Perceptual metric for color transfer methods

H. Hristova O. Le Meur R. Cozot K. Bouatouch

Outline

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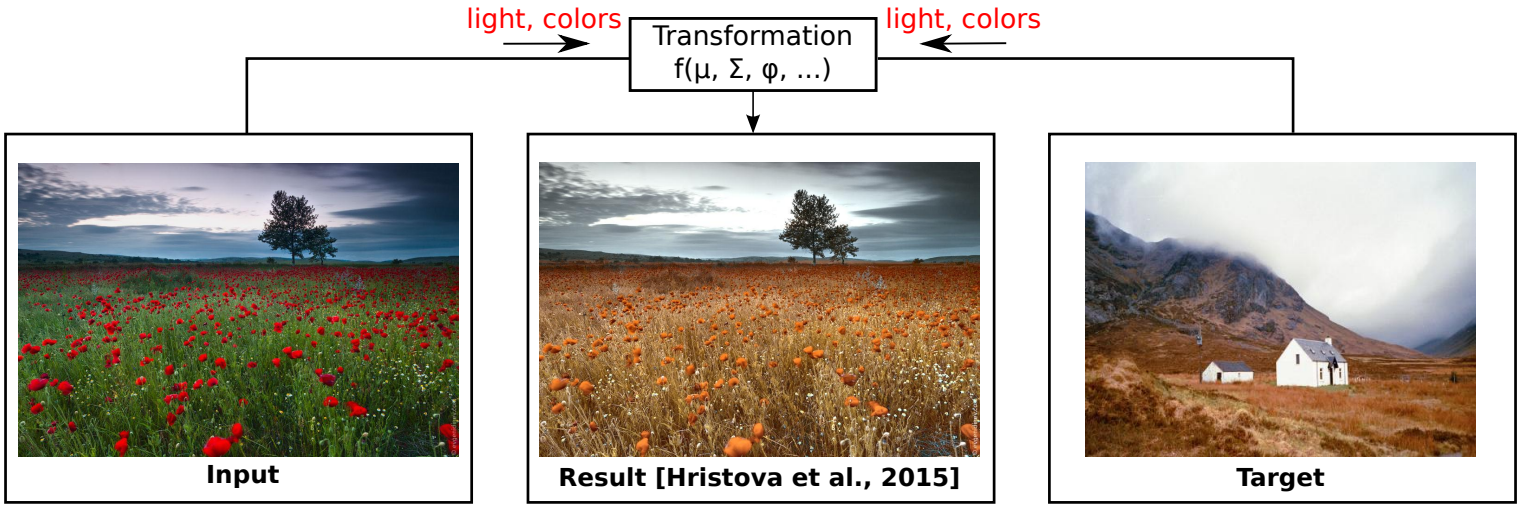
Color transfer

Overview

- Modification of the colors of an *input* image according to a *target* color palette;
- Statistical transformations between the input and target color distributions;
- Applications: image/video color grading [FPC*14, BSPP13], time-lapse image hallucination [SPDF13], etc.



Color transfer

Which one is best output?

- A number of plausible outputs;
- Lack of a ground truth.

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Quality assessment of color transfer

Subjective user study

- Efficient way to study the subjectiveness;

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Objective metrics:

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- Bhattacharya coefficient(result,target).

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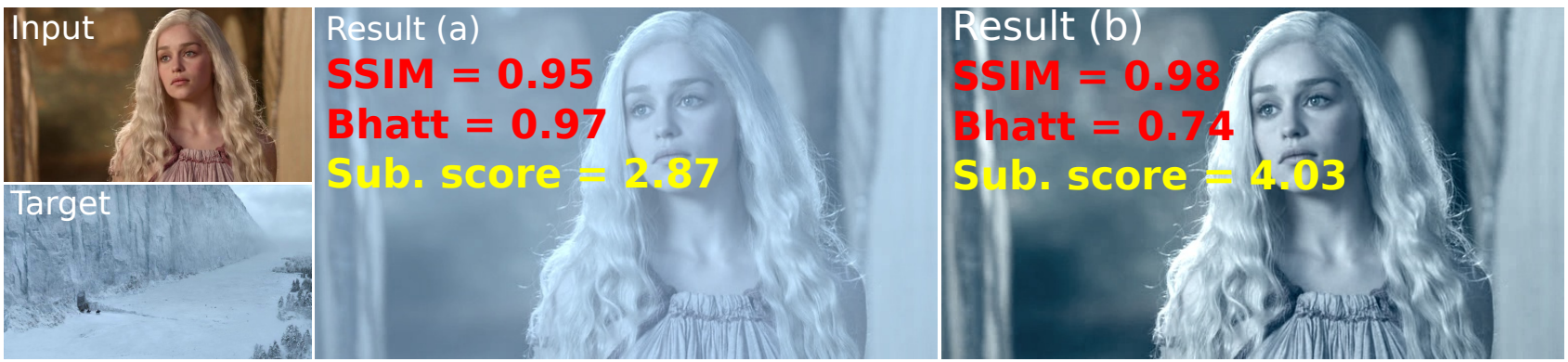

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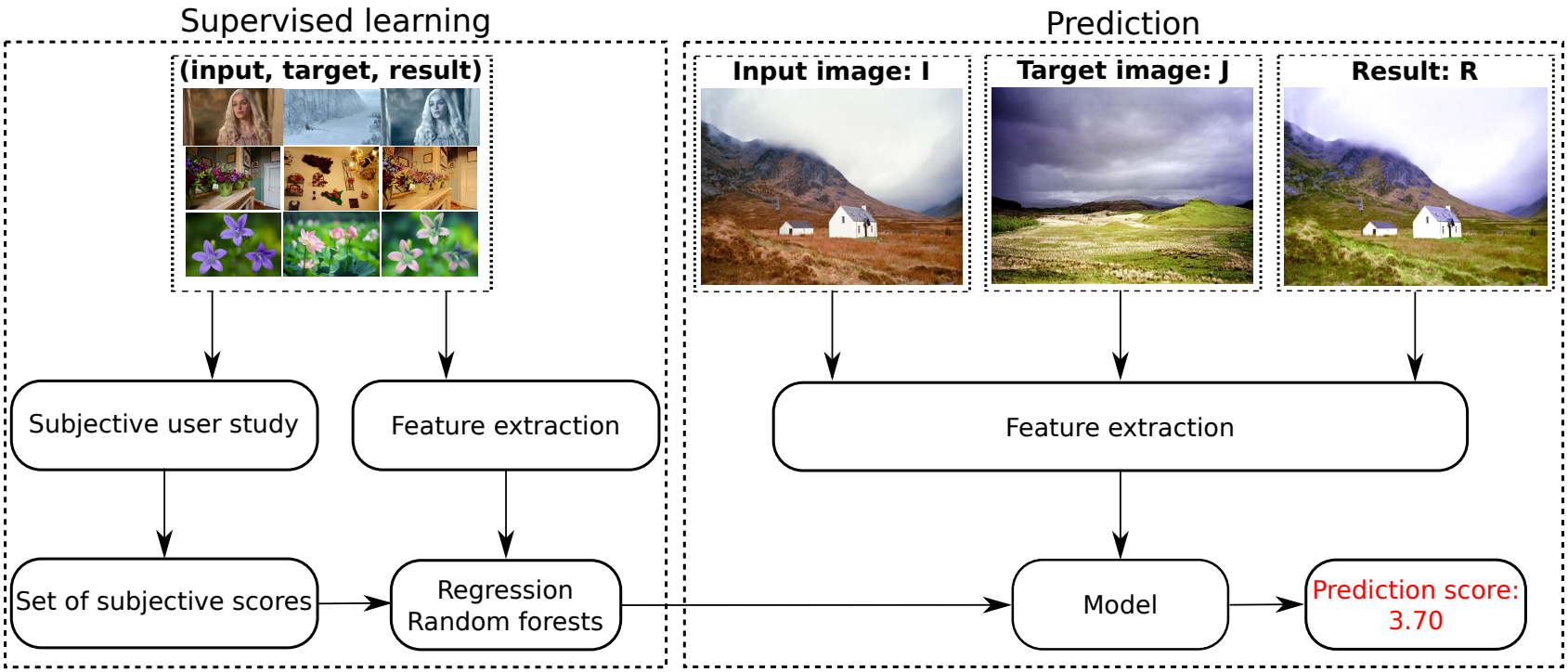
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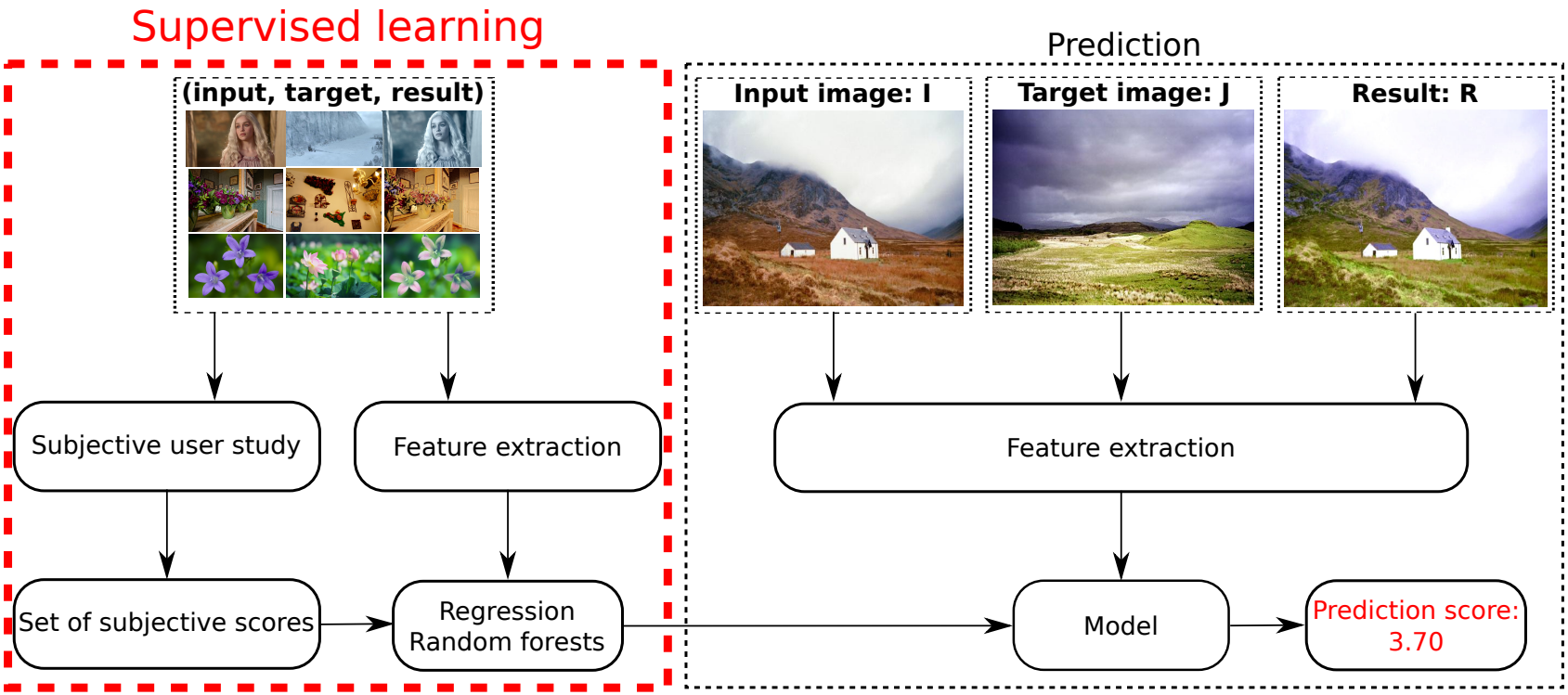
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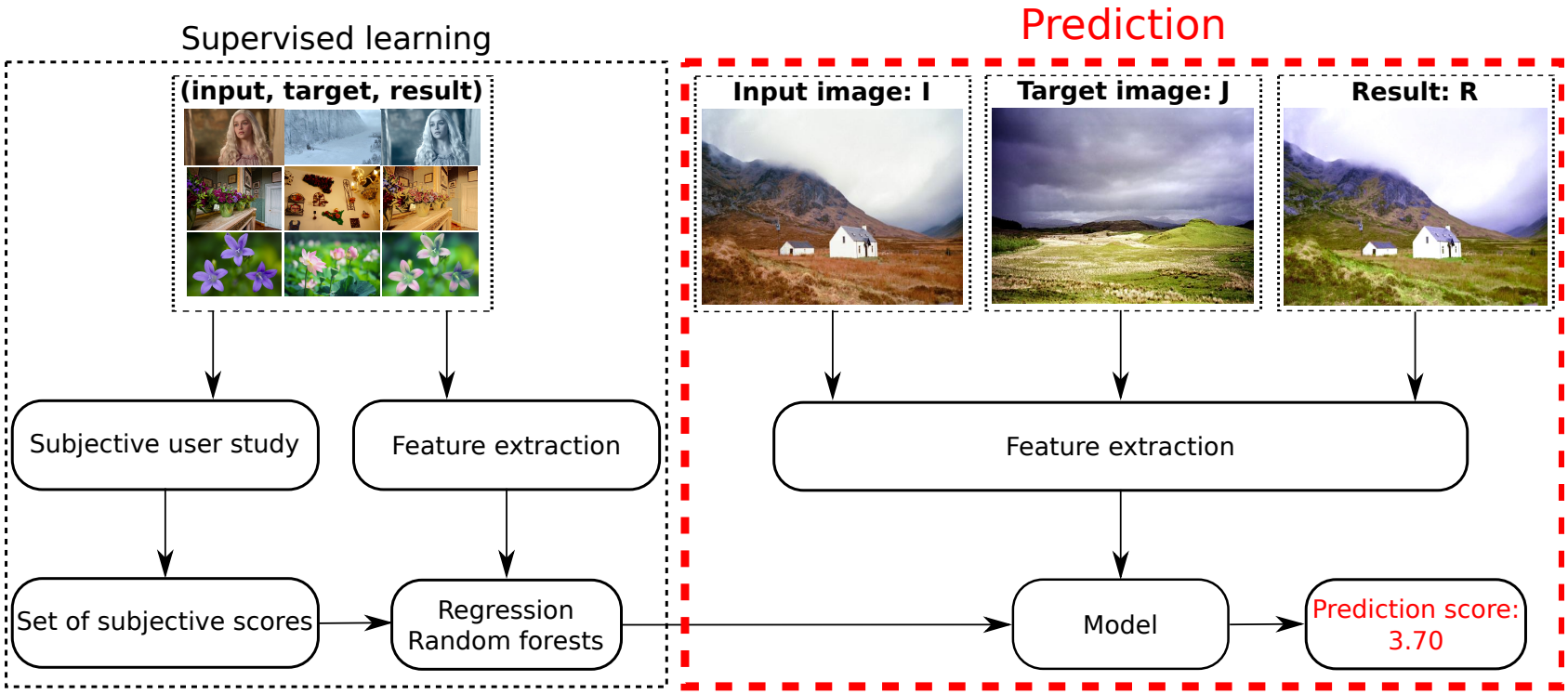
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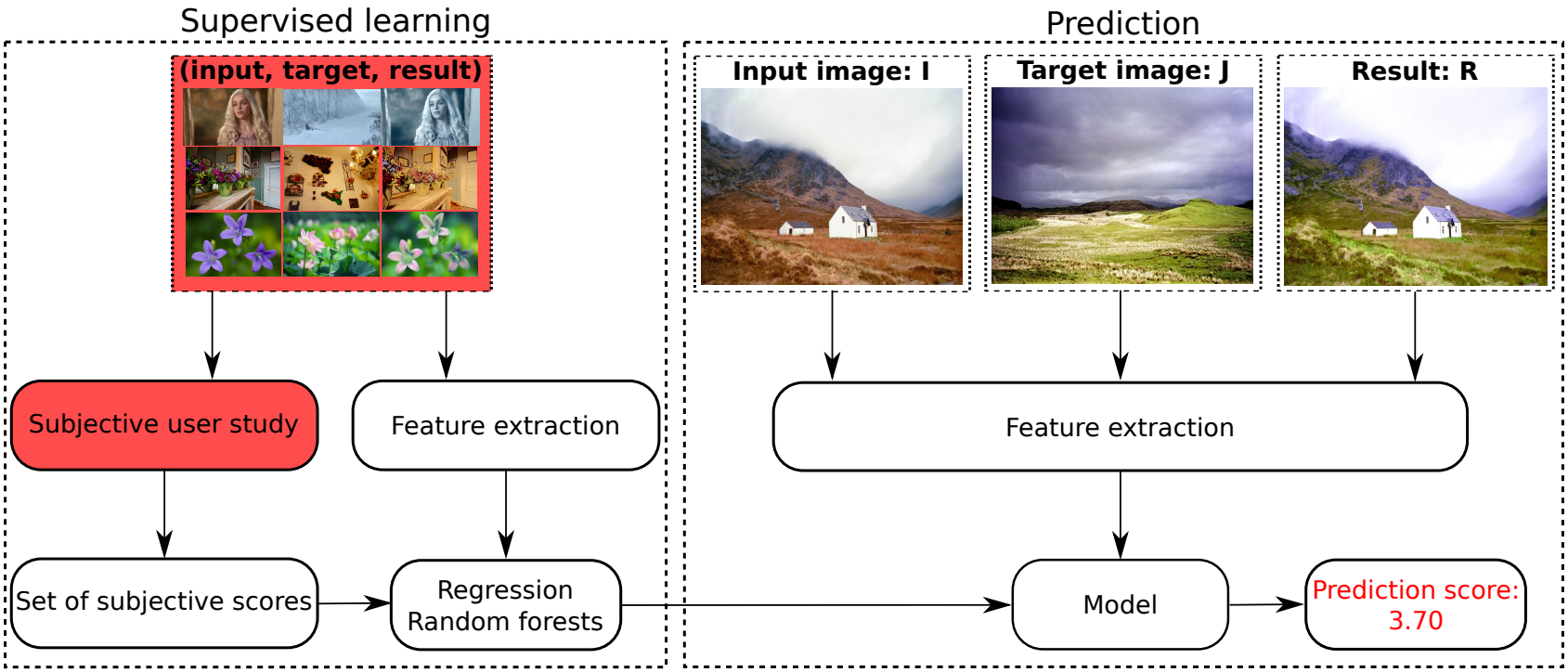
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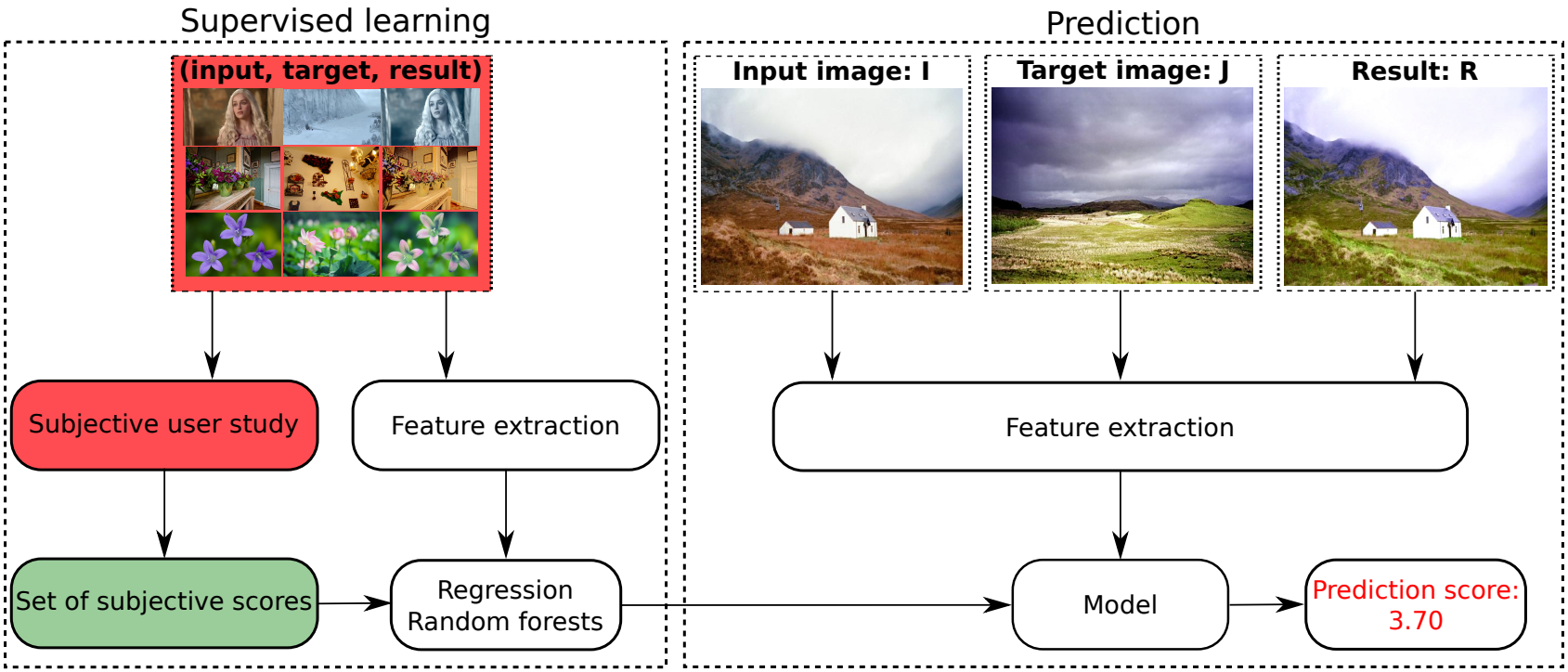
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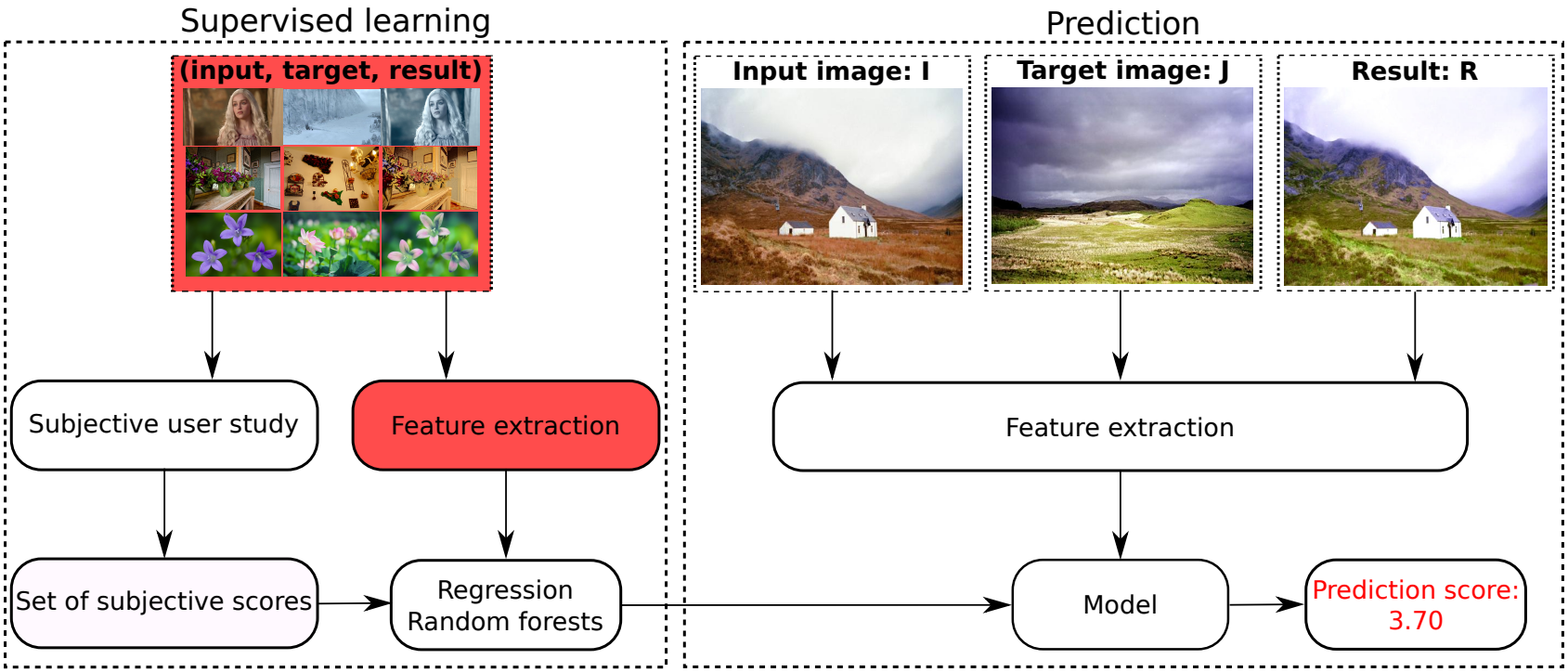
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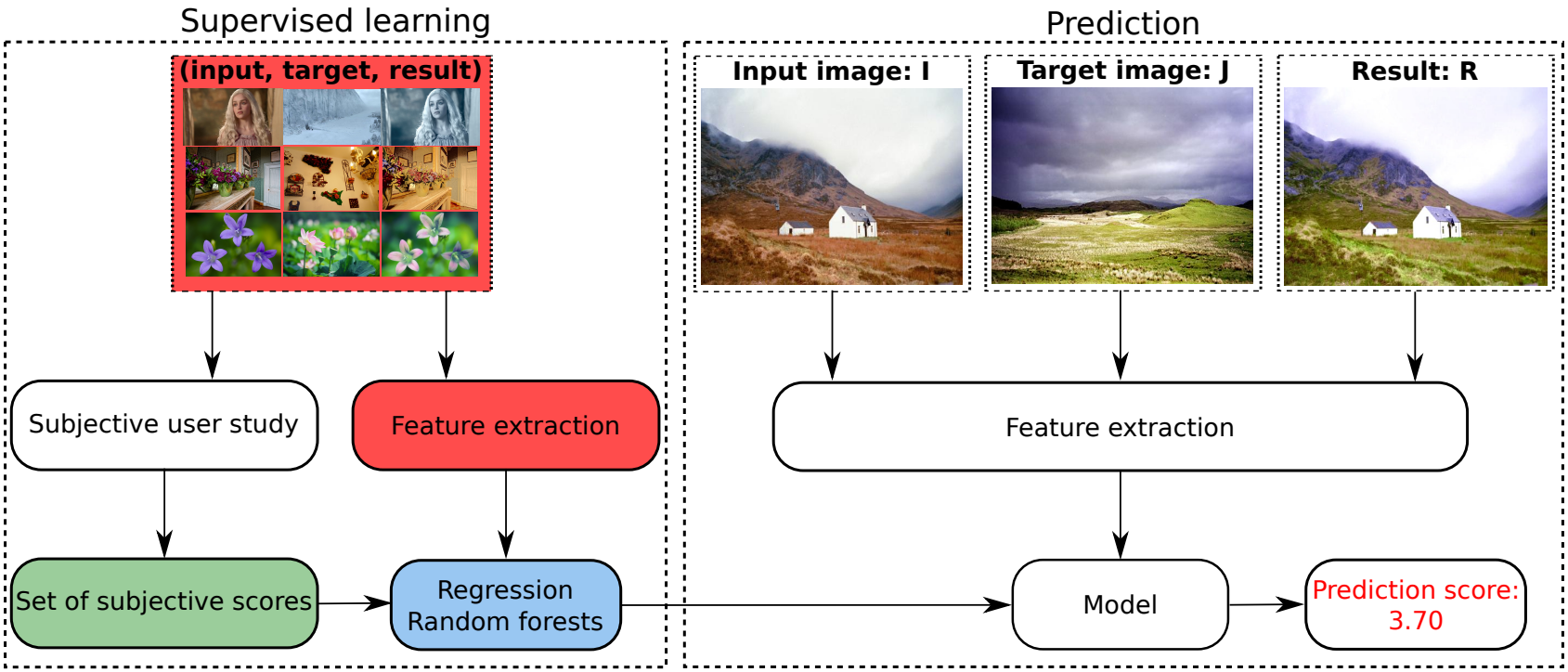
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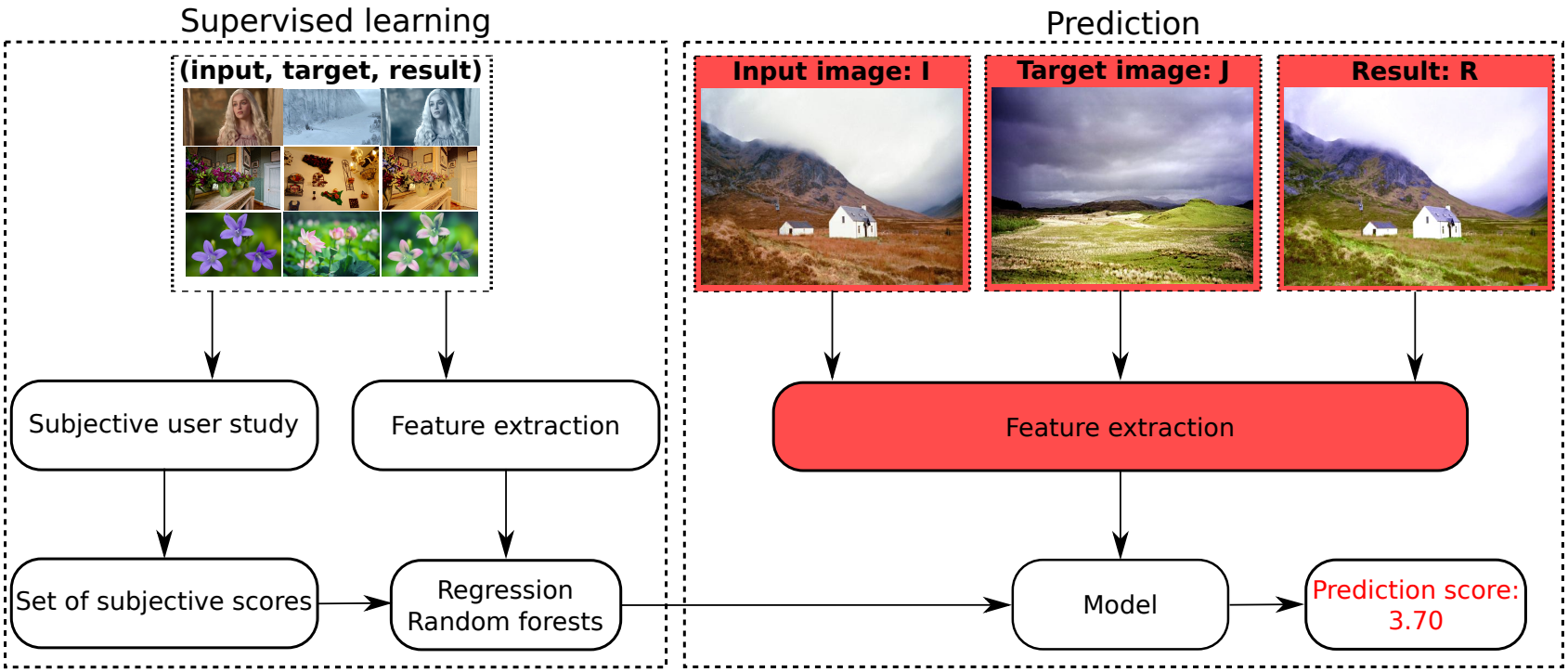
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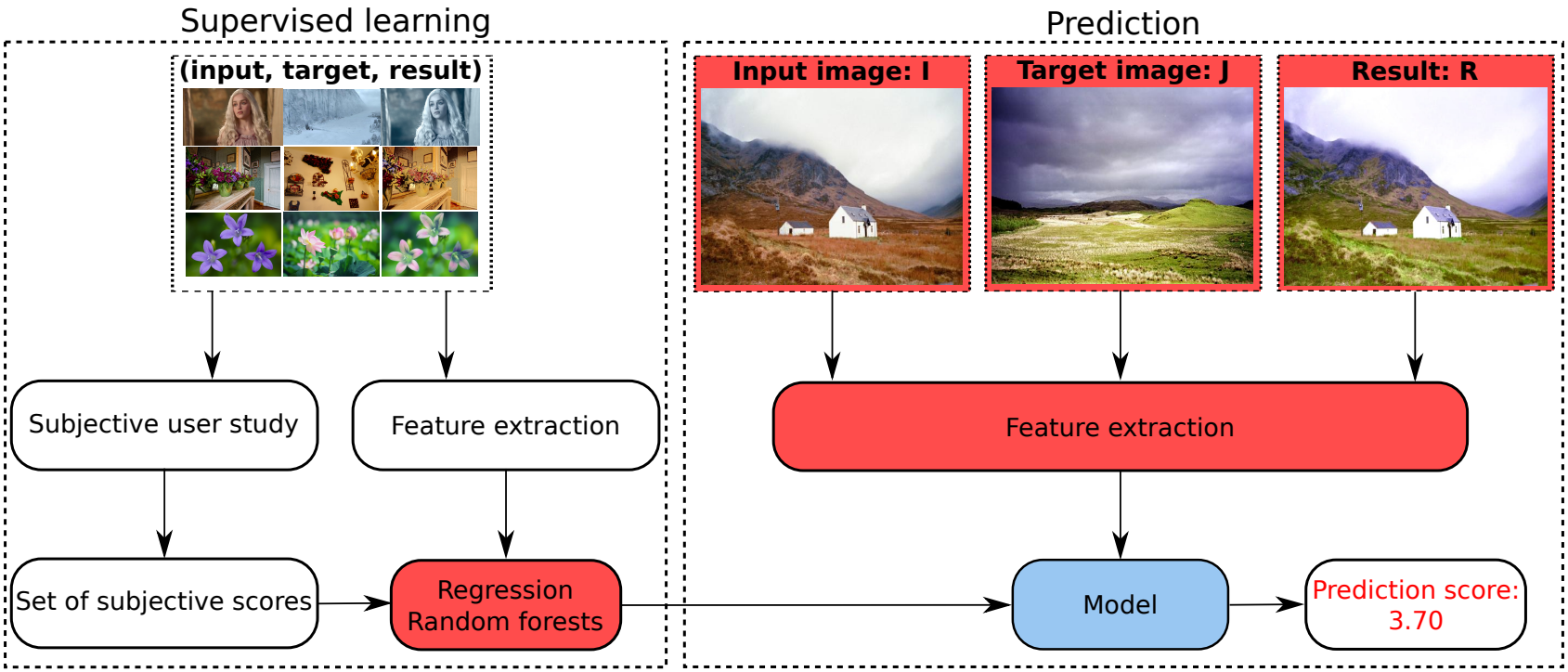
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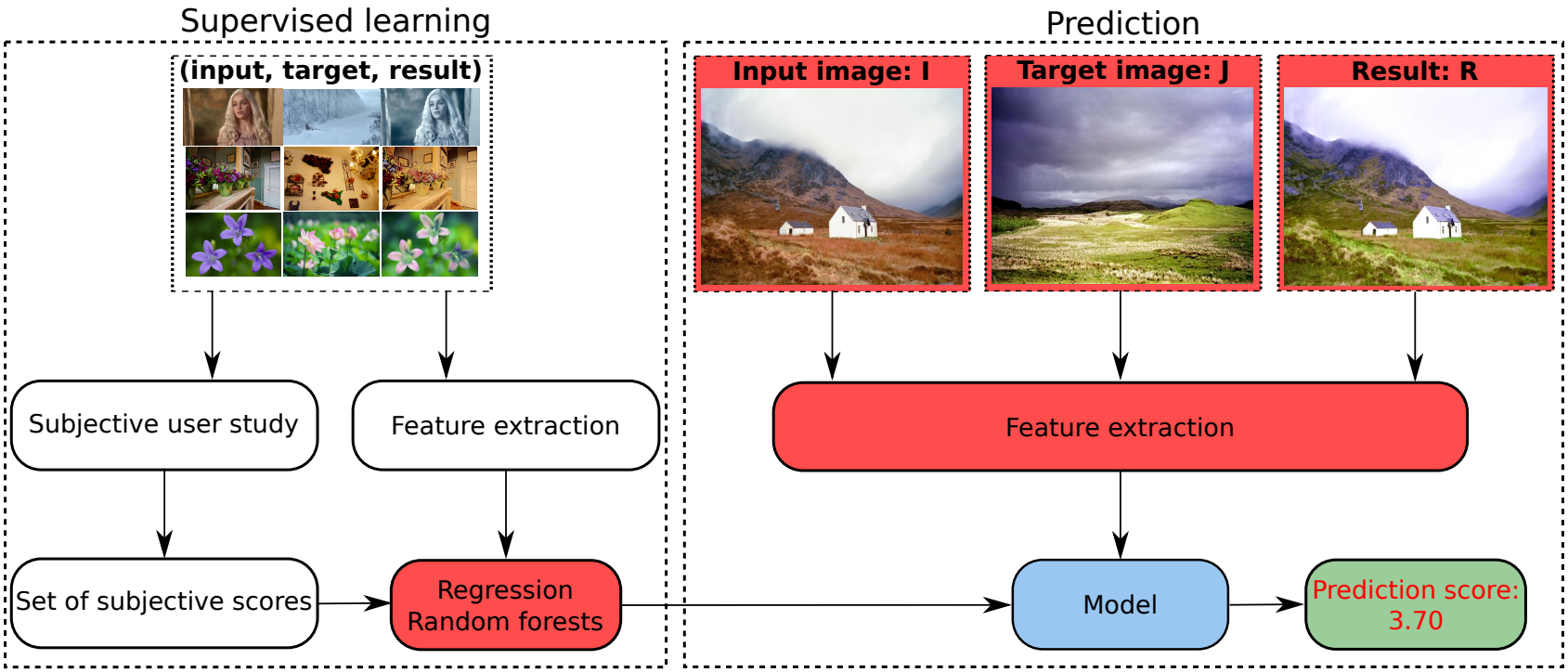
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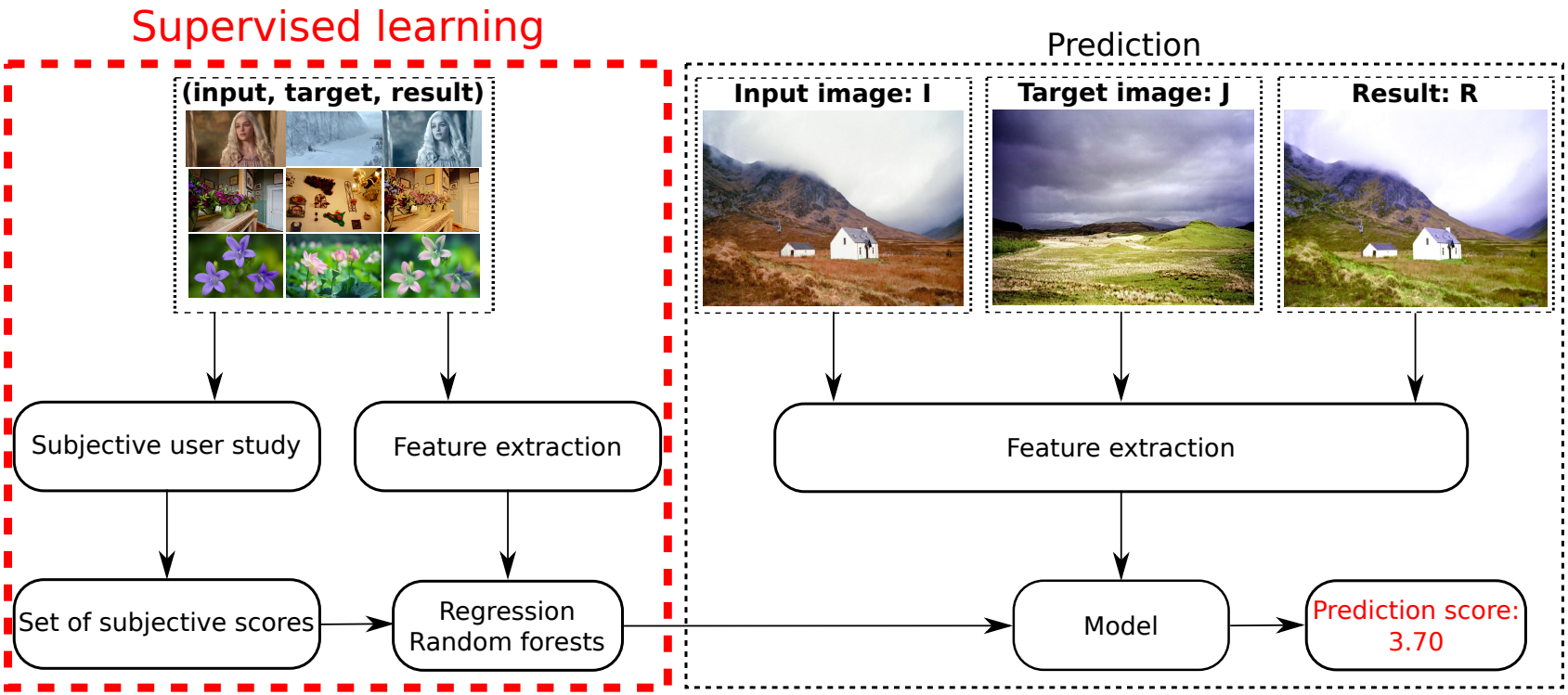
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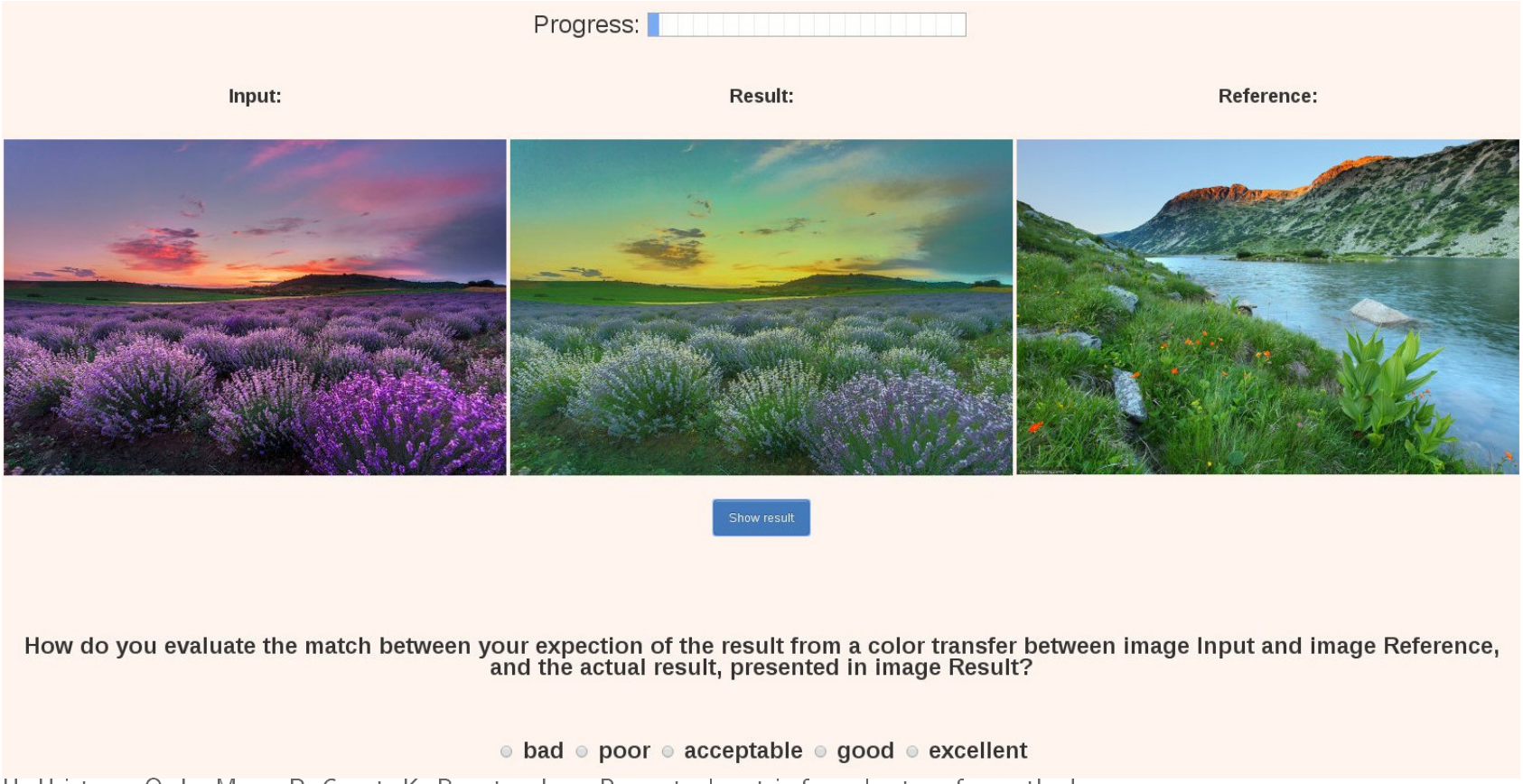
- 5-point scale.

User study

Platform

20 users evaluated the results of the color transfer methods individually using our specially designed *online platform*.



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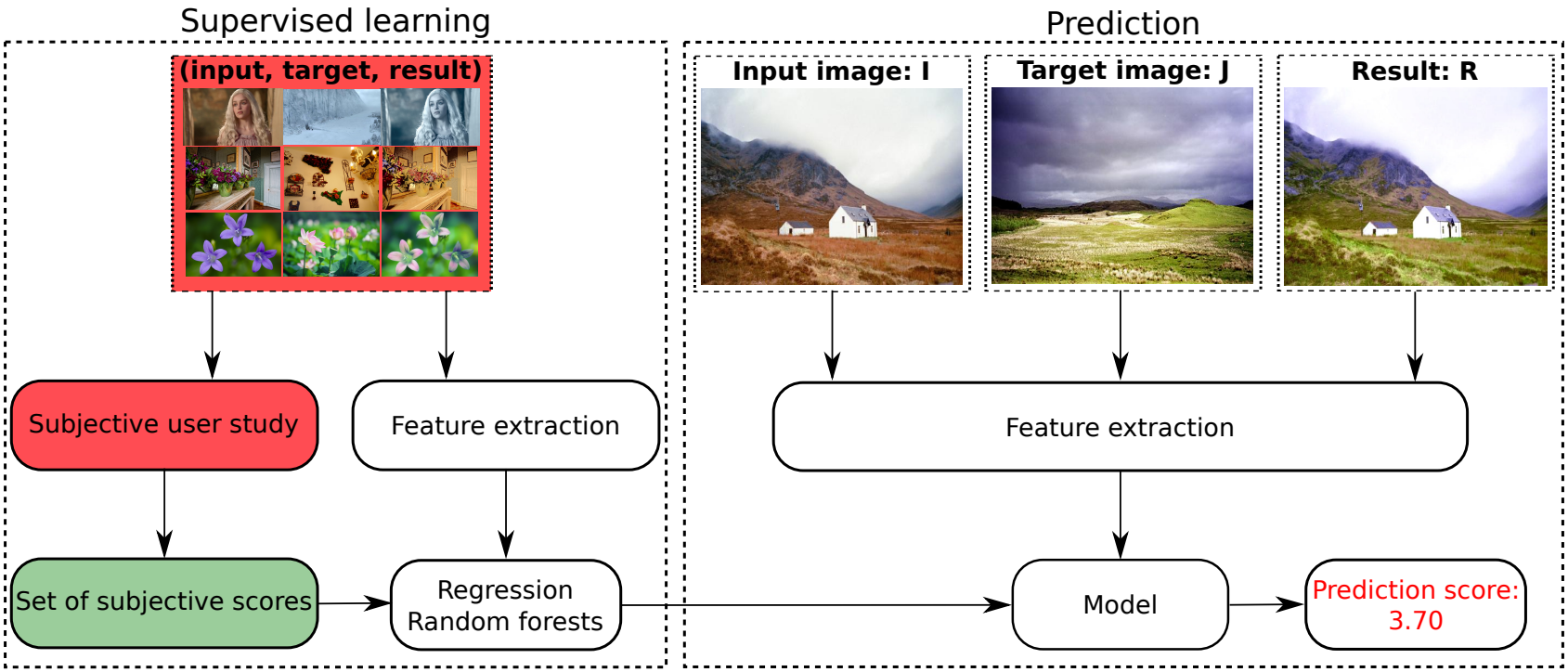
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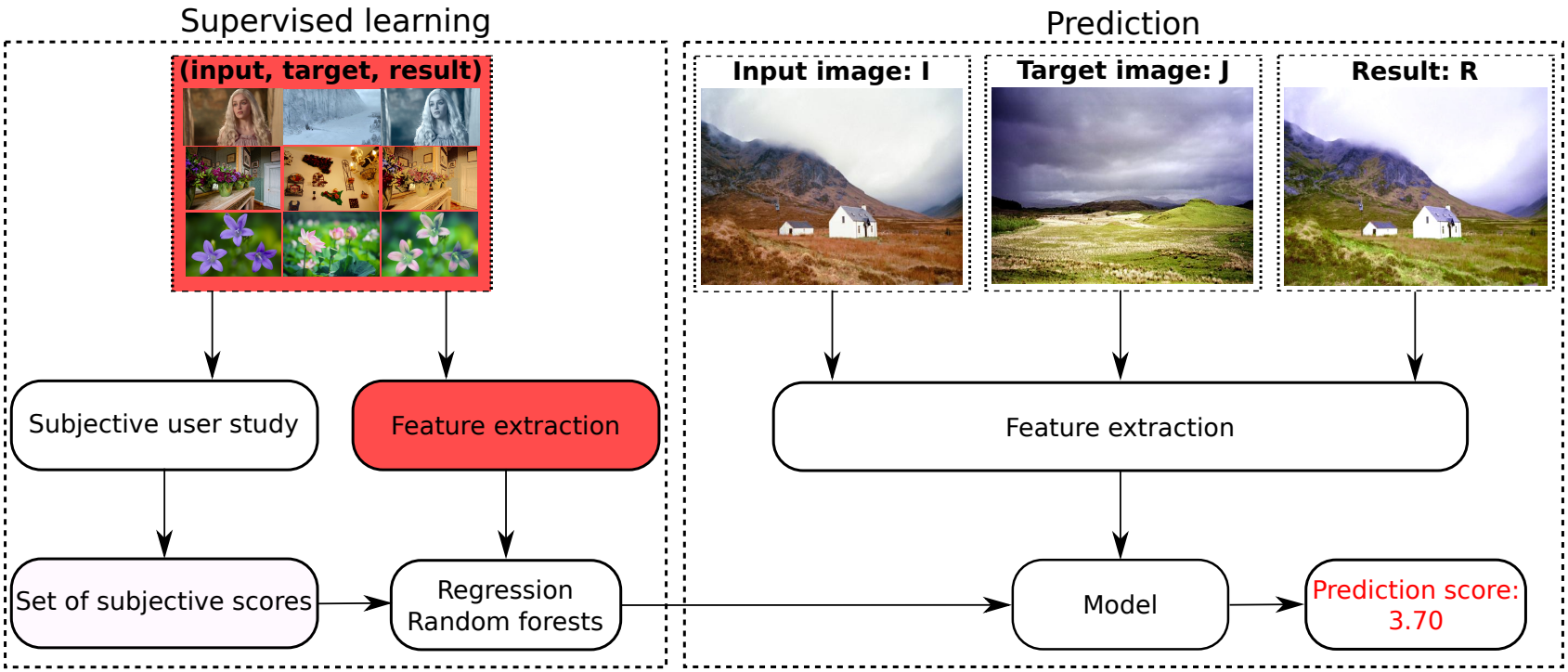
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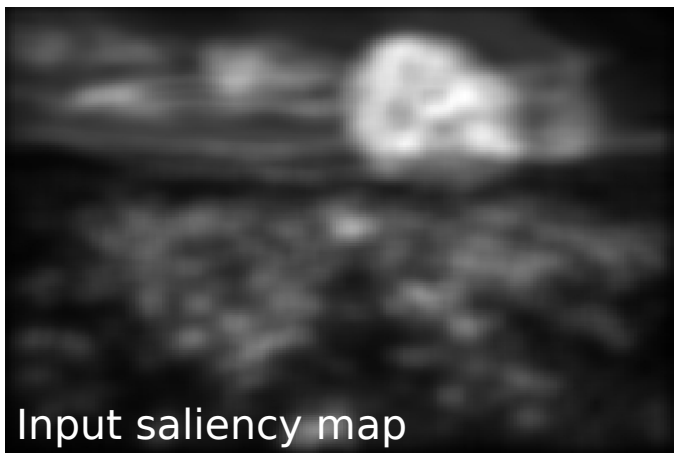

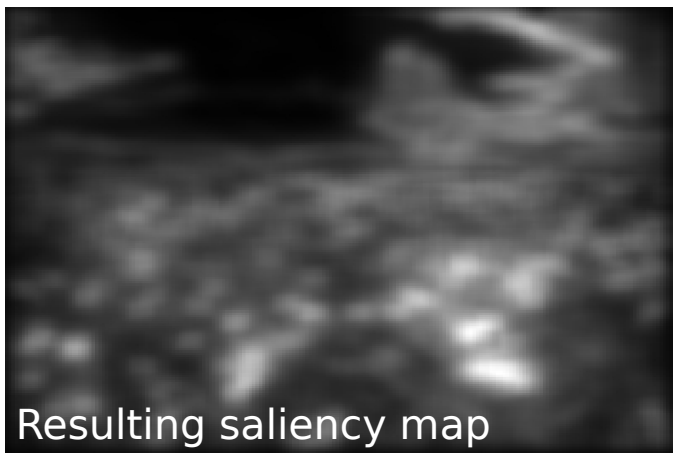

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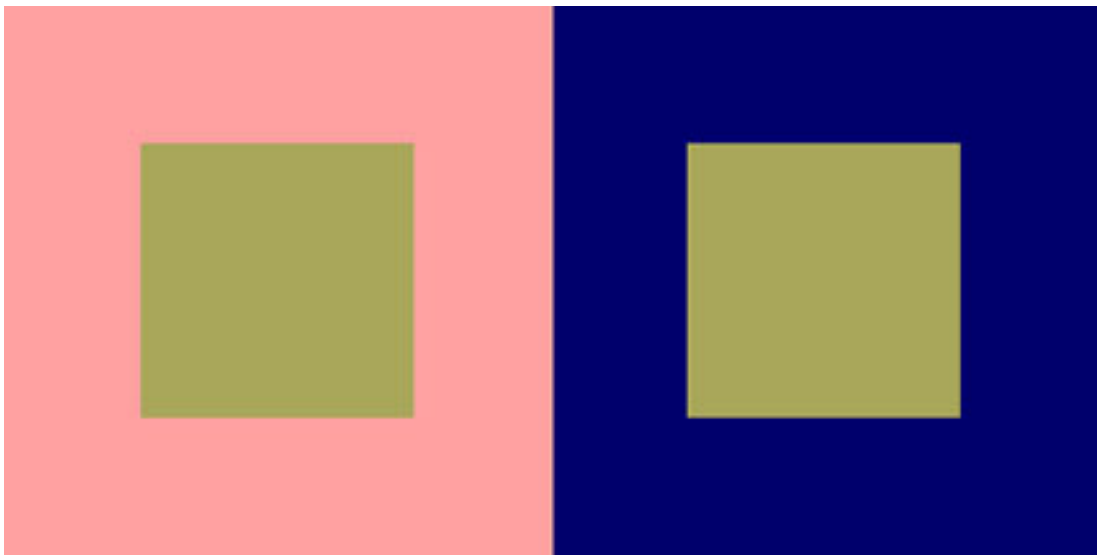

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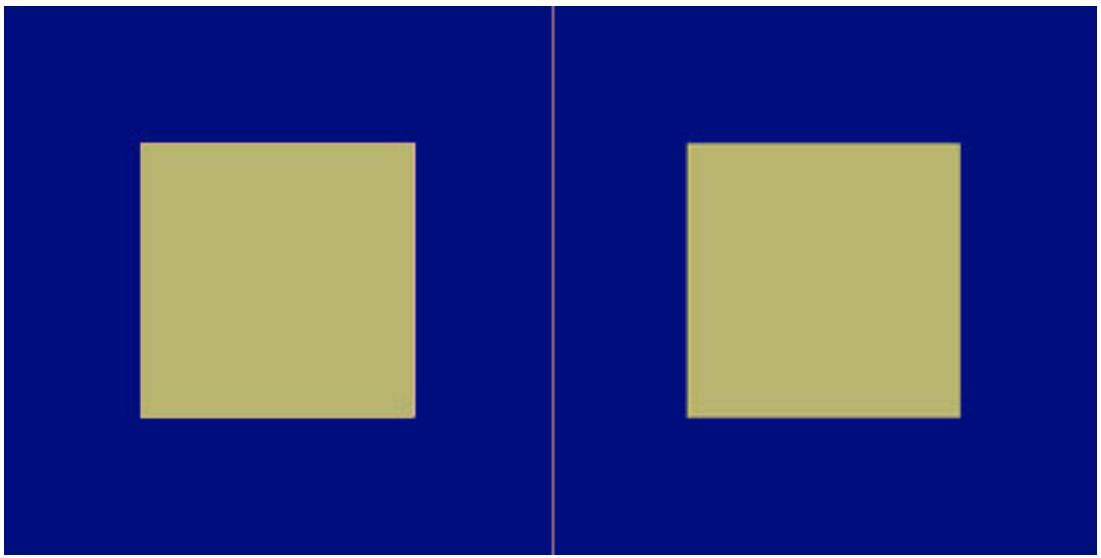

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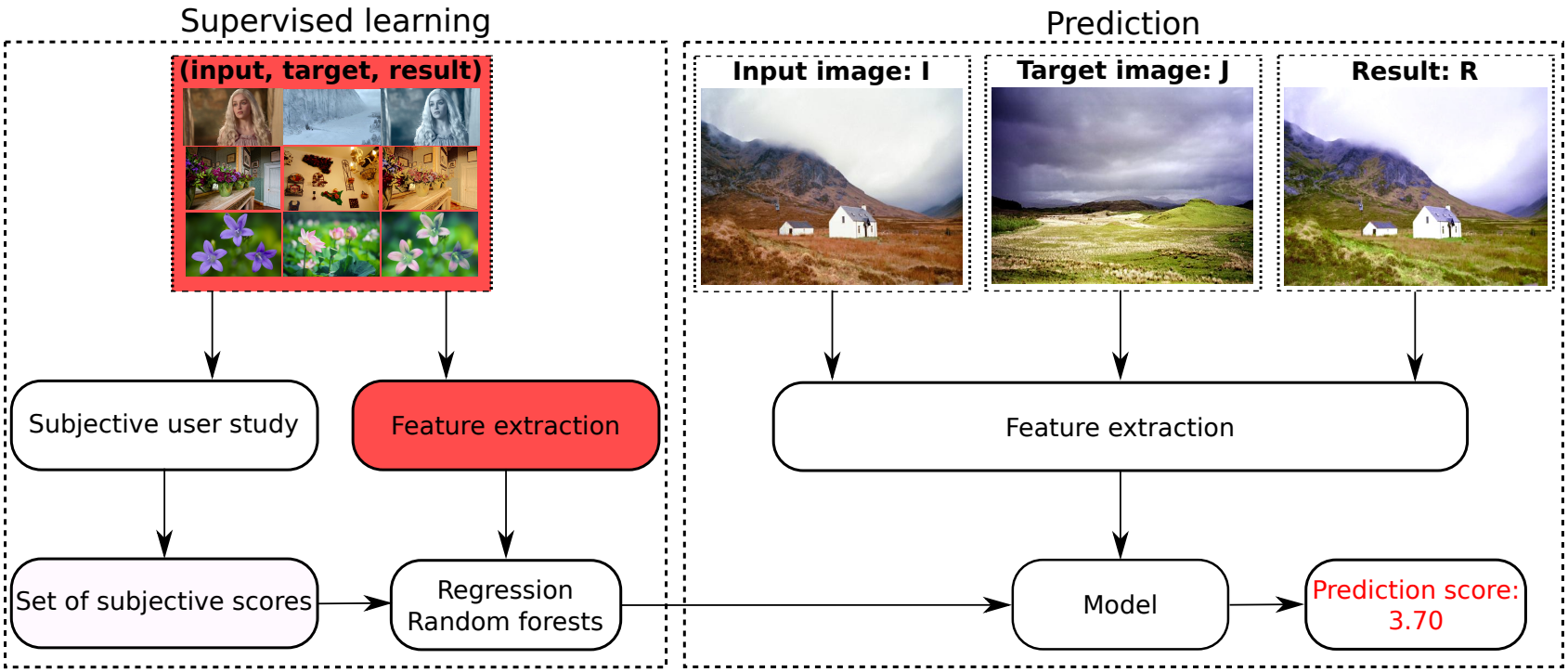
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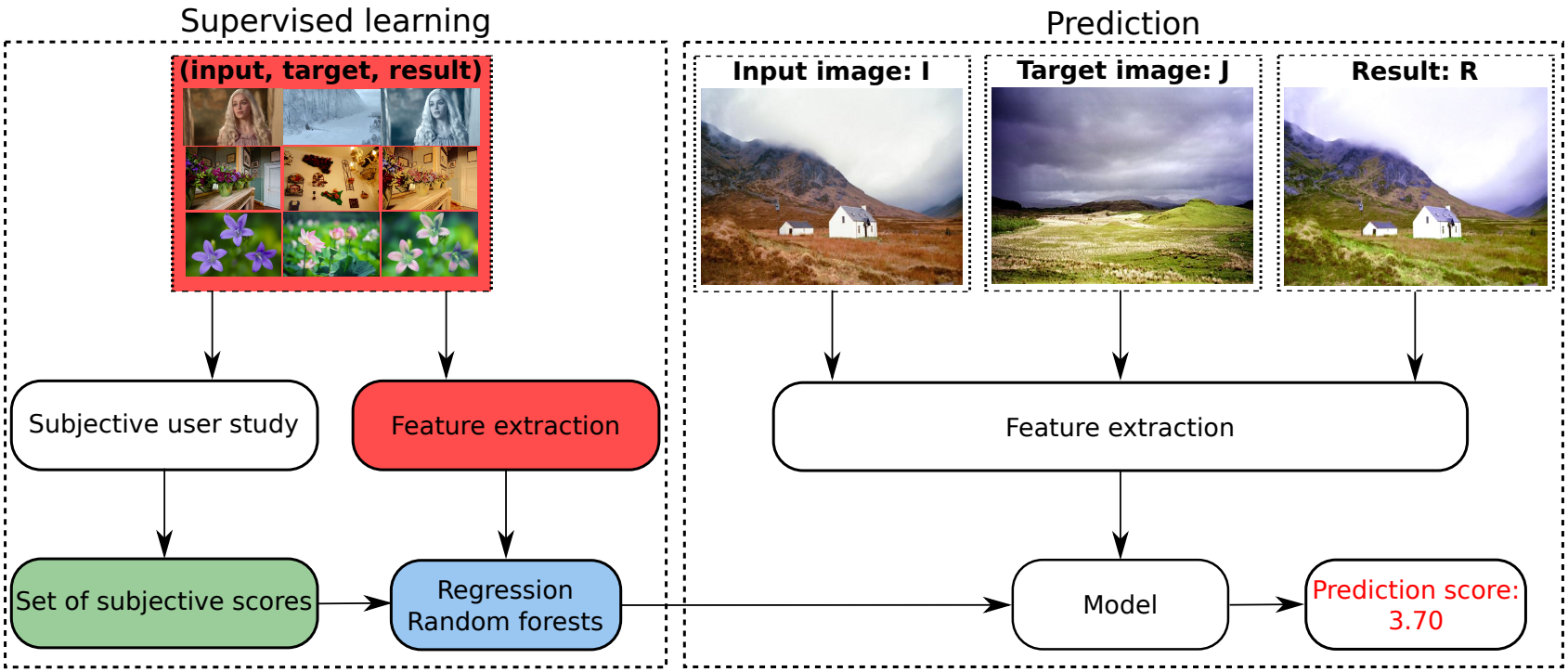
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Perceptual model

Main goal

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Solutions

- Linear regression;
- Non-linear regression;
- Random forests.

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- **Box-and-Whisker plots for the score distributions;**
- The model using random forests most accurately describes the subjective scores;
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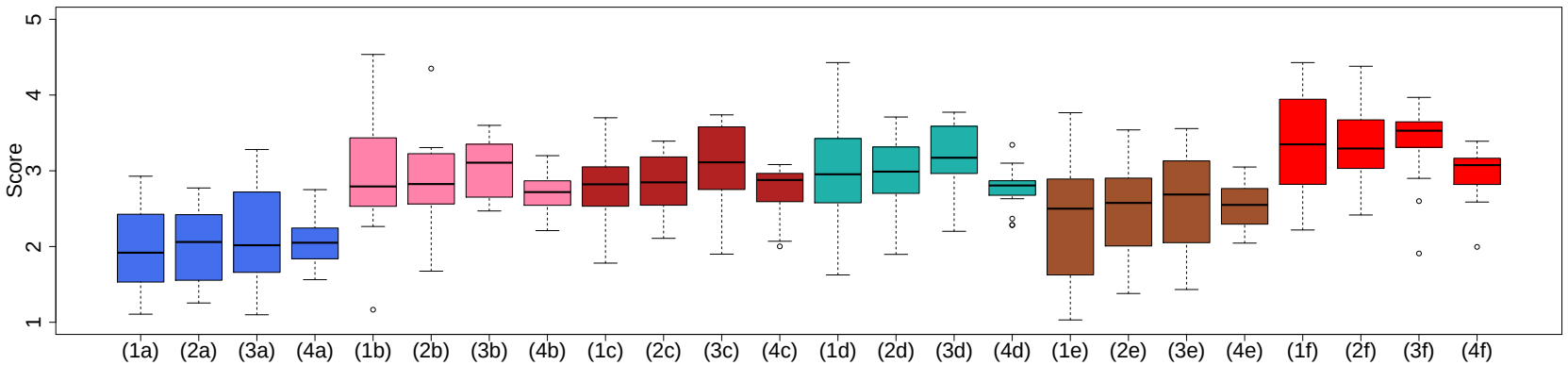

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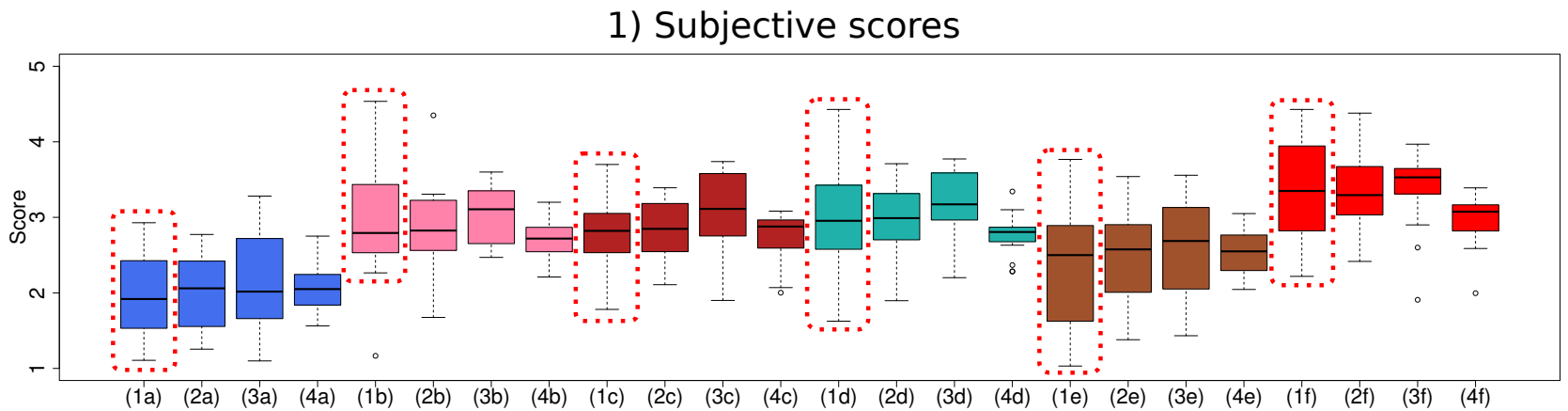

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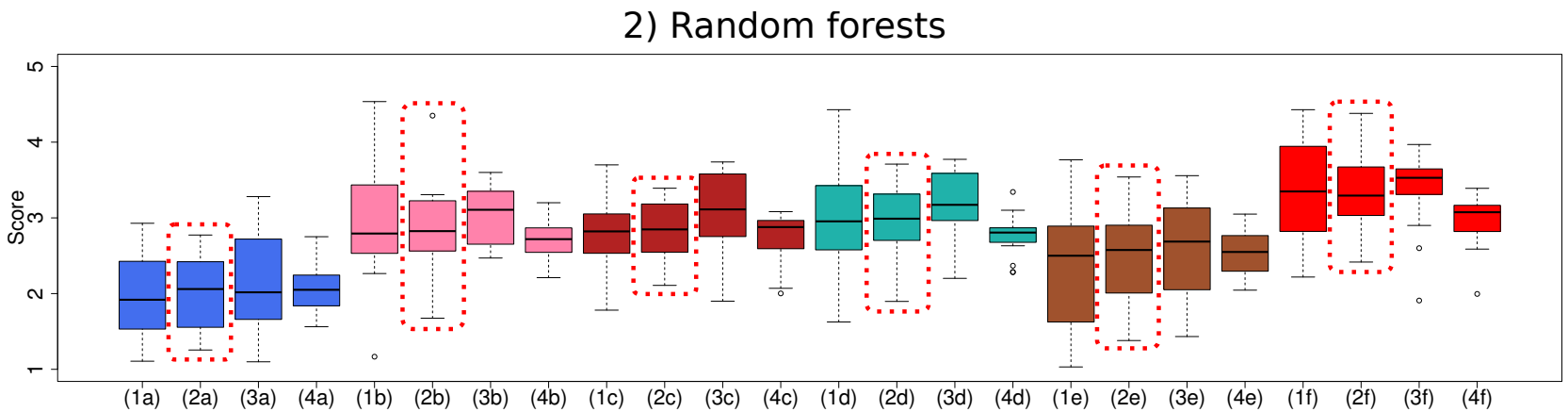

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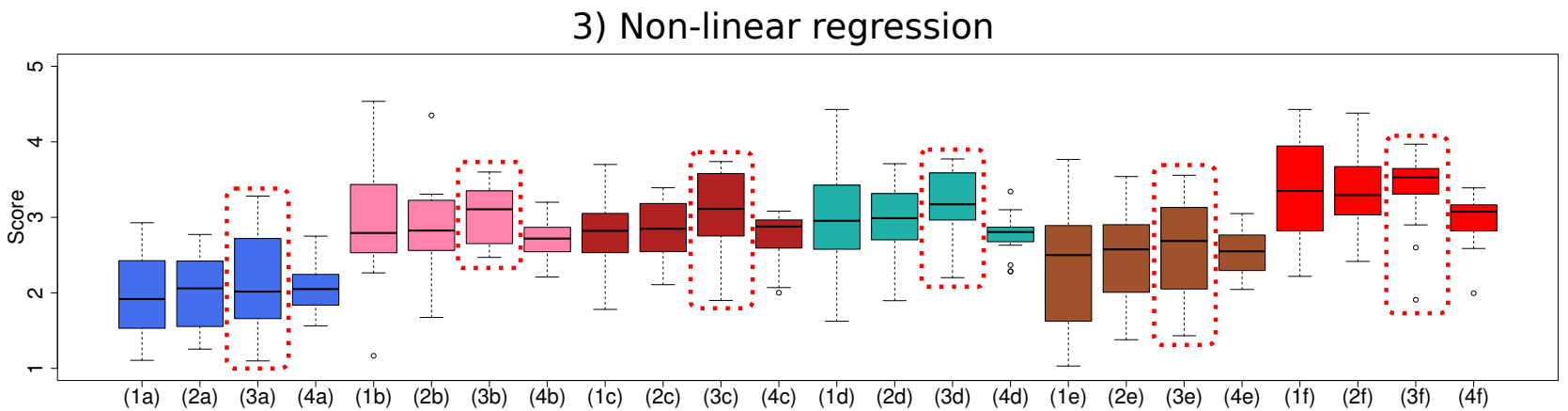

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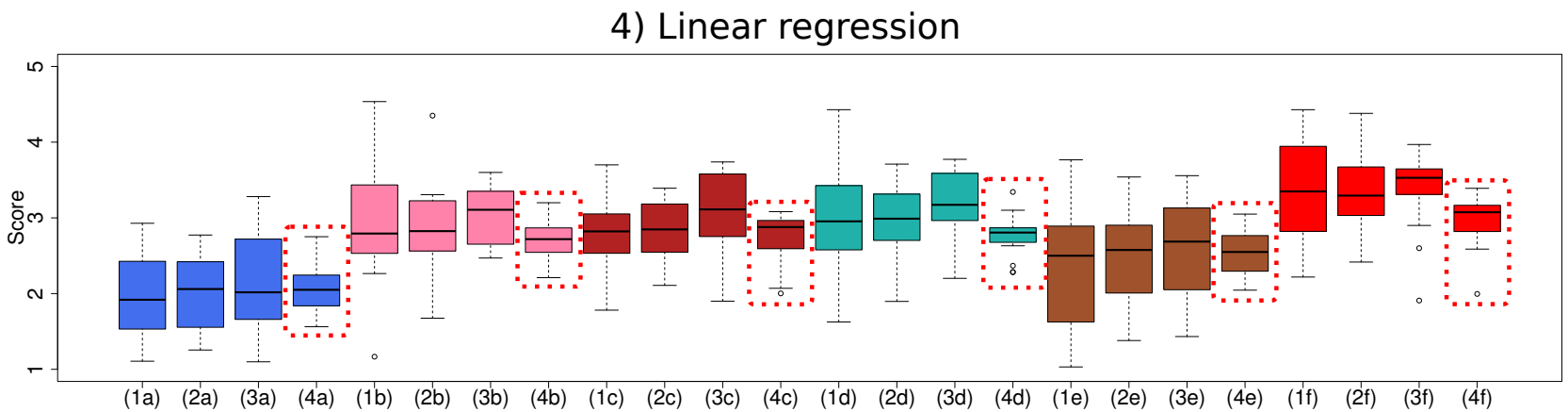

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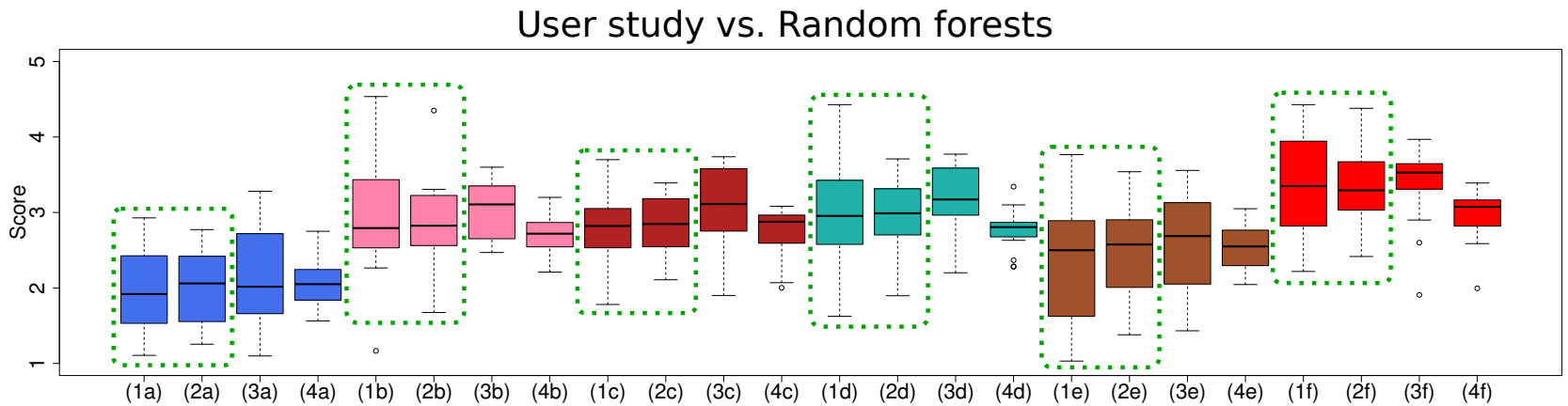

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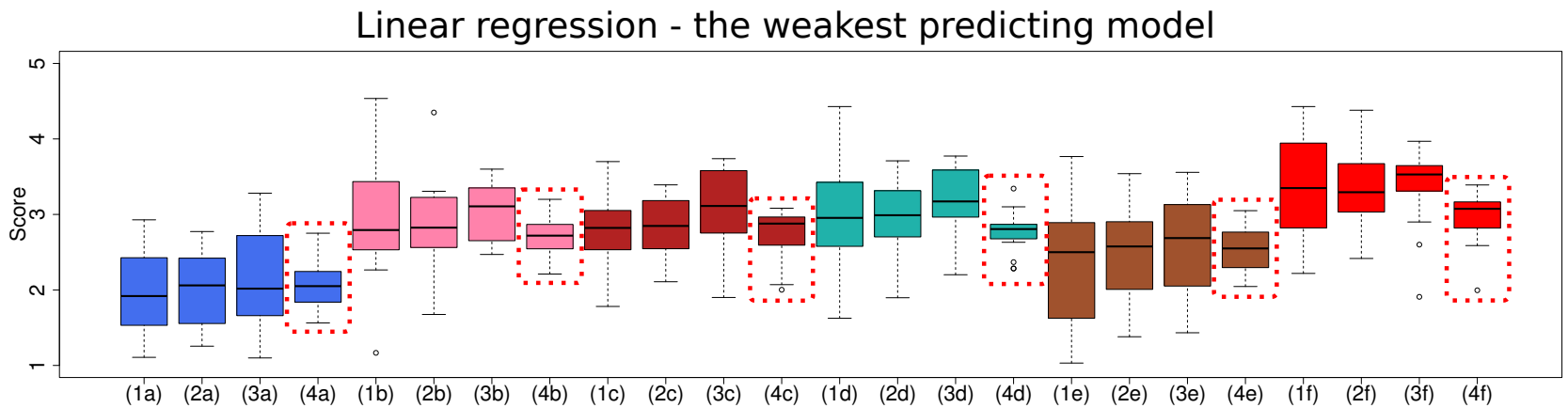

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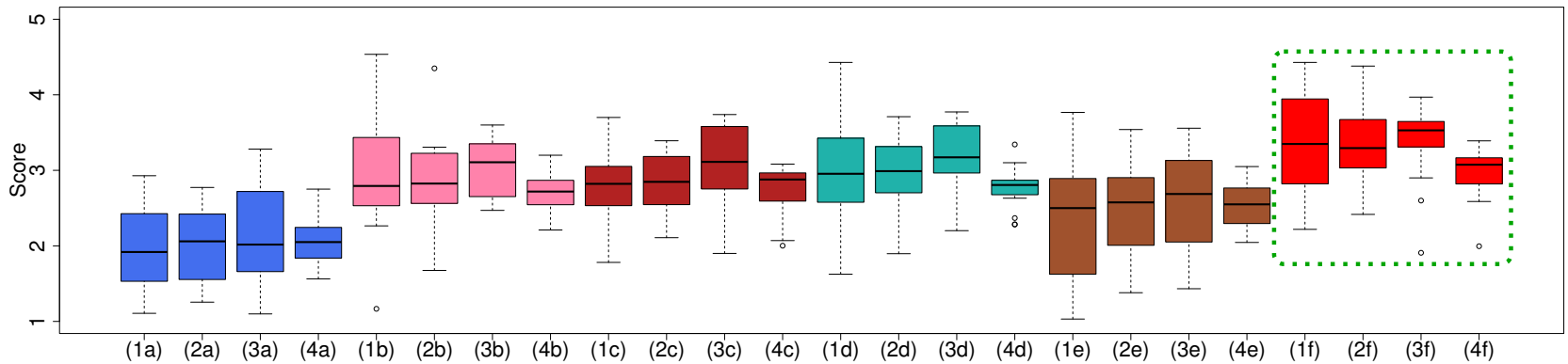

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Cross-validation

- K-fold cross-validation with 10 folds;

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Cross-validation

- K-fold cross-validation with 10 folds;
- Correlation between the model and the user study;
- Mean square error (MSE).

	Random forests	**Linear**	**Non-linear**
Corr	0.765 ± 0.133	0.567 ± 0.135	0.644 ± 0.157
MSE	0.472	0.808	0.889

Table: Correlation $\pm$ standard deviation and MSE over all 10 test sets in our cross-validation.

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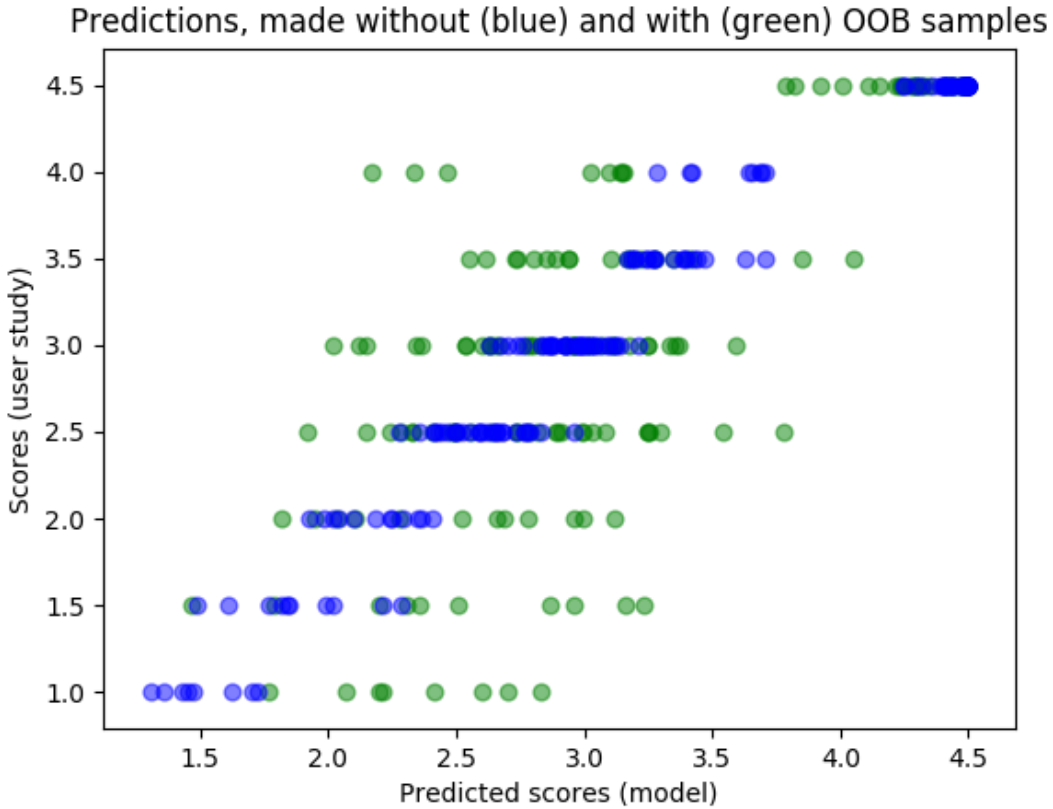

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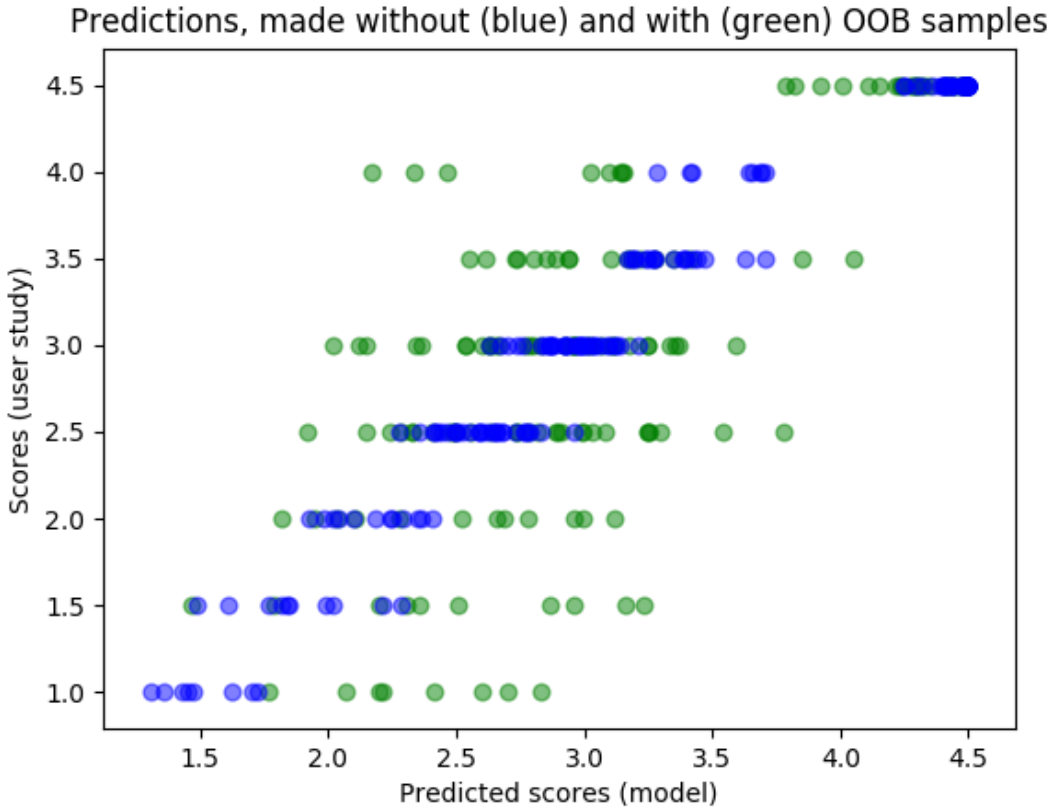
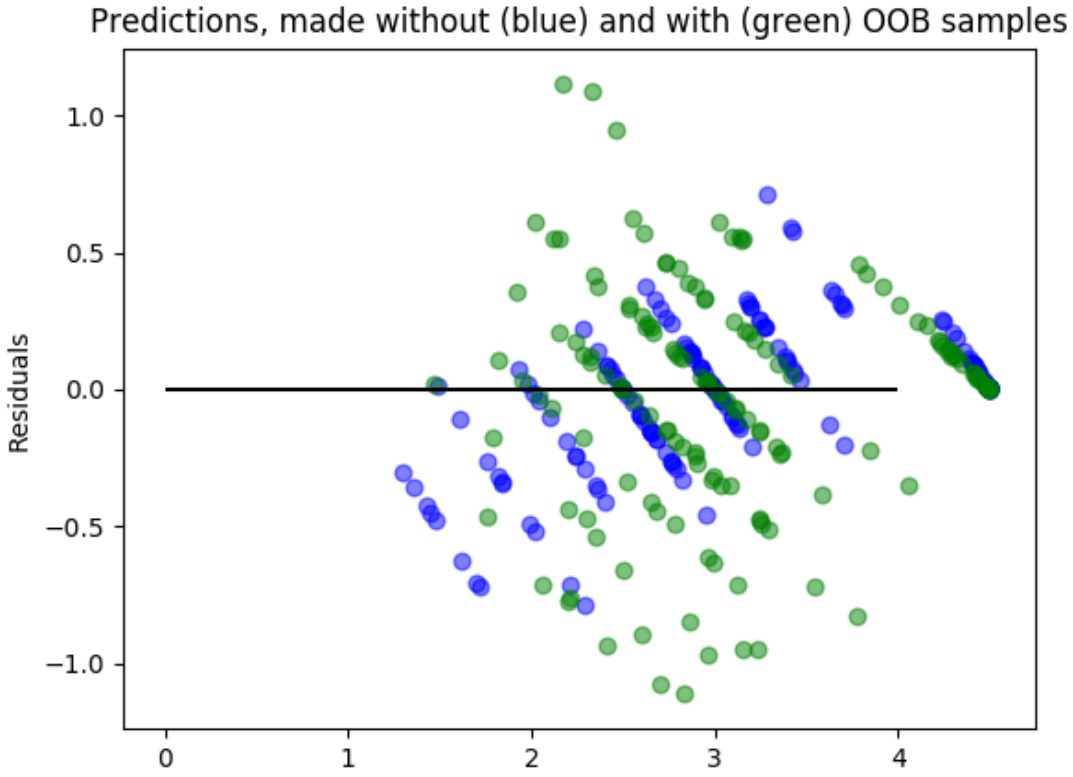
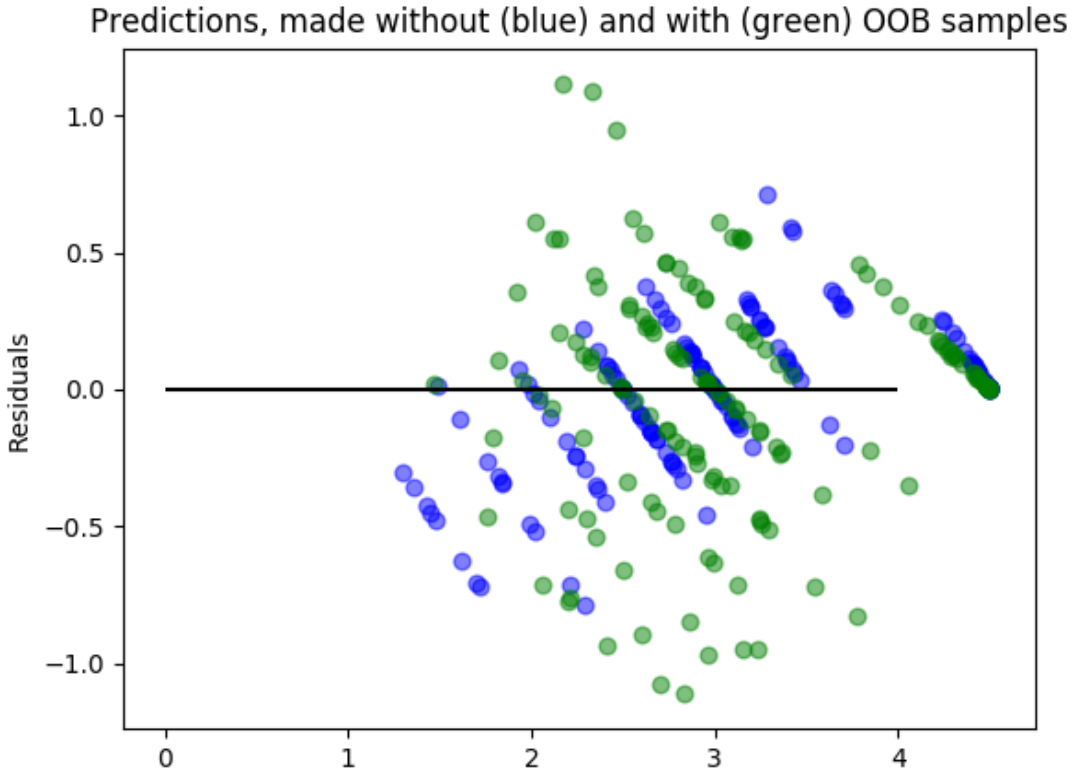


The plot shows the high correction between subjective scores and predicted scores (with and without OOB samples).

Residuals

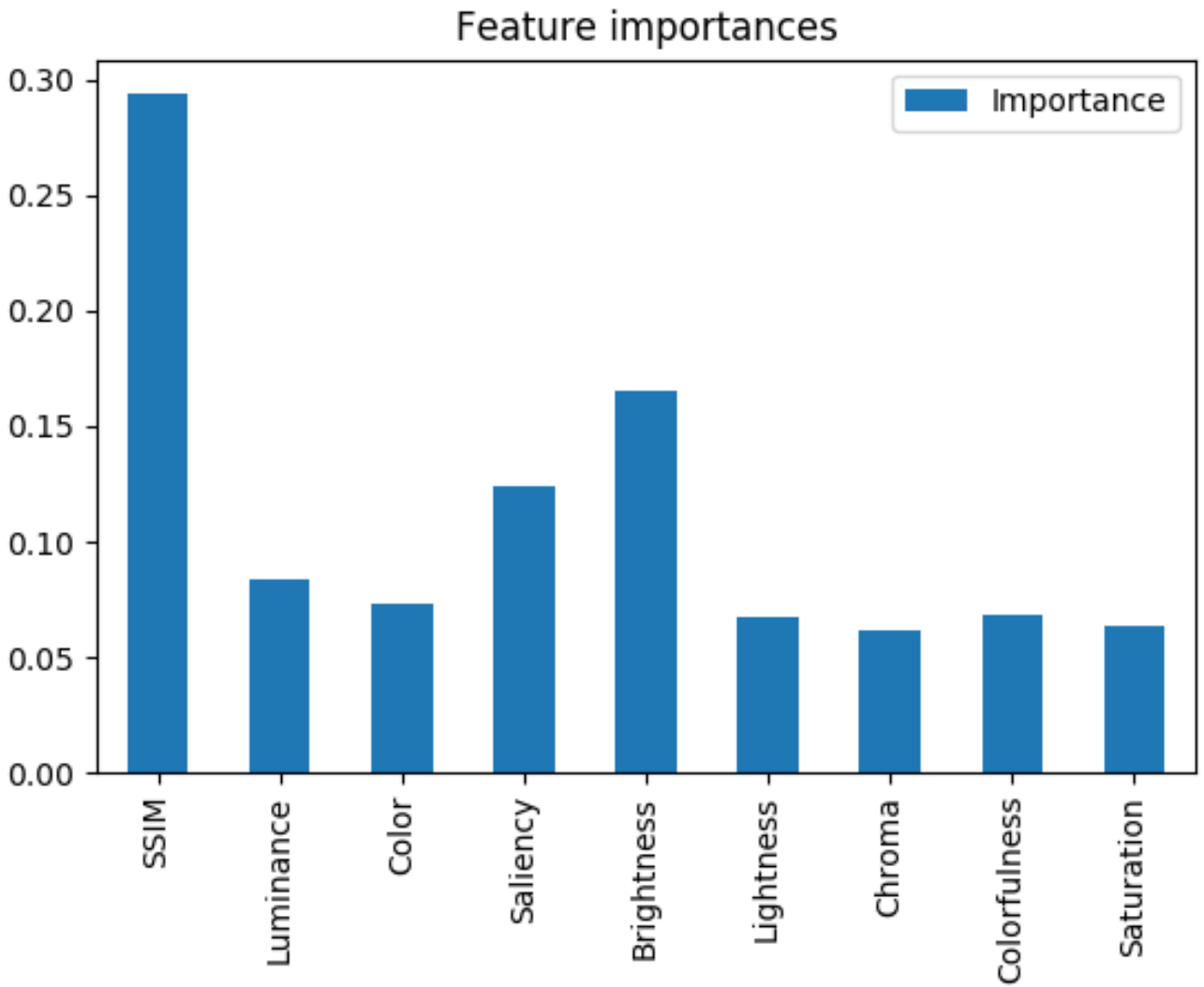

Predictions, made without (blue) and with (green) OOB samples
Residuals
1.0
0.5
0.0
−0.5
−1.0
0
1
2
3
4

Residuals

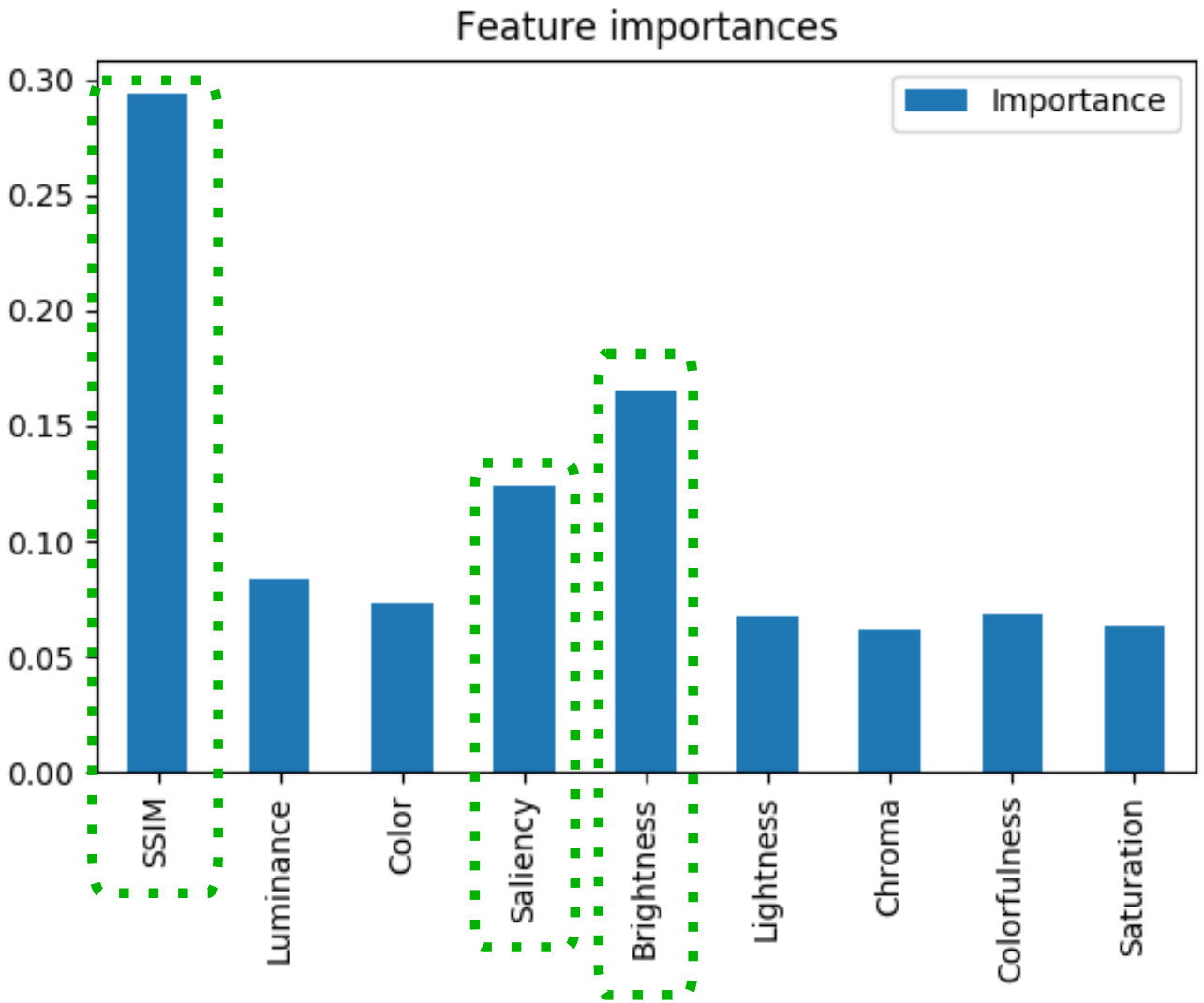


Residuals: in the interval [-1.5, 1.5] and symmetrical around the x-axis; random patterns.

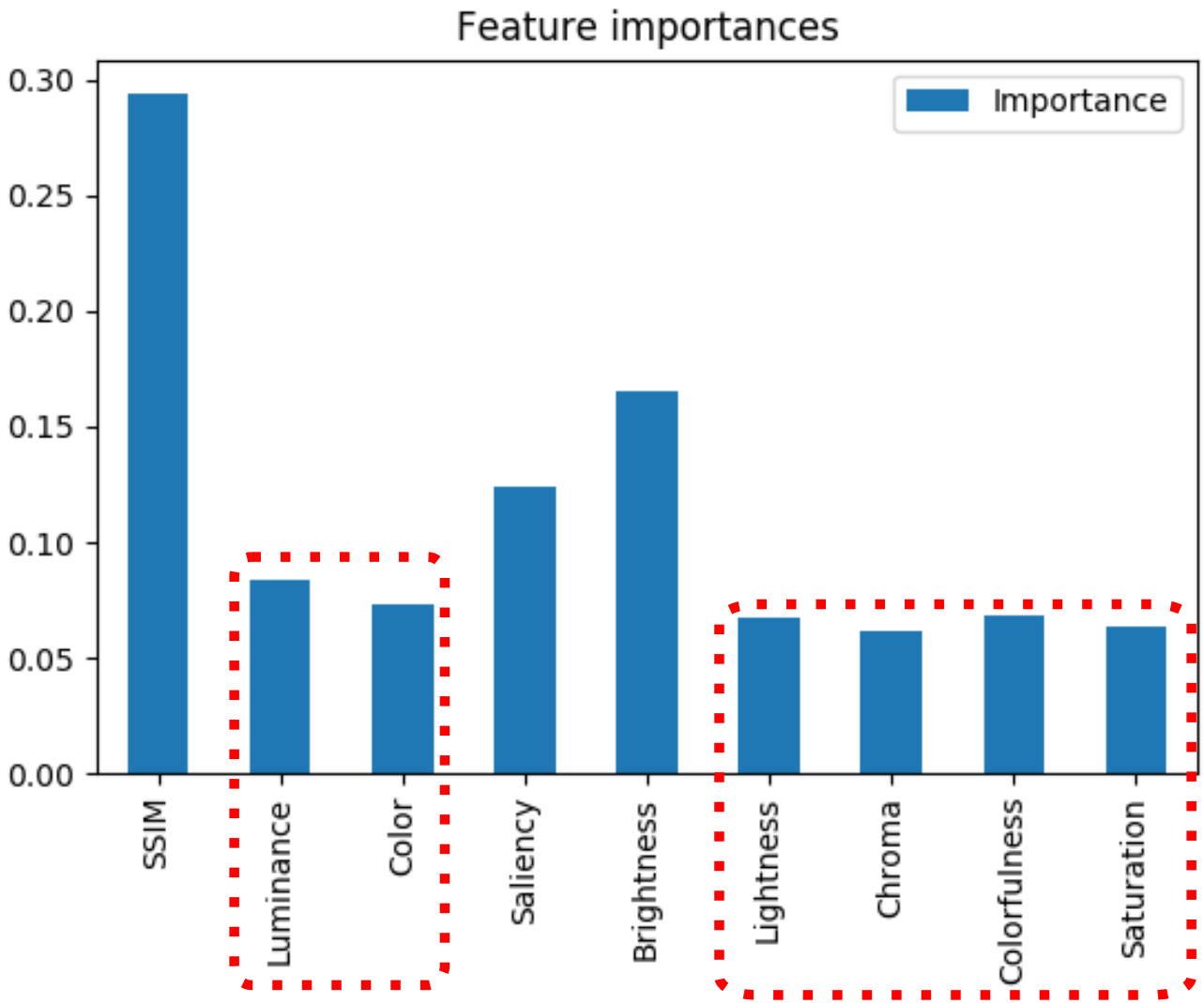
Feature importances



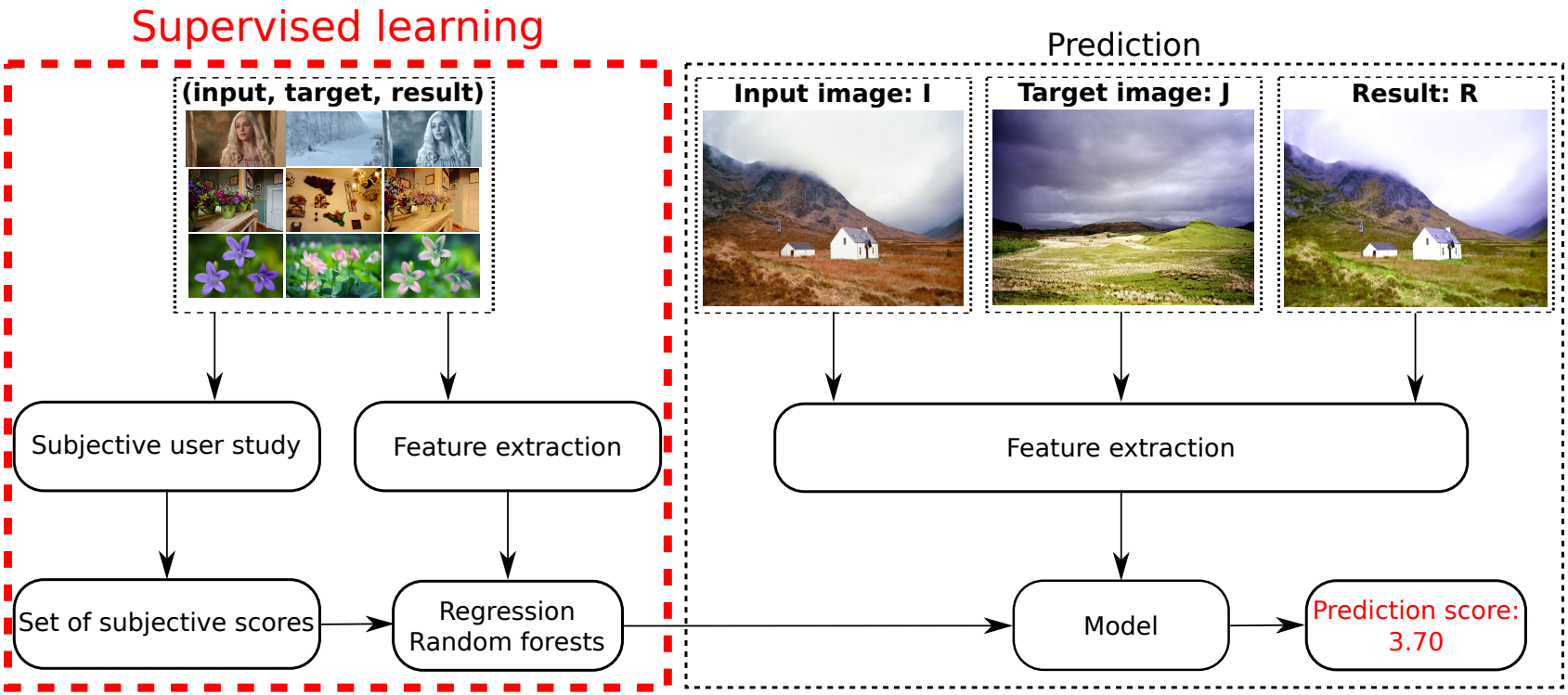
Feature importances



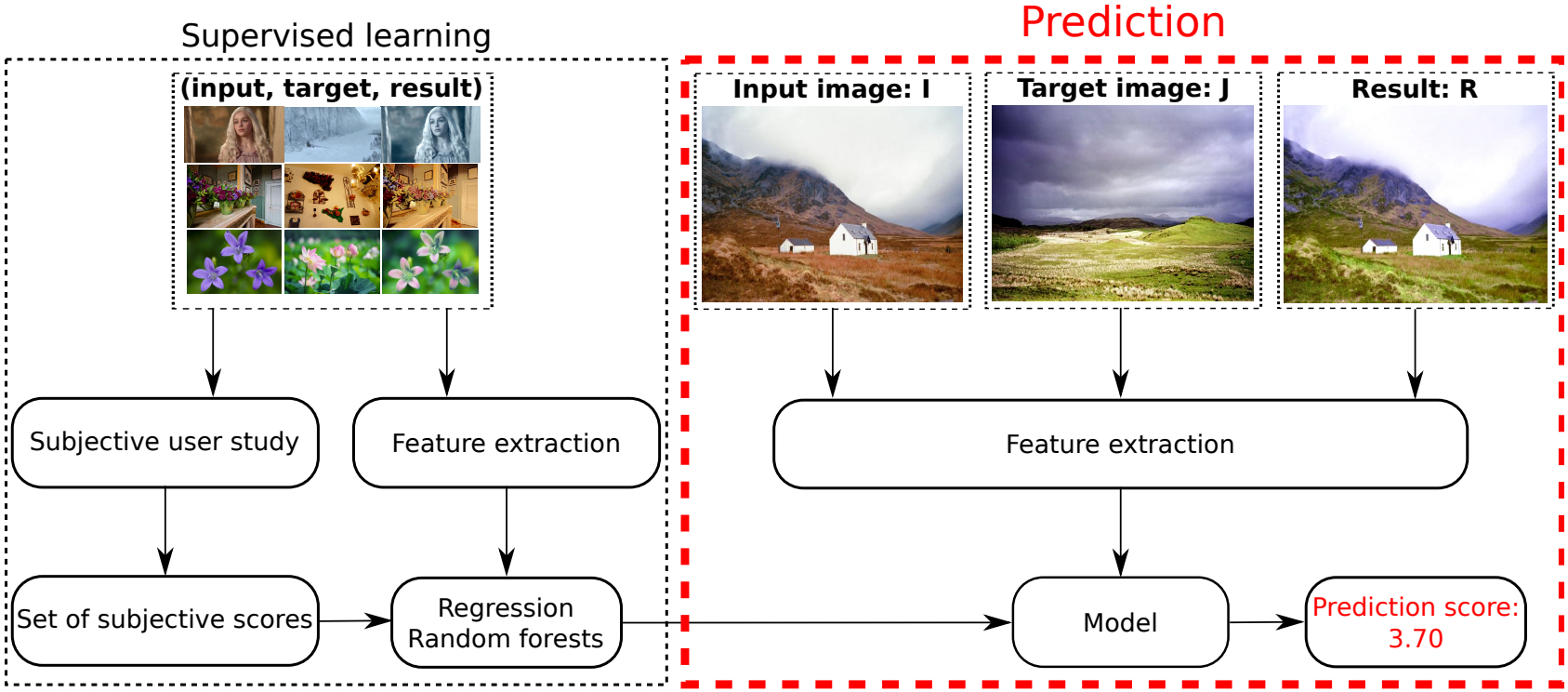
Feature importances



Flowchart


Supervised learning
(input, target, result)
Subjective user study
Feature extraction
Set of subjective scores
Regression
Random forests
Prediction
Input image: I
Target image: J
Result: R
Feature extraction
Model
Prediction score:
3.70

Flowchart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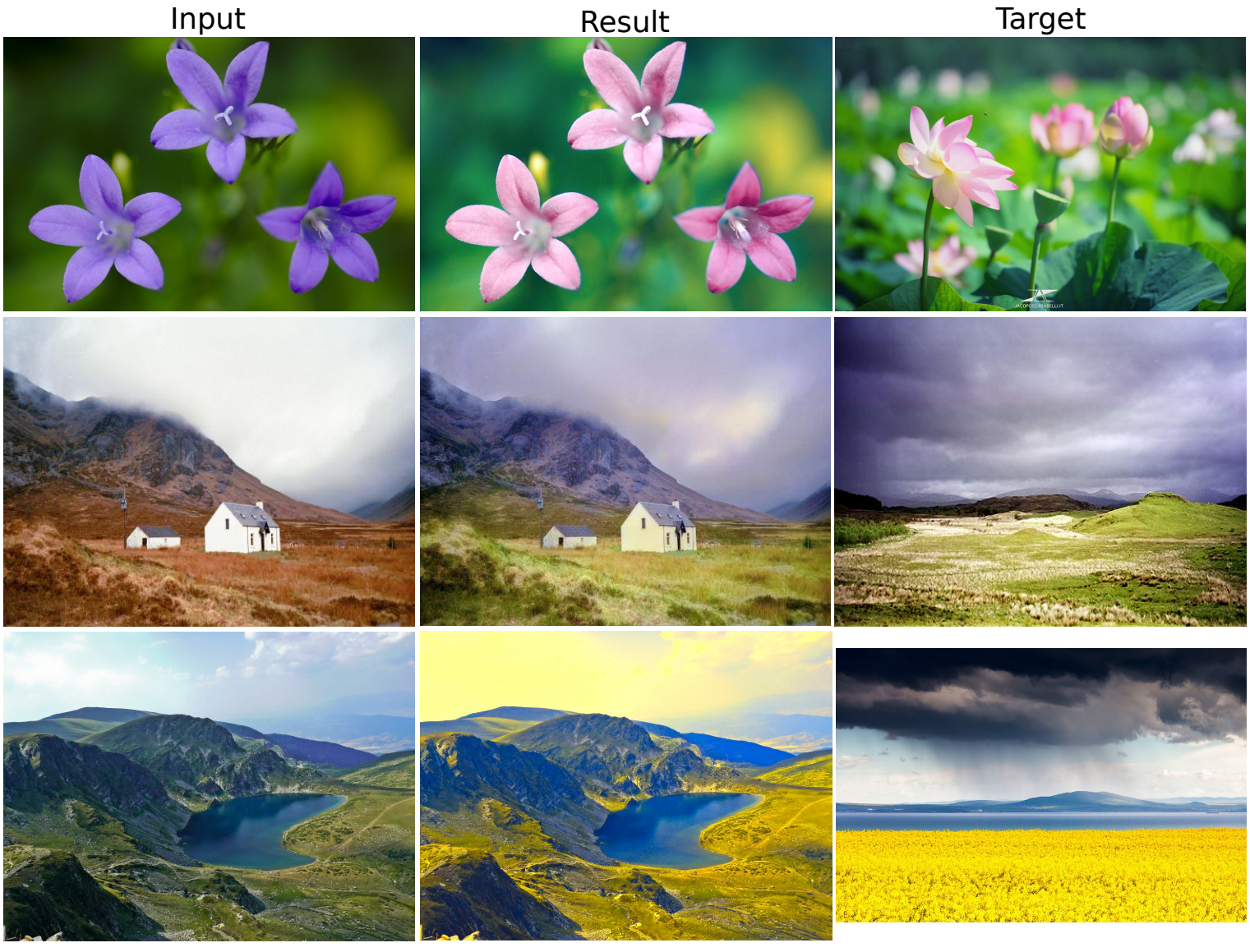
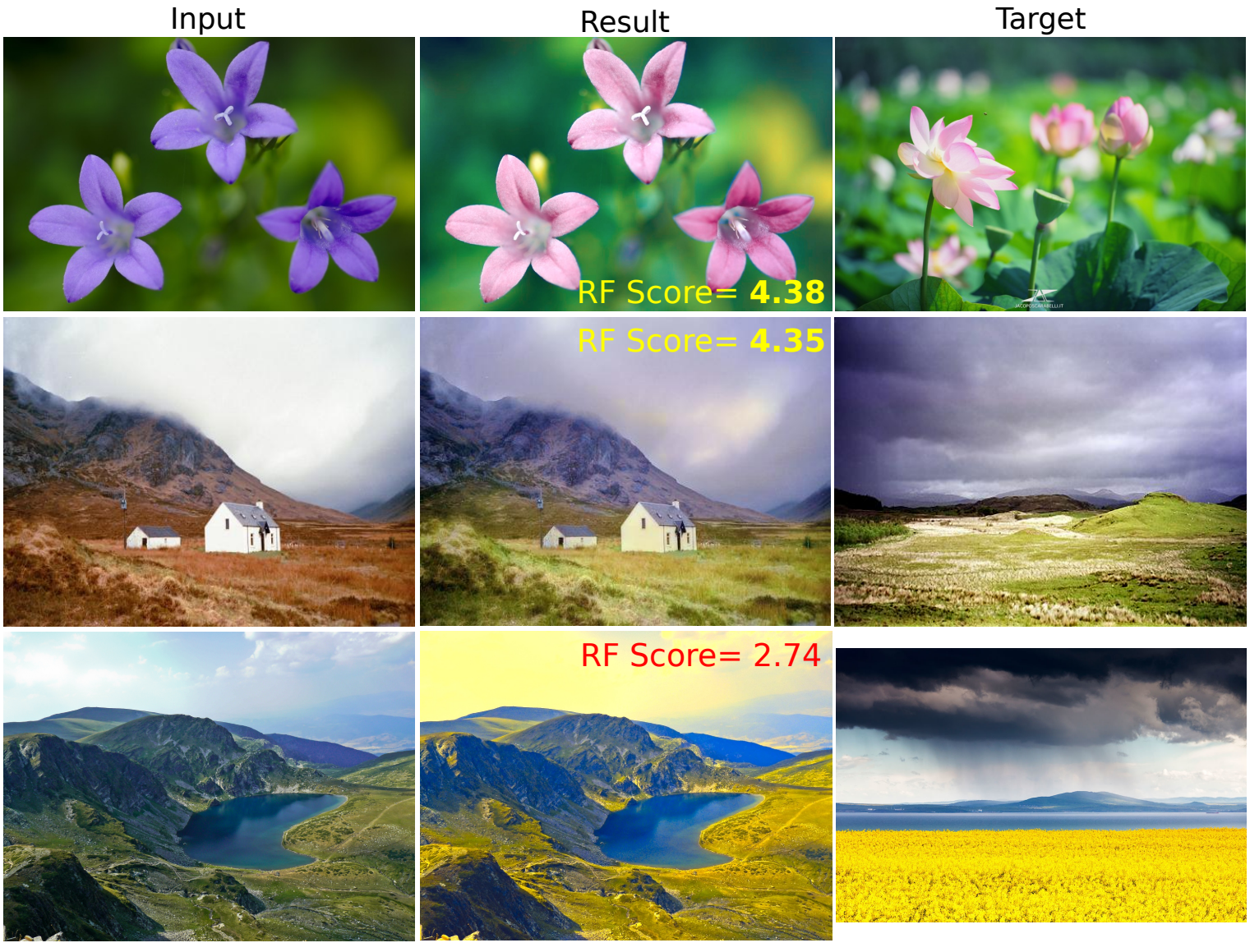
Results



Results



Conclusion

Advantages

- The first attempt to compute a perceptual metric considering an ensemble of objective metrics;
- Designed to evaluate the quality of color transfer methods.

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Advantages

- The first attempt to compute a perceptual metric considering an ensemble of objective metrics;
- Designed to evaluate the quality of color transfer methods.

Limitations

- Not suitable for evaluating style transfer methods;
- Not suitable for methods which modify texture or use paintings/sketches as target images.

References I

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Questions?

Thank you for your attention!

For more information, please visit

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Coefficient of determination

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- OOB error: 0.58.