QUALITY ANALYSIS of ADDITIVE MANUFACTURING Using DEEP LEARNING

PROJECT TOPIC

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Content

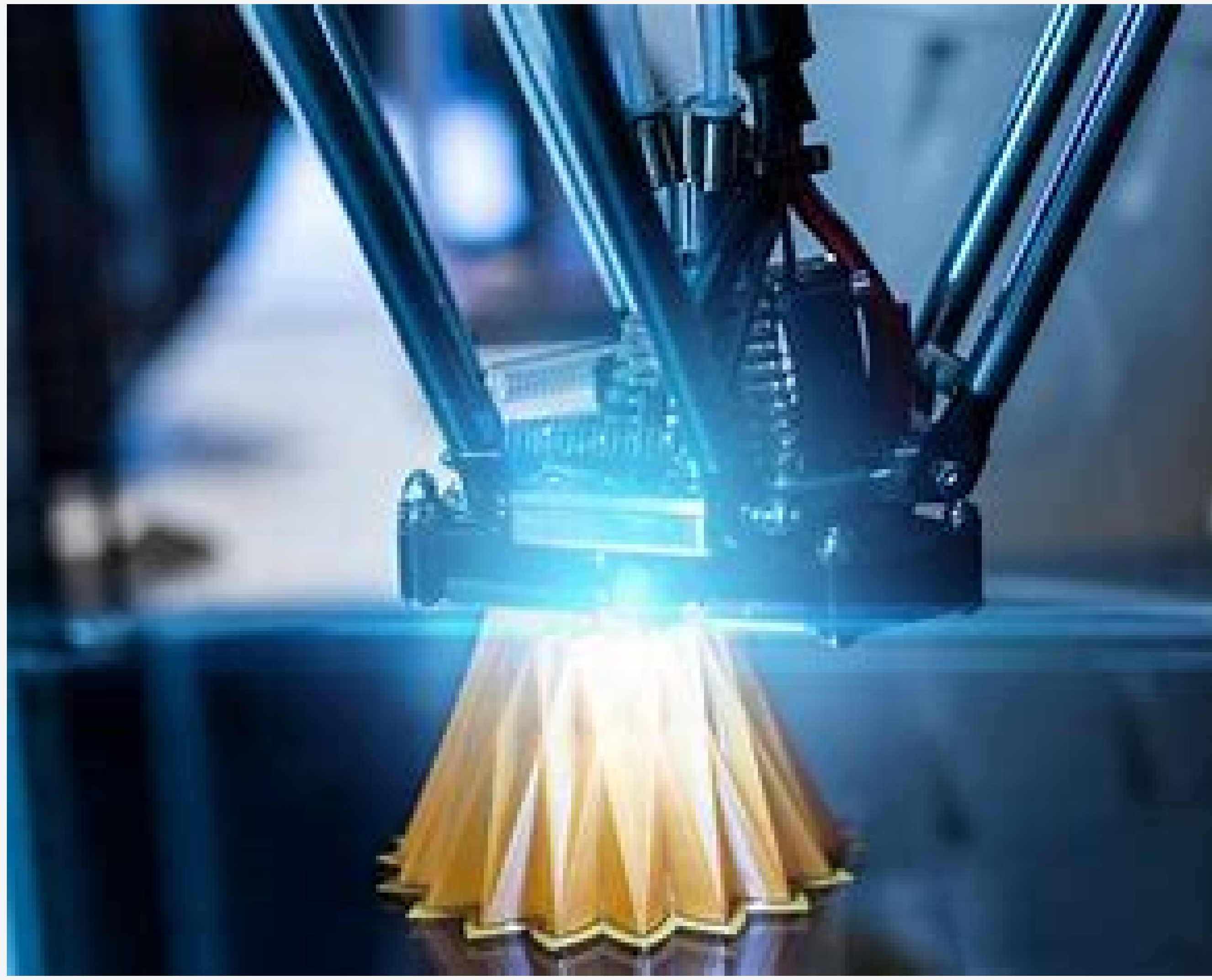
INTRODUCTION

Additive manufacturing (AM), also known as 3D printing, is a transformative manufacturing technology that enables the creation of three-dimensional objects by adding material layer by layer, based on a digital design file.

Additive manufacturing has applications across various industries, including aerospace, automotive, healthcare, consumer goods, and electronics.

01 ACCORDING TO A REPORT BY GRAND VIEW RESEARCH, THE GLOBAL ADDITIVE MANUFACTURING MARKET SIZE WAS VALUED AT USD 12.6 BILLION IN 2020 AND IS EXPECTED TO REACH USD 49.1 BILLION BY 2028

02 ADDITIVE MANUFACTURING TECHNOLOGIES SUPPORT A WIDE RANGE OF MATERIALS, INCLUDING POLYMERS, METALS, CERAMICS, AND COMPOSITES.



DEFECTS IN ADDITIVE MANUFACTURED PRODUCTS

01	POROSITY
02	SURFACE ROUGHNESS
03	MISALIGNMENT
04	DELAMINATION

All the above mentioned defects could be deteced earlier in the manufacturing process using Deep Learning , leading to improved quality control and reduced waste.

Why Additive Manufacturing Requires Deep Learning and Deep Belief Networks

Additive manufacturing produces complex, high-dimensional data that traditional methods find difficult to analyze. Deep learning and Deep Belief Networks (DBNs), with their sophisticated pattern recognition abilities, can extract critical insights from this data to enhance decision-making and operational efficiency. DBNs, structured with multiple layers of stochastic, hidden variables, learn progressively complex data representations crucial for detecting intricate patterns and anomalies in the manufacturing process.

They employ unsupervised learning to identify hidden structures within the raw data from sensors and machines. These networks also model intricate dependencies between manufacturing parameters, improving the precision of control mechanisms. Moreover, DBNs can integrate their insights into control systems in real-time, enabling dynamic adjustments that maintain optimal manufacturing conditions

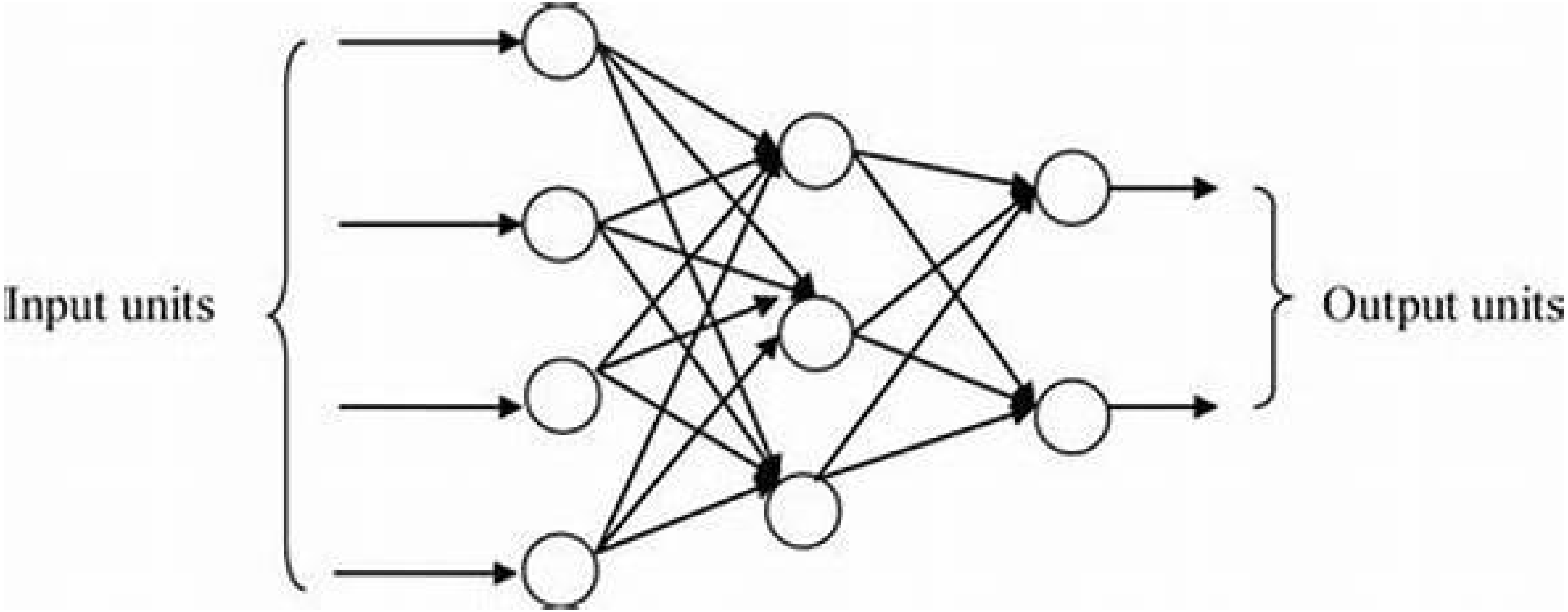
DBN

A Deep Belief Network is a type of artificial neural network architecture that consists of multiple layers of latent variables (hidden units) arranged in a hierarchical manner.

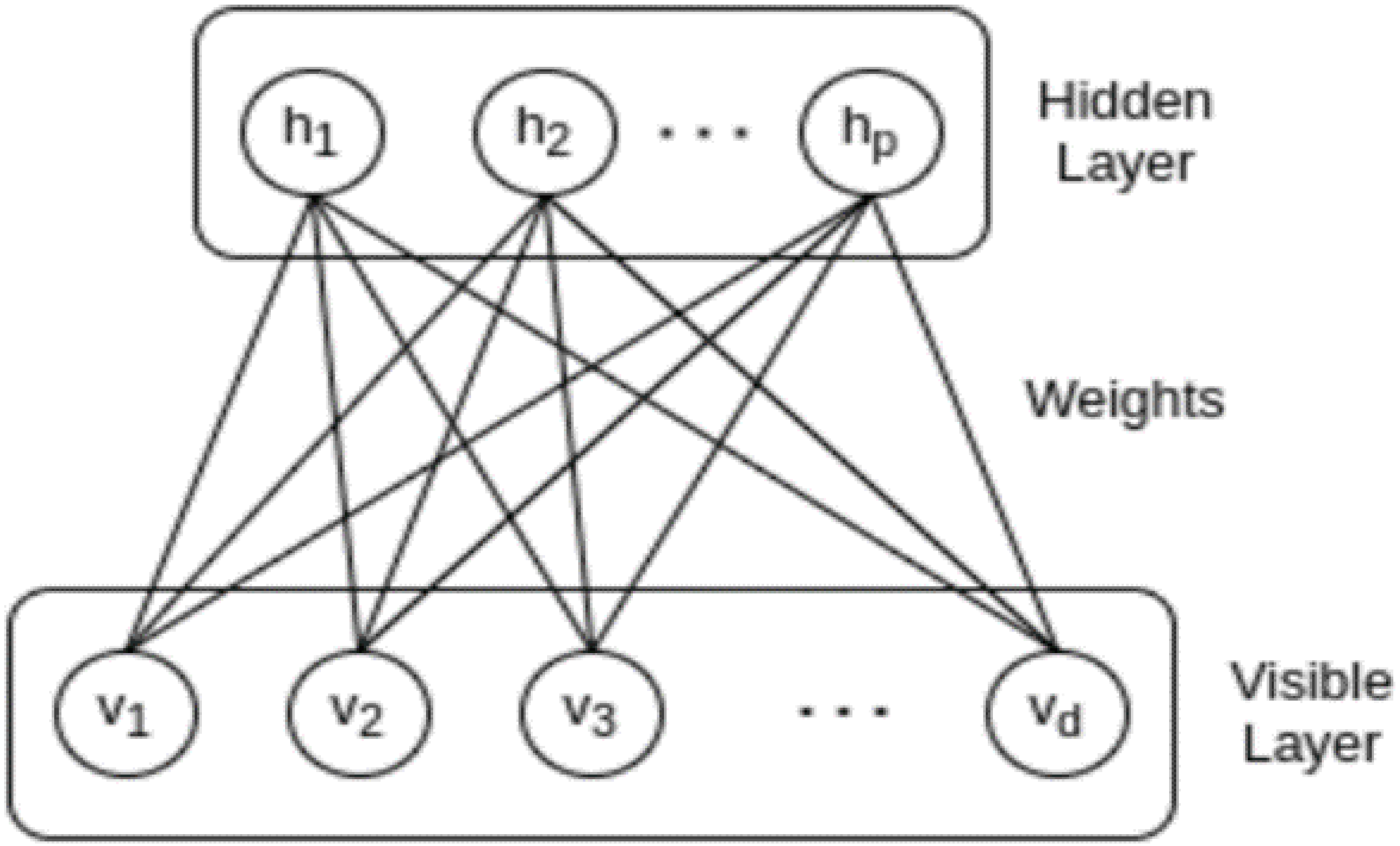
DBN's are composed of two main types of layers:

- A stack of Restricted Boltzmann machines (RBMs)
- Additional layer that serves as a classifier or regression layer.

DBN



Restricted Boltzmann Machine

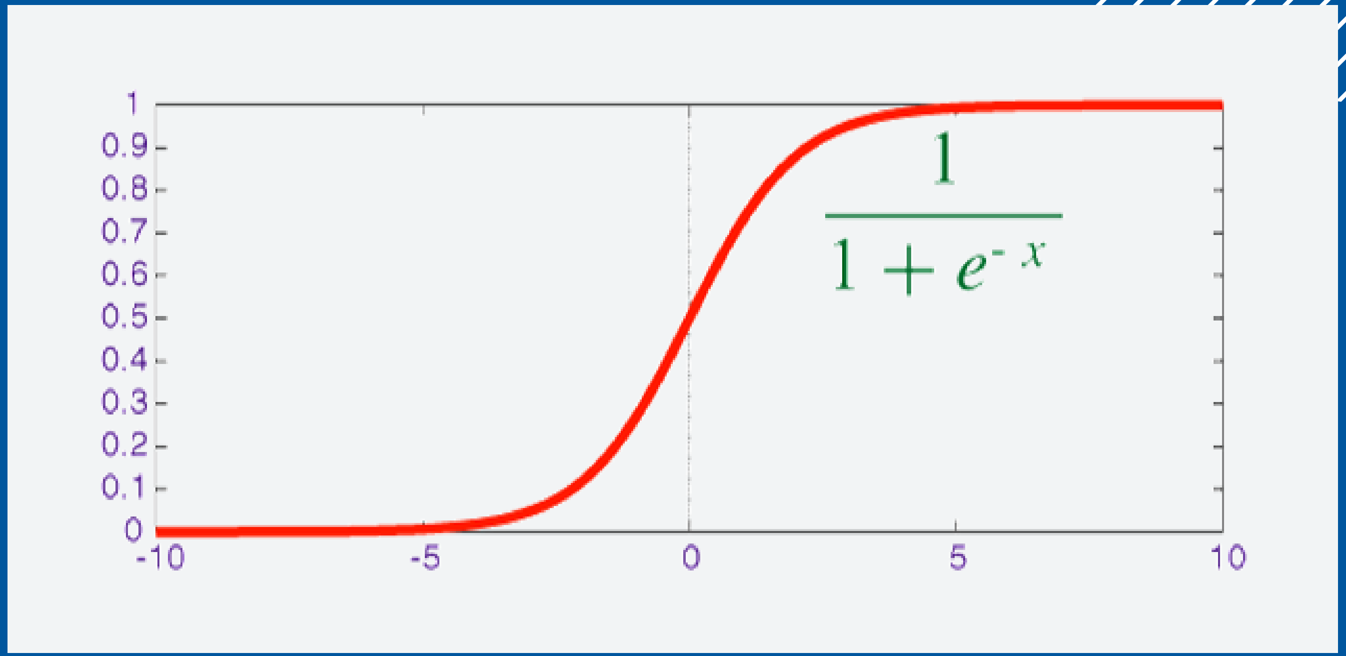


RBM composed of set of visible and hidden layer, where each visible nodes in visible layer is connected with each node of the hidden layer.

The only difference between BM and RBM is that there is no connection between nodes of the same layer in RBM.

SIGMOID FUNCTION

The sigmoid function are considered to be the building blocks of DBNs.



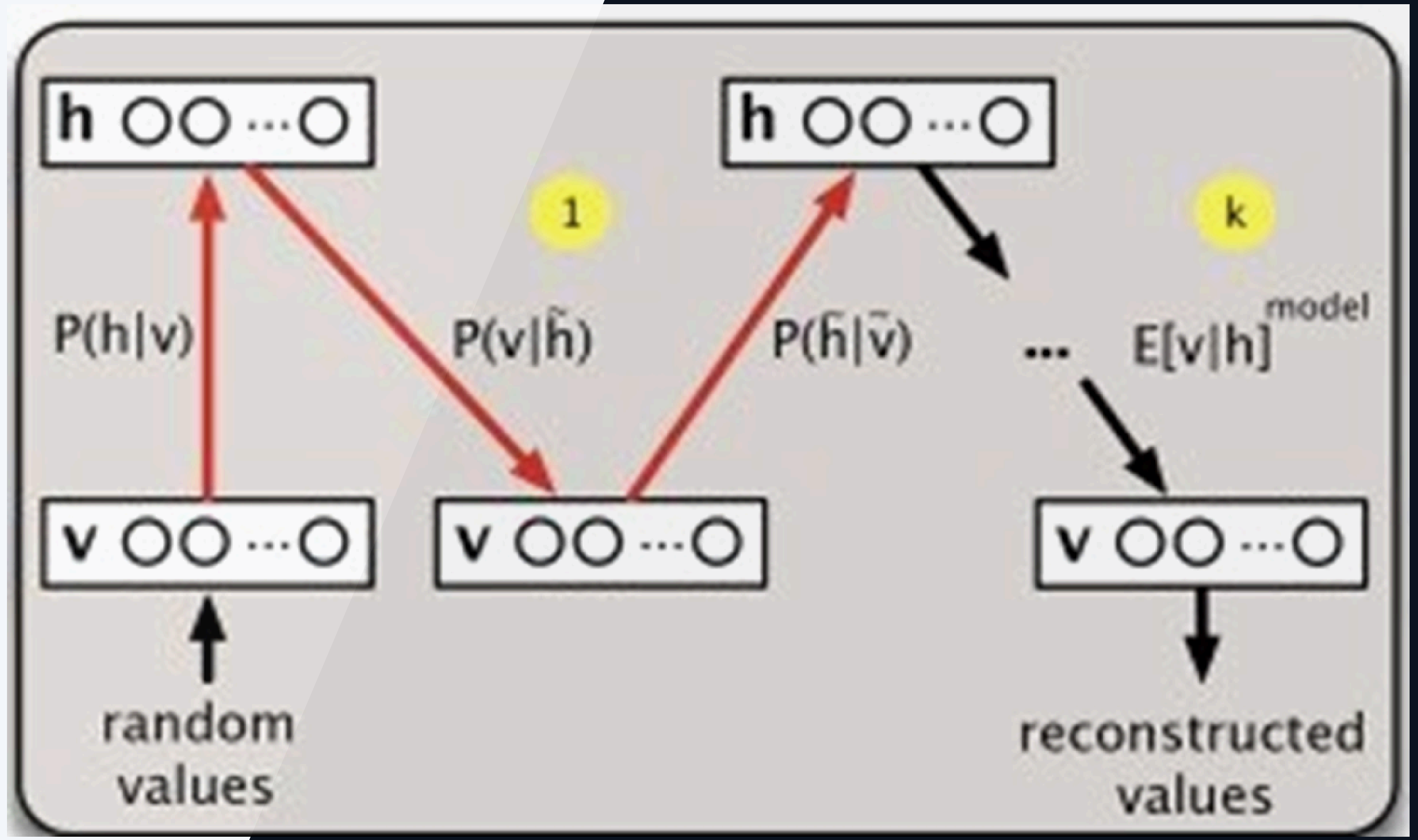
Activation Function in RBMs:

In RBMs, neurons in both the visible and hidden layers typically use the sigmoid function as their activation function. This function maps the input to a value between 0 and 1, which can represent probabilities.

Contrastive Divergence

The RBM is trained using a technique called contrastive divergence, which involves computing the difference between the input data and the reconstructed data, and using this difference to update the weights.

During the training process, the model is initialized with random weights and is iteratively trained to generate new samples that are similar to the input data. The positive phase of the training process involves sampling from the data distribution to generate a data sample, while the negative phase involves sampling from the model distribution to generate a model sample. The difference between the two distributions is used to update the weights of the model, so that the model distribution becomes more similar to the data distribution.



Reconstruction Error

Mean Square Error

Error Squared

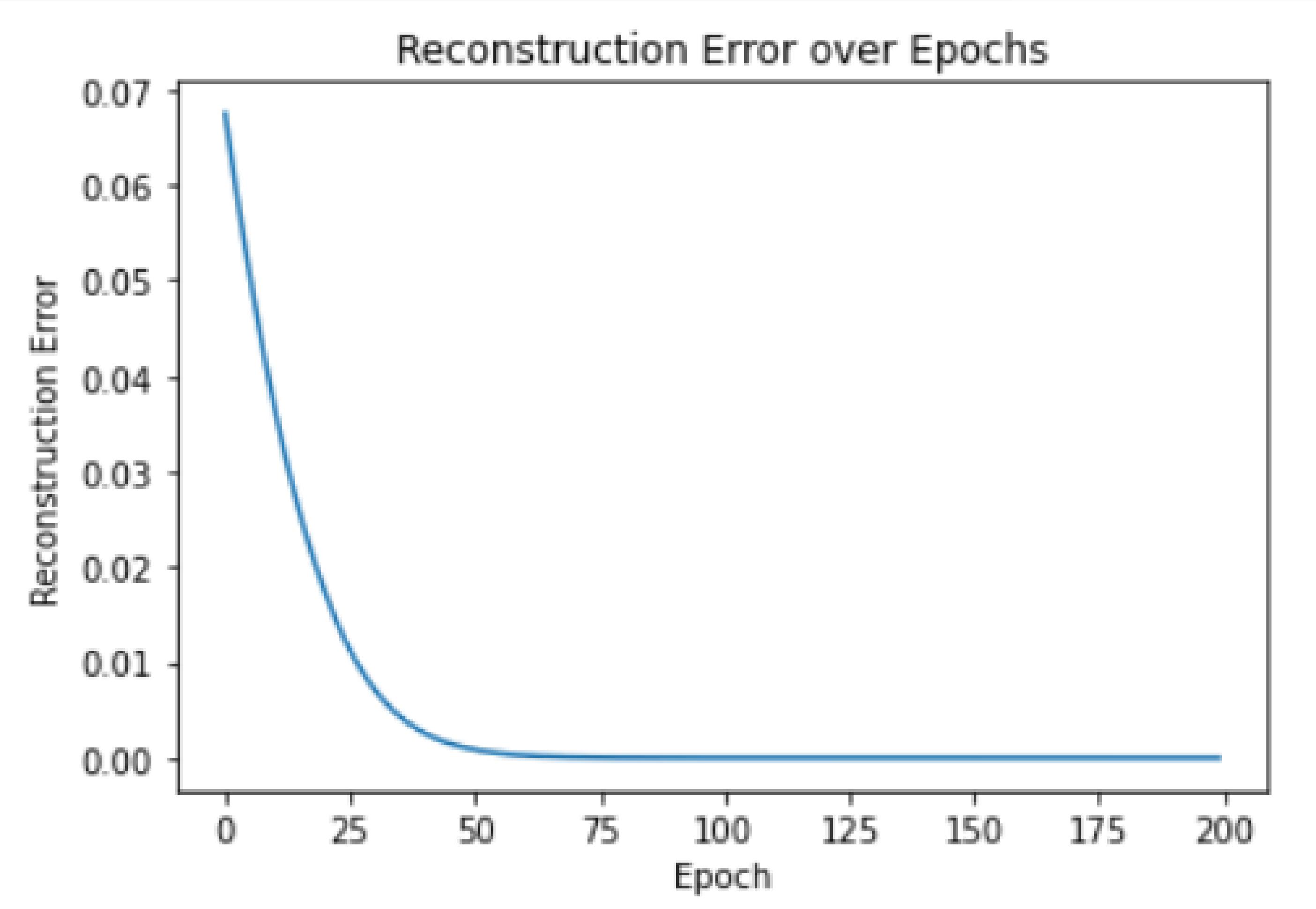
$$\mathrm{MSE} = \boxed{\frac{1}{n}\sum_{i=1}^{n}}\left(\boxed{Y_i - \hat{Y}_i}\right)^{\boxed{2}}$$

real value predicted value

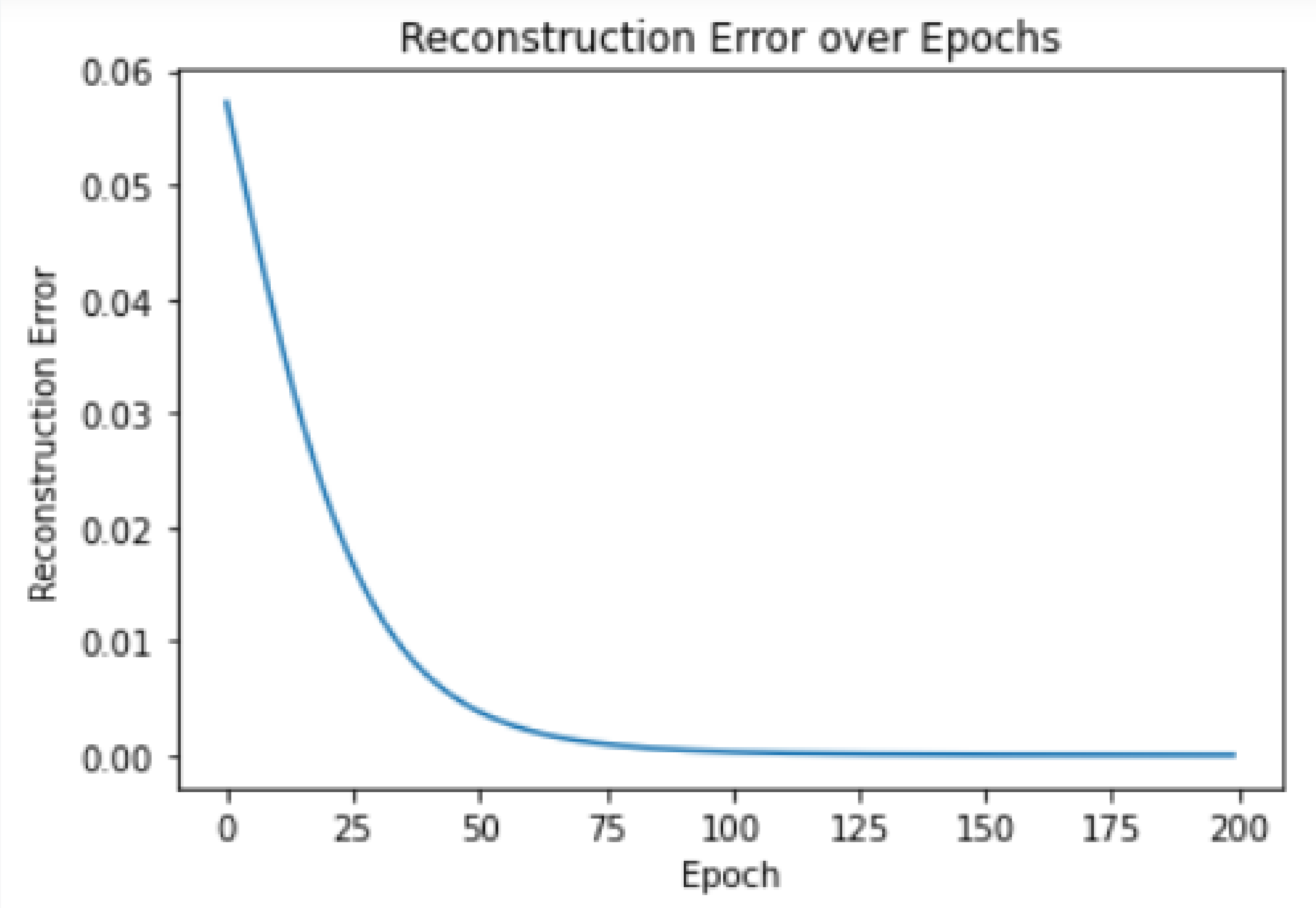
$$\boxed{Y_i} - \boxed{\hat{Y}_i}$$

Model Development Stages and Results

DBN MODEL FOR 1 ARRAY INPUT



RBM 1

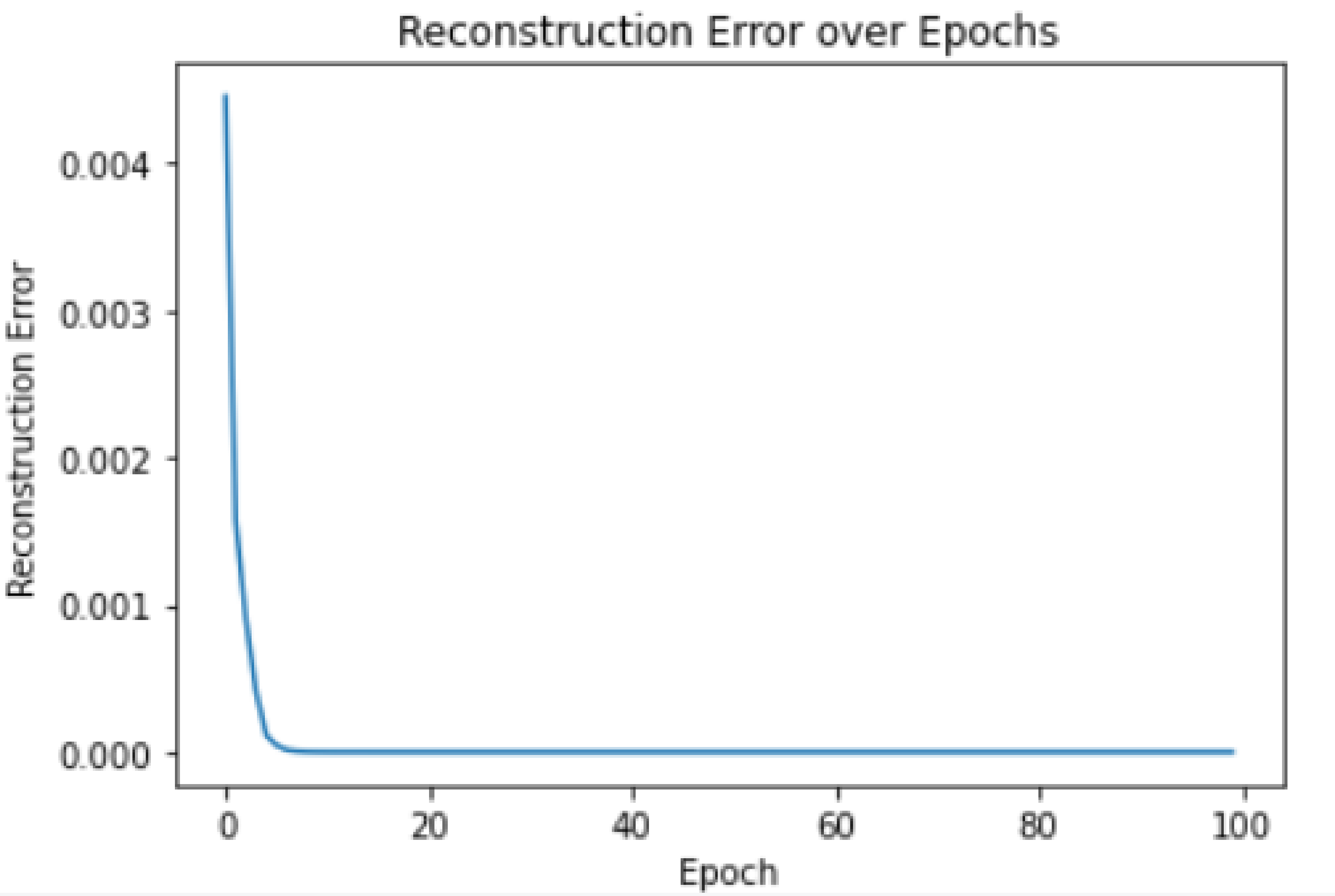


RBM 2

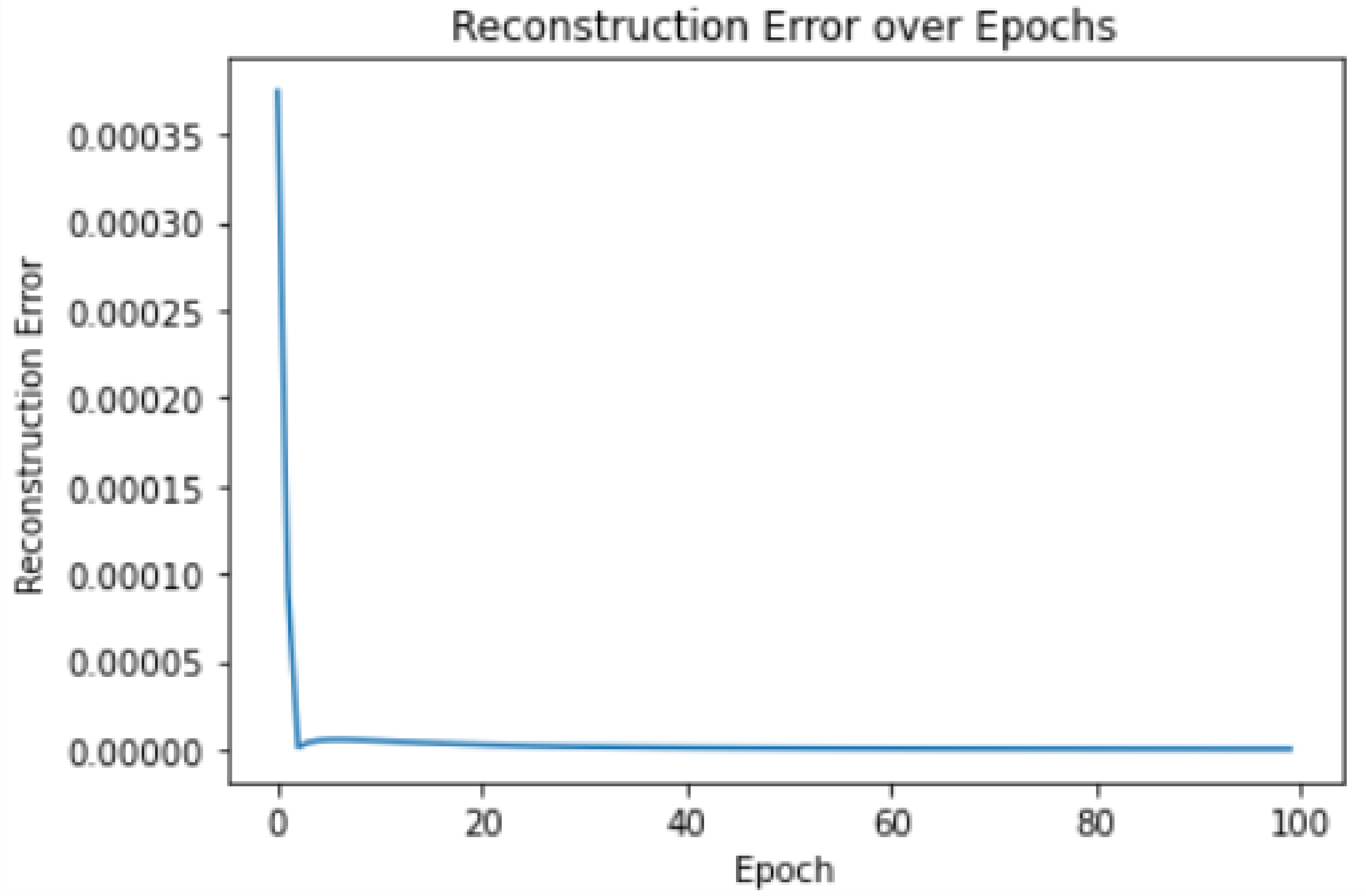
ORIGINAL INPUT: 1.0000, 0.4286, 0.0000, 0.1429
RECONSTRUCTED INPUT: 0.9742, 0.4315, 0.0196, 0.1147

MEAN SQUARED ERROR (MSE): 0.0004638550655978127
STRUCTURAL SIMILARITY INDEX (SSIM): 0.9963283583538571

DBN MODEL FOR 1 IMAGE INPUT



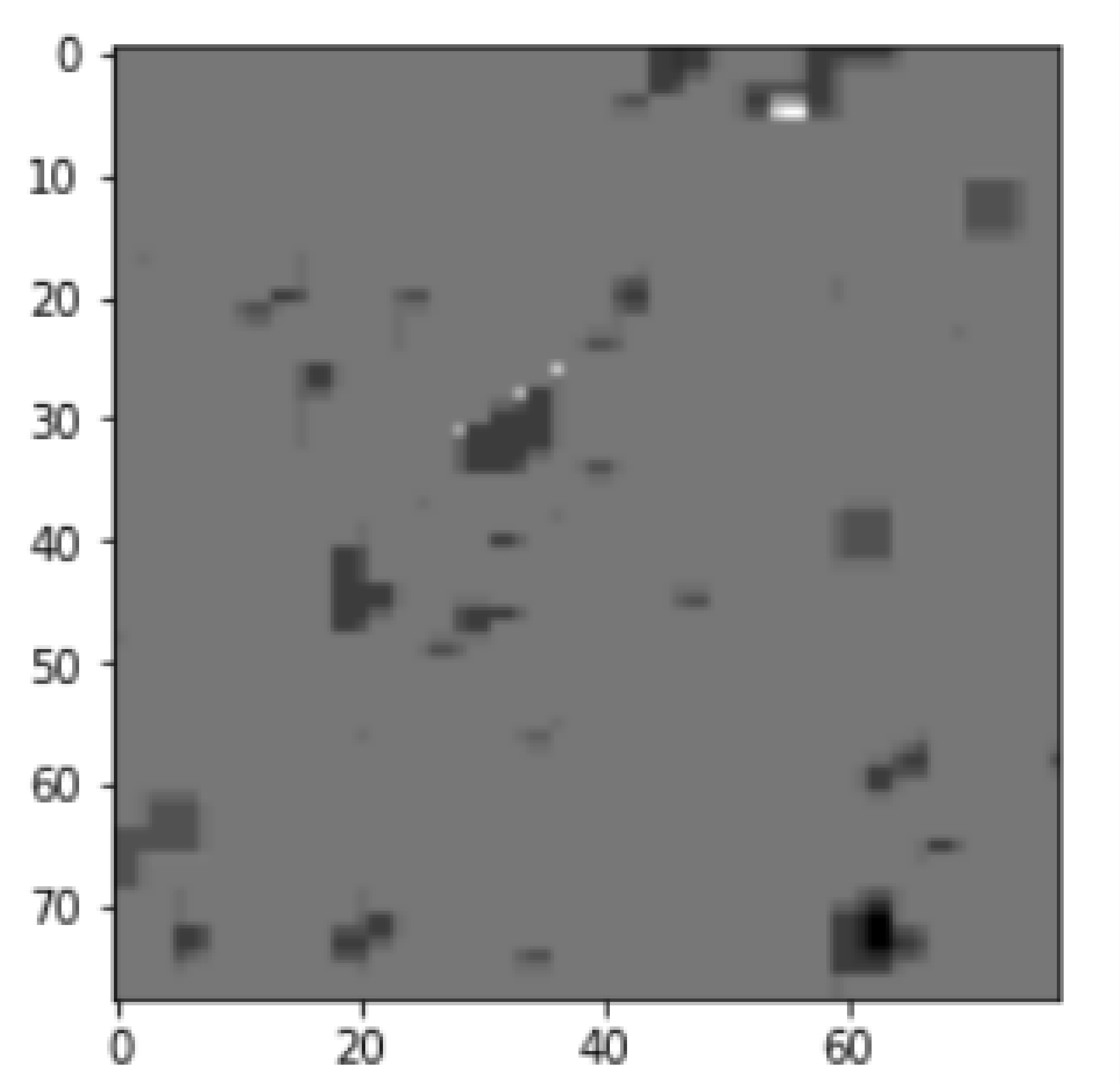
RBM 1



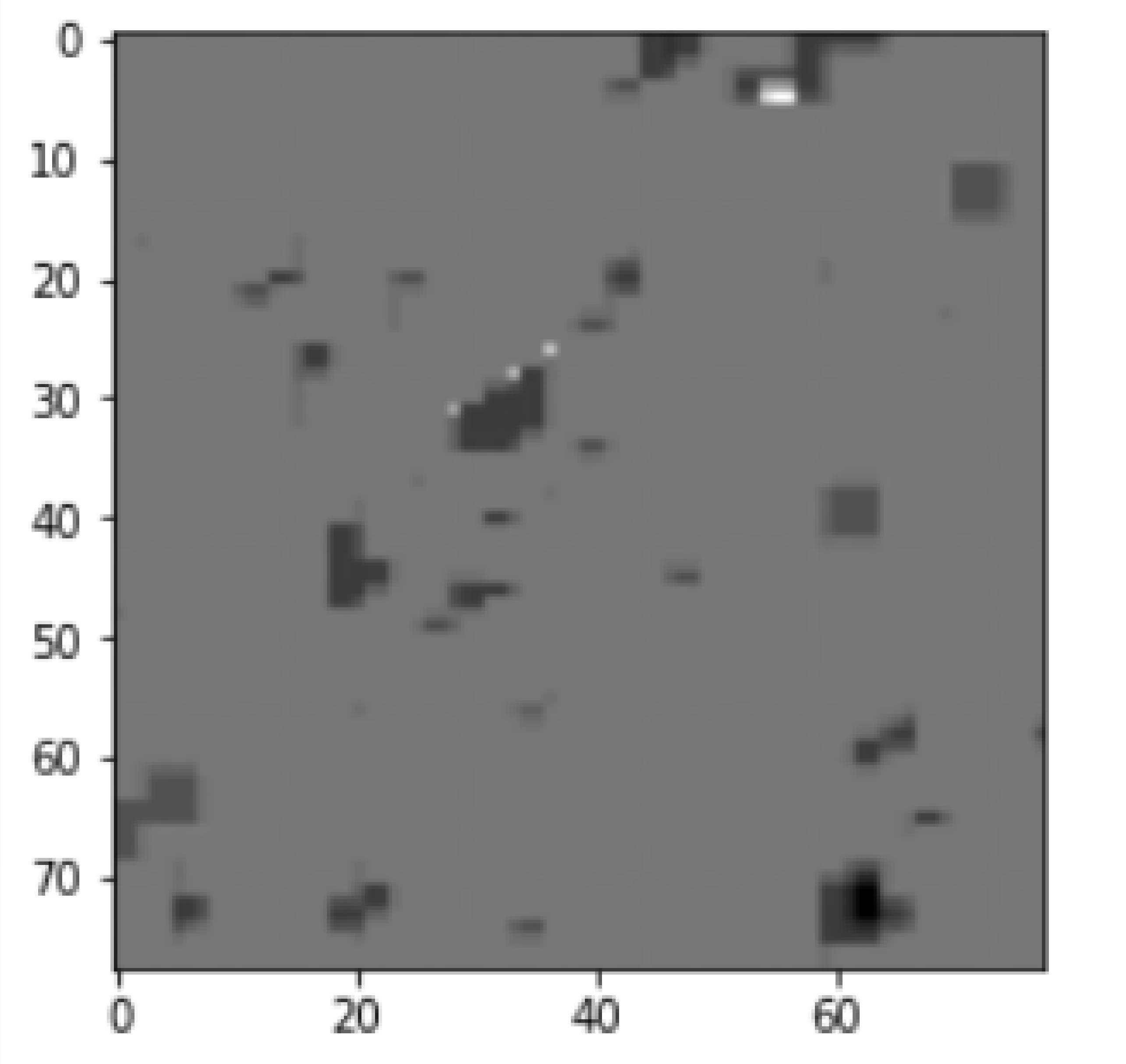
RBM 2

DBN MODEL FOR 1 IMAGE INPUT

Original Input



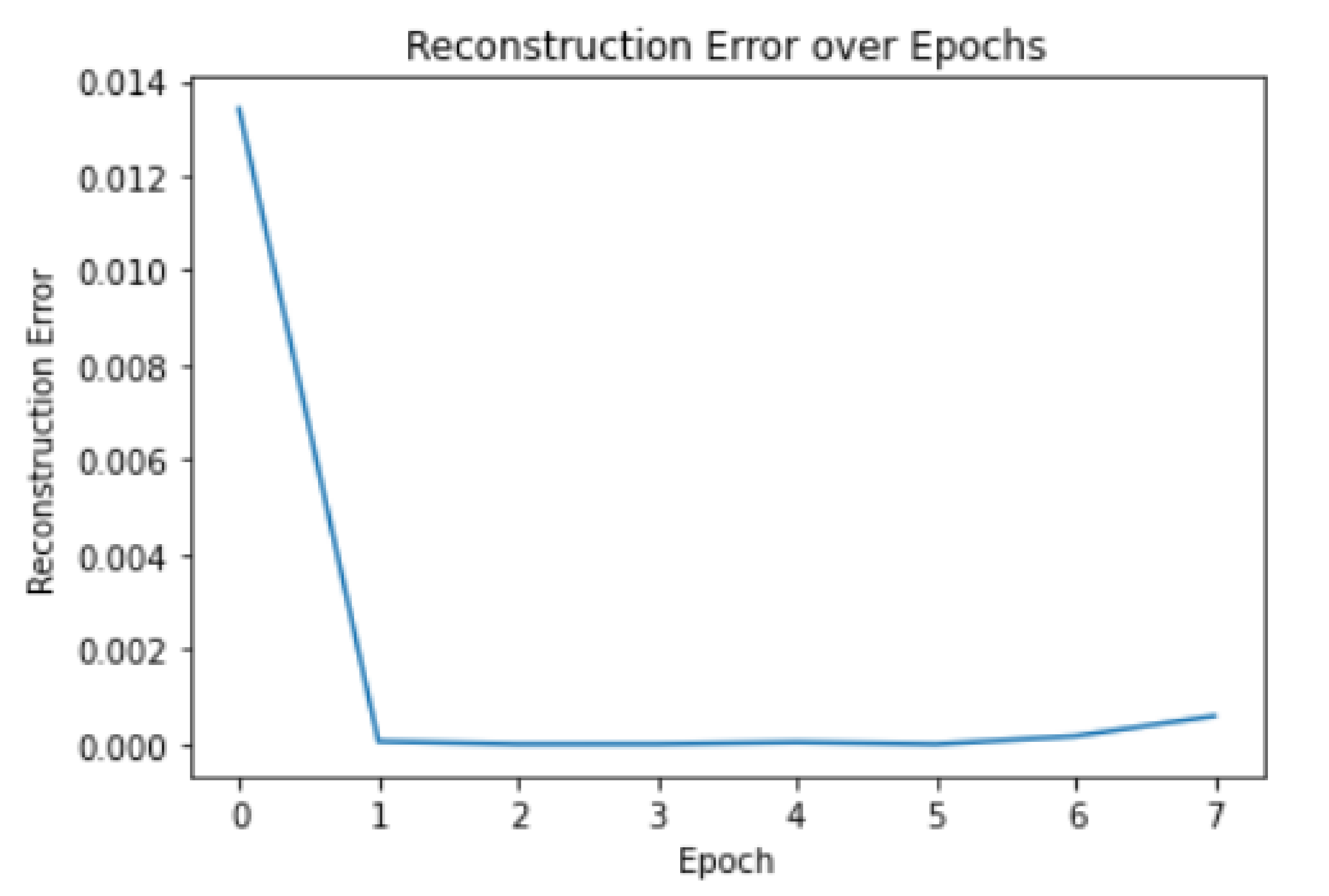
Reconstructed Input

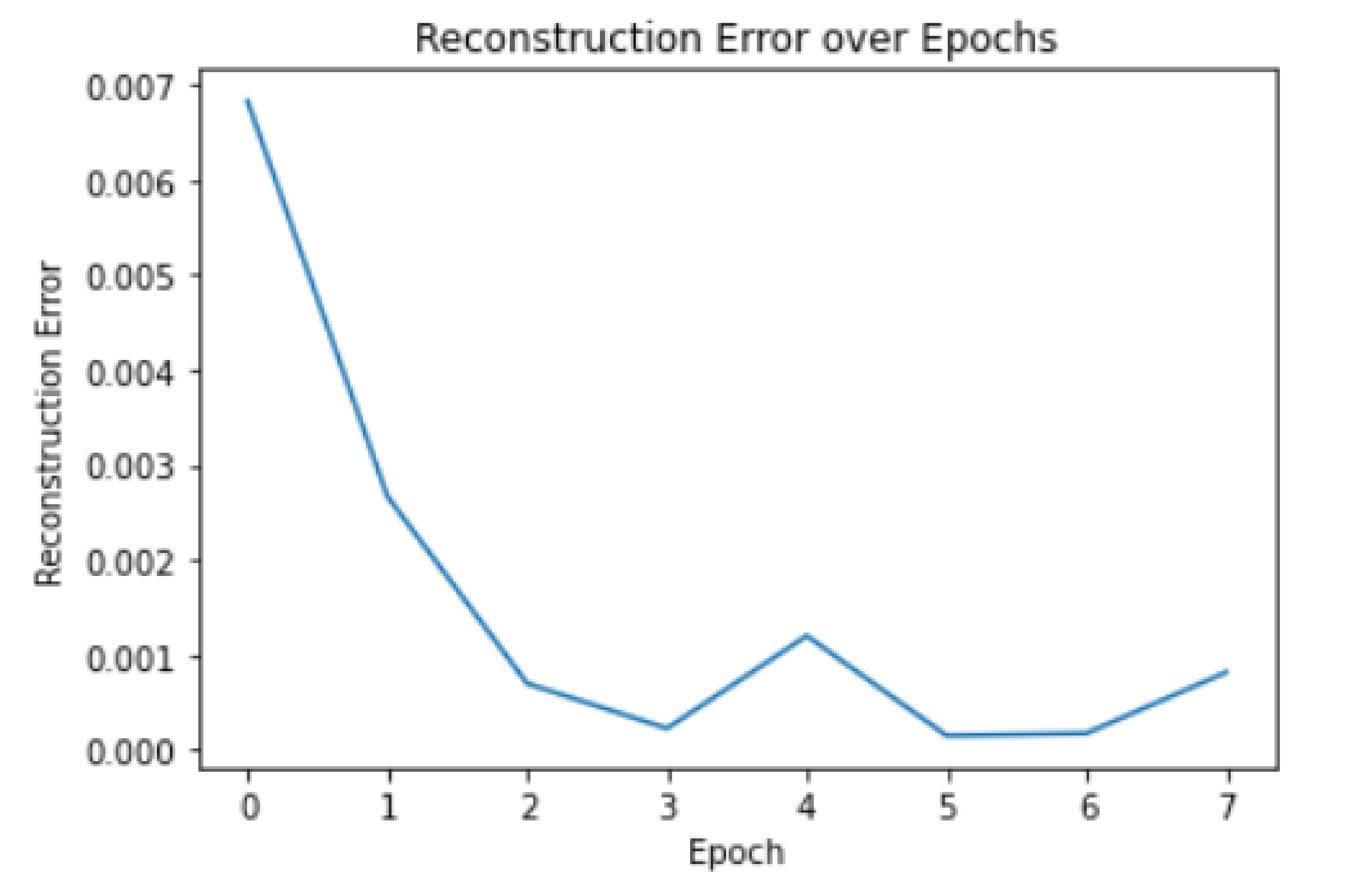


MEAN SQUARED ERROR (MSE): 1.8698348469570192E-07

STRUCTURAL SIMILARITY INDEX (SSIM): 0.9996652662087209

DBN MODEL (DATASET)



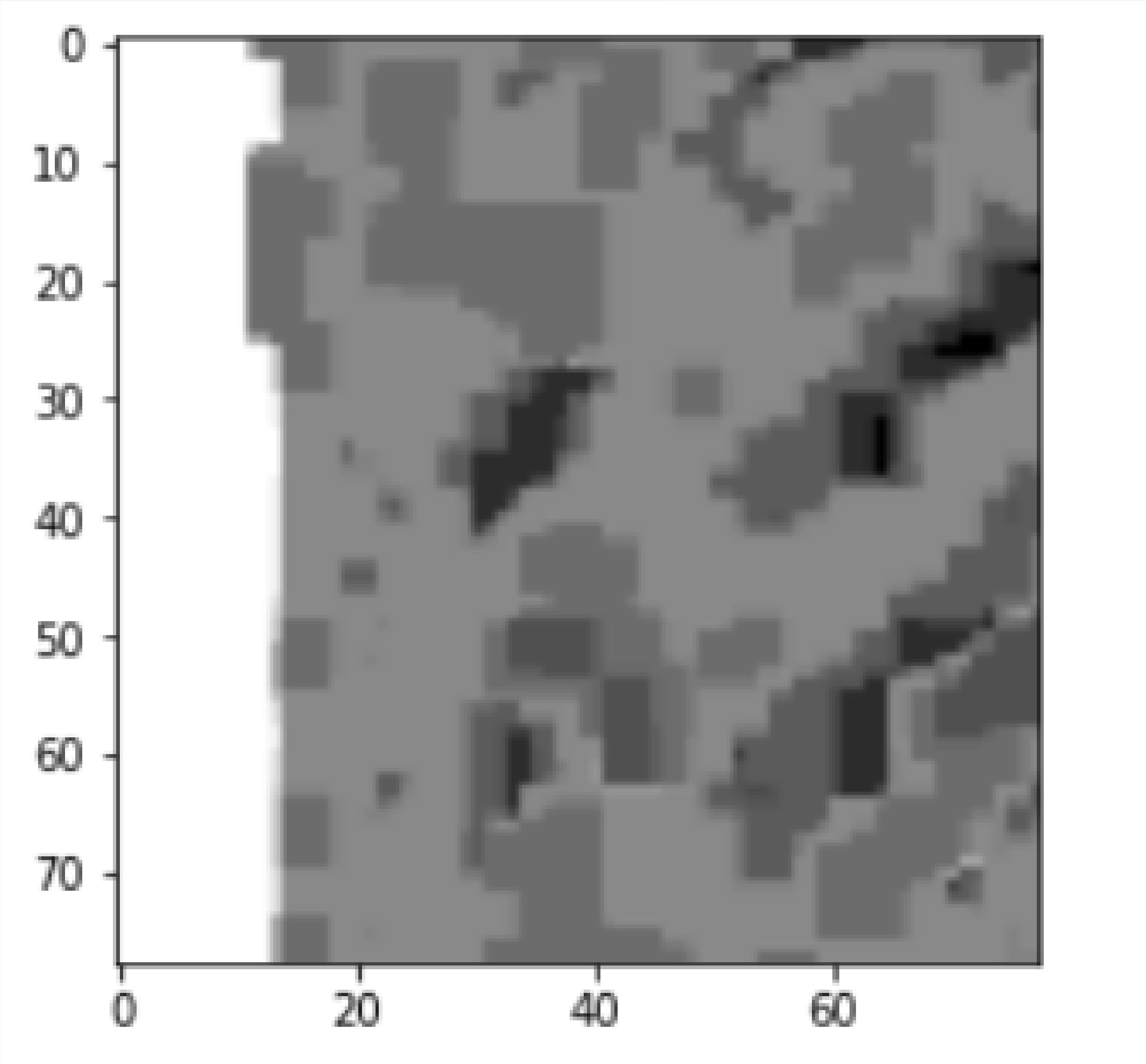


RBM 1

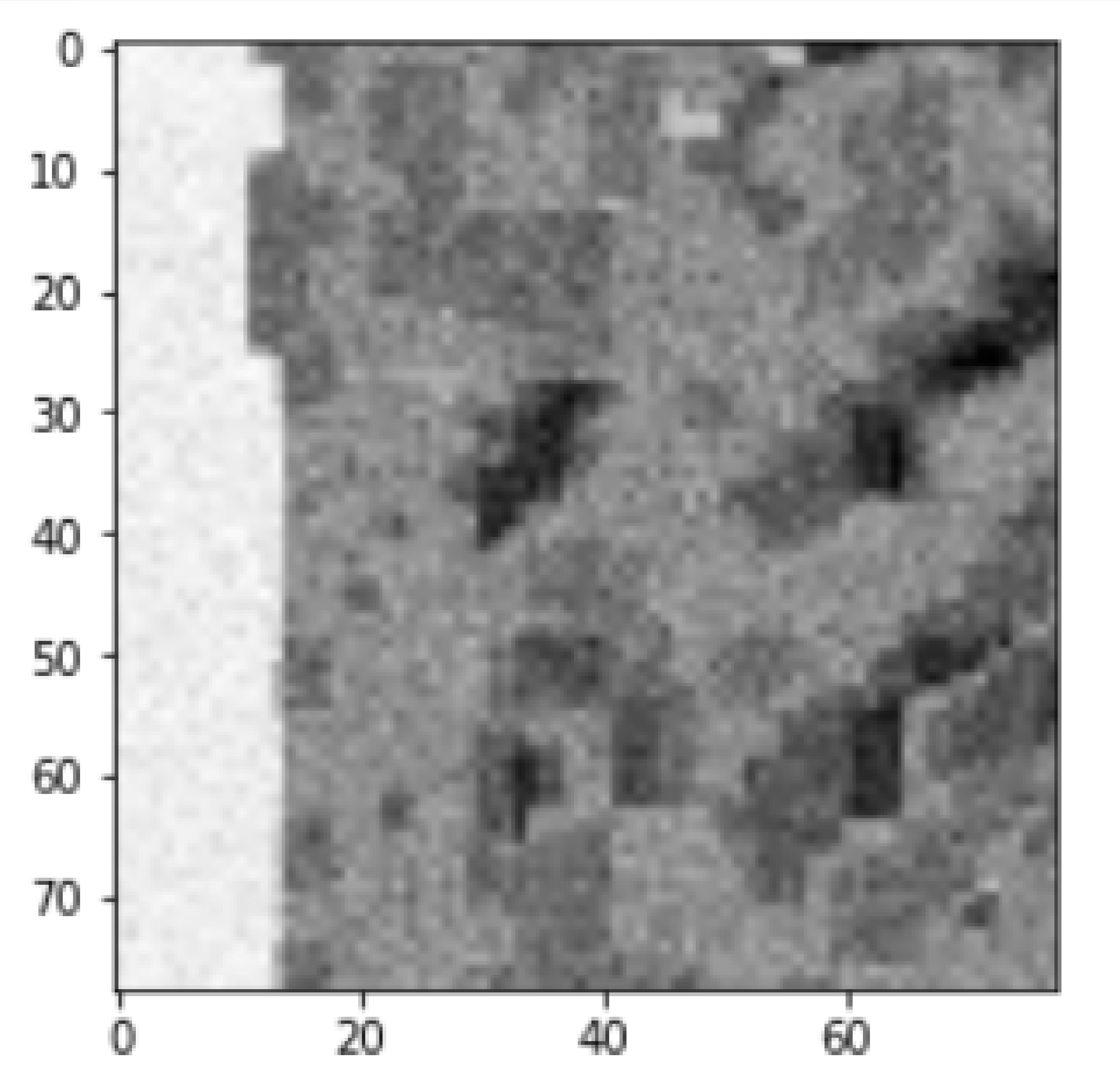
RBM 2

DBN MODEL (DATASET)

Original Input



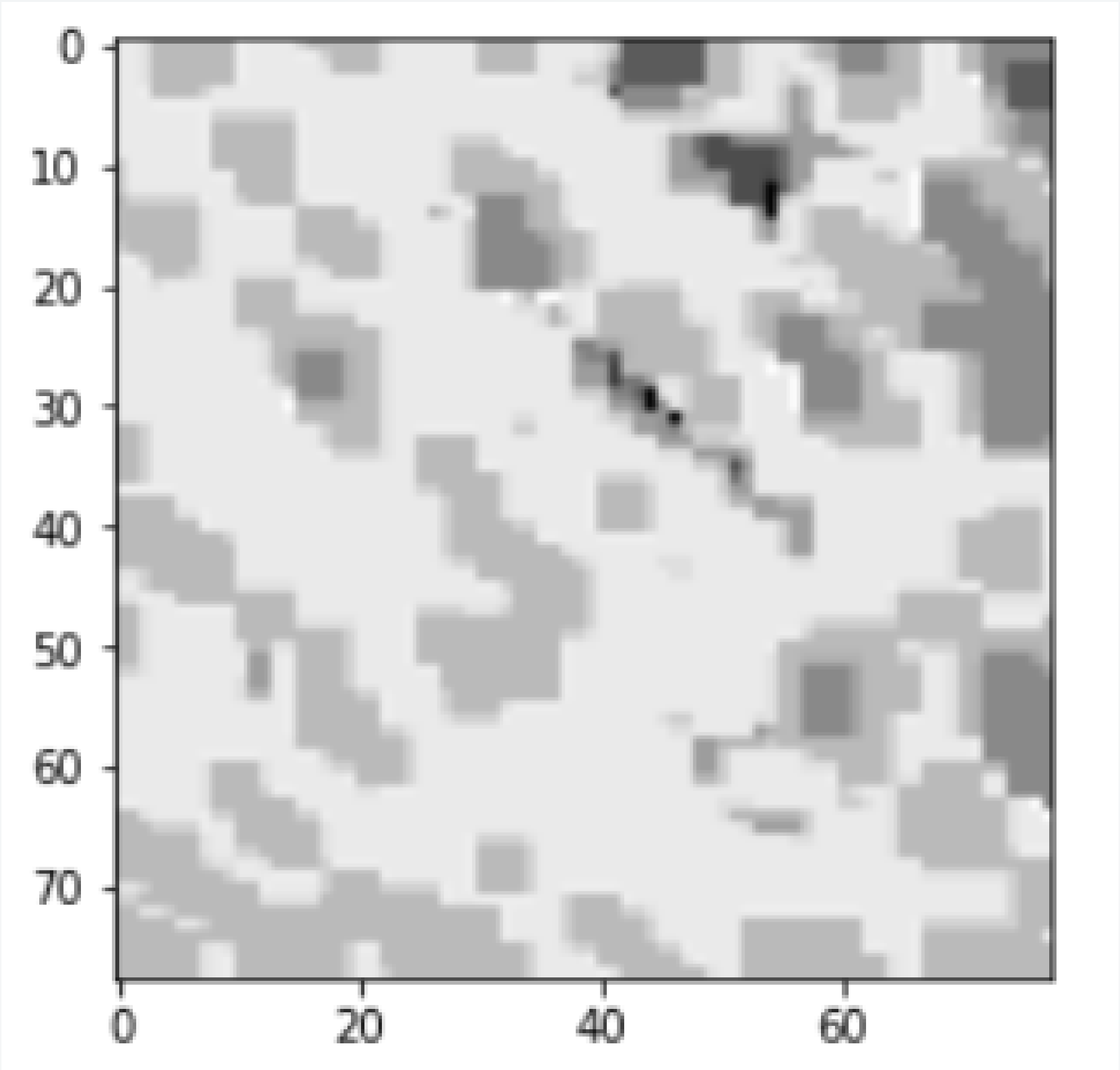
Reconstructed Input



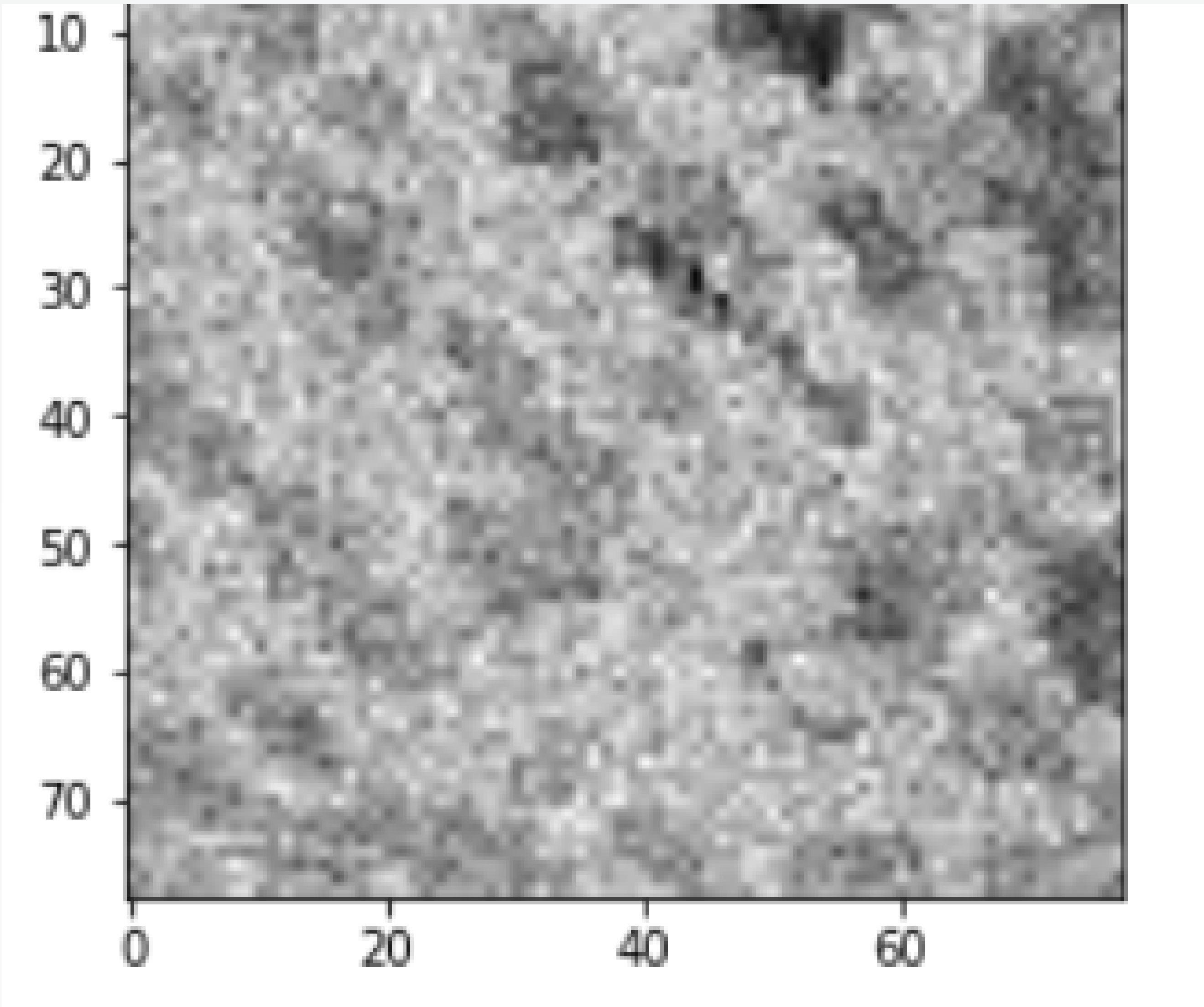
MEAN SQUARED ERROR (MSE): 0.004013116905838251
STRUCTURAL SIMILARITY INDEX (SSIM): 0.9968641291328348

DBN MODEL (DATASET)

Original Input



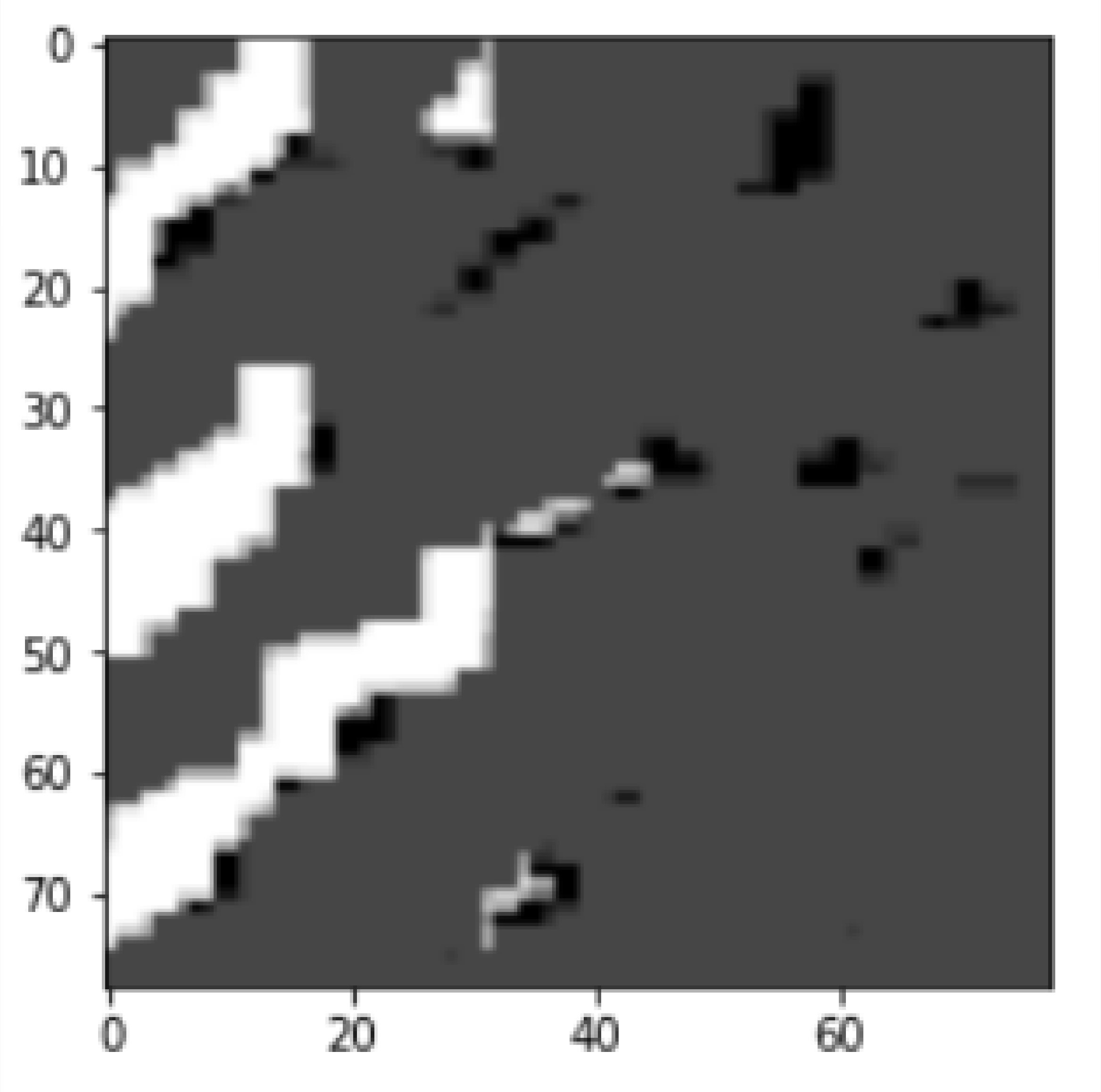
Reconstructed Input



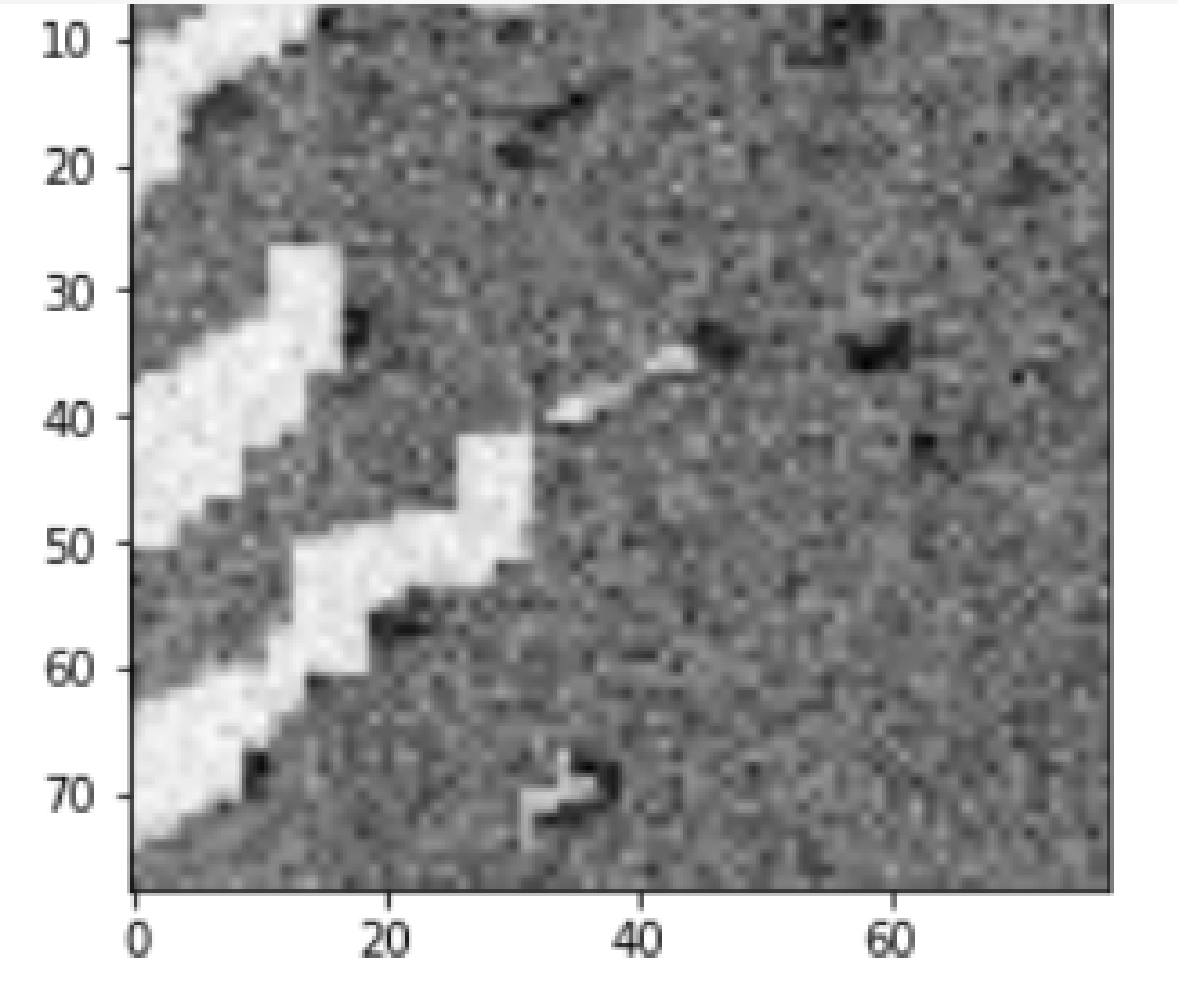
OMEAN SQUARED ERROR (MSE): 0.0030524018220603466
STRUCTURAL SIMILARITY INDEX (SSIM): 0.9998158261826956

DBN MODEL (DATASET)

Original Input

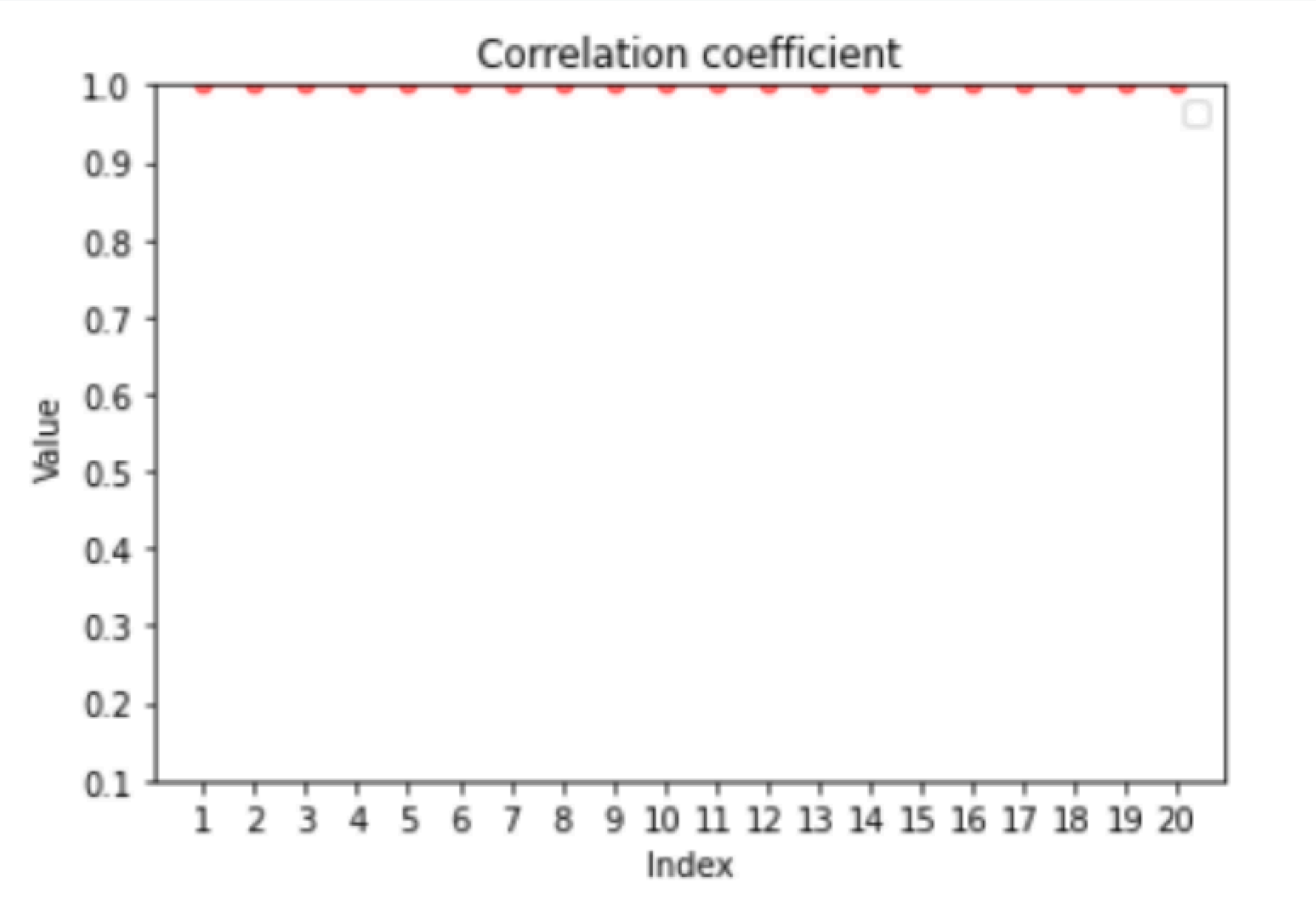


Reconstructed Input



MEAN SQUARED ERROR (MSE): 0.0004100725054740906
STRUCTURAL SIMILARITY INDEX (SSIM): 0.99047194958828585

DBN MODEL (DATASET)



CORRELATION INDEX
FOR ENTIRE DATASET

FURTHER WORKS

- MODEL OPTIMIZATION TO REDUCE THESPREAD IN SSI
- ADDITION OF SOFTMAX LAYER TO ENABLE THE MODEL TO CATEGORIZE THE ADDITIVELY MANUFACTURED PRODUCTS
- IMPROVEMENT OF ACCRUACY
- FINAL REPORT

DBN CLASIFICATION MODEL

Dataset 1:
Train dataset size: 80 Images
Test dataset size: 20 Images
Accuracy of the network on training 80 images: 70 %

Dataset 2:
Train dataset size: 160 Images
Test dataset size: 40 Images
Accuracy of the network on the 80 training images: 71 %

Dataset 3:
Train dataset size: 800 Images
Test dataset size: 200 Images
Accuracy of the network on training 80 images: 75 %

Dataset 4:
Train dataset size: 8000 Images
Test dataset size: 2000 Images
Accuracy of the network on training 80 images: 77 %

DBN CLASIFICATION MODEL