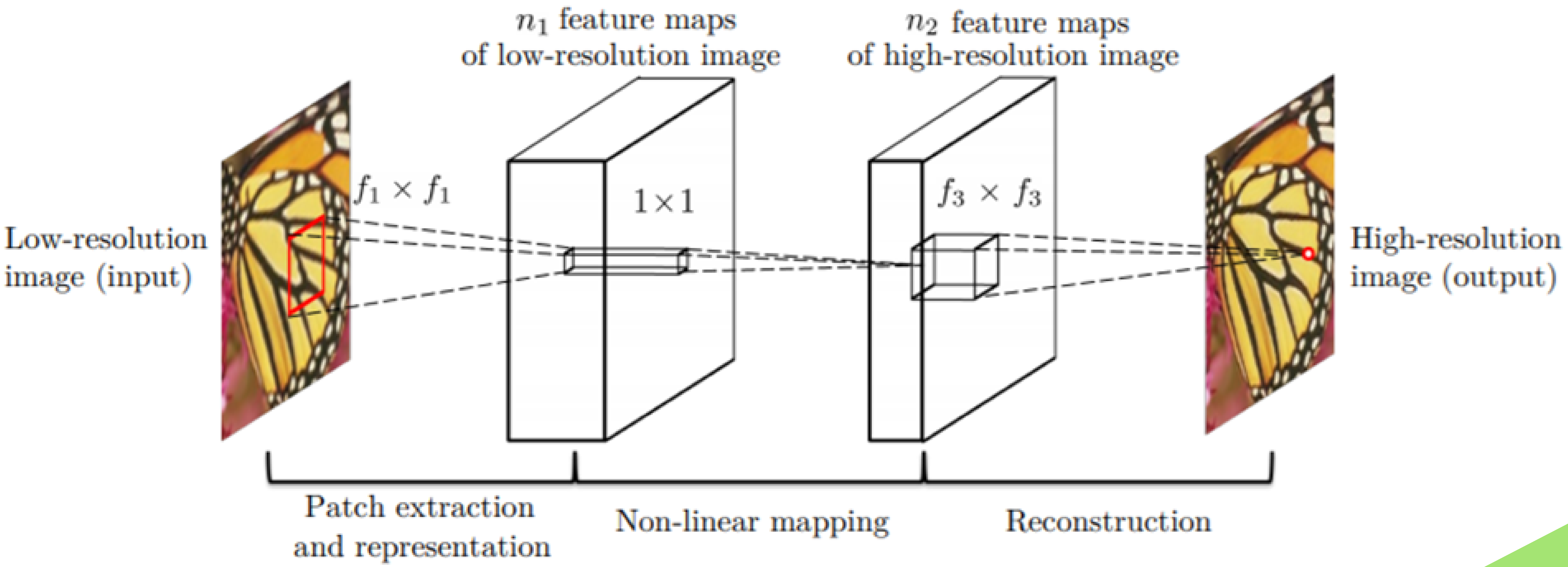
```
Model: "decoder"
_________________________________________________________________
 Layer (type)                Output Shape
=================================================================
 decoder_input (InputLayer)  [(None, 256)]

 dense (Dense)               (None, 1568)

 reshape (Reshape)           (None, 7, 7, 32)

 conv2d_transpose (Conv2DTra  (None, 14, 14, 32)
 nspose)

 conv2d_transpose_1 (Conv2DT  (None, 28, 28, 64)
 ranspose)

 conv2d_transpose_2 (Conv2DT  (None, 56, 56, 128)
 ranspose)

 conv2d_transpose_3 (Conv2DT  (None, 112, 112, 64)
 ranspose)

 conv2d_transpose_4 (Conv2DT  (None, 224, 224, 128)
 ranspose)

 decoder_output (Conv2DTrans  (None, 224, 224, 3)
 pose)
```

Model Training : UNET

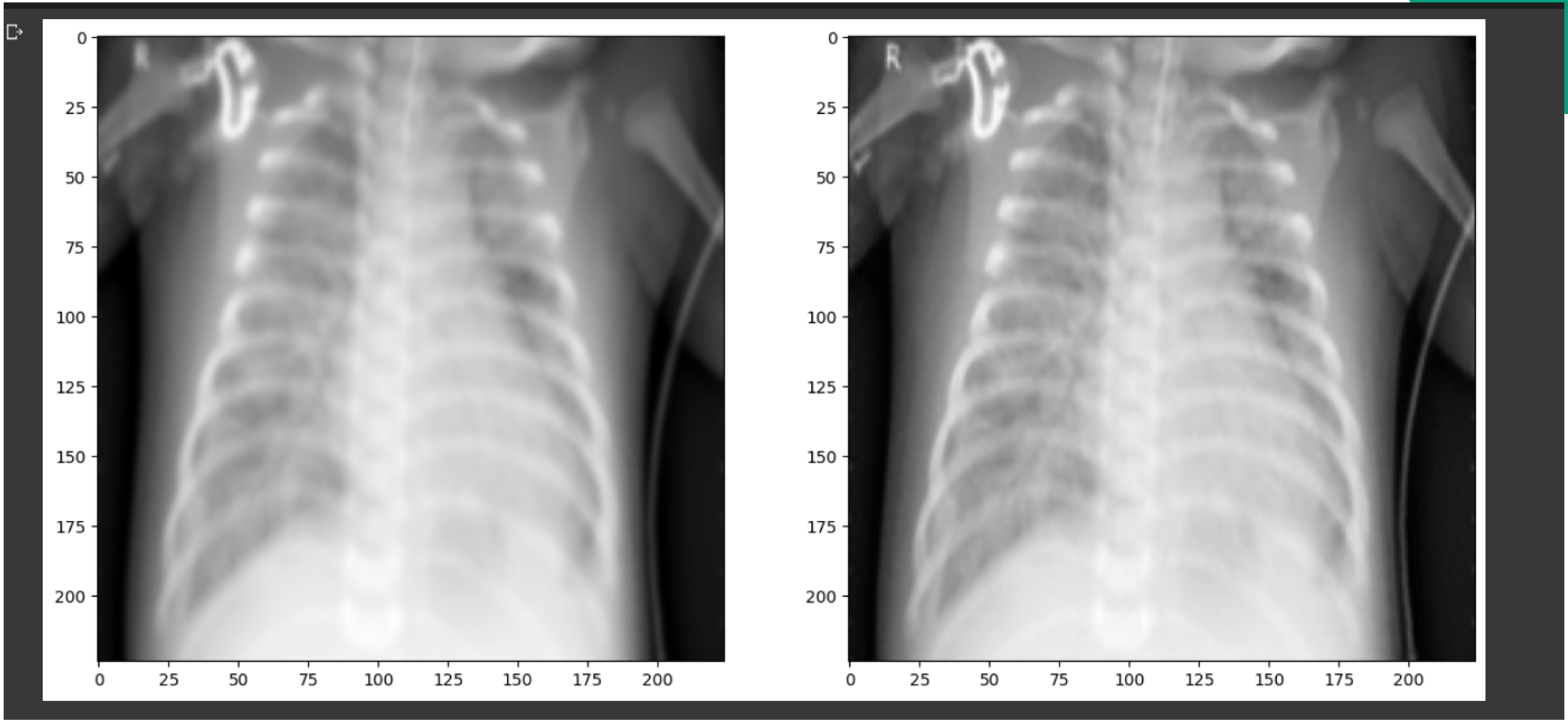


Activation function	ReLU
Layers	23
Downsampling	Upsampling

Implementation of SRCNN Model

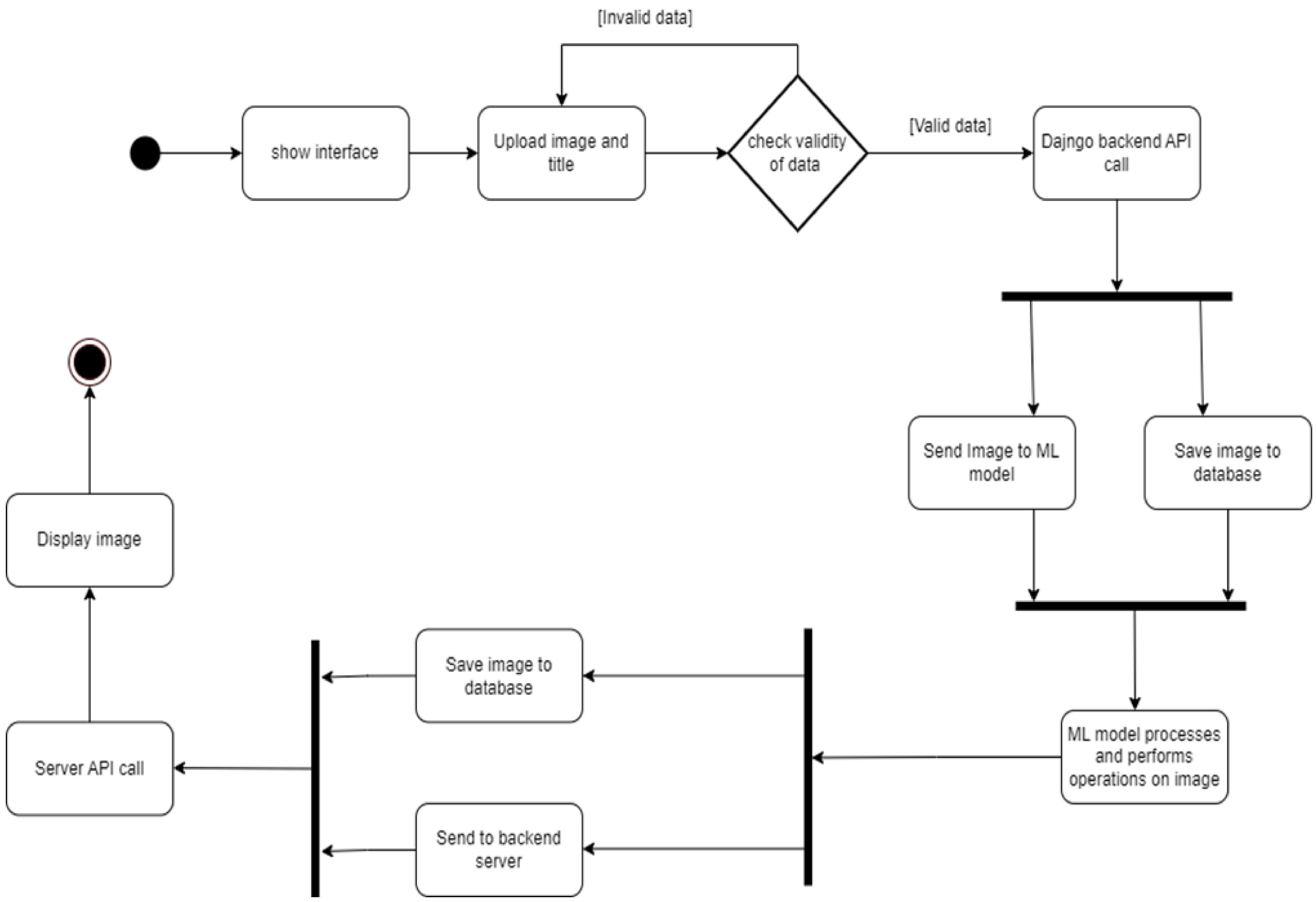


SRCNN Architecture

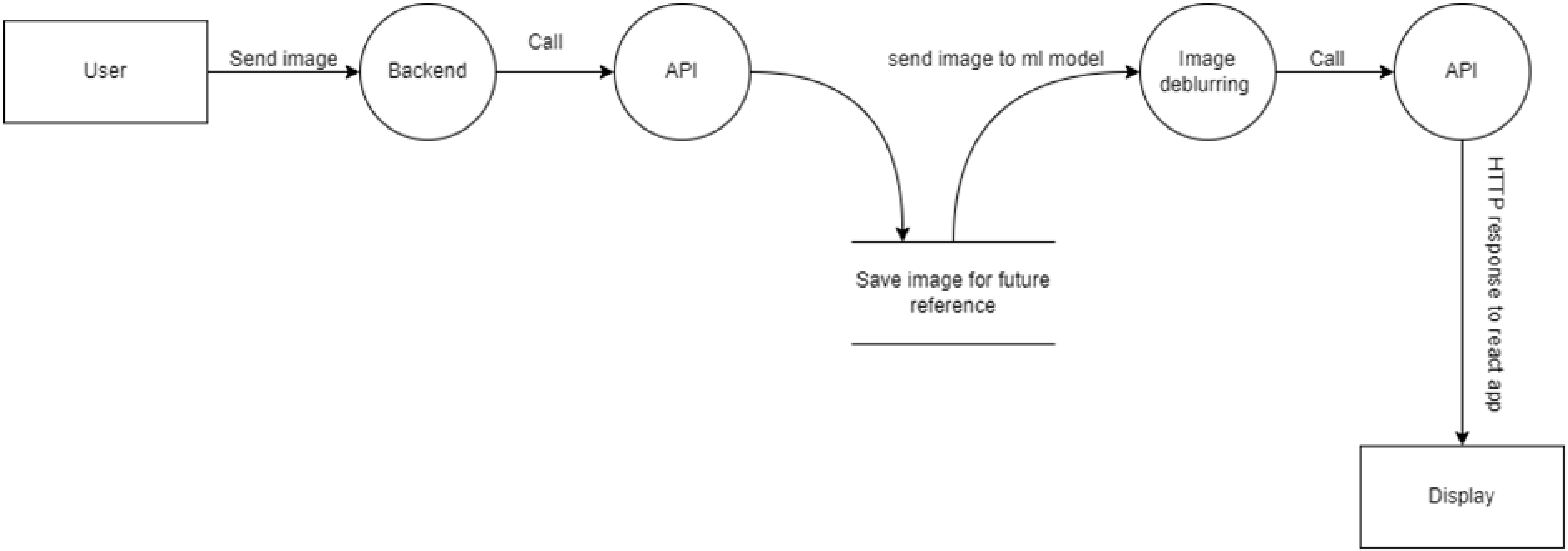


Results of SRCNN

1. Blurred Image 2. Deblurred Im

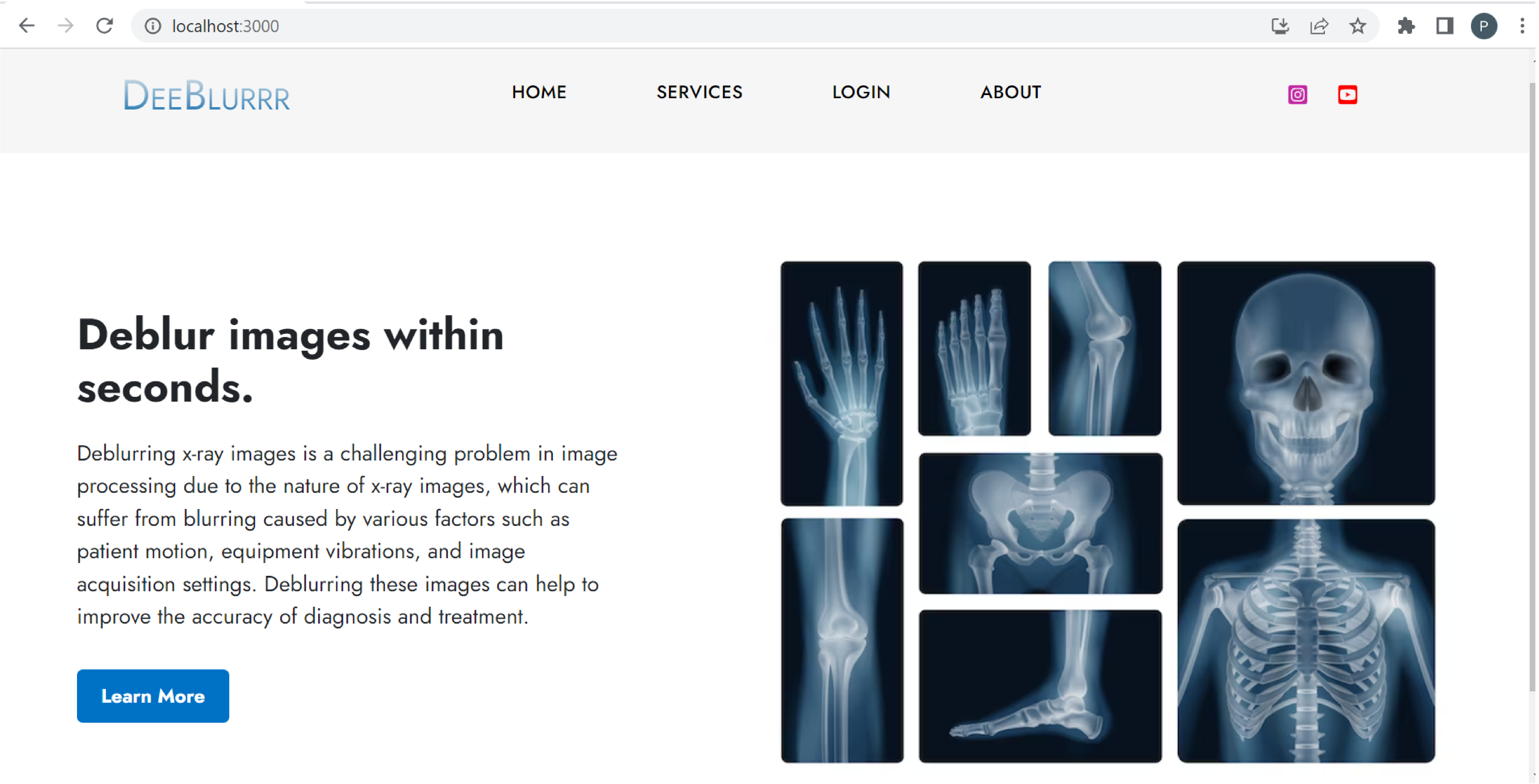


Activity Diagram of of X-ray image deblurring system


User
Send image
Backend
Call
API
send image to ml model
Image deblurring
Call
API
Save image for future reference
HTTP response to react app
Display

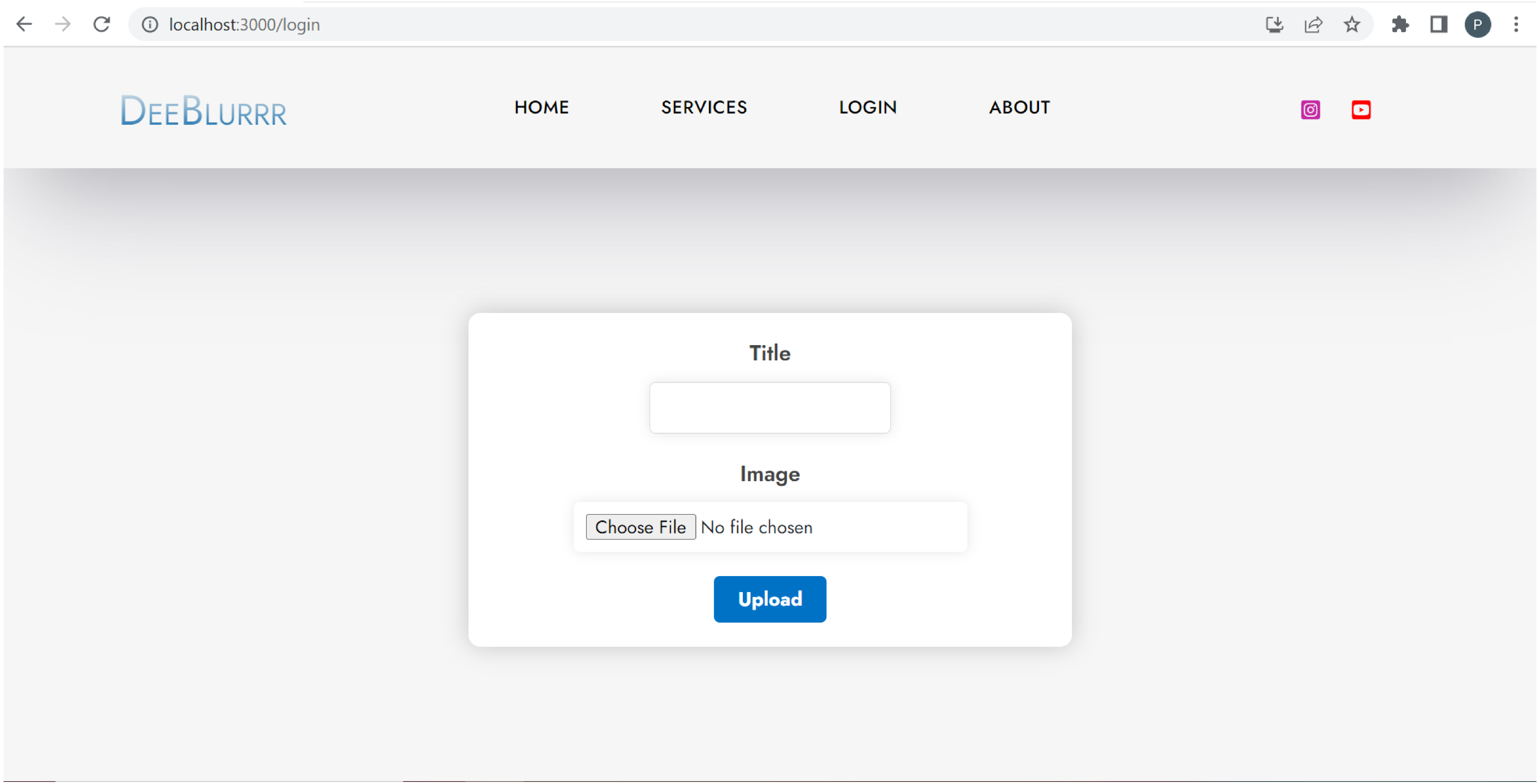
DFD

Implementation of Web Application



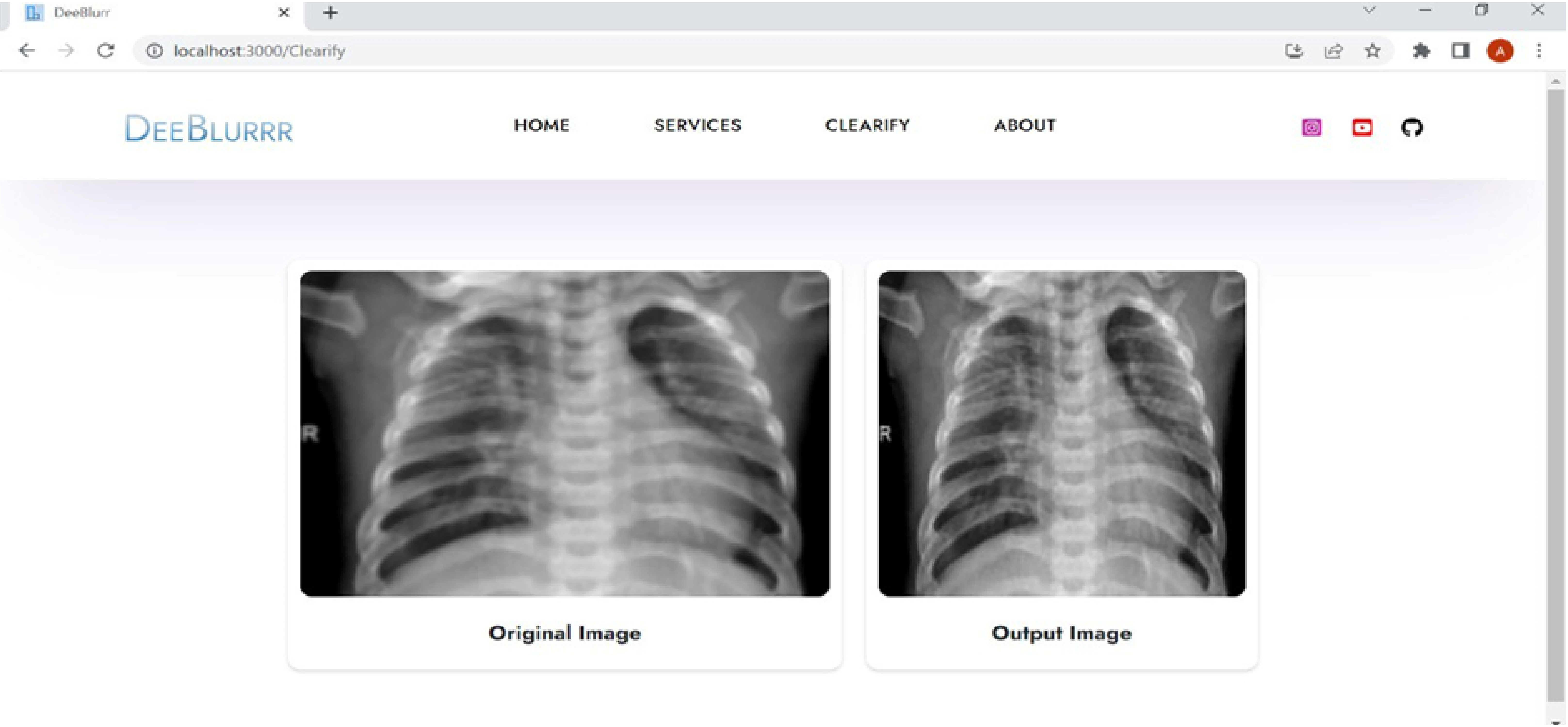
Home Page

Implementation of Web Application



Upload Blurred Image

Implementation of Web Application



Result of Image Deblurring

Future Scope

- The results were satisfactory with test and validation data, they are not perfect when compared with high resolution X-ray images. The models were trained for only Gaussian Blur type.We need to train the models for much bigger dataset of varying blur type which will demand high end GPU and computing resources.

- The proposed system can be integrated with digital X-ray machines for Hassle free deblurring of X rays. With such integration the objective of limiting retakes would be achieved.

- The Real-world dataset of Blurred and corresponding sharp X ray image could be obtained to train the model more precisely. Such a trained deep learning model will have high accuracy and reliability too.

- With more advanced image processing algorithms such as Deblur GAN and other pretrained models, deblurring procedure on a larger dataset could be achieved much faster and accurate.

Thank You!