High dynamic range
Image forensics

CONTENTS

01 Introduction

HDR image

Restriction of camera sensors' dynamic range → Easy to be overexposed or underexposed

mHDR

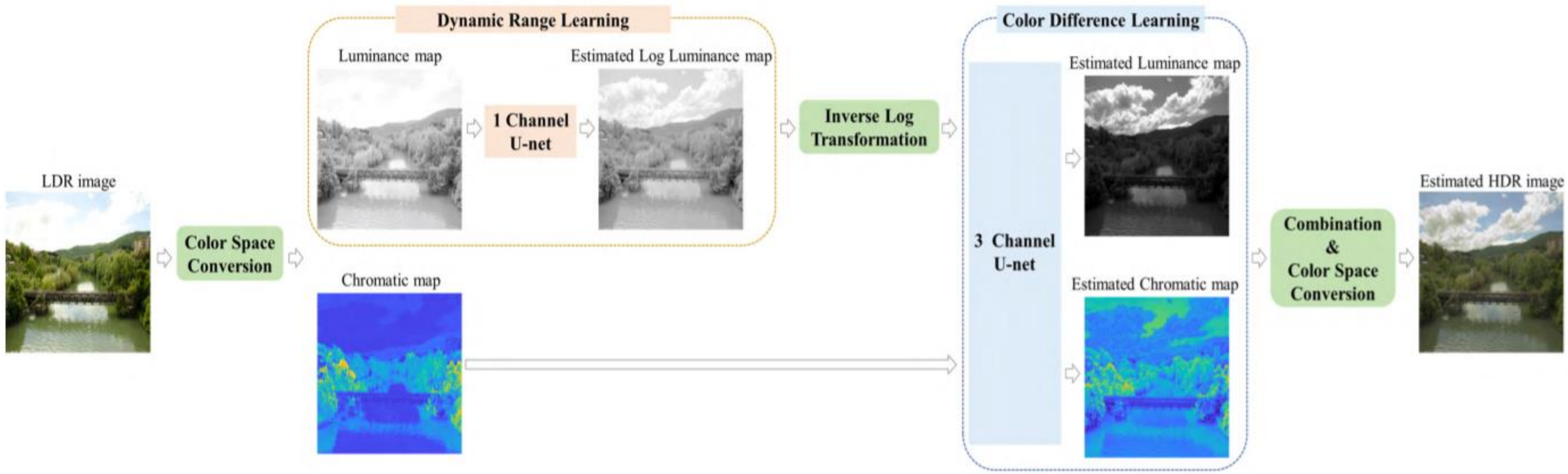
Fusing the overexposed image and underexposed image can preserve the complete information of the scene

iHDR

Generate HDR image from one LDR using iTMO

iHDR, mHDR were hardly distinguished by naked eyes
→ Performed mHDR image and iHDR image classification based on CNN
→ Proposed network learns and detects statistical changes of the luminance channel of HDR image automatically

01 High Dynamic Range Image(iHDR)



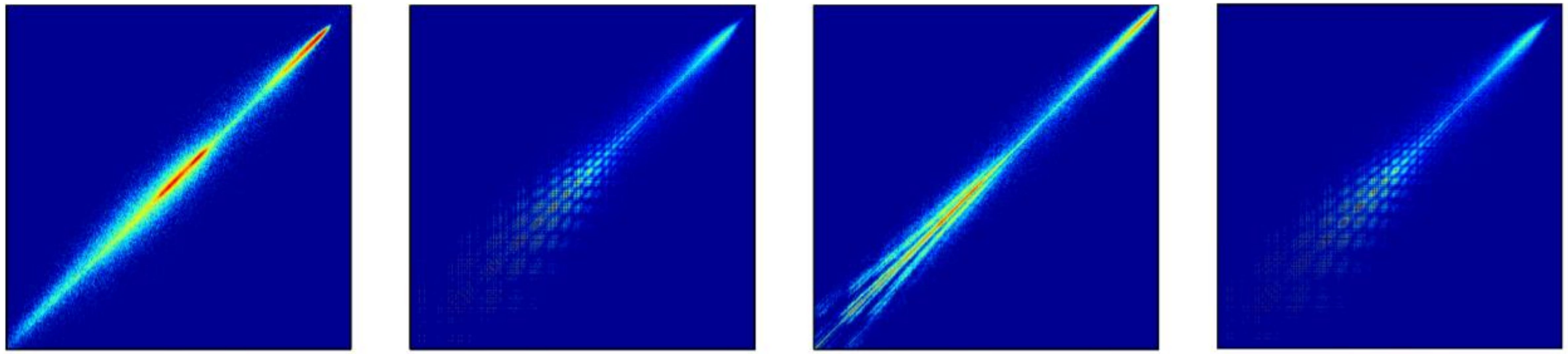
1. Extract the luminance and chromatic information from the LDR image
2. Estimate the luminance of the HDR from the luminance of the LDR (using Dynamic Range Learning model)
3. Estimate the chromatic information of the HDR by using the estimated HDR luminance (using Color Difference Learning model)
4. Recombine the estimated luminance and chromatic information

01 High Dynamic Range Image

(a) (b) (c) (d) (e)

mHDR has more luminance details compared to iHDR image

Joint histogram (joint probability or co-occurrence matrix of neighboring pixels)



(a) mHDR (b) iHDR, Akyüz *et al.* [6] (c) iHDR, Huo *et al.* [14] (d) iHDR, Kovaleski and Oliveira [15]

iHDR images is sparser than that of mHDR image, especially in small pixel values

02 Pre-processing

1. Manipulation of generating HDR images mainly function on luminance channel
2. In RGB channel, the objects and edges of the scene can be interference when using CNNs to learn features automatically.

Luminance channel

$$L = 0.2126 * R + 0.7152 * G + 0.0722 * B$$

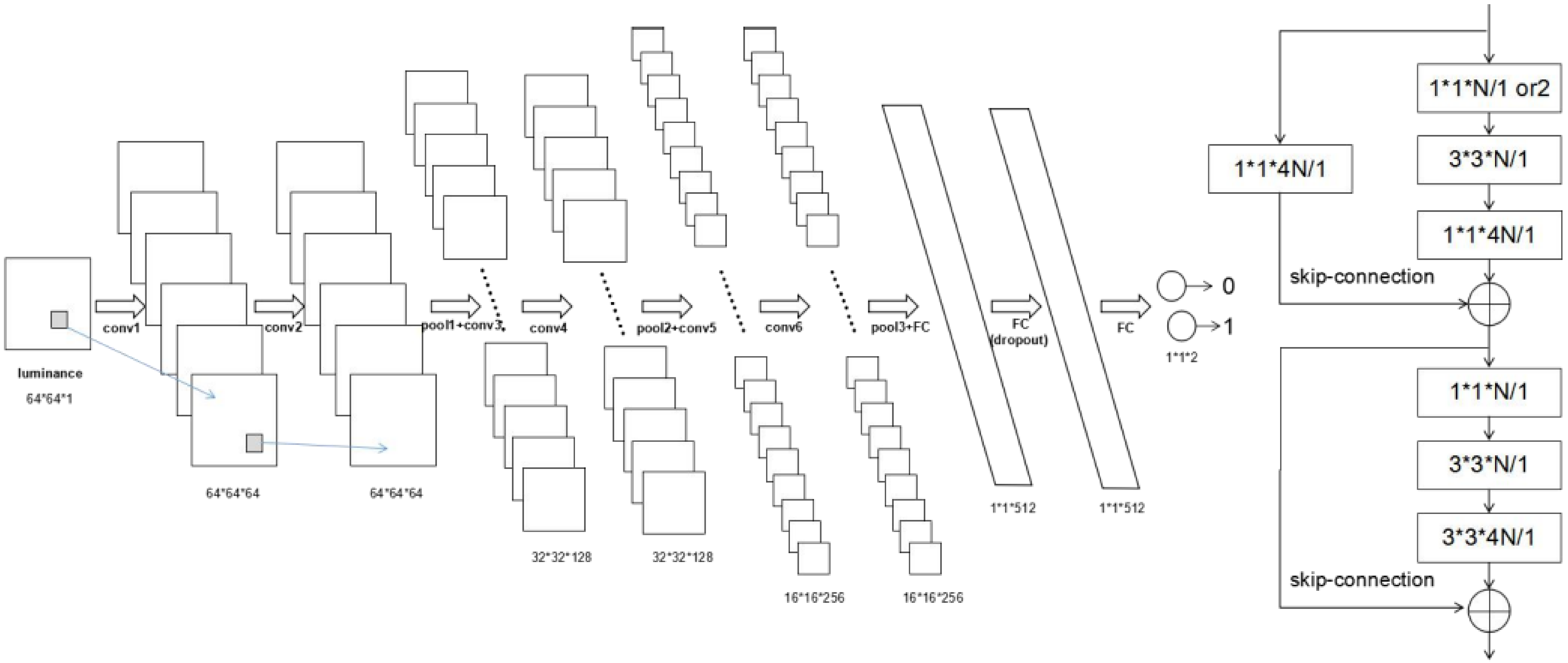
The maximum and minimum luminance values of different HDR image vary largely across different image → compensate image-dependent peak brightness in HDR image.

Transform

$$l_{i,j} = \log(L_{i,j} + \varepsilon) \qquad \varepsilon = 10^{-6}$$

02 CNN

Without residual block vs with residual block - Guide the feature extraction automatically



02 CNN

Without residual block vs with residual block

Without residual block

- ReLU activation function
- Max-pooling
- Dropout in fully connected layer
- Cross entropy loss function
- Softmax activation

With residual block

- Replace all convolutional layers with residual blocks
- Before residual blocks, add large kernel convolution layer and overlapping average pooling layer
- Second fully-connected replace by average pooling

03 Experiment

Dataset(mHDR) - 458

- Meylan created 14 mHDR images;
- Fairchild created 106 mHDR images;
- HDRSID dataset contains 232 mHDR images;
- Online data includes 106 images.

Pick out 406 mHDR images whose scene is not very similar to each other

Dataset(LDR) - 406

Mitadobe5k(high-quality, high-resolution image)
Pick out randomly

Dataset(iHDR) – 406

Create iHDR image(for kinds of iTMOs)

For train
Divide into 64x64
Shuffle completely
(60000 image blocks, ratio of mHDR and iHDR blocks is 1:1)

Dataset 1.0(for verification)
Pick out 40 images for iHDR, mHDR
Divide into 64x64
Shuffle completely

Dataset 2.0(for verification)
Remaining image blocks

03 Experiment

Advantage of using log domain luminance

	Plain	Res
Normalized pixel value	92.55%	90.71%
Log domain luminance	94.15%	93.36%

Plan vs Residual block

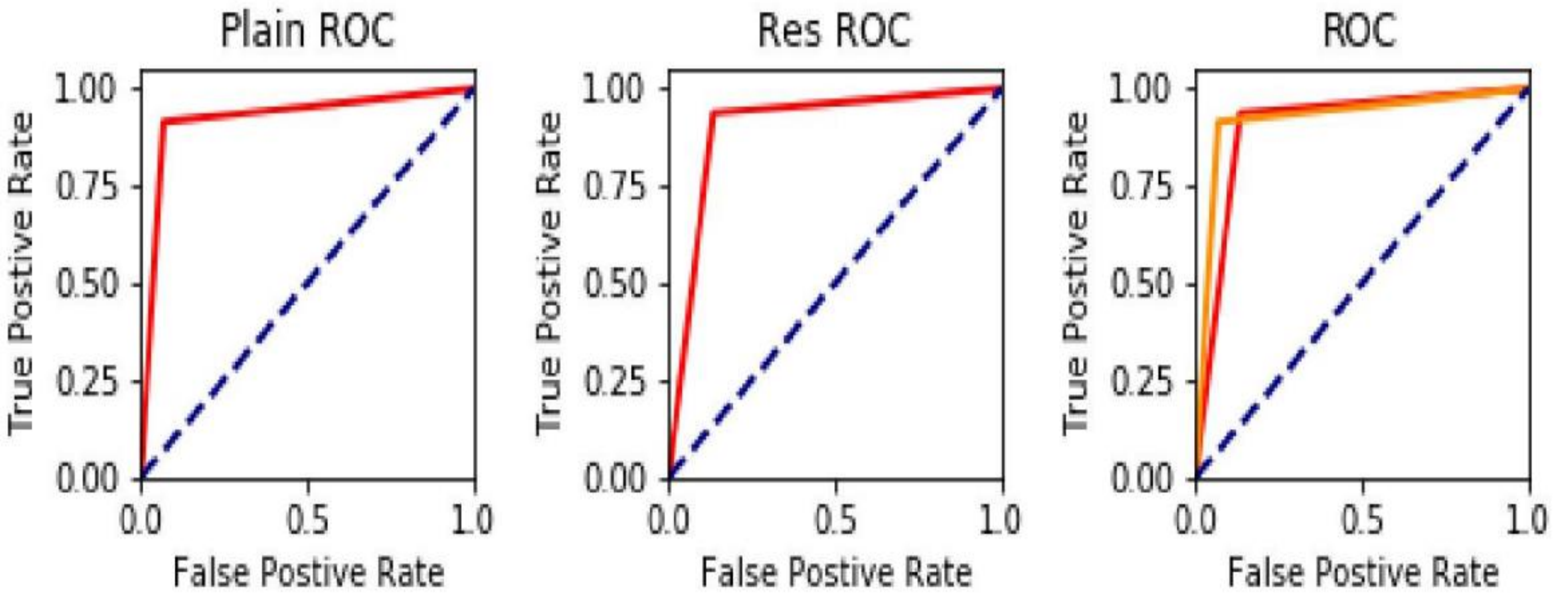


Table 2. Performance on verification dataset.In verification dataset 1.0, the accuracy after MVS is in the bracket.

			Plain	Res
Verification 1.0	ihdr	acc	93.26(100)	86.61(100)
		AUC	92.29	90.16
	mhdr	acc	91.33(100)	93.70(100)
		AUC	93.17	94.55
Verification 2.0	accuracy		94.09	93.70