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Delaunay Triangulation Data Augmentation guided by Visual Analytics for Deep Learning

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Introduction

Image classification problems can be effectively solved by Convolutional Neural Networks (CNNs) [1]-[3]. But CNNs require a high number of supervised training examples to avoid model overfitting.

Machine learning solutions include (a) data augmentation and (b) transfer learning.

However, those approaches for (a) do not usually exploit the user in machine learning loop.

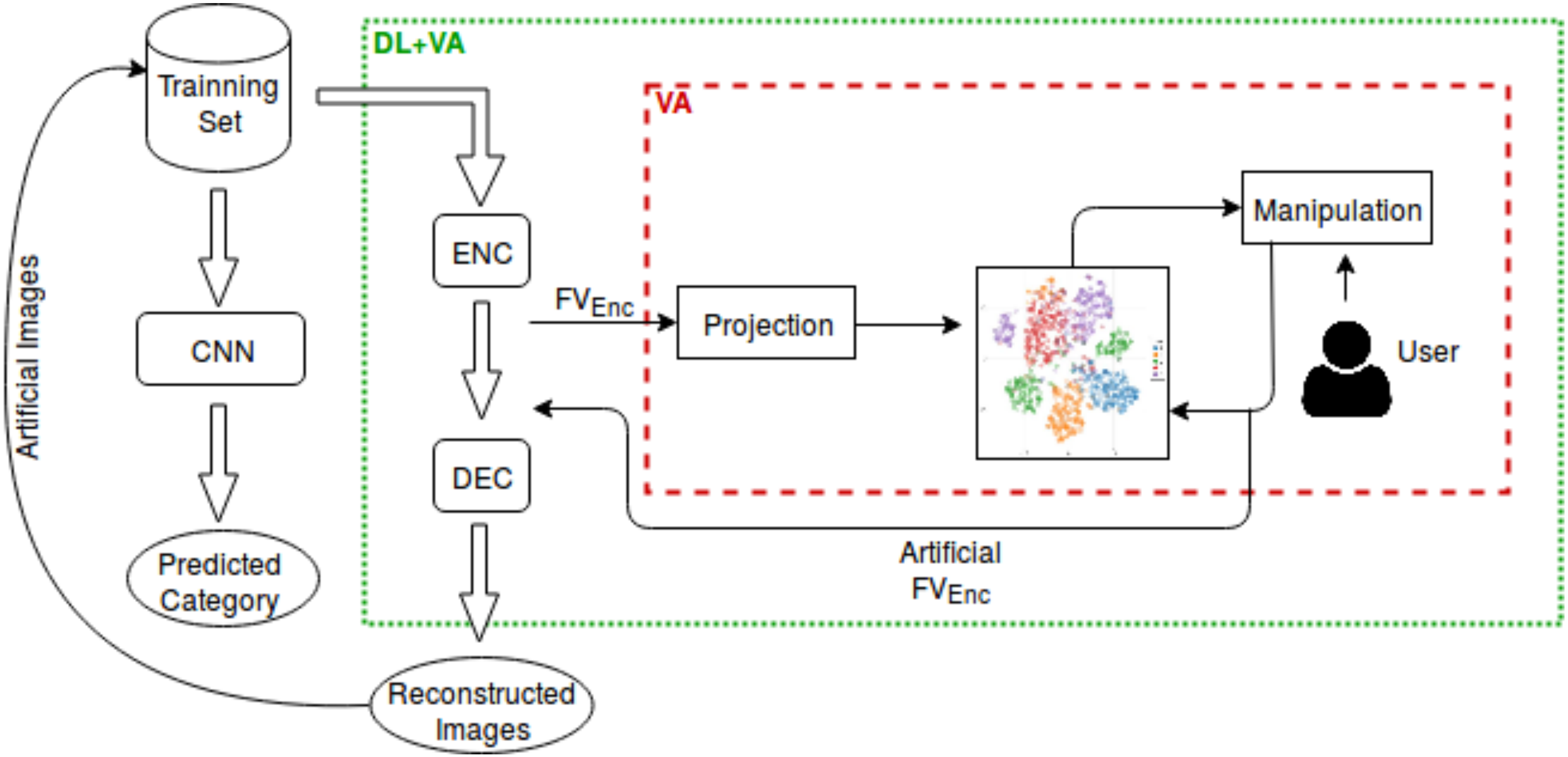
Objectives

In this work, we present a framework for interactive data augmentation using VA that exploits:

1) the user to increase a 2D projection and create new samples;

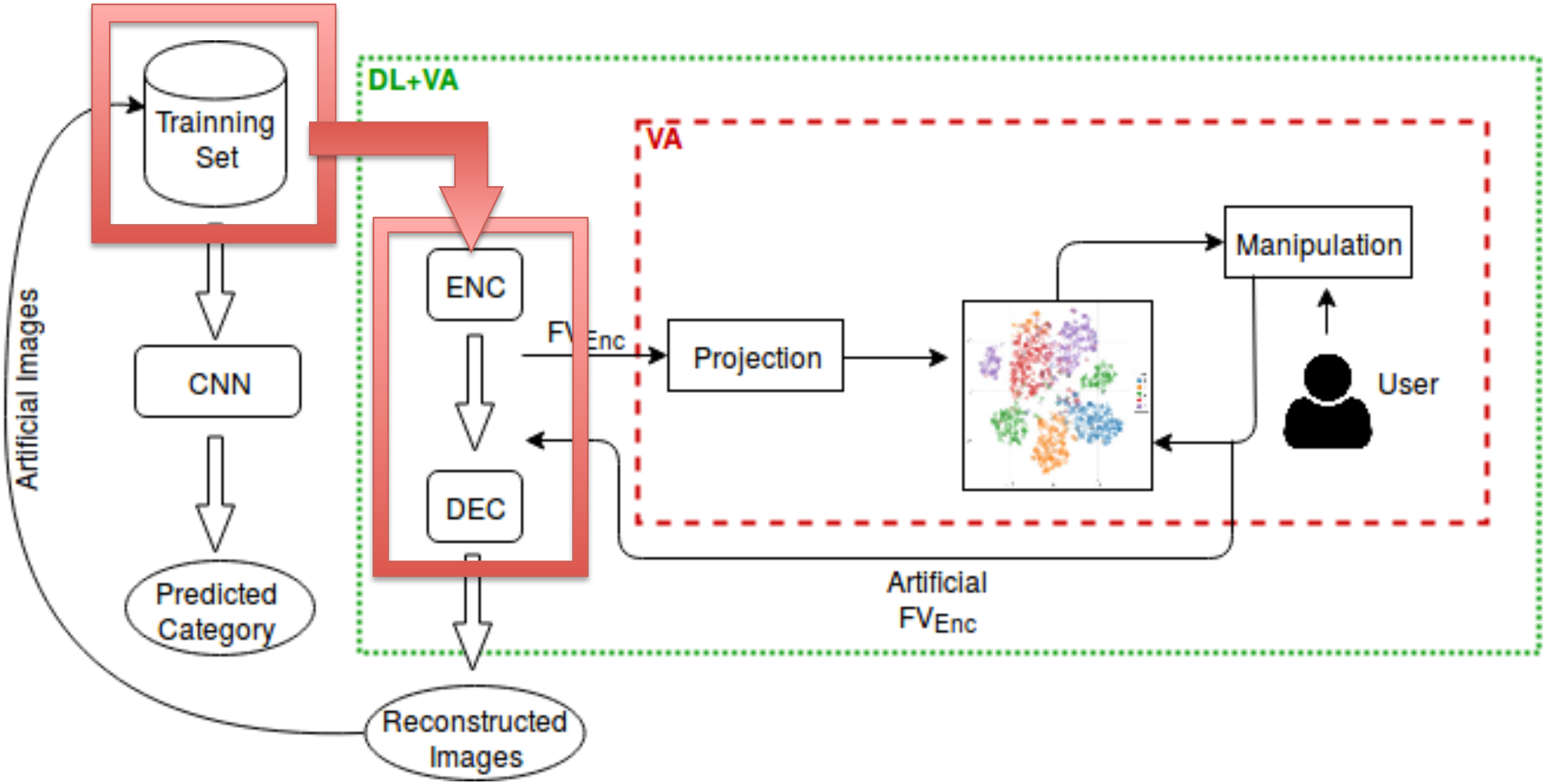
2) the Encoder-Decoder Neural Networks (EDNNs) [14]-[17] to generate artificial images.

Method



Trainning Set
CNN
Predicted Category
Artificial Images
DL+VA
VA
ENC
DEC
FVEnc
Projection
Manipulation
User
Artificial FVEnc
Reconstructed Images

Method


Trainning Set
CNN
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Artificial Images
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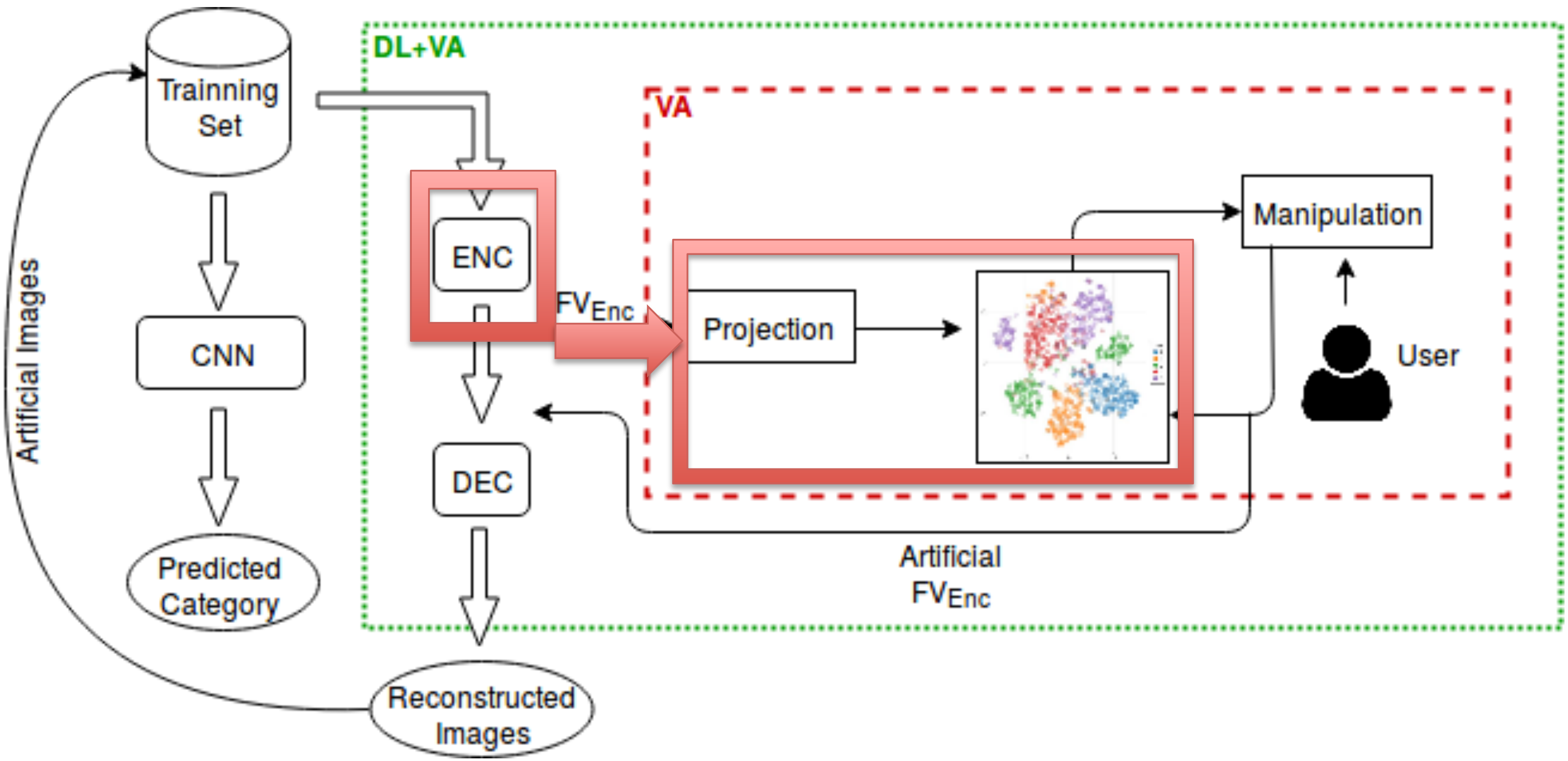
ENC
DEC
FV_{Enc}
VA
Projection
Manipulation
User
Artificial FV_{Enc}
Reconstructed Images

Method


DL+VA
VA
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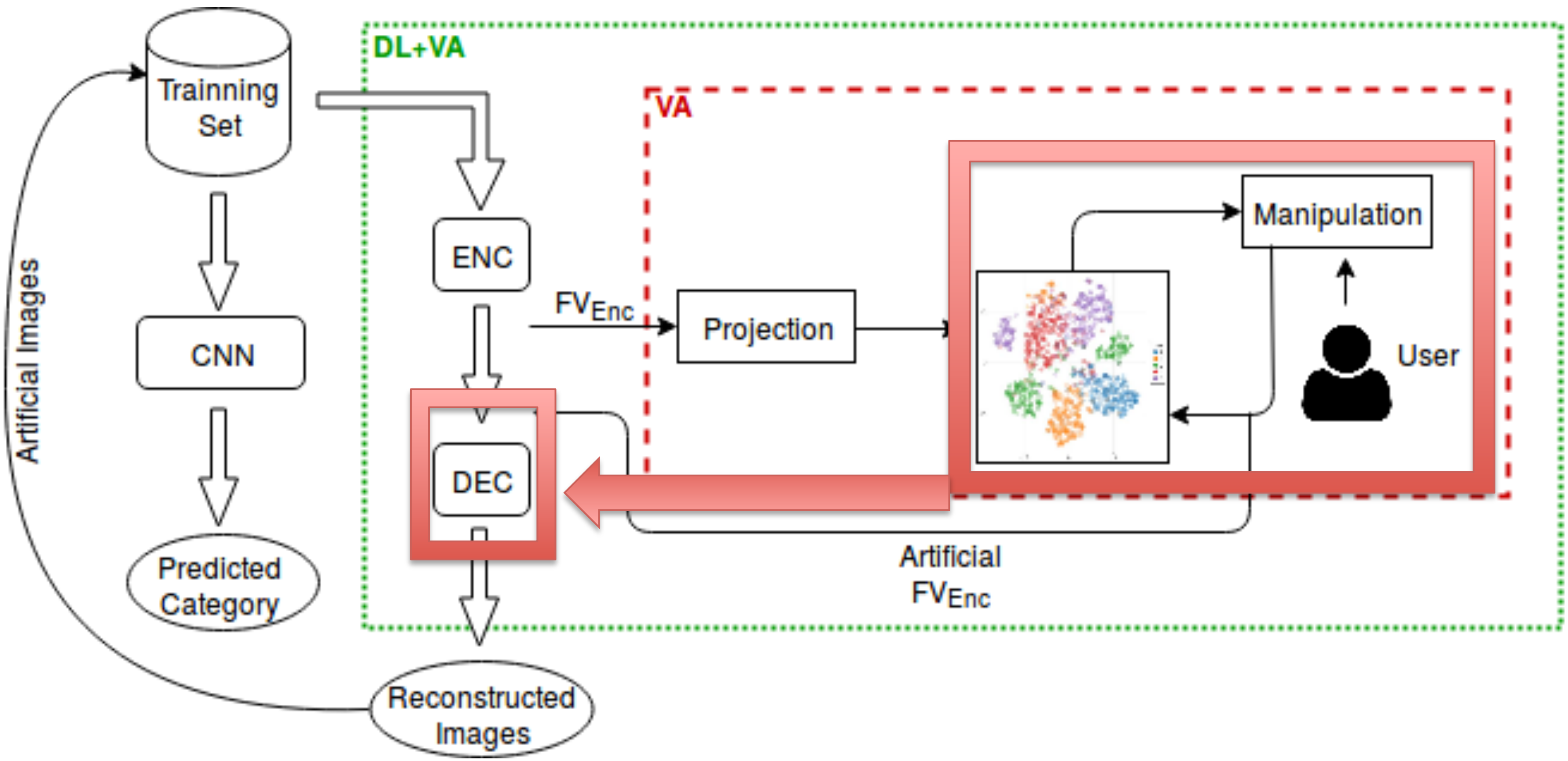
Artificial Images

Method


DL+VA
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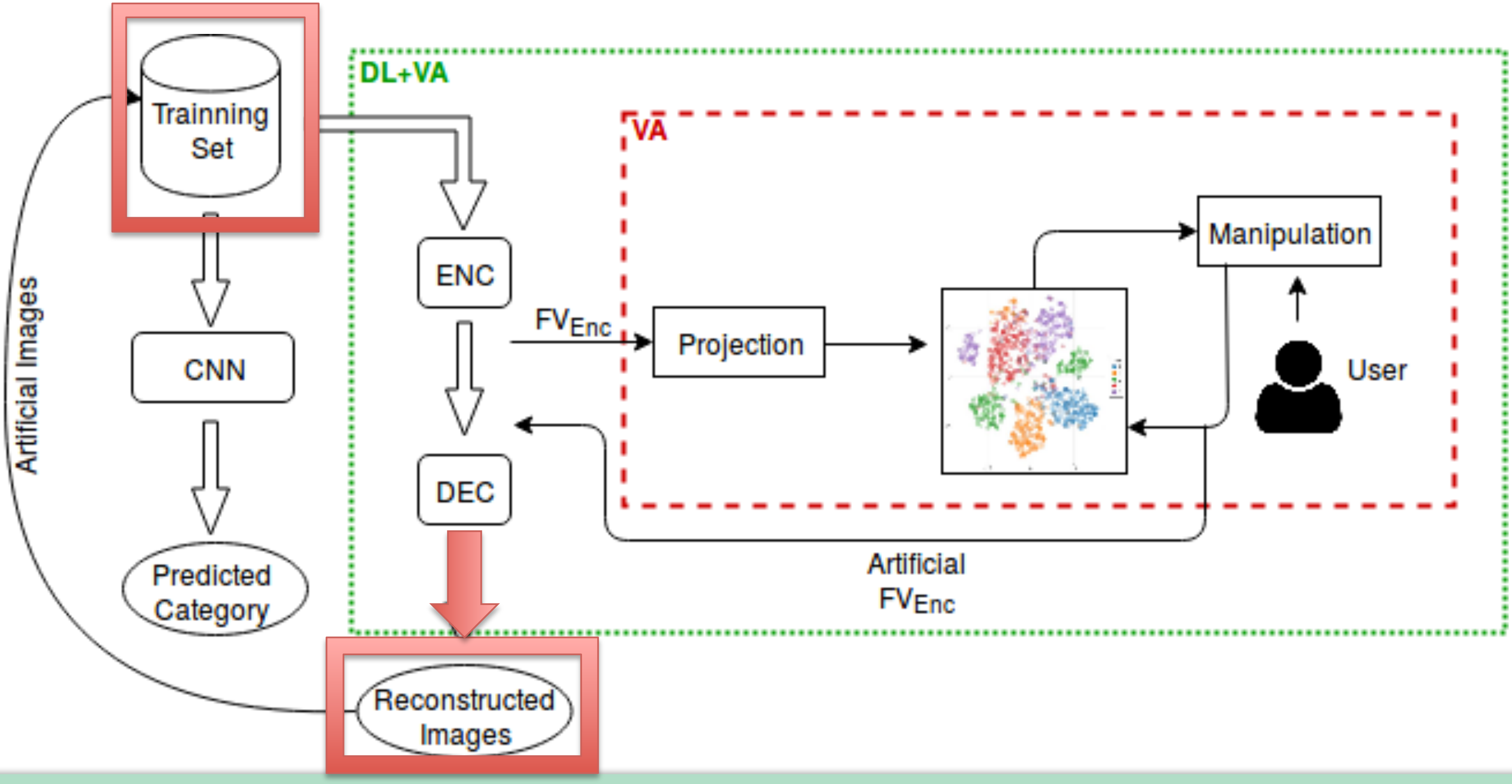
Method


Trainning Set
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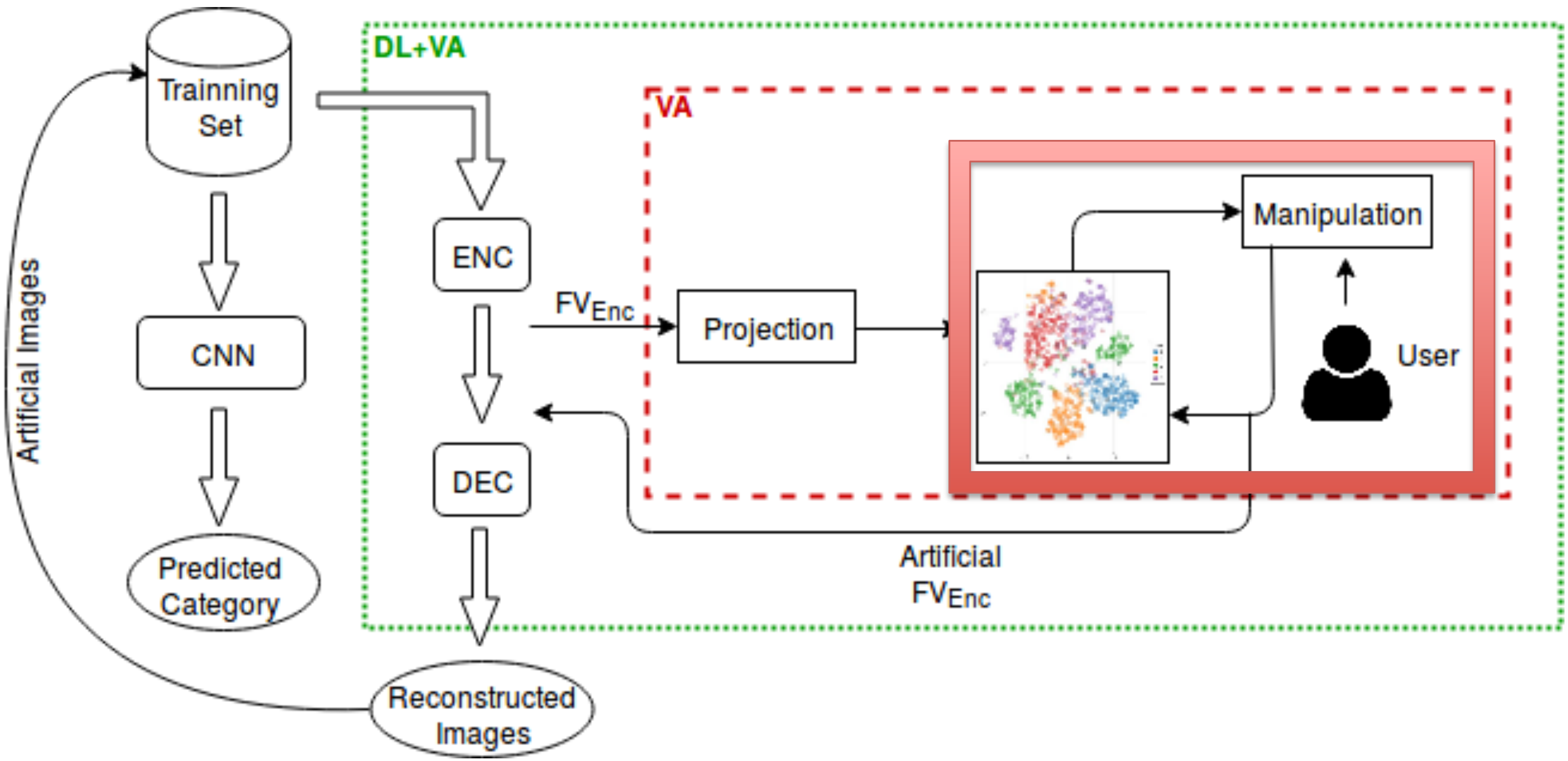
Method


DL+VA
VA
Trainning Set
CNN
Predicted Category
ENC
DEC
FVEnc
Projection
Manipulation
User
Artificial FVEnc
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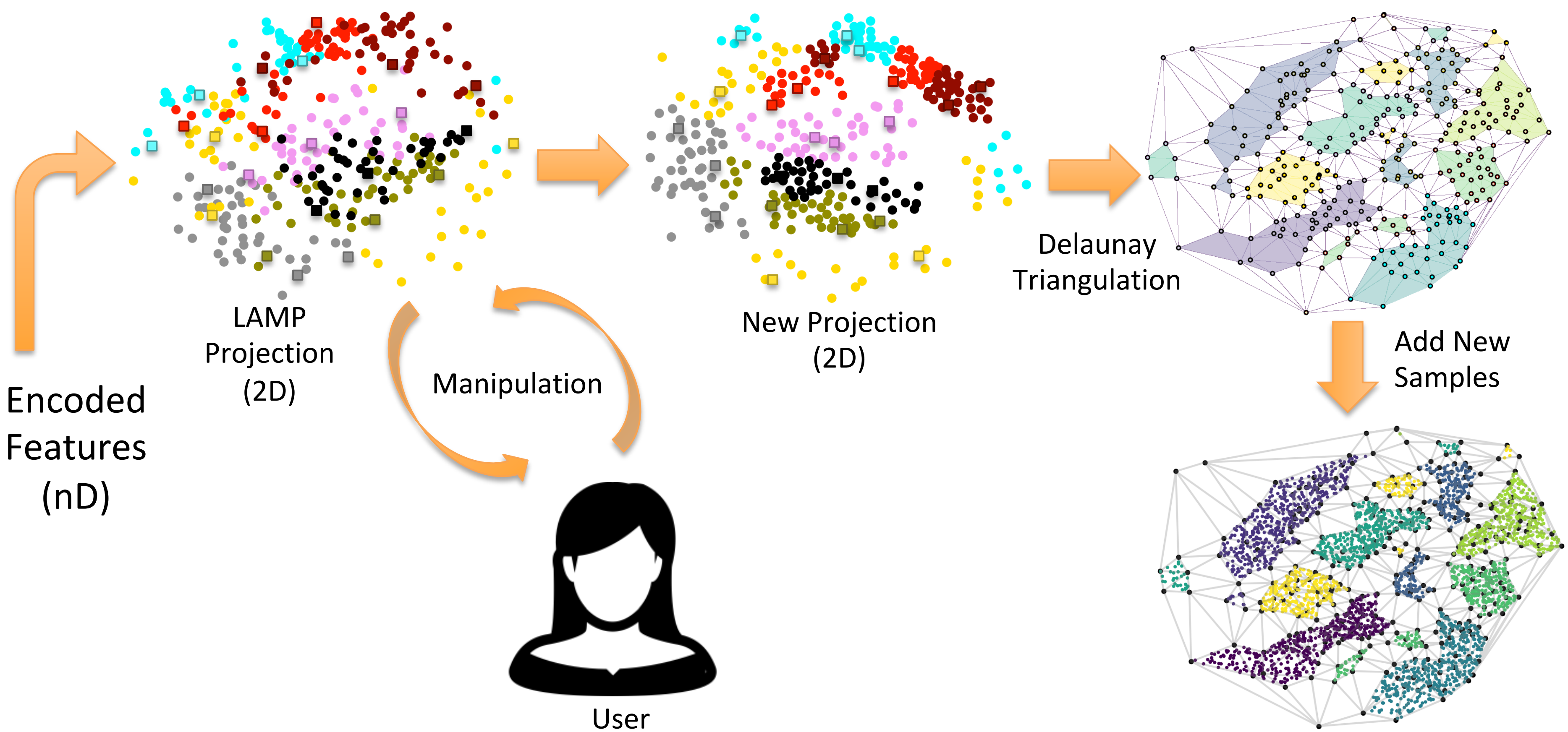
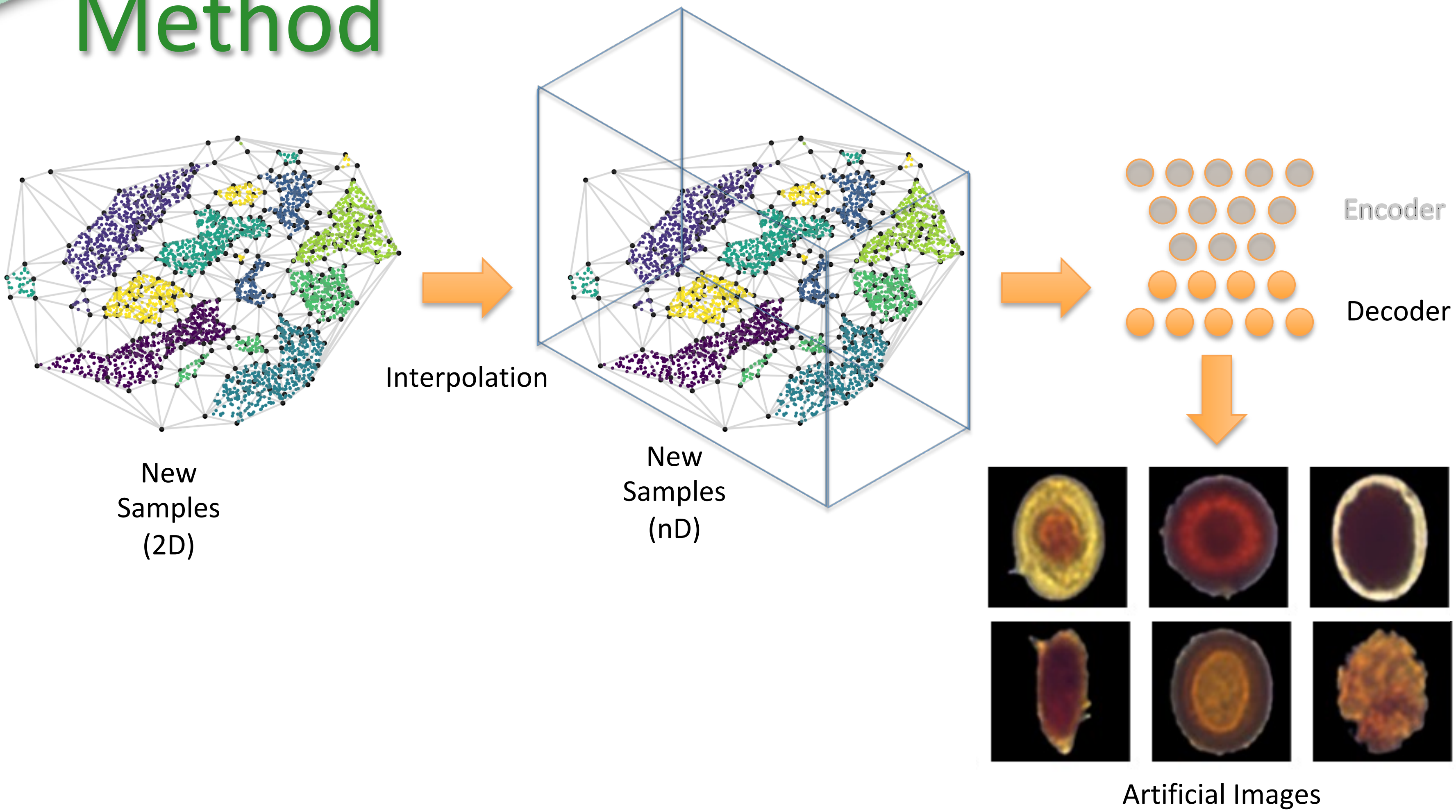
Artificial Images

Method


Encoded Features (nD)
LAMP Projection (2D)
Manipulation
User
New Projection (2D)
Delaunay Triangulation
Add New Samples

Method


Interpolation
New Samples (2D)
New Samples (nD)
Encoder
Decoder
Artificial Images

Experimental Setup

Dataset:

Real-word problem: Parasites dataset

12,691 images of Helminth eggs.

8 classes and 1 similar class.

Train: 360 images ≈ 2,5%

Test: remaining

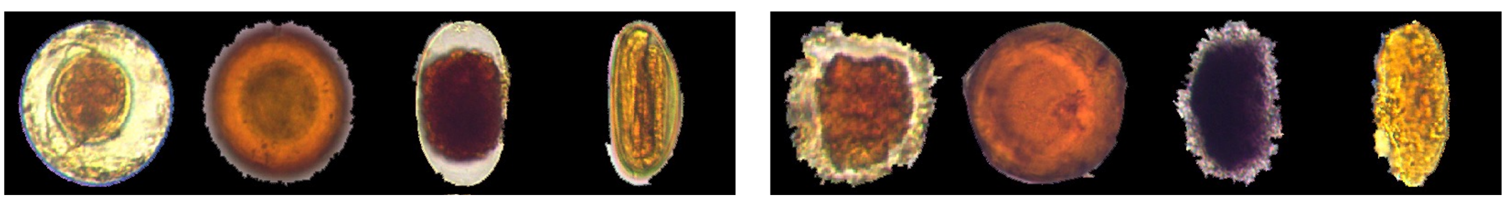


Fig. 2. Real images (left) of helminth eggs, one for each specie, and examples of similar impurities (right).

Results and Discussion

CNN trained by Filter Learning		Kappa (gain)	Accuracy (gain)
Parasites without impurity	Augmented data (LAMP + triangulation interpolation)	0.1383	0.1181
	Augmented data (LAMP + triangulation interpolation + concat.)	0.1475	0.1259
Parasites with impurity	Augmented data (LAMP + triangulation interpolation)	0.1230	0.2085
	Augmented data (LAMP + triangulation interpolation + concat.)	**0.2835**	**0.4235**

Table: Gain (%) of data augmentation with CNN trained by Filter Learning on Parasites dataset.

Conclusion

We have presented a Visual Analytics system to improve the performance of CNN-based image classification by data augmentation.

Also, we demonstrated the advantages of the proposed system for simple and complex scenarios, as created from a real problem — the diagnosis of helminth eggs in humans.

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