

Historical Style Generator (*HStyle*)

Project Book

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Table of Contents

Introduction	13
System Purpose	13
Document Conventions	13
Intended Audience and Reading Suggestions	13
Terminology	13
Literature Review	16
Abstract	16
First Approach - Using Deep Learning	16
Second Approach - Using Computer Vision Methods	24
Neural Style Transfer Model - First Approach	26
Concepts and Principles	26
Content Loss	26
Style Loss	26
Gram Matrix	26
Total variation loss	27
Total loss	27
Model Architecture	27
Elements to experiment	27
Computer Vision Methods - Second Approach	28
Using Kanungo noise model	28
Binarization	28
Distance Transform	28
Probability calculation	28
Seed Threshold	29
The Model We Will Use	29
Kanungo noise model	29
Noise region	29
Noise generation	29

Software Project Management Plan (SPMP)	30
Project Organization	30
Process Model	30
Organizational Structure	30
Managerial Process	30
Management Objectives and Priorities	30
Assumptions, Dependencies, and Constraints	30
Risk Management	31
Technical Process	33
Methods, Tools and Techniques	33
Work Packages, Schedule	35
Work Packages	35
Dependencies	35
Resource Requirement	36
Schedule	36
Software Requirements Specification (SRS)	37
Overall Description	37
Product Perspective	37
Product Functions	37
User Classes and Characteristics	38
Operating Environment	38
Design and Implementation Constraints	38
User Documentation	38
Assumptions and Dependencies	38
Assumptions	38
Dependencies	39
External Interface Requirements	39
User Interfaces	39
Hardware Interfaces	39
Software Interfaces	39

Communications Interfaces	39
System Features	39
Historical document synthesis	39
Description and Priority	39
Stimulus/Response Sequences	40
Functional Requirements	40
About	41
Description and Priority	41
Stimulus/Response Sequences	41
Functional Requirements	41
Other Non-functional Requirements	42
Performance Requirements	42
Safety Requirements	42
Security Requirements	42
Software Quality Attributes	42
Results	43
Original content image	43
Dilate content image	43
Binary content image	44
Binary-dilated content image	44
Average historical pixels background for content image	45
Average historical pixels background for dilated content image	45
Average historical pixels background for binary content image	46
Average historical pixels background for binary-dilated content image	46
Evaluation	47
Results for image readability	47
Result for image historical look:	48
Conclusion	48
References	49
Appendix A - Experiments Analysis	51

Fast arbitrary image style transfer	51
Experiment 1	51
Content Input	51
Style Input	51
Results	51
Discussion	52
Experiment 2	52
Content Input	52
Style Input	52
Results	52
Discussion	52
Neural Style Transfer	53
Content layers	53
Style layers	57
Weights	57
Experiment 1	58
Content Input	58
Style Input	58
Results	58
Weight 0	59
Weight 1	60
Weight 2	61
Weight 3	62
Weight 4	63
Weight 5	64
Weight 6	65
Weight 7	66
Weight 8	67
Experiment 2	68
Content Input	68
Style Input	68

Results	68
Weight 0	69
Weight 1	70
Weight 2	71
Weight 3	72
Weight 4	73
Weight 5	74
Weight 6	75
Weight 7	76
Weight 8	77
Experiment 3	78
Content Input	78
Style Input	78
Results	78
Weight 0	79
Weight 1	80
Weight 2	81
Weight 3	82
Weight 4	83
Weight 5	84
Weight 6	85
Weight 7	86
Weight 8	87
Experiment 4	88
Content Input	88
Style Input	88
Results	88
Weight 0	89
Weight 1	90
Weight 2	91
Weight 3	92

Weight 4	93
Weight 5	94
Weight 6	95
Weight 7	96
Weight 8	97
Experiment 5	98
Content Input	98
Style Input	98
Results	98
Weight 0	99
Weight 1	100
Weight 2	101
Weight 3	102
Weight 4	103
Weight 5	104
Weight 6	105
Weight 7	106
Weight 8	107
Experiment 6	108
Content Input	108
Style Input	108
Results	108
Weight 0	108
Weight 1	1
Weight 2	111
Weight 3	111
Weight 4	112
Weight 5	113
Weight 6	114
Weight 7	116
Weight 8	117

Experiment 7	118
Content Input	118
Style Input	118
Results	118
Weight 0	118
Weight 1	120
Weight 2	121
Weight 3	122
Weight 4	123
Weight 5	124
Weight 6	125
Weight 7	126
Weight 8	127
Experiment 8	128
Content Input	128
Style Input	128
Results	128
Weight 0	129
Weight 1	130
Weight 2	131
Weight 3	132
Weight 4	133
Weight 5	134
Weight 6	135
Weight 7	136
Weight 8	137
Experiment 9	138
Content Input	138
Style Input	138
Results	138
Weight 0	138

Weight 1	140
Weight 2	141
Weight 3	142
Weight 4	143
Weight 5	144
Weight 6	145
Weight 7	146
Weight 8	147
Experiment 10	148
Content Input	148
Style Input	148
Results	148
Weight 0	148
Weight 1	150
Weight 2	151
Weight 3	152
Weight 4	153
Weight 5	154
Weight 6	155
Weight 7	156
Weight 8	157
Experiment 11	158
Content Input	158
Style Input	158
Results	158
Weight 0	158
Weight 1	160
Weight 2	161
Weight 3	162
Weight 4	163
Weight 5	164

Weight 6	165
Weight 7	166
Weight 8	167
Experiment 12	168
Content Input	168
Style Input	168
Results	168
Weight 0	168
Weight 1	170
Weight 2	171
Weight 3	172
Weight 4	173
Weight 5	174
Weight 6	175
Weight 7	176
Weight 8	177
Experiment 13	178
Content Input	178
Style Input	178
Results	178
Weight 0	178
Weight 1	180
Weight 2	181
Weight 3	182
Weight 4	183
Weight 5	184
Weight 6	185
Weight 7	186
Weight 8	187
Experiment 14	188
Content Input	188

Style Input	188
Results	188
Weight 0	188
Weight 1	190
Weight 2	191
Weight 3	192
Weight 4	193
Weight 5	194
Weight 6	195
Weight 7	196
Weight 8	197
Experiment 15	198
Content Input	198
Style Input	198
Results	198
Weight 0	198
Weight 1	200
Weight 2	201
Weight 3	202
Weight 4	203
Weight 5	203
Weight 6	204
Weight 7	205
Weight 8	206
Experiment 16	208
Content Input	208
Style Input	208
Results	208
Weight 0	208
Weight 1	1
Weight 2	211

Weight 3	212
Weight 4	212
Weight 5	213
Weight 6	214
Weight 7	215
Weight 8	216
Appendix B - Project Data	218
English Data	218
Modern English	218
Cropping	218
Hebrew Data	218
Modern Hebrew	218
Changing Type	218
Rotating	218
Cropping	218
Trehoulding	218
Cairo Geniza Historical Hebrew	218
Middle Ages Historical Hebrew	218
Arabic Data	218
Modern Arab	218
Changing Type	218
Historical Arab	218
Latin Data	219
Historical Latin	219

Introduction

1. System Purpose

Historical documents can reveal a lot of information, such as form of writing, wording, content that did not exist and more. Since those documents are usually written in diaries, pages or letters that have a final lifespan, there are certain periods that lack historical documents. The lack of data restricts us from using the power of deep learning and machine learning models, because most of these models require a large amount of data (big data).

HStyle lets users synthesize a historical document. What does this mean? Given two documents, one is a historical document (the style), and the other is a modern document (the content), *HStyle* will transfer the style from the historical document to the modern document. This system is based on a deep learning model and computer vision techniques and will be a web based application.

2. Document Conventions

This document uses the following conventions:

- Important terms and headings will be marked in **bold**.
- Heading one, Heading two, Heading Three, Heading Four, Normal text will correspond to these font sizes: 16, 14, 13, 12, 11.
- System name will be marked in *italic*.

3. Intended Audience and Reading Suggestions

HStyle is a web based application for the historical style document synthesis. *HStyle* is implemented under the guidance of college advisors. This system is useful for any user who wishes to synthesize new documents with historical style.

Anyone with some programming experience and familiarity in Python, can understand this document. The document is intended for developers, software architects, testers, project managers and documentation writers.

4. Terminology

User	Any human being who is interacting with the software is a user
System	The package of all the components which takes input and gives output to demonstrate the features of the software is called a system
Machine Learning	Machine Learning(ML), is the field of study that gives computers the capability to learn without being explicitly programmed
Deep Learning	Deep Learning(DL), is a subfield of ML concerned with algorithms inspired by the structure and function of the brain called artificial neural networks

Computer Vision	Computer Vision (CV), Computer vision is an interdisciplinary scientific field that deals with how computers can gain high-level understanding from digital images or videos
Big Data	Big Data is a collection of data that is huge in volume, yet growing exponentially with time
Python	Python is an interpreted, high-level and general-purpose programming language
convolutional neural network	convolutional neural network (CNN) is a class of deep neural networks, most commonly applied to analyzing visual imagery
VGG16	VGG-16 is a convolutional neural network that is 16 layers deep
VGG19	VGG-19 is a convolutional neural network that is 19 layers deep
Generative adversarial network	Generative adversarial network(GAN) is a machine learning model in which two neural networks compete with each other to become more accurate in their predictions
SC-GAN	Type of GA called self-attention conditional GAN.
AdaIN	Adaptive Instance Normalization (AdaIN) is a normalization method that aligns the mean and variance of the content features with those of the style features
Gram Matrix	In linear algebra, the Gram matrix of a set of vectors in an inner product space is the Hermitian matrix of inner products, whose entries are given by
Activation layer	The activation function is a mathematical “gate” in between the input feeding the current neuron and its output going to the next layer
LSTM	Long short-term memory (LSTM) is an artificial recurrent neural network architecture used in the field of deep learning
StyleGAN	StyleGAN is a type of generative adversarial network
Neural Style Transfer	Neural Style Transfer (NST) refers to a class of software algorithms that manipulate digital images, or videos, in order to adopt the appearance or visual style of another image
CycleGan	The CycleGAN is a technique that involves the automatic training of image-to-image translation models without paired examples
Content image	Image representing content
Style image	Image representing style
Binary image	A binary image is one that consists of pixels that can have one of exactly two colors, usually black and white
Degradation	The condition or process of degrading or being degraded
Euclidean distance	In mathematics, the Euclidean distance between two points
Gradient descent	Gradient descent is a first-order iterative optimization algorithm for finding a local minimum of a differentiable function

Epoch	An epoch is a term used in machine learning and indicates the number of passes of the entire training dataset the machine learning algorithm has completed
Angular	Angular is a platform for building mobile and desktop web applications
Hypertext Markup Language	Hypertext Markup Language (HTML) is the standard markup language for documents designed to be displayed in a web browser
Cascading Style Sheets	Cascading Style Sheets is a style sheet language used for describing the presentation of a document written in a markup language such as HTML
JavaScript	JavaScript, often abbreviated as JS, is a programming language that conforms to the ECMAScript specification
TypeScript	TypeScript is a programming language developed and maintained by Microsoft
FastAPI	FastAPI is a modern, fast (high-performance), web framework for building APIs with Python 3.6+ based on standard Python type hints
RESTful API	A RESTful API is an architectural style for an application program interface (API) that uses HTTP requests to access and use data
Uvicorn	Uvicorn is a lightning-fast ASGI server implementation, using uvloop and http tools
Tensorflow	An end-to-end open source machine learning platform for everyone
OpenCV	OpenCV is a library of programming functions mainly aimed at real-time computer vision

Literature Review

1. Abstract

Historical documents can reveal a lot of information, such as form of writing, wording, content that did not exist and more. Since those documents are usually written in diaries, pages or letters that have a final lifespan, there are certain periods that lack historical documents. The lack of data restricts us from using the power of deep learning and machine learning models, because most of these models require a large amount of data (big data). In this study we want to test whether it is possible to synthesize historical documents using two sources: a historical document (as a style) and an image of modern handwritten text (as a content).

2. First Approach - Using Deep Learning

Transferring the style from one image into another can be considered a problem of texture transfer. In texture transfer the goal is to synthesize a texture from a source image while constraining the texture synthesis to preserve the semantic content of a target image.

In the papers of Gatys et.al. [1] and [2], the researchers discovered a new technique for texture synthesis, an artificial system based on a deep neural network that creates artistic images of high perceptual quality. In those studies, the researchers used a CNN (Convolutional Neural Network) called VGG19 from the Caffe deep learning framework explained in [3] which is known as a deep network to classify images. The researchers used the output of the middle layers in the CNN network to extract the representation of the images. In each layer a representation of the image is created, and it is possible by rebuilding this representation to see the content obtained from this layer and take the output from the layer in which the representation of content and style is ideal.

As you can see in Figure 1 the researchers found that in the first layers the output of the layers is almost identical to the original image, while the content is in the higher layers (deeper in the neural network).

In addition, the researchers found that the style of an image can be described by the means and correlations across the different feature maps. Therefore, they calculate a Gram matrix that includes this information by taking the outer product of the feature vector with itself at each location and averaging that outer product over all locations.

To connect the content representation and the style representation, the researchers create a new image that matches the two representations while reducing the distance and loss of information until reaching an acceptable threshold.

In this study, the researchers were able to come to the understanding that there is a clear separation between content and style and that images can be combined to produce a synthesis of a particular style on a source image, as can be seen in Figure 1.

In addition, the researchers came to the understanding that there is a trade-off between content and style, which means that coefficients can and should give more importance to the content of the image or the style of the image in order to achieve desired results.

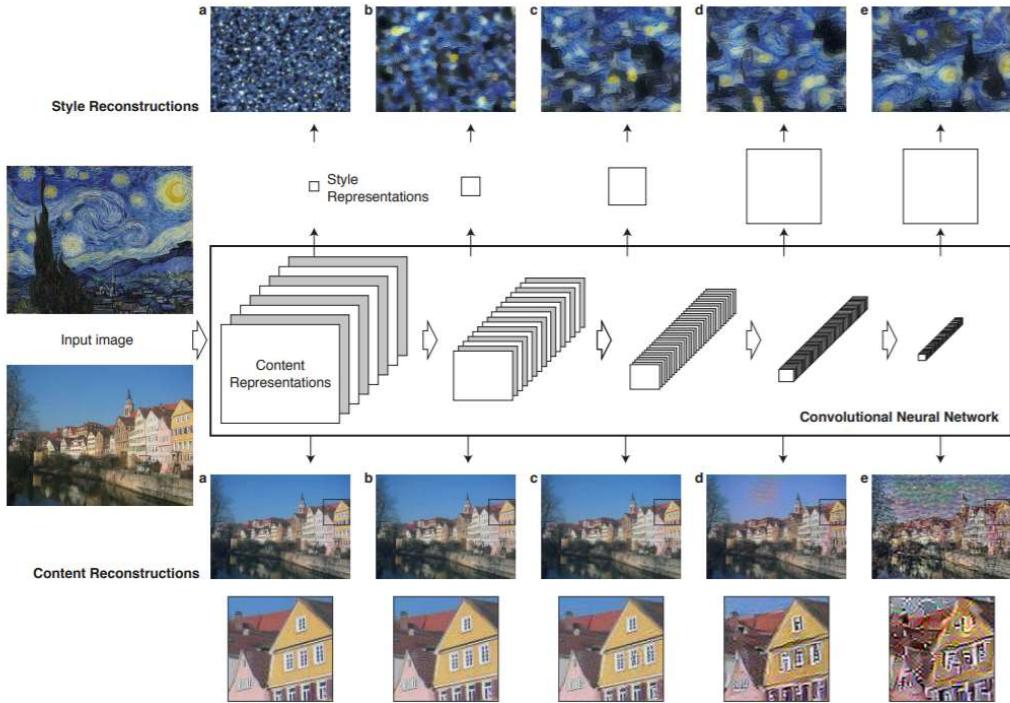


Figure 1 – Taken from “Image Style Transfer Using Convolutional Neural Networks”. The Figure shows the content and style in the VGG network.

Based on Gatys et.al papers [1] [2], a few papers were released about image style transfer, some of these papers use the original VGG19 architecture and some use additional techniques or models.

In the paper of Ter-Sarkisov [4] the researcher tries to transfer style from the logos of heavy metal bands onto corporate logos using a VGG16 network.

The researcher used the VGG16 CNN architecture to extract style and content. Like the original paper [2], in this research he used the same technique to extract the style from heavy metal bands logos and apply them onto corporates logos technique (they performed experiments trying to find which layers are best for extracting content and style).

It was found that there is a significant trade-off between content and style in order to maintain the logo readable. Since the researcher only wanted to transfer the font style, he suggests that this model is not suitable for this mission and that maybe it needs to be approached in a different way. Some of his results are visible in Figure 2.

	amazon		Microsoft
MEGADETH	amazon		Microsoft
MANOWAR	amazon		Microsoft
	amazon		Microsoft
DOOM	amazon		Microsoft
	amazon		Microsoft

Figure 2 – Taken from “Network of Steel: Neural Font Style Transfer from Heavy Metal to Corporate Logos”. The Figure shows the company logos with metal bands style.

Although Ter-Sarkisov [4] says this technique is not the best for the text, in the paper of Atarsaikhan et.al. [9] the researchers generate fonts by using neural style transfer. The VGG16 model was used to extract and determine the content representation of a source image and feature maps of a style image to synthesize them together. It was found that α (the coefficient of content representation) should be bigger than β (the coefficient of style representation) in order to give the content more importance. The researchers showed that it is possible to generate readable fonts using neural network approach. They observed that font style can only be transferable if style images contain multiple characters. Also, the researchers managed to transfer a non-font style to sources like icons and graphs. In addition, they found that if the difference between source and style is large the result characters will be illegible. Some of their results are illustrated in Figure 3.

	Arabic	Japanese	Korean	Cyrillic
Style Images	مرحبا أنا الكورية حاللغة اليابانية عيشفياليا باهذا هياللغة يتحدث هاكثير من الناس	あいうえお かきくけこ 日本漢字 変換文字	안녕하세요 저는한국어 입니다나는 일본어를좋	МОНГОЛ ФЦЖЬШ ЙЫБӨАЛ ДПЯЧЁЮ
Content Image	ABCDEF HIJKLM OPQRST UVWXYZ	ABCDEF HIJKLM OPQRST UVWXYZ	ABCDEF HIJKLM OPQRST UVWXYZ	ABCDEF HIJKLM OPQRST UVWXYZ
Results	ABCDEF HIJKLM OPQRST UVWXYZ	ABCDEF HIJKLM OPQRST UVWXYZ	ABCDEF HIJKLM OPQRST UVWXYZ	ABCDEF HIJKLM OPQRST UVWXYZ

Figure 3 – Taken from “Neural Font Style Transfer”. The Figure shows the results of transferring style to content image from English content and foreign languages.

The works of Ter-Sarkisov [4] and Atarsaikhan et.al. [5] study the style transfer on isolated words and letters and not full sentences or documents. In addition, they focus on font transformation and not the background and paper style that is very important in the field of historical documents. In the paper of Gomez et.al. [6], the researchers suggest a new architecture that learns the features that encode a certain text style and can transfer them to other text instances while preserving their content. In addition, they built a model that transfers style to only desired image pixels. The researchers used a VGG16 model for style transfer and two different models for selective style transfer (transfer style to only desired image pixels).

They found out that the style transfer model is able to learn text styles as the characters shapes, line style, and colors, and to transfer it to an input text preserving the original characters. Some of their results shown in Figure 4 and Figure 5.

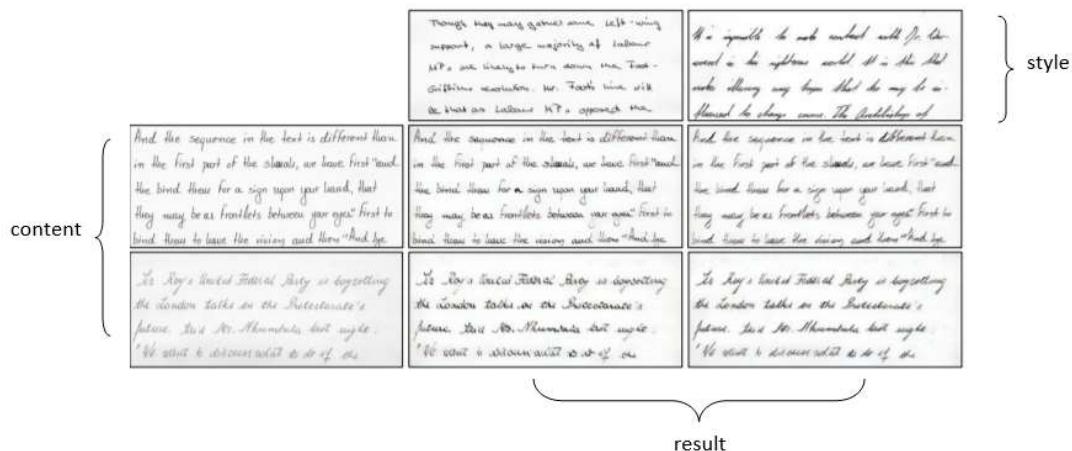


Figure 4 – Taken from “Selective Style Transfer for Text”. The Figure shows the result of their model to transfer content with given style.

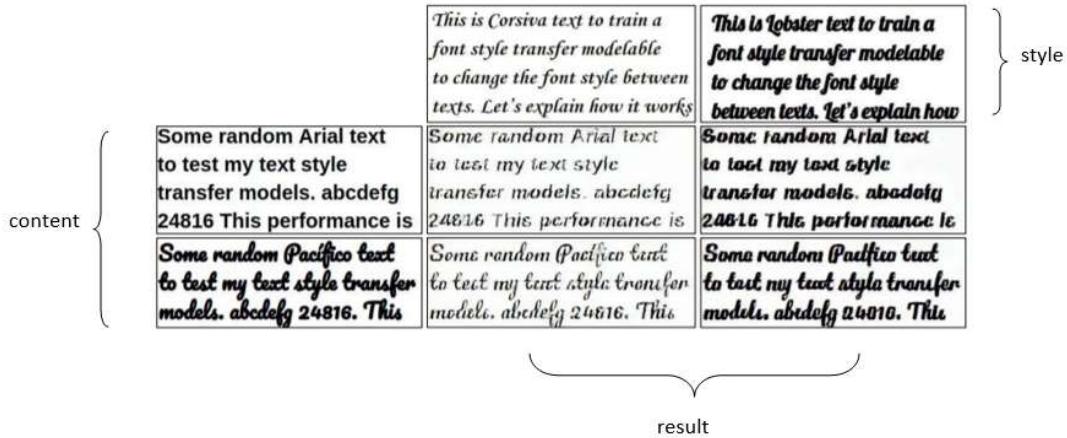


Figure 5 – Taken from “Selective Style Transfer for Text”. The Figure shows the result of their model to transfer content with given style.

Some researchers combined the original model architecture with VGG19 with other techniques, like in the paper of Guan et.al. [7]. The work proposes a style conditioned generative adversarial network (SC-GAN). This network is used to transfer the styles of real handwriting images to skeleton images extracted from handwriting samples to generate photo-realistic text line images. In their paper the researchers used a VGG19 model to extract content and style from given images. First, given a content image they create a skeleton image. Then the skeleton and style image are given to a VGG19 model and combined after that by a generator that uses AdalN and a discriminator GAN model. In this paper the researchers showed that they can create synthetic images, whose styles look quite similar with the corresponding style images. Some of their results are presented in Figure 6.

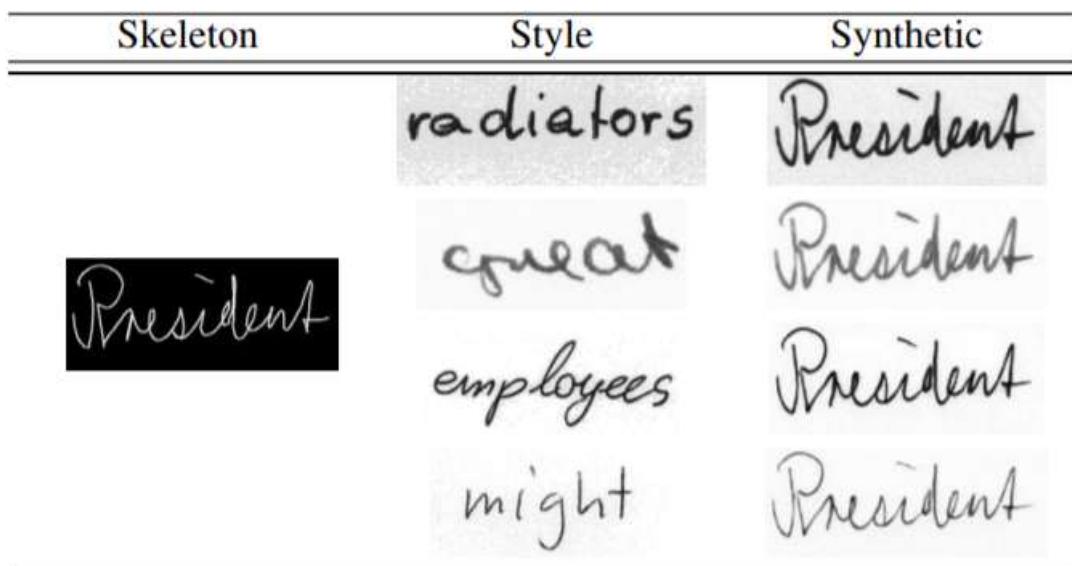


Figure 6 – Taken from “Improving Handwritten OCR with Augmented Text Line Images Synthesized from Online Handwriting Samples by Style-Conditioned GAN”. The Figure shows the results of transferring style to skeleton image.

Another example is the paper of Kang et.al. [8]. The researchers suggest a generator aimed at transferring writing style features from one sample to another in an

image-to-image translation approach.

Given a pair of handwritten word images (Loading..., Loading...), the proposed module extracts content and style using the VGG19 model, and then combined by another model to generate a new handwritten word image. To combine the content and style, instead of using Gram matrix, they used a generator model that consists of two residual blocks with AdaIN normalization layers followed by four convolutional modules with nearest neighbor up-sampling, and a final tanh activation layer. Some of their results are illustrated in Figure 7, and as we can see from it, the researchers managed to combine style and content to a new image.

	pair 1	pair 2	pair 3	pair 4	pair 5	pair 6	pair 7	pair 8
Input	x_i he the wither could and this would teach	x_j in give replied He darling had They not						
content and style output	\bar{x}_{ii} he the wither could and this would teach	\bar{x}_{ij} he the wither could and His would teach	\bar{x}_{ji} in give replied the darling had They not	\bar{x}_{jj} in give replied the darling had They not				

Figure 7 – Taken from “Distilling Content from Style for Handwritten Word Recognition”.

The Figure shows the results of transferring style to content given style and content image.

Similar to Guan et.al. [7] and Kang et.al. [8], in the paper of Liu et.al. [9] the researchers propose a word image generating method called Synth-Text Transfer Network (STN). They use an Encoder-AdaIN-Decoder architecture, where the encoder is a pre-trained VGG-19 with first few layers fixed in order to encode both content and style images. The decoder is learned to invert the AdaIN output to the image spaces. The AdaIN layer is used to conduct style transfer in the feature space. Then, they compute the content loss and the style loss by using the same VGG encoder. The researchers found that AdaIN is the most proper module for arbitrary style transfer. However, they mentioned that their method has limitations in the case where the style image has complicated background texture or uncommon font. Some of their results are shown in Figure 8.

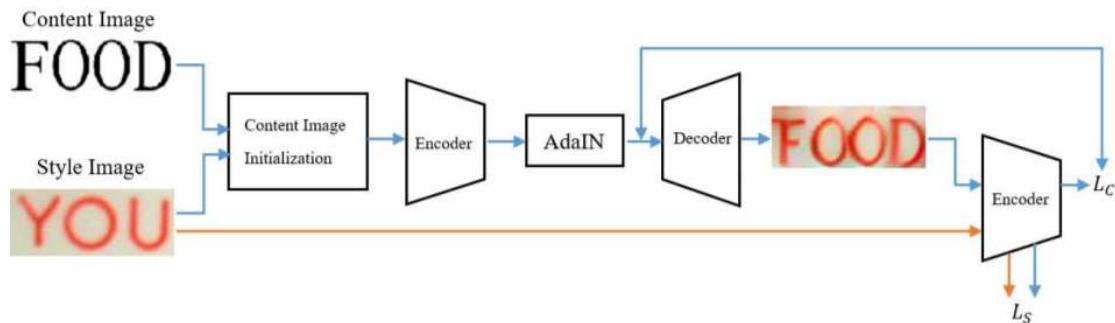


Figure 8 – Taken from “Synthesizing Scene Text Images for Recognition”. The Figure shows the Encoder-AdaIN-Decoder architecture of the proposed method.

In addition, there are different attempts to transfer image style in writing with different models and techniques.

For example, in the paper of Mayr et.al. [10] the researchers present a method for online handwriting synthesis, given a handwritten sample they produce a new style-adapted realistic-looking text.

In this paper the researchers tested their model on words and sentences. In order to extract the content they use Graves' algorithm (LSTM), and in order to extract the style and combine it with the content they used the pix2pix generator network. To conclude, the researchers managed to create a fully automatic method to imitate handwriting using spatial-temporal style transfer. Some of their results are shown in Figure 9.

Input	You have killed my love. You used to	You have killed my love. you used to stir my
input style combined with content	If we desire to avoid insult we must be able to repel it If we desire to secure peace one of the most powerful	I we desire to · avoid insult we must · be able to repel · it if we desire · to secure peace one · of the most powerful

Figure 9 – Taken from “Spatio-Temporal Handwriting Imitation”. The Figure shows the results of transferring input handwriting style to different texts.

Another example is the paper of Davis et.al. [11]. The researchers present a GAN for generating images of handwritten lines conditioned on arbitrary text and style vectors. Given three inputs, content, style and noise, the model generates handwriting. The researchers used a big and complex model made of six models in order to get the final result: (1) A generator network G to produce images from spaced text, a style vector and noise-based on StyleGAN; (2) A style extractor network S, that produces a style vector from an image and the recognition predictions; (3) A spacing network C, which predicts the horizontal text spacing based on the style vector; (4) A patch-based convolutional discriminator D; (5) A pretrained handwriting recognition network R to encourage image legibility and correct content; (6) A pre-trained encoder E, to compute a perceptual loss. This method has presented a system capable of directly generating the pixels of a handwriting image of arbitrary length. Their model can extract a style from example images and their method does well at capturing the variations of global style in handwriting, such as slant and size. Some of their results are illustrated in Figure 10.

down William Appleton	gazed at recently; and I have
down William Appleton	gazed at recently; and I have
Variable image length	Direct pixel prediction

Figure 10 – Taken from “Text and Style Conditioned GAN for Generation of Offline Handwriting Lines”. The Figure shows the results of mimicking two authors style, top sentence is the original author writing bottom is generated sentence.

All the mentioned papers (NST and GAN) focus more on the font transfer of the writing and less on the style of the document and the other aspects of the document. In addition, none of the papers try to implement the transfer on a full document image.

In the paper of Pondenkandath et.al. [12] the researchers apply document style transfer on historical documents. They use two models and compare results between them. The first model is GAN (cycleGAN) and the second model is VGG-19 CNN. The main motivation of this research is to generate massive synthetic datasets of "historical" documents which can be used for the training of document analysis systems. The researchers found that the synthetic images generated by the cycleGAN appear significantly better than those generated with NST. The researchers notice many similarities between the target domain samples and the synthetic samples. The overall style content of the target domain is well expressed. However, in a structural content point of view the initials are not well detected and expressed. The two column-mode is not at all expressed. When considering the synthetic documents produced with the NST, the structural content is better preserved. However, the style is mixed and standardized over the entire synthetic document, leading to the presence of a lot of colored artifacts. Also, the font does not change as compared to the synthetic images generated by the GAN. Some of their results are shown in Figure 11.



Figure 11 – Taken from “Historical Document Synthesis with Generative”. The Figure shows the source transform given target with cycleGAN and NST.

As we can see there are various researches dealing with synthesizing writing/fonts from style image into content image. These studies are a great base for our research, but are missing a few aspects of what we want to investigate. Most of the discussed above

work/deal with words/sentences/short paragraphs but not with *full* document images. In addition, all these papers do not consider the background/paper style to be part of the wanted style to transfer and they work with grey/binary images. The only paper that tries to create a full document is the paper of Pondenkandath et.al. [12], but this work is tested only on Latin languages and focuses more about the font and less about the style of the document. In our project, the goal is to transfer historical style (color, degradation of document and more features). In addition, we want to explore this transformation with the original simple model using VGG19 and not using GAN, transformers, and complex models.

To conclude, from the researches available today it seems our research is possible. We will want to answer a few questions in our research. Our main research question is (1) “Is it possible to transfer style from a full historical document image to a modern document image by using the simple image transfer style model?”. Additional questions we would like to explore (2) “What is the ratio/trade-off between content and style?”, (3) “Can we perform style transfer on documents that are not written in the same language?”.

3. Second Approach - Using Computer Vision Methods

In the case that the deep learning approach will not result in good historical synthesis there are computer vision methods that can enable us to create text degredation. These degredation texts can be pasted onto historical style background images, which will create a historical synthesis document.

In the papers of Kieu et.al. [13] the researchers suggest a technique for character degradation. This technique enables the synthesis of degradation on a character. The technique includes image binarization, probabilities and computer vision methods. This technique only works on grayscale images. As you can see in Figure 12 the results of degradation of a character from Kieu et.al. [13] paper.

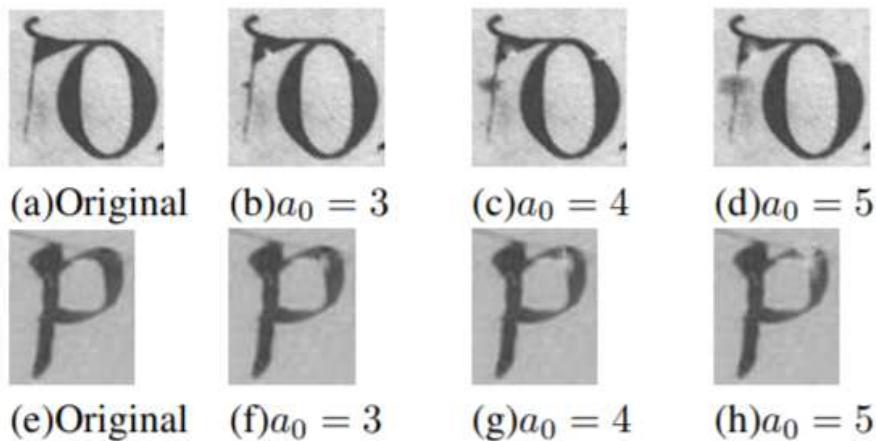
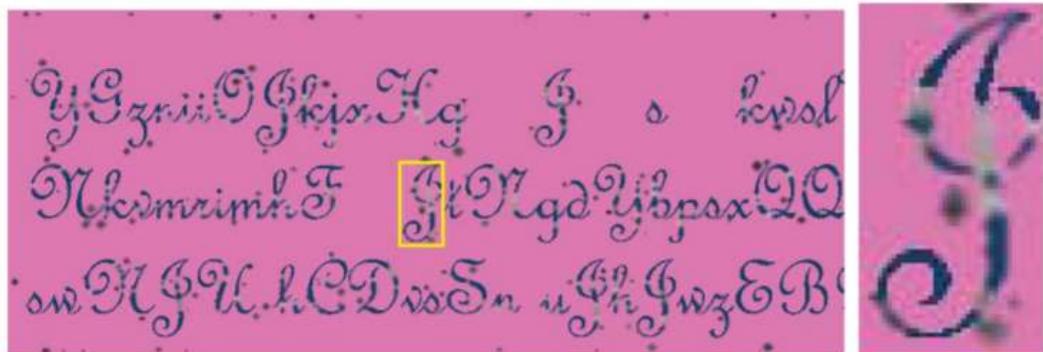


Figure 12 – Taken from “A character degradation model for grayscale ancient document images”. The Figure shows the degraded images with the seed-points fixed.

If images are color images we can use a similar technique suggested in Luyen et.al. [14] paper that works on color images. As you can see in Figure 13 the results of degradation of a color image paragraph from Luyen et.al. [14] paper.



*Figure 13 – Taken from “A Character Degradation Model for Color Document Images”.
The Figure provides the degraded image of the original one with 1616 seed-points. The
right image represents the zoomed parts of the left image.*

Neural Style Transfer Model - First Approach

Our system is based on the NST, the concepts and use is explained in this section.

1. Concepts and Principles

1.1. Content Loss

This function helps to check how similar the generated image is to the content image. It gives the measure of how far (different) are the features of the content image and target image. We will pass the network both the desired content image and our generated image. This will return the intermediate layer outputs from our model. Then we simply take the Euclidean distance between the two intermediate representations of those images. The loss equation:

$$L_{Content}^l = \sum_{i,j} (C_{i,j} - P_{i,j})^2$$

↑ ↑ ↑
Content loss Content image Generated image

1.2. Style Loss

Style Loss measures how different the generated image, in terms of style features, is from your style image. But it's not as straightforward as content loss. The style representation of an image is given by Gram Matrix. The loss equation:

$$L_{style}^l = \frac{1}{4 * N^2 * M^2} \sum_{i,j} (G_{i,j}^s - G_{i,j}^p)^2$$

↑ ↑ ↑ ↑ ↑
Style loss Generated Generated Gram Gram matrix
 Image image matrix for generated
 Dimensions Size for style image

1.3. Gram Matrix

The Gram Matrix G is the set of vectors in a matrix of dot products. To get the results, the matrix is multiplied by its transpose matrix, its equation is as follows:

$$G_{i,j}^l = \sum_k F_{i,k}^l F_{j,k}^l$$

↑ ↑ ↑
Gram Matrix Original Transpos
 Matrix Matrix e Matrix

1.4. Total variation loss

It was observed that optimization to reduce only the style and content losses led to highly pixelated and noisy outputs. To cover the same, total variation loss was introduced. The total variation loss is analogous to regularization loss. This is introduced for ensuring spatial continuity and smoothness in the generated image to avoid noisy and overly pixelated results.

1.5. Total loss

Loss function for considering all elements (content loss, style loss, variation loss). The loss equation:

$$L_{\text{total}}(i, j, k) = \alpha L_{\text{content}}(i, k) + \frac{\beta}{N} L_{\text{style}}(j, k) + \gamma L_{\text{variation}}(k)$$

The diagram illustrates the components of the total loss equation. It shows the equation $L_{\text{total}}(i, j, k) = \alpha L_{\text{content}}(i, k) + \frac{\beta}{N} L_{\text{style}}(j, k) + \gamma L_{\text{variation}}(k)$. Blue arrows point from labels on the left to specific terms or coefficients in the equation. The labels are: 'Total loss' pointing to the first term $\alpha L_{\text{content}}(i, k)$; 'Content image' pointing to the second term $\frac{\beta}{N} L_{\text{style}}(j, k)$; 'Style image' pointing to the third term $\gamma L_{\text{variation}}(k)$; 'Generated image' pointing to the fourth term $L_{\text{content}}(i, k)$; 'Content Weight' pointing to the coefficient α ; 'Number of style layers we used' pointing to the coefficient $\frac{\beta}{N}$; and 'Variation Weight' pointing to the coefficient γ .

2. Model Architecture

The NST technique is based on pre-pre-trained VGG19 DL model.

We will extract style from the next layers:

block1_conv1, block2_conv1, block3_conv1, block4_conv1, block5_conv1

And content we will test different content layers every time from these layers:

block5_conv2, block4_conv2, block3_conv4, block3_conv3, block3_conv2

Each iteration we will pass the content Image, style Image and generated image through the model and by our loss function we will apply gradient descent to our generated image to reduce loss.

The total of iteration (epochs and steps per epoch) our model will perform is 1000 total.

3. Elements to experiment

The next elements can be change and we will want to test their effect on our model result:

- ❖ α – content weight.
- ❖ β – style weight.
- ❖ γ – variation weight.

Computer Vision Methods - Second Approach

Using Kanungo noise model

A document degradation model for local distortions that are introduced during the printing, photocopying, and scanning processes.

This model is the base for our model, it helps us select the centers of the degraded region in the neighborhood of the characters.

Kanungo noise model has the following input parameters:

Loading...

Loading... - Is the constant probability of flipping for all pixels.

Loading... - Is the initial value for the exponential in the background probability equation of flipping pixel value.

Loading... - Is the decay speed of the exponential in the background probability equation of flipping pixel value.

Loading... - Is the initial value for the exponential in the foreground probability equation of flipping pixel value.

Loading... - Is the decay speed of the exponential in the foreground probability equation of flipping pixel value.

The steps in the Kanungo noise model:

1. Binarization

The first step of this model is to transform image to grayscale image and then create a binary image with a binarization method. We will use the OTSU method (same as the original paper suggests).

2. Distance Transform

The next step is to apply a distance transform method on the binary image. In order to get the distance to the closest boundary (character pixel) from each point.

3. Probability calculation

Calculate the probability for flipping each pixel in the grayscale image this means the probability the background pixel will become foreground pixel and foreground pixel will become background. The probability equation is as follows:

$$p = \begin{cases} \alpha_0 \times e^{-\alpha d^2} + \eta_1 & \text{if } P \text{ is foreground} \\ \beta_0 \times e^{-\beta d^2} + \eta_0 & \text{if } P \text{ is background} \end{cases}$$

4. Seed Threshold

We select a threshold for seed selection. Each pixel with a probability bigger or equal to threshold will be a seed for degradation.

The Model We Will Use

A local noise model for grayscale images. Its main principle is to locally degrade the image in the neighbourhoods of “seed-points” selected close to the character boundary. These points define the center of “noise regions”. The pixel values inside the noise region are modified by a Gaussian random distribution to make the final result more realistic. While Kanungo noise models scanning artifacts, our model simulates degradations due to the age of the document itself and printing/writing process such as ink splotches, white specks or streaks. The steps of this model:

1. Kanungo noise model

In order to get seed points to apply local degradation we apply the Kanungo noise model, the pixels that are flipped will be seeds (we don't need to take all of them but we will choose from them).

2. Noise region

For each seed we use to generate noise we will define a region. In this region we will apply our noise. In the original paper the used an ellipsis defined in the following way:

semi-major axis - defined as a and is equal to Loading...)
semi-minor axis - defined as b and is equal to Loading...
Loading... - is the pixel gradient value.
Loading... - is the max pixel gradient value.
Loading... - is an input parameter controlling the size of the noise regions.
Loading... - g is the flattening factor.

We will use a rectangle defined the following:

Half-diagonal - defined as a and is equal to Loading...)

3. Noise generation

For each seed we will generate gaussian noise in the defined region.
In the originale paper for each seed Loading... if its a background seed they calculated the average grayscale value of all foreground pixels and if its a foreground seed they calculated the average of all background pixels, the average is marked as Loading.... Next for each pixel Loading... on the edge of the ellipsis they calculated the average of its 8-neighbours, marked as Loading.... for each pixel on the line Loading...Loading... let's call it Loading... we will give it a normal distribution

value when Loading...is a input parameter and uLoading....

Loading... is the distance from Loading... to Loading... and Loading...is the distance from Loading... to Loading....

Software Project Management Plan (SPMP)

1. Project Organization

1.1. Process Model

The project will begin with researching for a proper technique to synthesis style. This includes preprocess, model creation and testing. After the research is done the team will create a basic web based application to show research results in an agile methodology.

1.2. Organizational Structure

Name	Role and Responsibilities
Dr. Irina Rabaev	Academic advisor, responsible for leading, assigning duties and ensuring assignments are finished on time.
Yahav Bar David	Student, responsible for development, researching and fulfilling assignments.
Leor Ariel Rose	Student, responsible for development, researching and fulfilling assignments.

2. Managerial Process

2.1. Management Objectives and Priorities

Team will have regular meetings and development processes will be consulted and accepted during these meetings.

Team Meetings - The team will meet twice weekly, once on Sunday and once on Wednesday. Each meeting will focus on planning, strategy and working collaboratively on the project.

Academic Advisor Meetings - Every two weeks on Sunday, the team will meet with their Academic advisor. The team will give a brief oral report of their progress over the last week. The team will submit any documents requiring the academic advisor's approval at these meetings. Academic advisors will consult with the process.

2.2. Assumptions, Dependencies, and Constraints

This section describes the assumptions, dependencies, and constraints that this project is based upon.

- This project will be web-based.
- Technical constraints:
 - No support for legacy browsers.

2.3. Risk Management

The goal of risk management is to identify and mitigate potential sources of expense or delay. Some risks are common to every project phase, and some risks are closely associated with a particular project phase. Risks for this project have been classified accordingly:

Common Risks:

- **Name** - Team Member Unavailability.

Description - During this project, it is almost certain that some members of the team will be unavailable for certain periods due to illness or emergency.

Probability - High

Impact - Low

Prevention - Team members will alert at the first opportunity regarding potential absences, and coordinate with other members of the team to cover their responsibilities for the duration of the absence.

- **Name** - Miscommunication.

Description - The volume of communication regarding this project almost guarantees that miscommunications will occur.

Probability - High.

Impact - Medium.

Prevention - The primary method of avoiding miscommunication is to document and verify verbal communications. For this project, the documentation and verification process will consist of meeting agendas, minutes and reports that will be shared.

- **Name** - Changes to Project Scope.

Description - Changes to project scope are a common request, but can derail project timelines.

Probability - High

Impact - High

Prevention - Every step will be defined and rethought in order to minimize changes to project scope.

Research Risks:

- **Name** - Misunderstanding of Problem Domain.

Description - There are many questions to be answered about how to apply document style transfer.

Probability - High.

Impact - High.

Prevention - Reading and expanding our knowledge and every step will be considered and advised by our academic advisor.

- **Name** - Applying Concepts and Techniques Wrongly.
Description - Document style transfer is a very complex idea and the techniques and mathematics are very confusing and hard to understand. This can cause applying these ideas wrongly.
Probability - High.
Impact - High.
Prevention - Checking and testing every step by all team members.
- **Name** - Uncompatible Resources for Research.
Description - Resources like GPU and computation power can affect the speed and the progress of the research, causing slower and inefficient research.
Probability - Medium.
Impact - Medium.
Prevention - No prevention can be applied in these circumstances.
- **Name** - Deep Learning Method Failure.
Description - Our first approach to solve this problem is with a deep learning model. This model can result in bad results.
Probability - High.
Impact - Low.
Prevention - No prevention can be applied but in case this does happen we have a plan b (our second approach).

Software Design Risks:

- **Name** - Incorrect Design.
Description - Design is the foundation of implementation, and errors in design can create an imperfect project.
Probability - High.
Impact - Medium.
Prevention - Design documents will face internal review within the team and must be approved by all team members.

Software Implementation Risks:

- **Name** - Lack of Experience with Relevant Technologies.
Description - Team members may not have experience with the technologies used in this project.
Probability - High.
Impact - Low.
Prevention - Work will be assigned according to experience with the relevant technology. Team members are encouraged to ask questions when faced with something they don't understand. Team members with experience are expected to assist less experienced members. Team members are expected to independently research technologies during the summer break.

Software Testing Risks:

- **Name** - Evaluation and Testing of model.
Description - One of the most difficult aspects in this project is how to test and evaluate the project.
Probability - High.
Impact - Low.
Prevention - Research will be done to understand various testing and evaluation techniques.

Software Delivery Risks

- **Name** - Incompatible Server Architecture.
Description - The finished web application will be dependent on a server environment chosen. Such environments vary in their support for web application programming languages and language versions. also this application will need hardware requirements relevant for this project.
Probability - High.
Impact - High.
Prevention - Document necessary requirements and validating the server contains them before deployment.

3. Technical Process

3.1. Methods, Tools and Techniques

The Methods, Tools and Techniques section aims to outline specific plans, methods, or tools to be used during the project.

Diagrams:

Team will use standard UML diagrams to represent data, relationships and requirements.

Programming Languages & Tools:

Team will utilize various programming languages and tools.

For task management:

- teamwork.

For client side development:

- Angular.
- HTML.
- CSS.
- TypeScript.
- Bootstrap
- Nginx

For server side development:

- Python.
- FastAPI.
- Uvicorn.
- Tensorflow.
- Keras.
- OpenCV.

For research:

- Google Colab

For version control:

- Github
- Google Drive

For diagrams:

- draw.io

Techniques:

- Neural Style Transfer.
- Generative Adversarial Network.
- Mathematical, Computer Vision and Deep Learning Techniques.

3.2. Software Documentation

Code will be documented inside the project by team members.

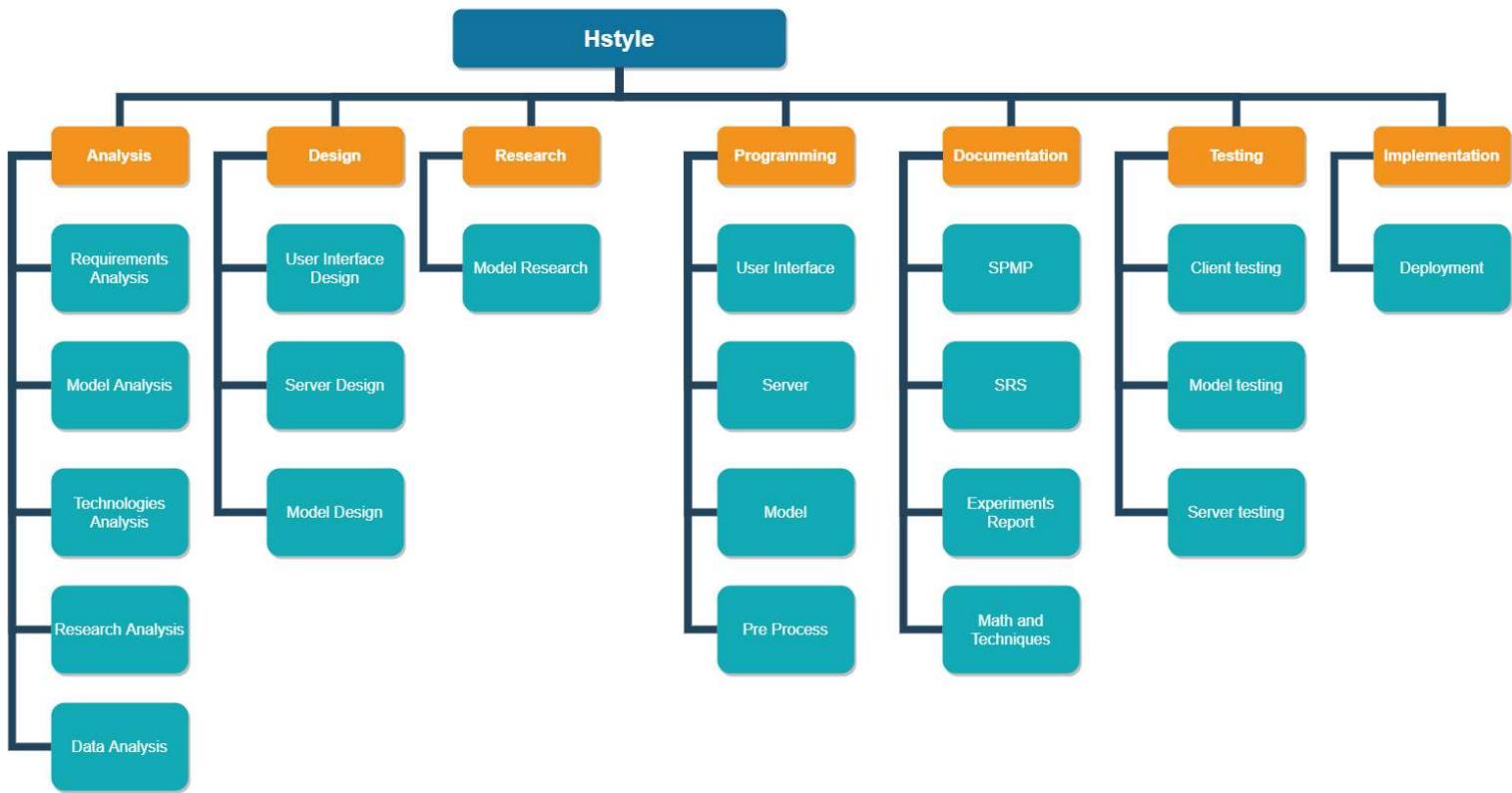
Project documentation can be found in the project's github repository (link included in document references) where every change is logged for version control. Any additional documentation will be in the project's google drive where every change is logged.

Documentation that will be included:

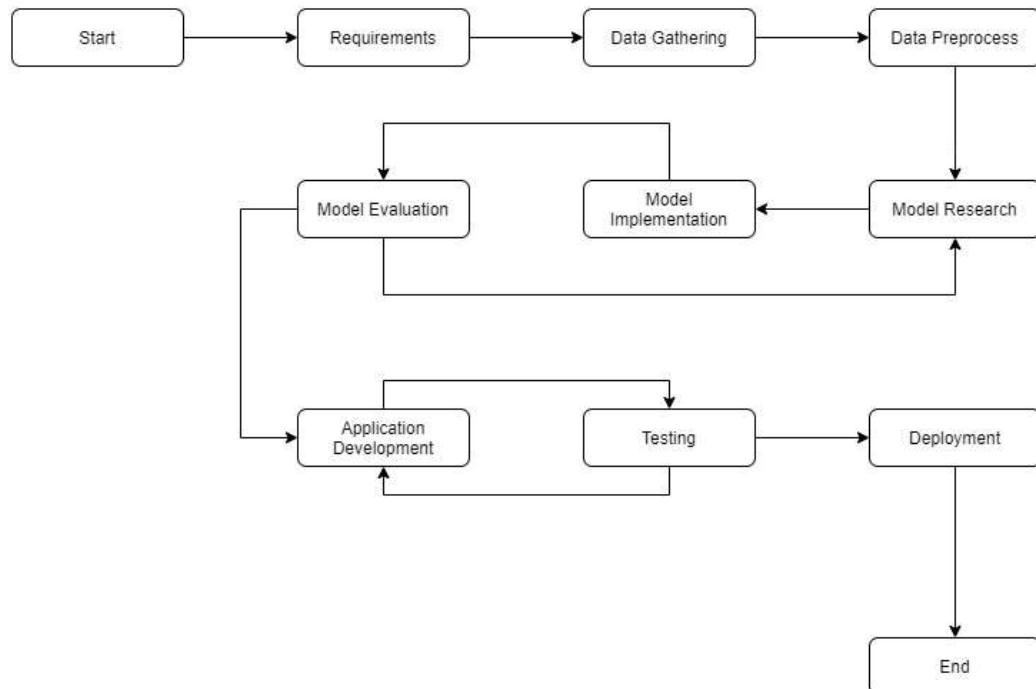
- Software Project Management Plan - Google drive.
- Software Requirements Specification - Google drive.
- Research Techniques - Google Drive.
- Deployment of project - Github.
- Project description - Github.

4. Work Packages, Schedule

4.1. Work Packages



4.2. Dependencies



4.3. Resource Requirement

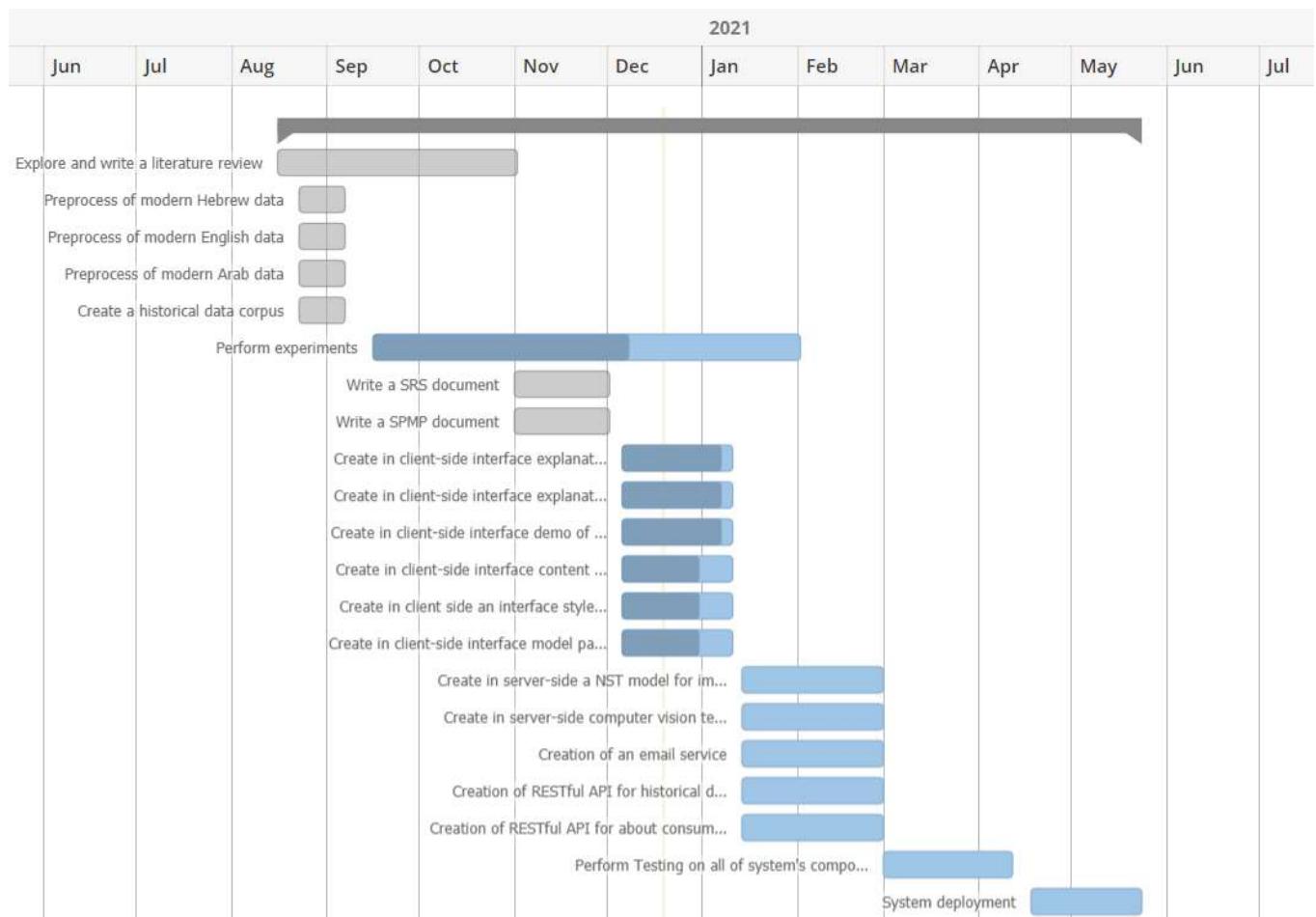
Hardware:

- Two laptops - one for each of the team members.

Software:

- Zoom for meetings.
- Google Colab for experiments.
- Google Drive for documentation and file storage.
- Server for deployment.
- teamwork application.

4.4. Schedule



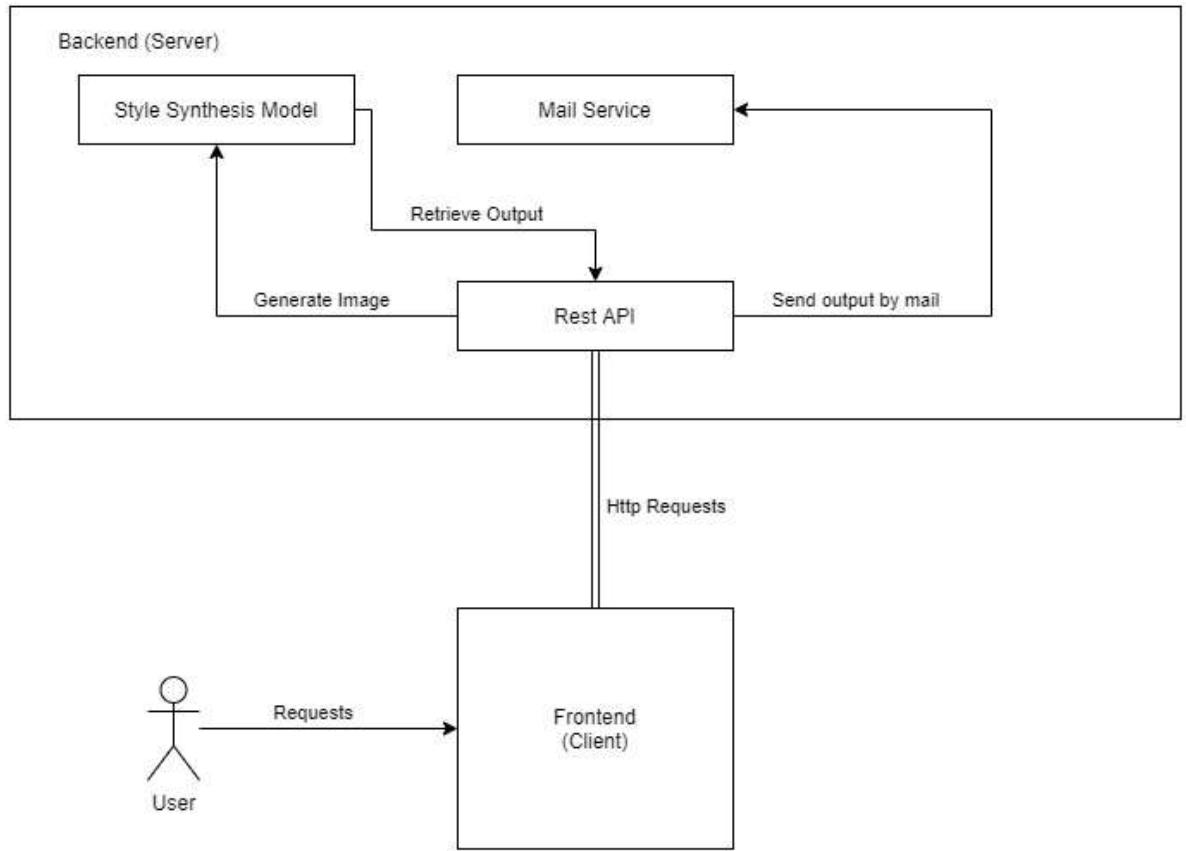
Software Requirements Specification (SRS)

1. Overall Description

1.1. Product Perspective

HStyle is a new, innovative and self-contained full stack application (client-server), with the purpose to let anyone synthesize a historical document. *HStyle* consists of following components:

High level view system diagram



1.2. Product Functions

HStyle enables the end-user to generate a historical style document from one of the appropriate inputs:

- User modern document and a historical document.
- User modern document and one of our historical documents presented in the client side.
- One of our modern documents and one of our historical documents presented on the client side.

Output will be displayed to or sent to user email (by user selection) to spare the user the waiting of the image creation.

1.3. User Classes and Characteristics

HStyle has only one type of user and it is any user that wishes to use the client side of this application to synthesize a historical document.

1.4. Operating Environment

For the user, *HStyle* will operate on the latest versions of Google Chrome, Mozilla Firefox, Microsoft Edge and Opera. Users will be able to use the application using computers and mobile devices.

For deployment, *HStyle* will need a cloud server that able to host a TensorFlow application with these requirements:

- Operating system:
 - Any OS capable of running TensorFlow models. We use a Windows 10 64 bit.
- Central processing unit:
 - Any CPU capable of running a server and TensorFlow models. We use for production an Intel I78750H (9M Cache, up to 4.10 GHz) CPU.
- Graphics processing unit:
 - Any GPU capable of running TensorFlow models. We use for production a Nvidia GeForce GTX 1050 Ti GPU.
- RAM:
 - Enough RAM capable of running a server and TensorFlow models. We use 12GB RAM for production.
- Disk Memory:
 - Enough disk space to contain the project and its runtime. We use 60GB for production.

1.5. Design and Implementation Constraints

- Heavy processing power for running deep neural networks for image style transfer.

1.6. User Documentation

No need for user documentation because *HStyle* is a web application, where all necessary actions will be explained in the application.

1.7. Assumptions and Dependencies

1.7.1. Assumptions

The basic assumption is that the user input images are in the same format as the given images in the client application. That means that the content is a textual image and style is a historical image.

1.7.2. *Dependencies*

For user usage there are no dependencies. For deployment, the dependencies are included in the GitHub repository (link in references).

2. External Interface Requirements

2.1. User Interfaces

The user interfaces will be a web application. This web application will include the following pages:

- A page to get information on this project, including research ,demo, researchers and more, This page is called an about page.
- A page to apply a historical style synthesis. This page will include the option to upload content and style images and to get other input fields for model parameters. Users will be given the option to select from preexisting images to test the application.

Inputs will be entered via standard web controls such as combo box, check box, text box, calendar, etc. Navigation and acceptance will be handled with buttons.

2.2. Hardware Interfaces

HStyle is a cross platform application and doesn't need any hardware from its users except regular hardware for browsing the web.

2.3. Software Interfaces

HStyle is a cross platform application and doesn't need any software from its users except regular software for browsing the web.

2.4. Communications Interfaces

- The client side will communicate with the server using an HTTP protocol.
- The server side will send output from the DL model by SMTP protocol.

3. System Features

3.1. Historical document synthesis

3.1.1. *Description and Priority*

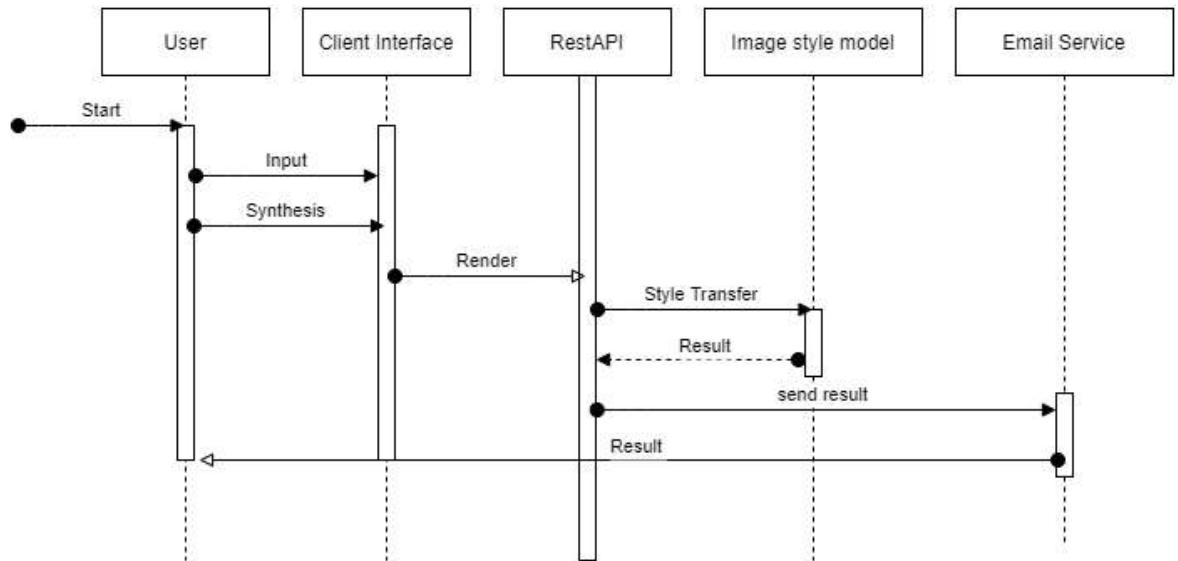
End-user can generate a historical style document from one of the appropriate inputs:

- User's modern document and a historical document.
- User's modern document and one of our historical documents presented in the client side.
- One of our modern documents and one of our historical documents presented on the client side.

Output will be displayed to or sent to user email (by user selection) to spare the user the waiting of the image creation.

Priority - high.

3.1.2. *Stimulus/Response Sequences*



3.1.3. *Functional Requirements*

REQ-1 – Preprocess of modern Hebrew data:

- In order to begin the research of creating a model to synthesis style we need to first create the correct data for the process.

REQ-2 - Preprocess of modern English data:

- In order to begin the research of creating a model to synthesis style we need to first create the correct data for the process.

REQ-3 - Preprocess of modern Arab data:

- In order to begin the research of creating a model to synthesis style we need to first create the correct data for the process.

REQ-4 - Create a historical data corpus:

- In order to begin the research of creating a model to synthesis style we need to first create the correct data for the process.

REQ-5 - Create in server-side a NST model for image style transfer:

- In order to synthesize style we first need to create a model that transfers the style appropriately.

REQ-6 - Create in server-side computer vision techniques to improve or change system's results:

- In order to improve or change results we want to enable users to apply computer vision techniques on input images.

REQ-7 – Creation of an email service:

- In order to send the user the model's output and to not make the user wait for the process this system needs to send the output by an email service if the user selects this option.

REQ-8 - Creation of RESTful API for historical document synthesis consumption:

- In order to communicate between users and our model we need a RESTful API.

REQ-9 - Create in client-side interface content image selection and image upload section:

- In order to get a content image from a user we need to create an option to upload an image or to select from given images.

REQ-10 - Create in client-side interface style image selection and image upload section:

- In order to get a style image from a user we need to create an option to upload an image or to select from given images.

REQ-11 - Create in client-side interface model parameters selection section:

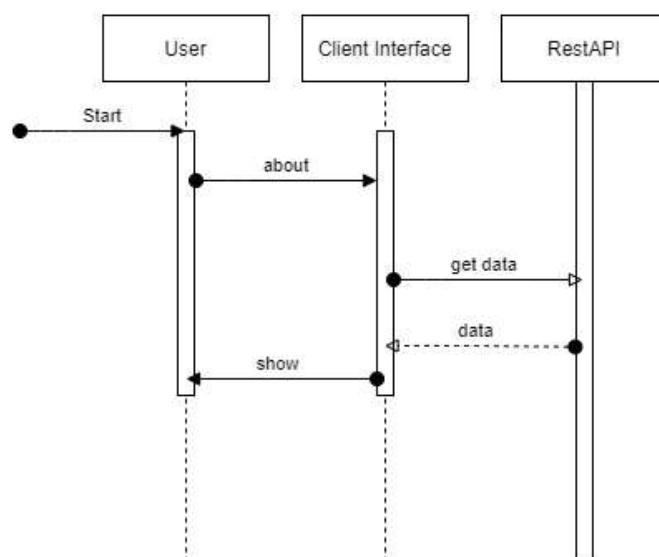
- In order to get a user's parameters to apply on model we need to create an option to select options.

3.2. About

3.2.1. Description and Priority

End-users can get information about the system including what the system is, details about the research, details about the researchers and more.

3.2.2. Stimulus/Response Sequences



3.2.3. Functional Requirements

REQ-12 - Create in client-side interface explanation section on *HStyle*:

- In order to give user information about the system we will create a section with system explanation.

REQ-13 - Create in client-side interface demo of *HStyle*:

- In order to show the user system's result we will create a section with system demo.

REQ-14 - Create in client-side interface explanation section of *HStyle*'s researchers:

- In order to give user information about the system researchers we will create a section with system researchers information.

REQ-15 - Creation of RESTful API for about consumption:

- This system includes a RESTful API in order to send the needed data to the client side.

4. Other Non-functional Requirements

4.1. Performance Requirements

The system must be interactive and the delays involved must be less. So, in every action-response of the system, there are no immediate delays.

Because the act of image style transfer is style consuming, the model should be optimized and output will be displayed to or sent to user email (by user selection) to spare the user the waiting of the image creation.

4.2. Safety Requirements

Software shall provide error handling to support functionality, software shall provide fault containment mechanisms to prevent error propagation. Software termination shall result in a safe system state.

4.3. Security Requirements

No security requirements.

4.4. Software Quality Attributes

Software quality requirements for this platform are:

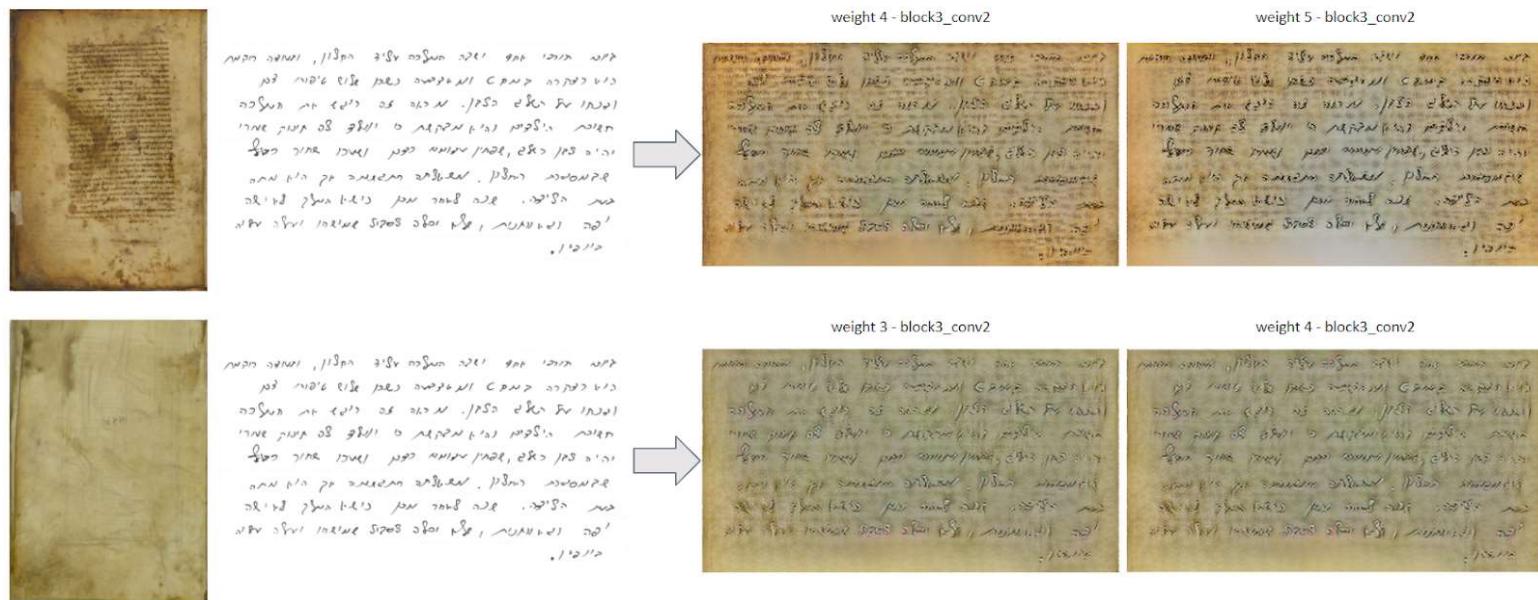
- Availability - The system will be available to access.
- Usability - The system is easy to handle and navigates in the most expected way with no delays. In that case the system program reacts accordingly and transverses quickly between its states.
- Performance – Performance of functions will be tested.
- Compatibility - Any additional feature that will be added should peacefully coexist with existing features.

Results

In our research, we performed multiple experiments, these are samples of them:

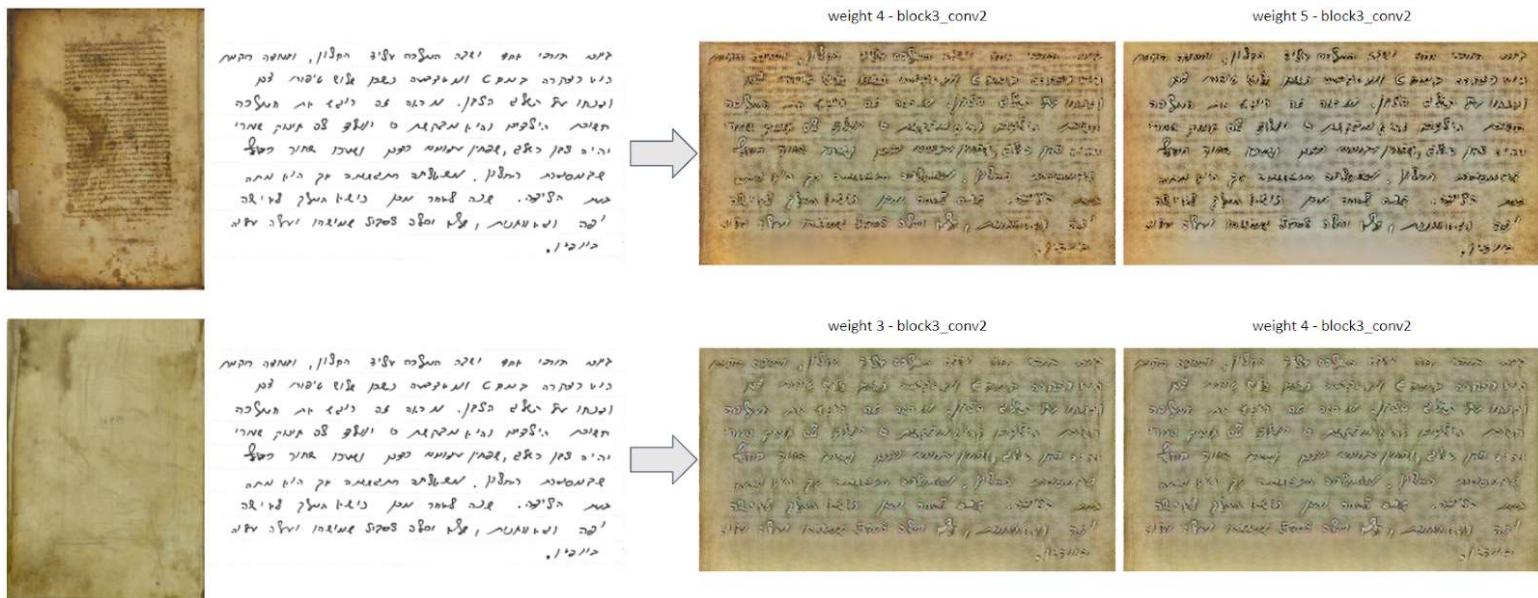
1. Original content image

Our first attempt was an original content and style image (with and without text) without any changes to the content image. We managed to pass the historical style to the content image, but the text is a bit blurry.



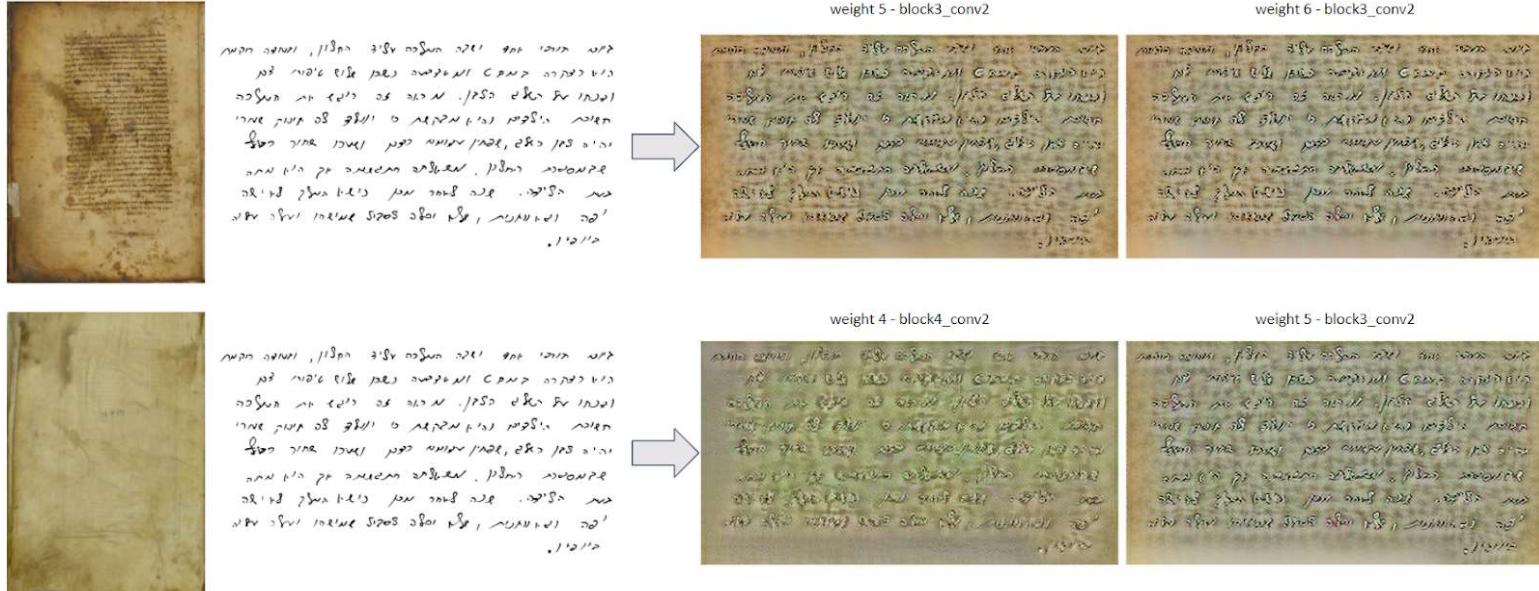
2. Dilate content image

In our second attempt we tried to change the content image with dilation in order to make the text thicker and to cause it to be less blurry. As we can see, we managed to improve the result readability with no harm to the historical style passing.



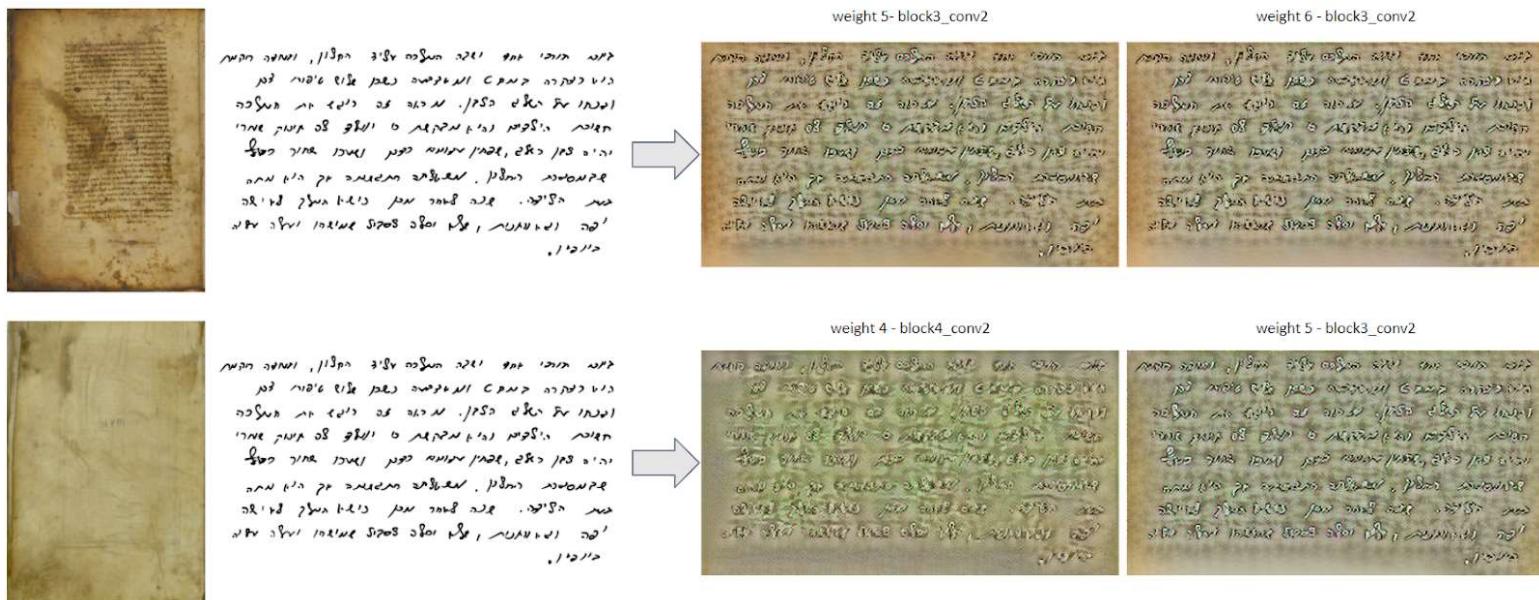
3. Binary content image

We saw that dilation helped improve the readability, so we thought that maybe binarization of the content image will have a similar effect. As we can see, the image is more readable but there is harm to the historical style passing.



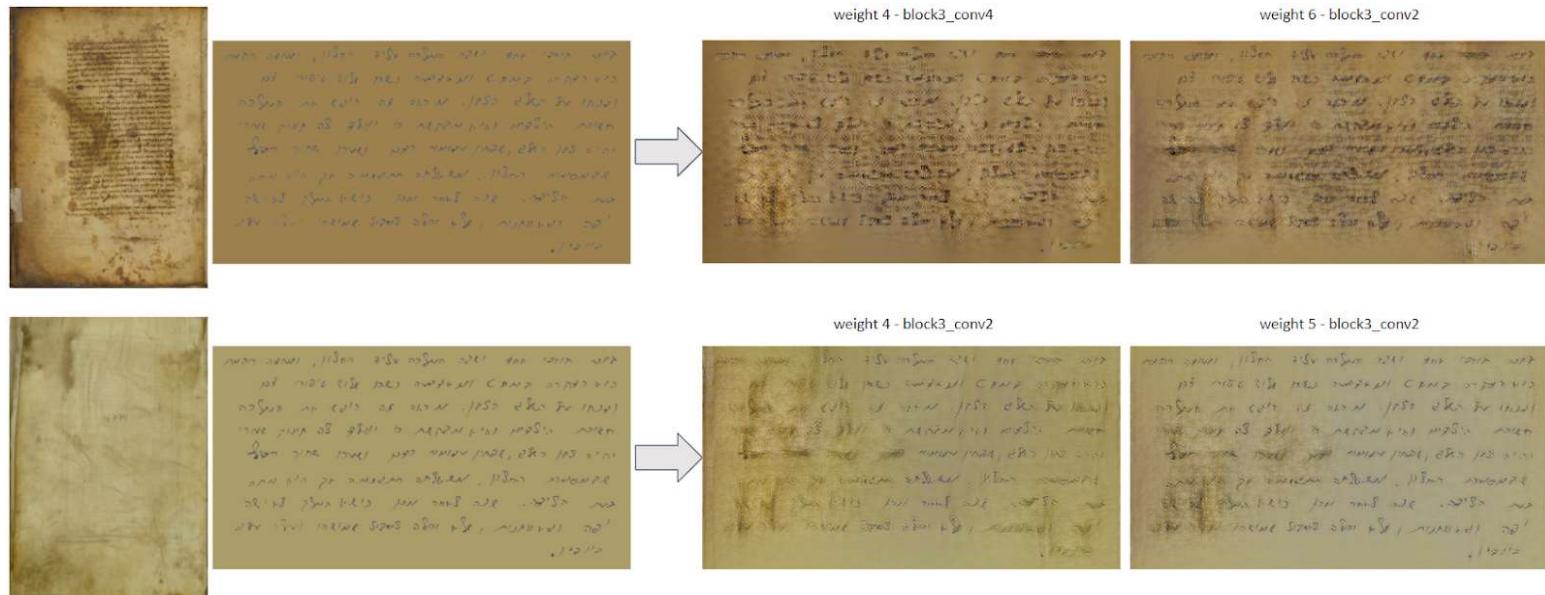
4. Binary-dilated content image

Next, we tried to apply dilation and binarization in order to see if the combination of these transformations can create a more readable result without harming the style. As we can see, the style is not good, probably because of the effect of the binarization as in experiment 3.



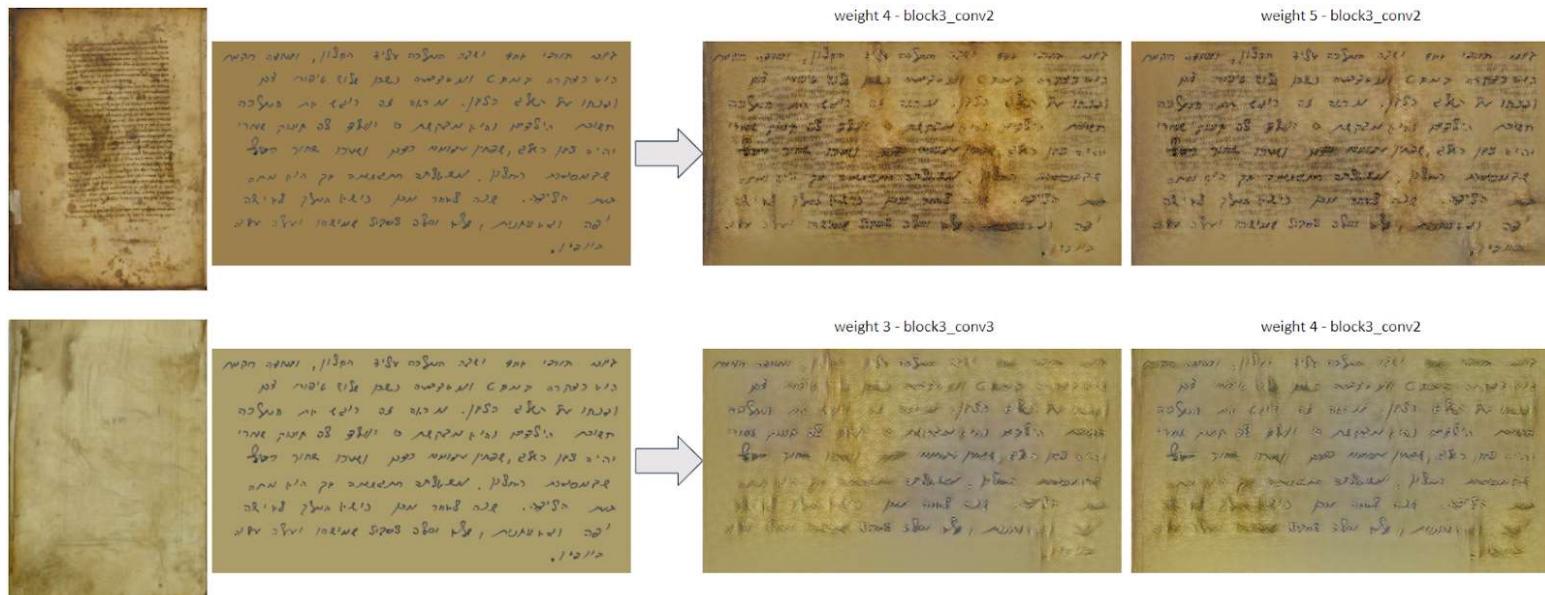
5. Average historical pixels background for content image

In this experiment we tried to make a better style transformation by changing the background of the content image from white to the average of the pixels in the historical style image. As we can see, the results are not readable but the style is better.



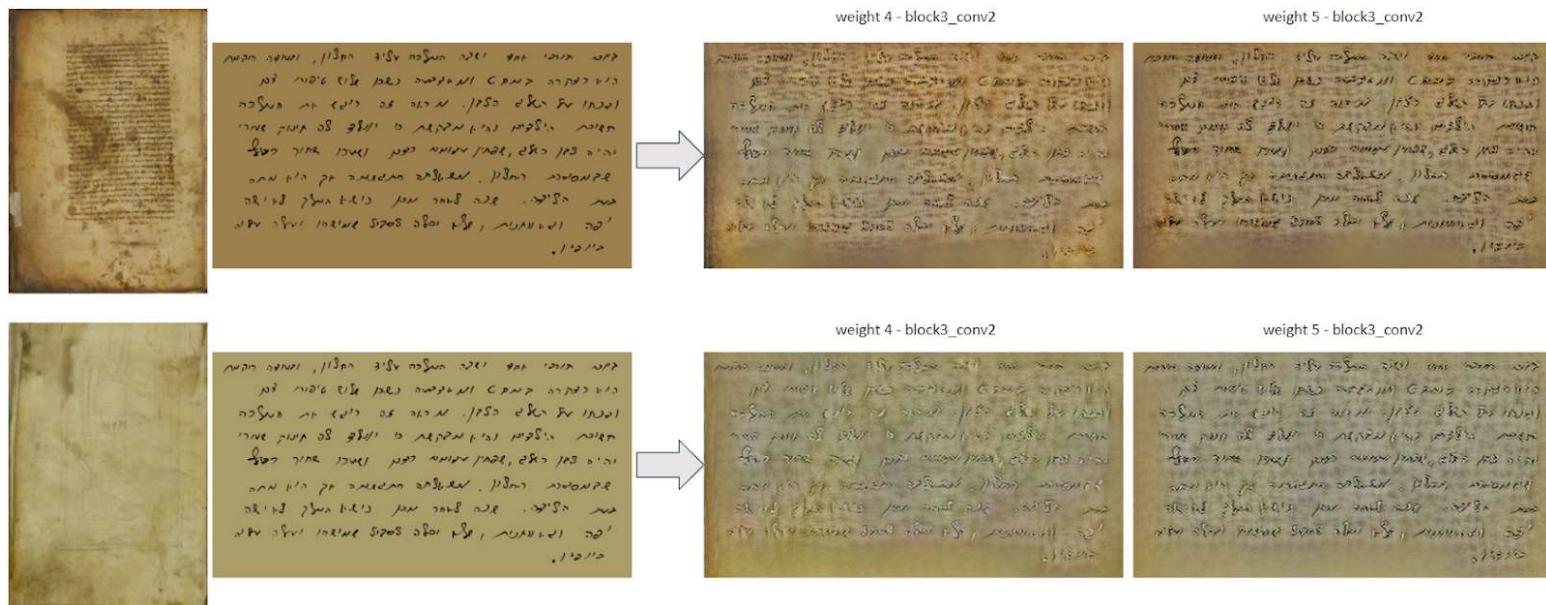
6. Average historical pixels background for dilated content image

As we managed to make the style transfer better in experiment 5, we wanted to try in this case too to apply dilation in order to improve the text readability as we saw in experiment 2. In this case, the text readability improved but still not good enough.



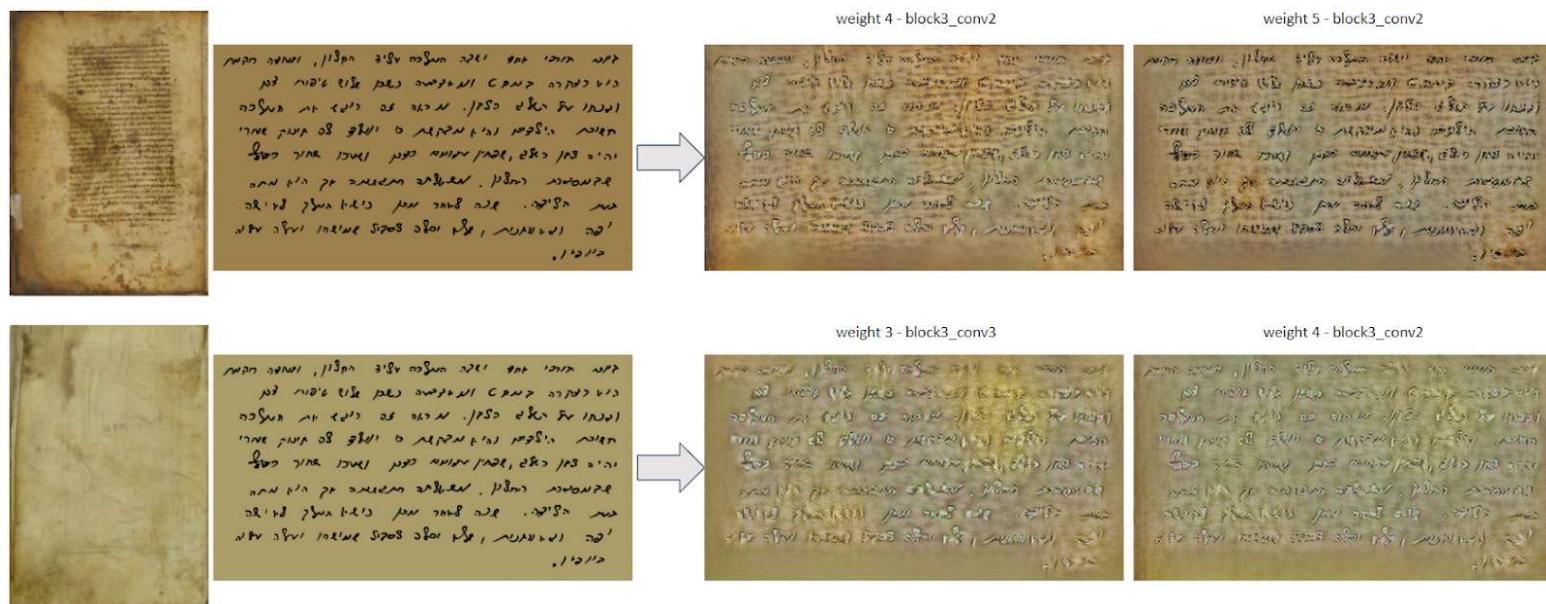
7. Average historical pixels background for binary content image

Although binarization had bad effects on the process, we thought that maybe the combination of changing the background and applying binarization will improve the readability and leave the style as is. As we can see, the readability and style improved but still other experiments were better.



8. Average historical pixels background for binary-dilated content image

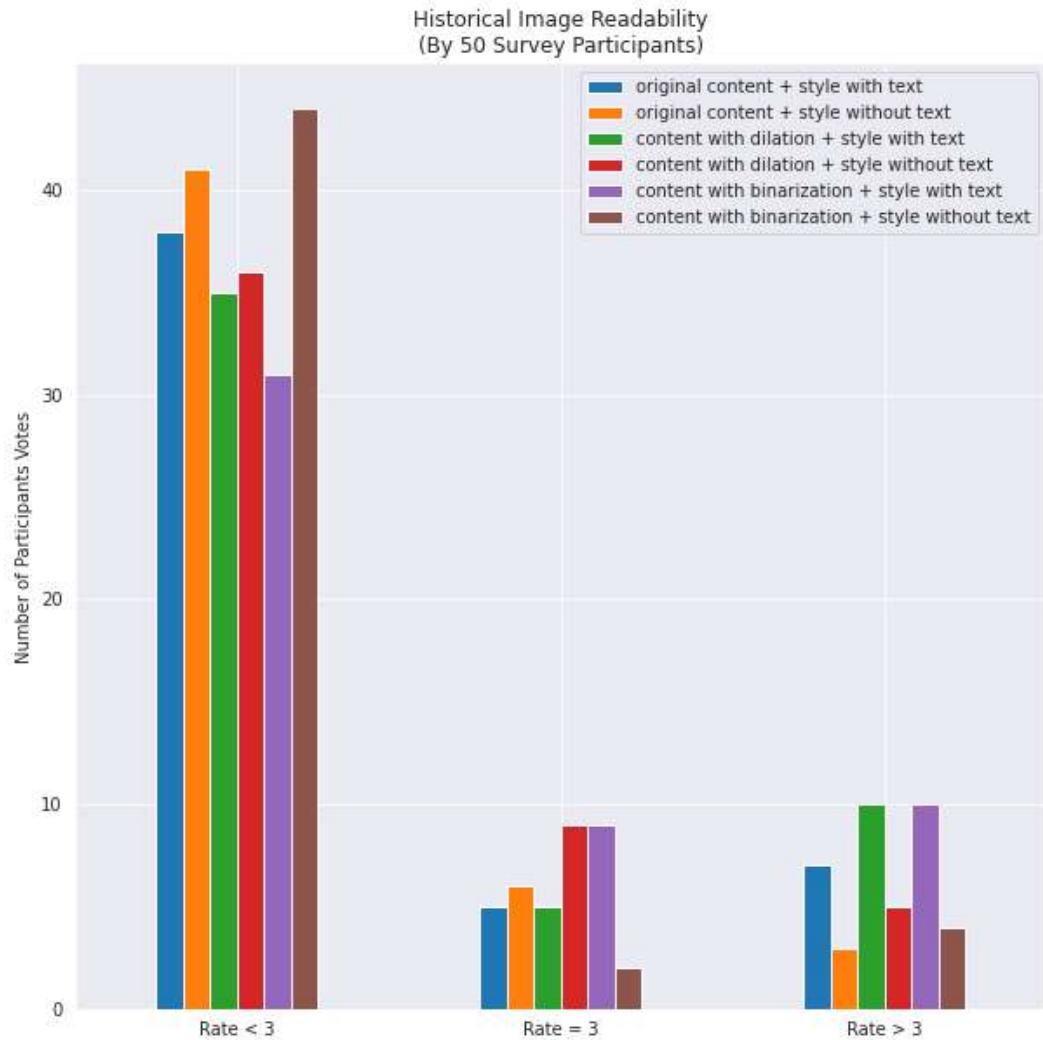
At Last, we tried combining all three methods in order to view the effect. Similar to the result in experiment 7, the style and readability were good but still other experiments were better.



Evaluation

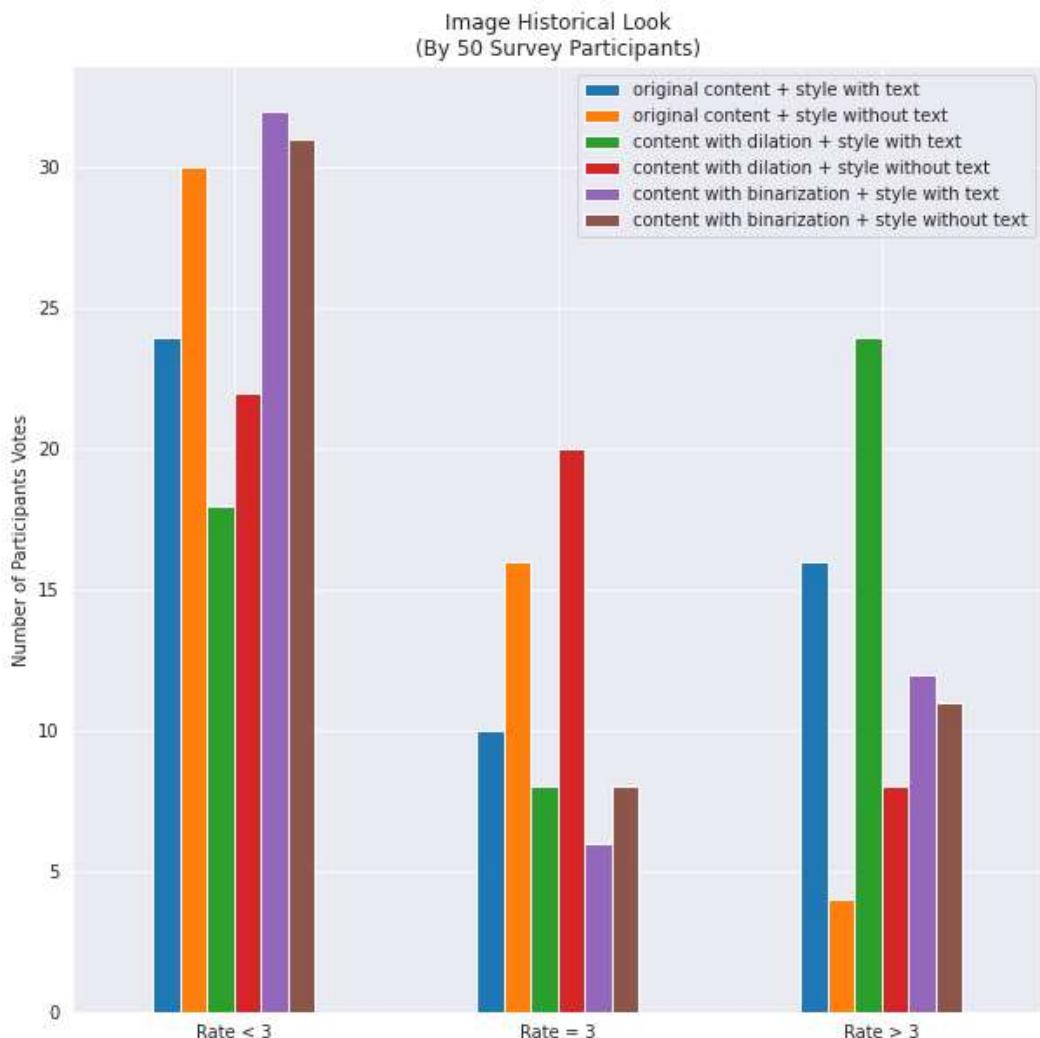
As we can see, in the results above we have three different techniques with good results (Original content image, Dilate content image, Binary content image). In order to evaluate and determine which technique is best, we performed a survey of 50 participants and asked them to rate image readability and image historical look, 1-being the lowest (poor), 5-being the highest (great).

Results for image readability



As we can see, 'dilate content image' and 'binary content image' get the highest amount of votes for rate three and above, meaning, these results have the highest readability.

Result for image historical look:



As we can see, 'dilate content image' gets the highest amount of votes for rate three and above, meaning, these results have the most historical look.

Conclusion

To conclude, by testing multiple transformations, extraction of content representation from different deep learning layers and using different content weights we get the best results by applying dilation on the original content image, extracting the content image from layers 'block3-conv2' and content weight of 150 - 175.

When we try to apply binarization on the original content image it ruins the results. Also, when we try to change the content image background color to the average pixels from the style image, we get better results, but the dilation on the original content image made the best result.

To summarize, we managed to transfer an historical style on a modern content image and get good results.

References

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Appendix A - Experiments Analysis

1. Fast arbitrary image style transfer

Our first attempt in order to see if an images style approach can give good results was to try the fast image style transfer model. This model is pre trained that performs fast artistic style transfer that may work on arbitrary painting styles. In this model we cannot control the content and style weights but only give a content and style image.

1.1. Experiment 1

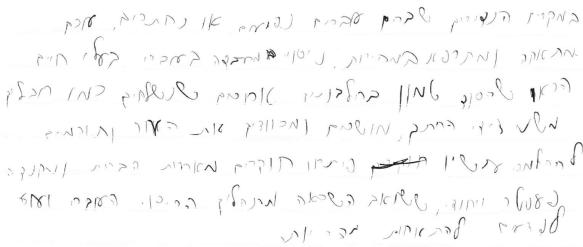
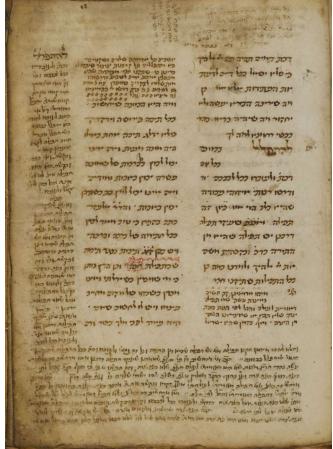
1.1.1. Content Input

This experiment used a modern hebrew handwritten document for content.

1.1.2. Style Input

This experiment used a hebrew middle age document with text for style.

1.1.3. Results

Content image	Style image
	
result	
	

1.1.4. Discussion

As we can see the results are not good, we get the style of the document but we also get a lot of the text in patterns.

1.2. Experiment 2

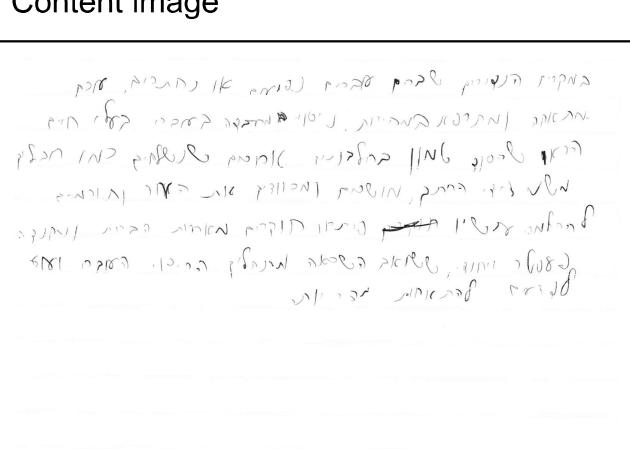
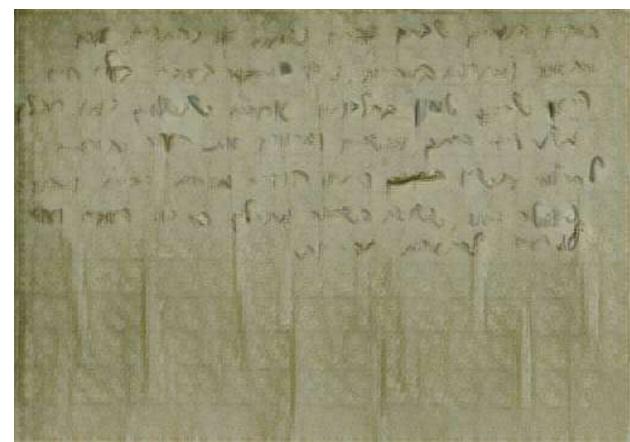
1.2.1. Content Input

This experiment used a modern hebrew handwritten document for content.

1.2.2. Style Input

This experiment used a hebrew middle age document without text for style.

1.2.3. Results

Content image	Style image
	
result	
	

1.2.4. Discussion

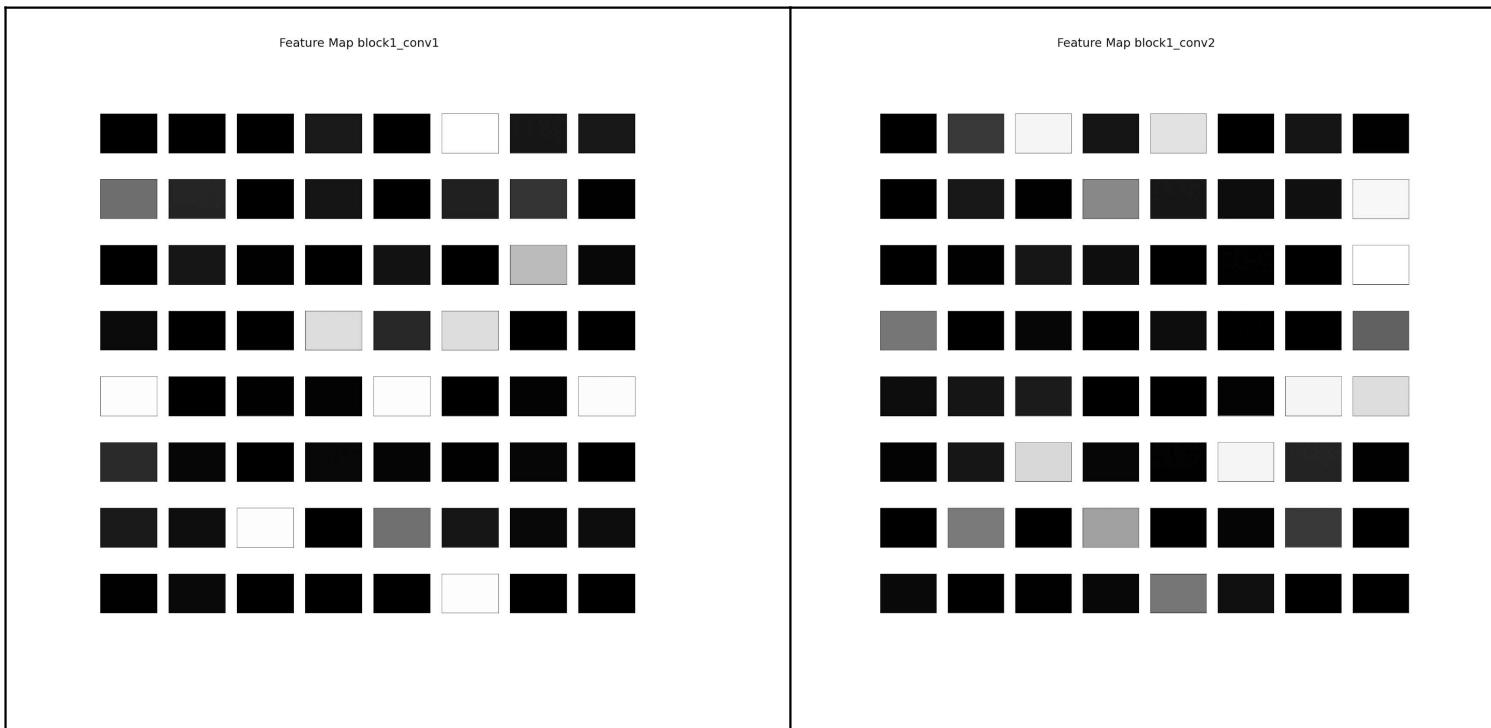
As we can see the results are better but still they are not very good, we get a style but it's not really the document style and text is a little unreadable.

2. Neural Style Transfer

After we saw in the fast arbitrary image style transfer that we can get a decent result but we need more control on the parameters we decided to try the Neural style transfer technique using a deep learning model. We experimented on different content layers and weights.

2.1. Content layers

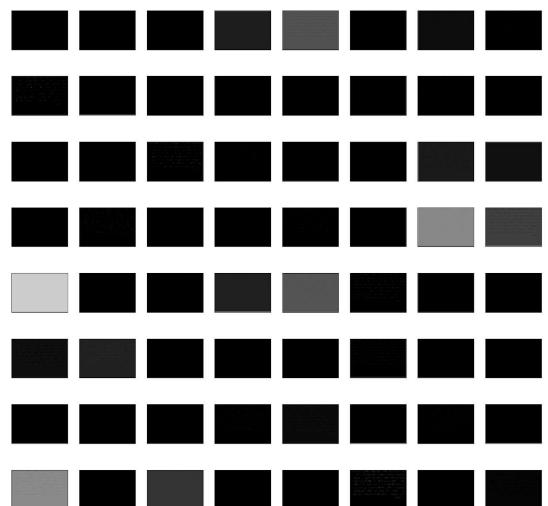
We visualized VGG19 layers feature maps in order to understand where we should take content. we visualized the output of relevant intermediate layers. The results are the following (pay attention that some layers have more than 64 feature maps but we displayed only 64 to get the intuition):



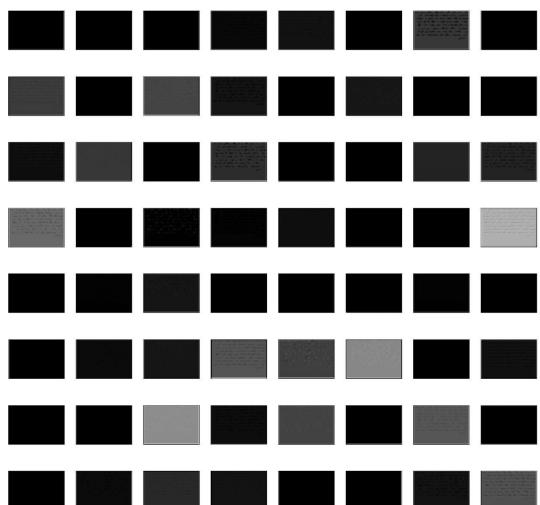
Feature Map block2_conv1



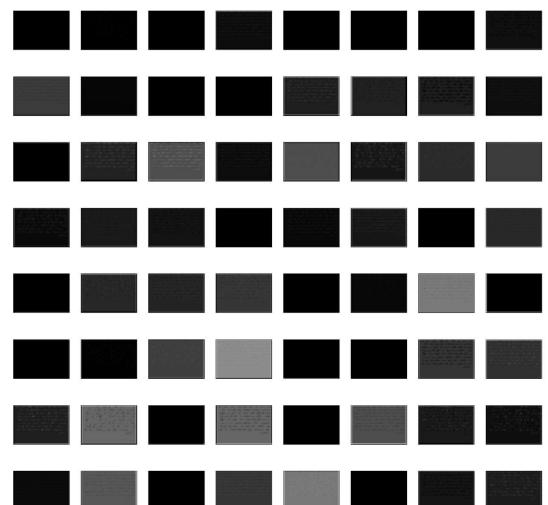
Feature Map block2_conv2



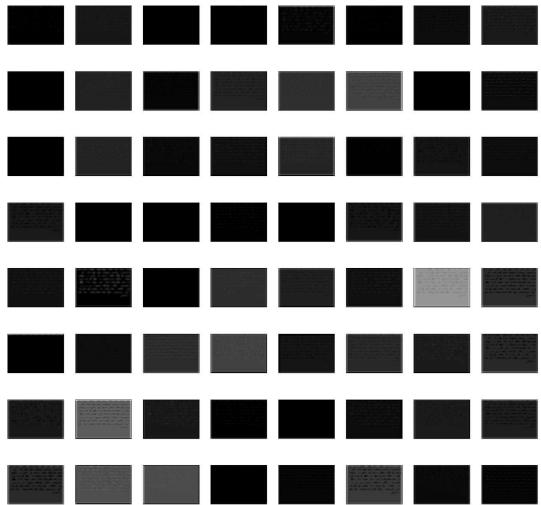
Feature Map block3_conv1



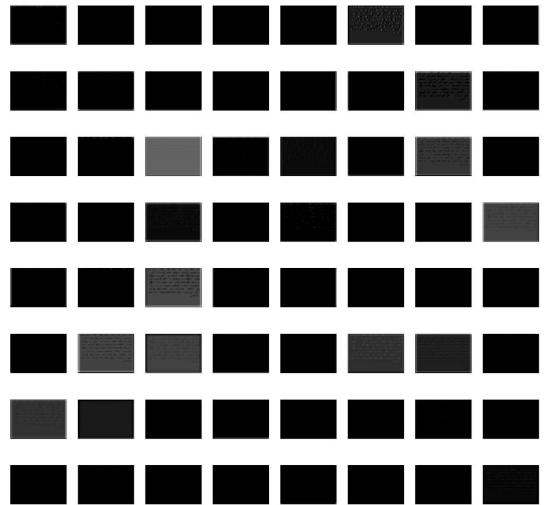
Feature Map block3_conv2



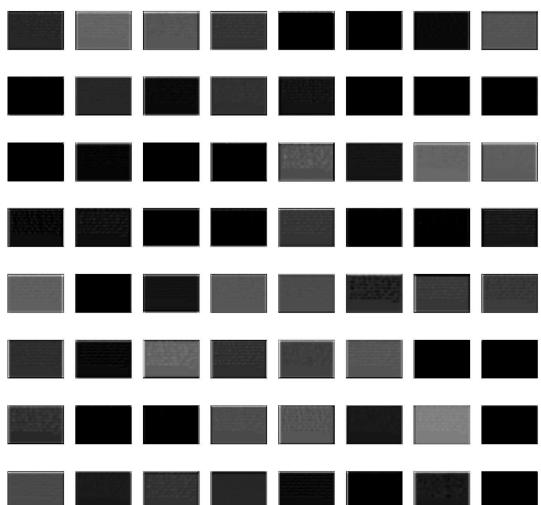
Feature Map block3_conv3



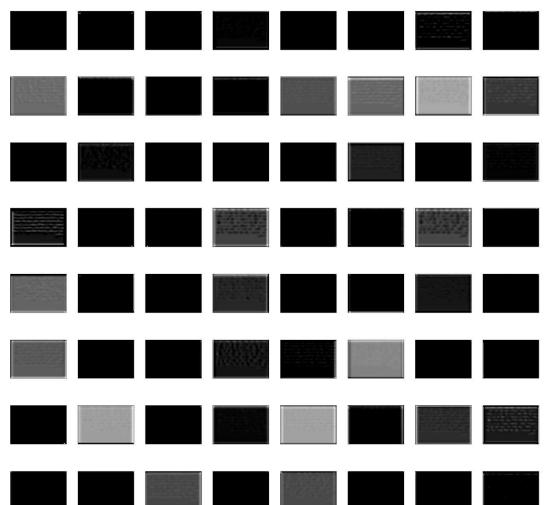
Feature Map block3_conv4



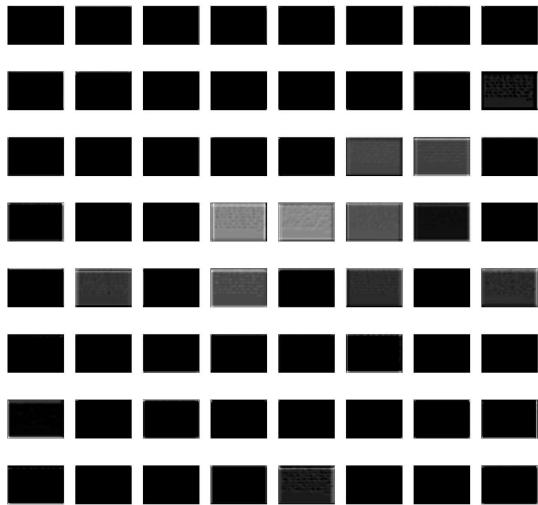
Feature Map block4_conv1



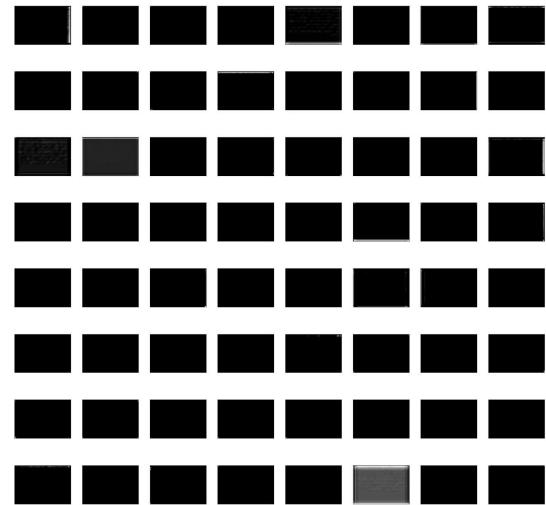
Feature Map block4_conv2



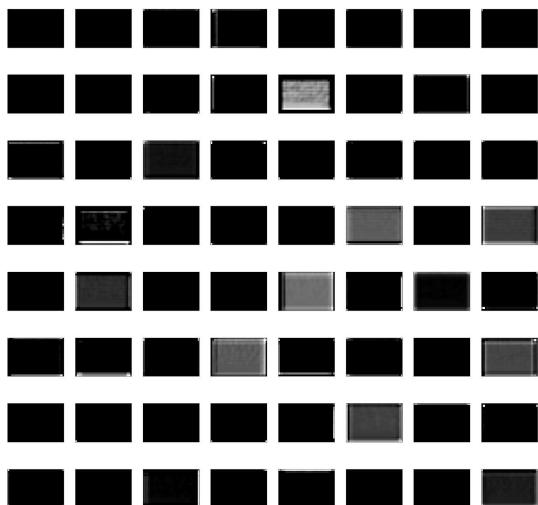
Feature Map block4_conv3



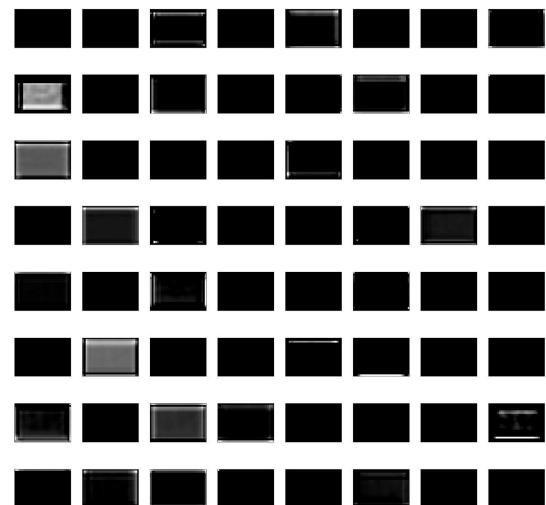
Feature Map block4_conv4



Feature Map block5_conv1



Feature Map block5_conv3



As we can see these layers are best to extract content from:

block4_conv2, block3_conv4, block3_conv3, block3_conv2

In addition we will test **block5_conv2** because it was the best in the original paper.

2.2. Style layers

We used the original paper style layers:

**block1_conv1, block2_conv1, block3_conv1, block4_conv1,
block5_conv1**

2.3. Weights

In each experiment we used the following Weights:

Index	Content weight (α)	Style weight (β)	Ratio (α/β)
0	1.00E+01	1.00E-02	1.00E+03
1	1.00E+02	1.00E-02	1.00E+04
2	1.25E+02	1.00E-02	1.25E+04
3	1.50E+02	1.00E-02	1.50E+04
4	1.75E+02	1.00E-02	1.75E+04
5	1.00E+03	1.00E-02	1.00E+05
6	1.50E+03	1.00E-02	1.50E+05
7	1.00E+04	1.00E-02	1.00E+06
8	1.00E+05	1.00E-02	1.00E+07

2.4. Experiment 1

2.4.1. Content Input

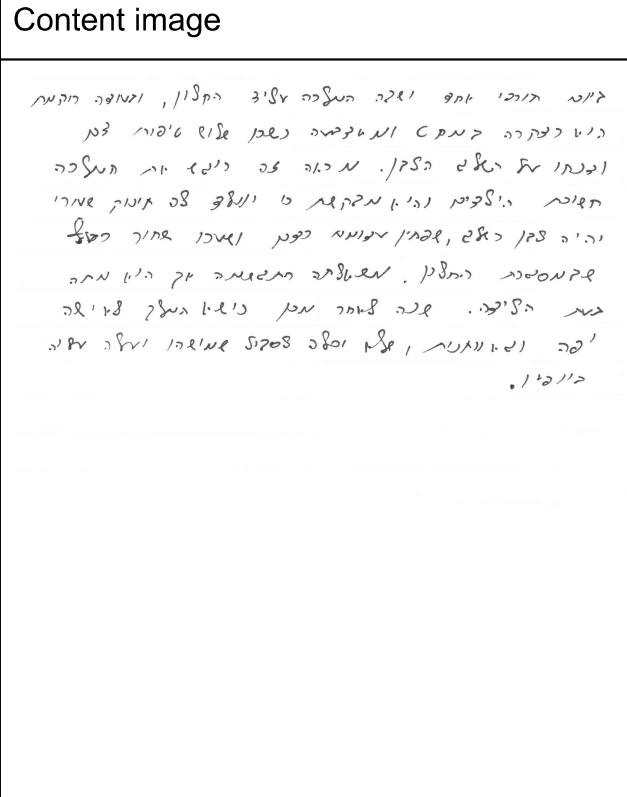
This experiment used a modern hebrew handwritten document for content.

2.4.2. Style Input

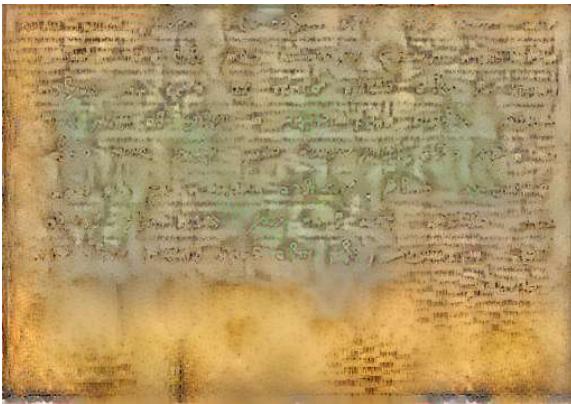
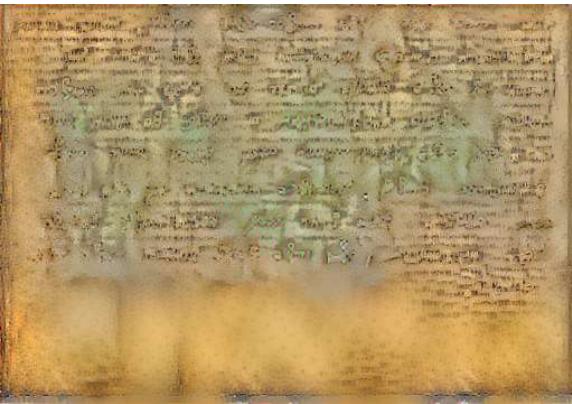
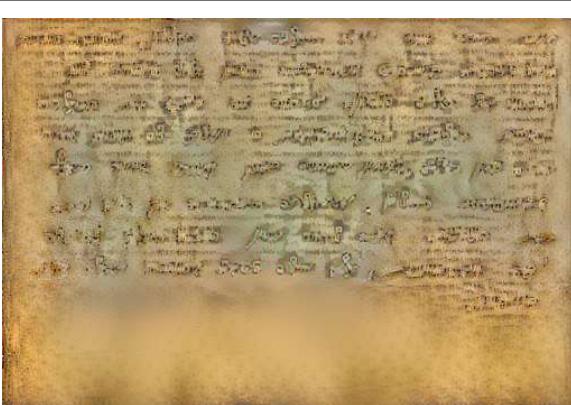
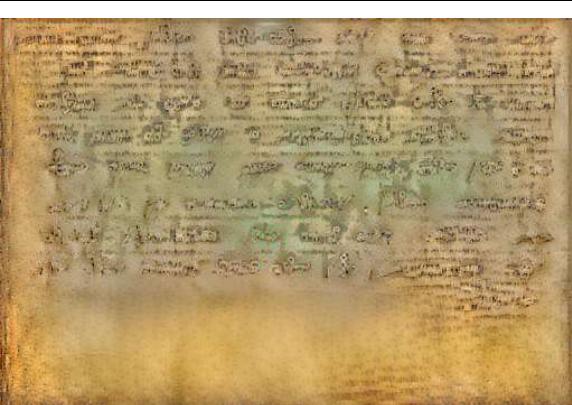
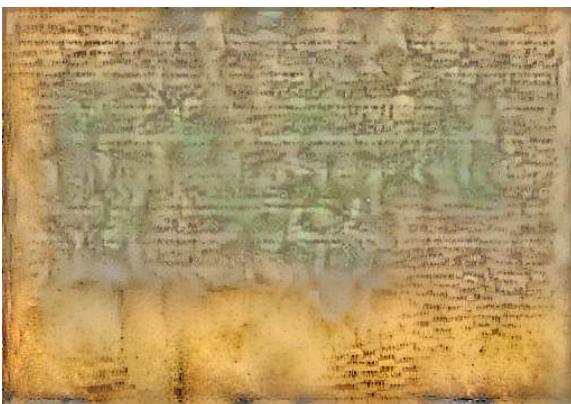
This experiment used a hebrew middle age document with text for style.

2.4.3. Results

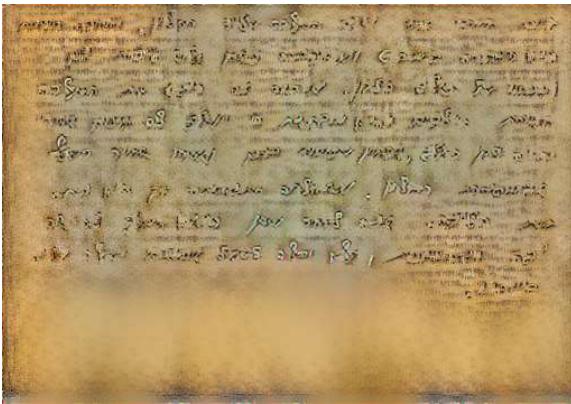
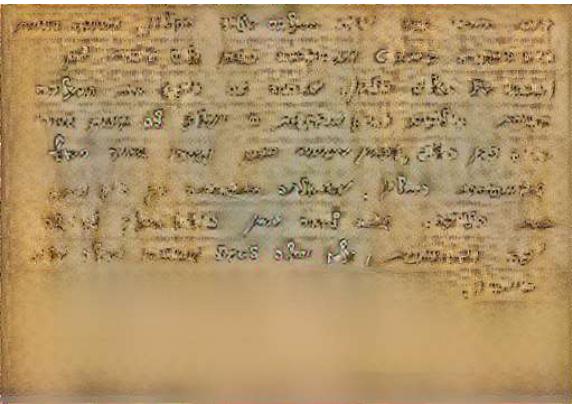
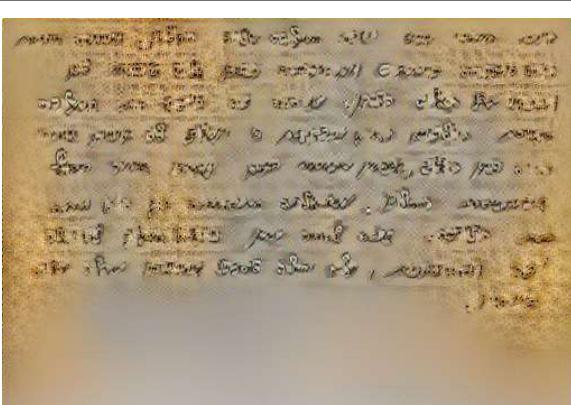
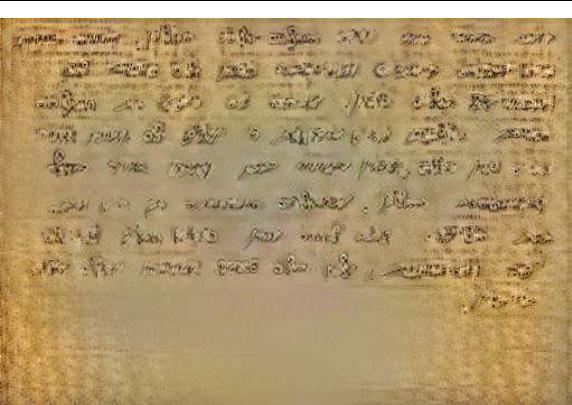
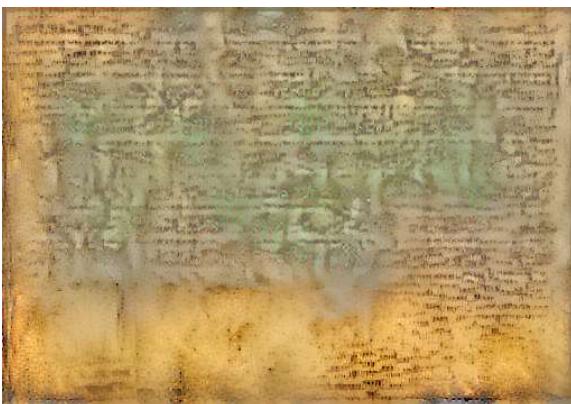
We will show samples of the results with each weight and content layer (style layers are the same).

Content image	Style image
	

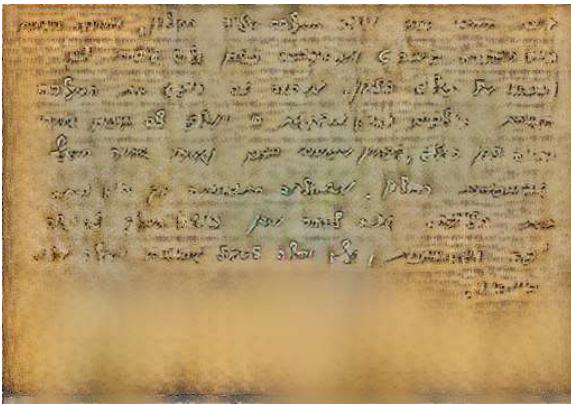
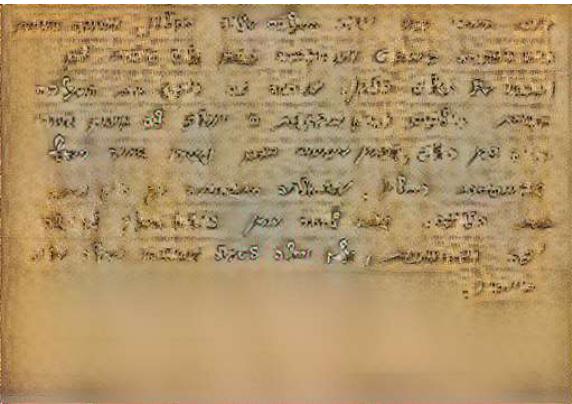
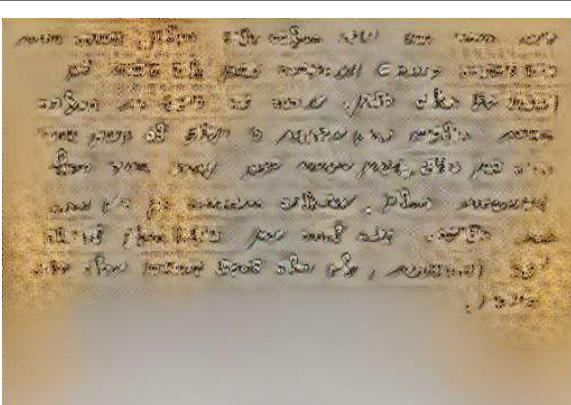
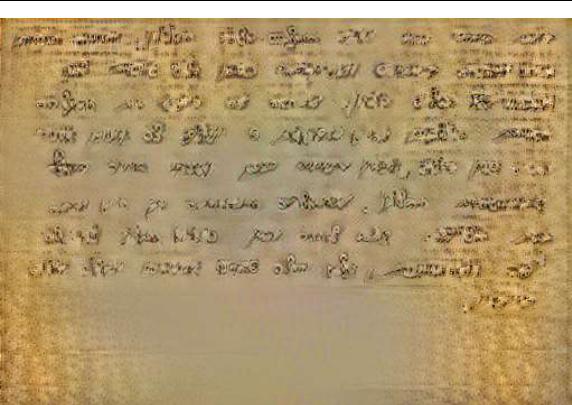
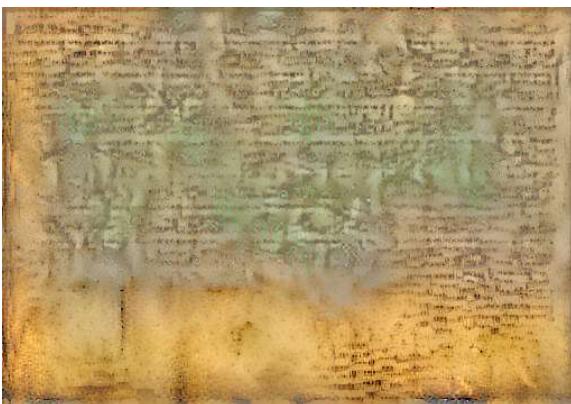
2.4.3.1. Weight 0

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

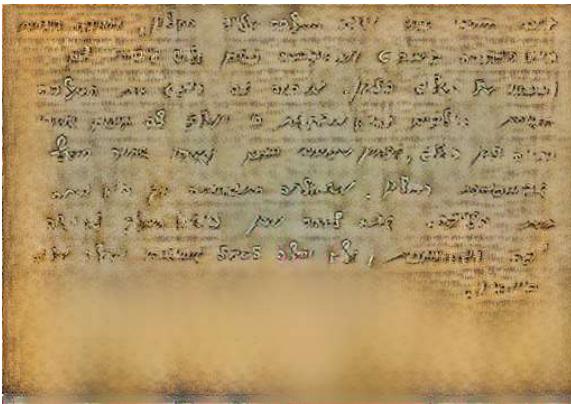
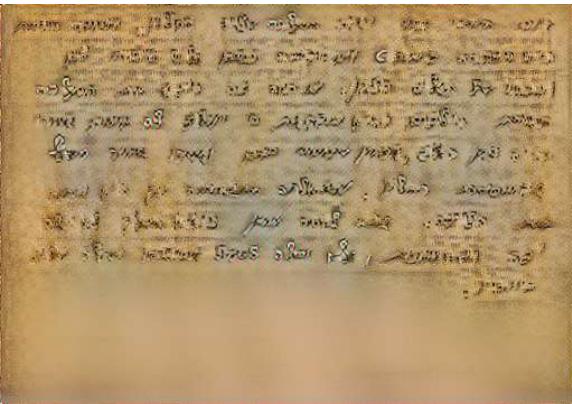
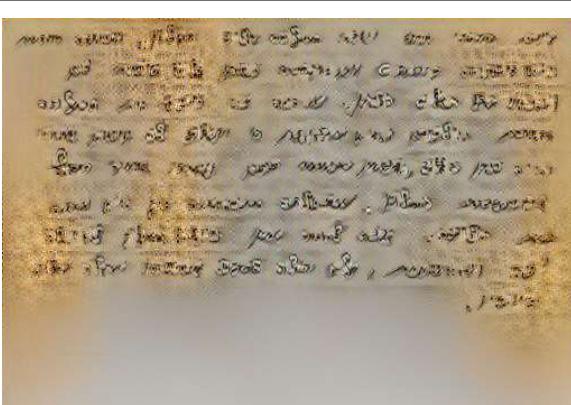
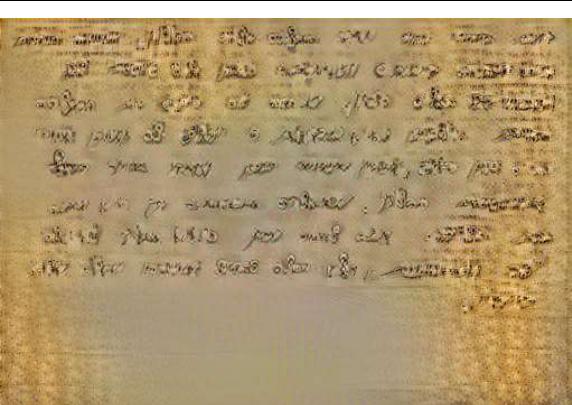
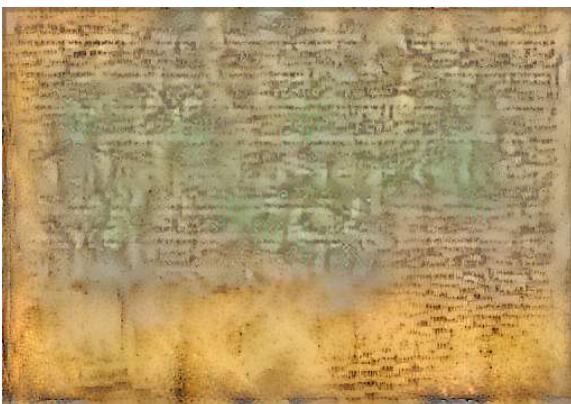
2.4.3.2. Weight 1

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

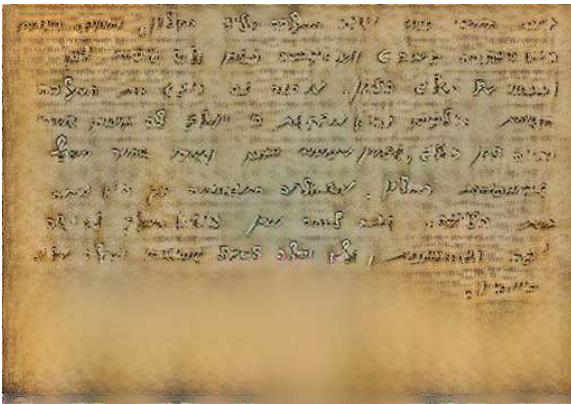
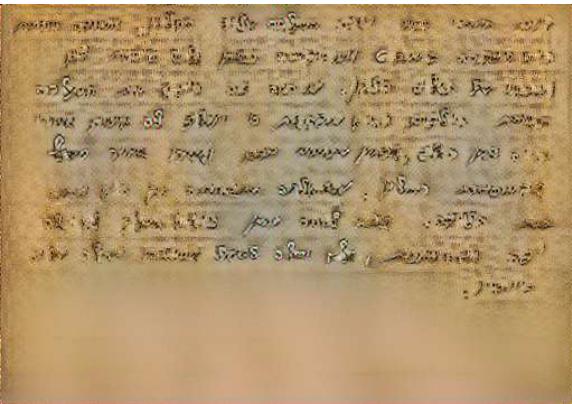
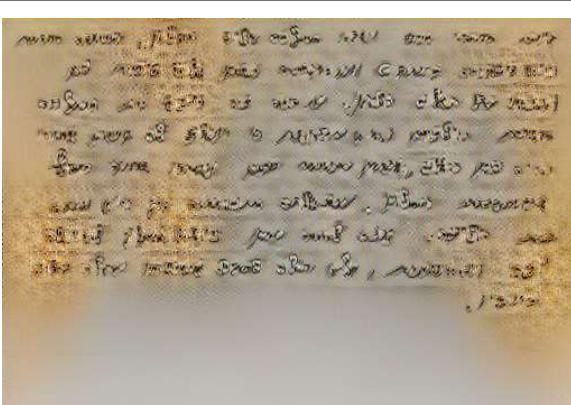
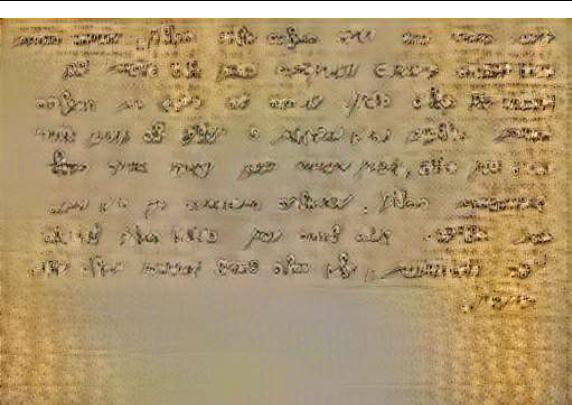
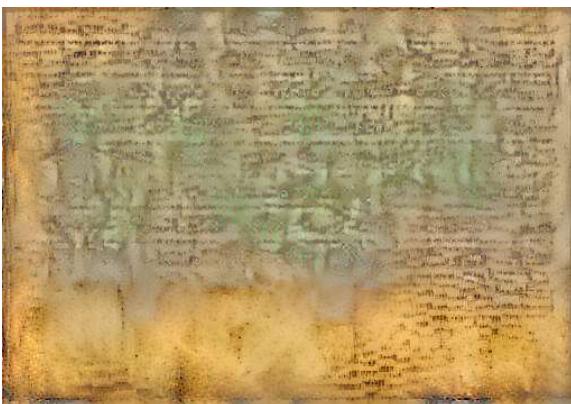
2.4.3.3. Weight 2

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

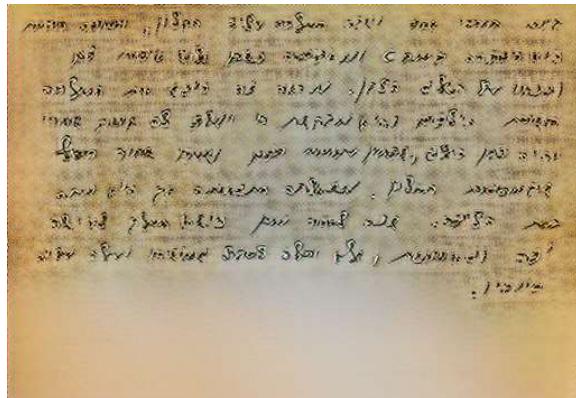
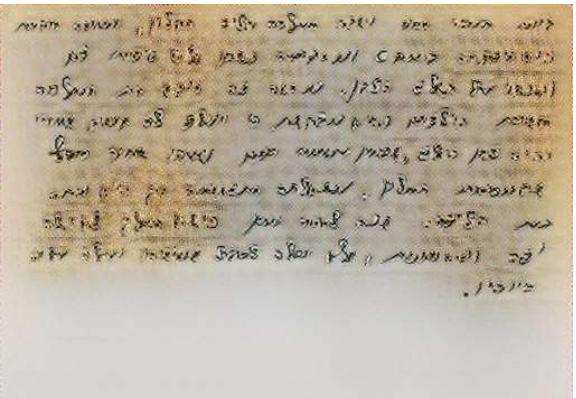
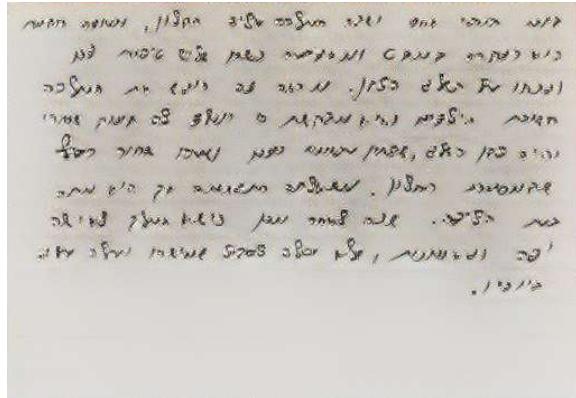
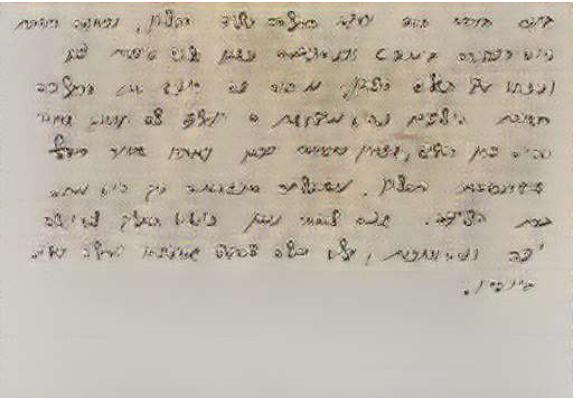
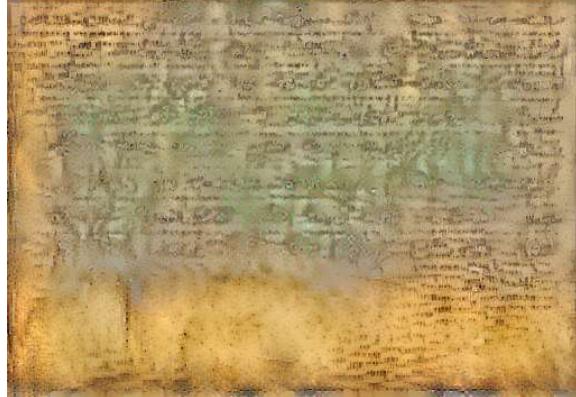
2.4.3.4. Weight 3

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

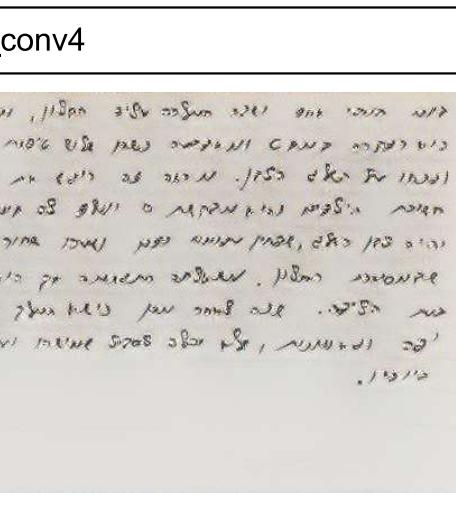
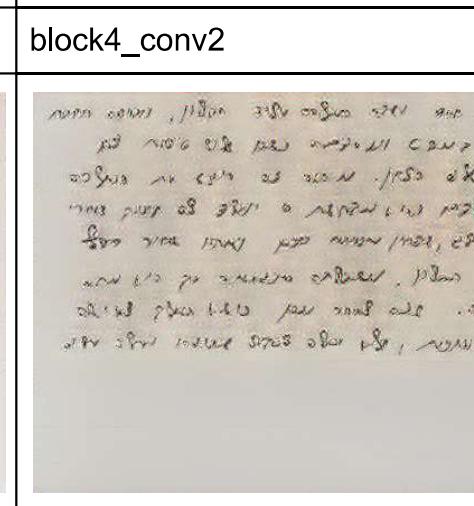
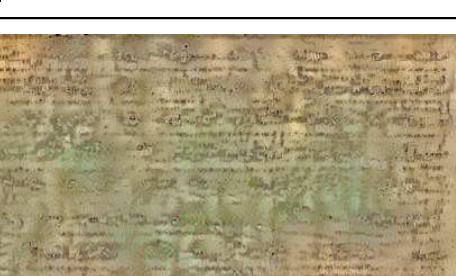
2.4.3.5. Weight 4

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.4.3.6. Weight 5

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.4.3.7. Weight 6

block3_conv2	block3_conv3
 <p>This image shows a page from a medieval manuscript. The text is written in two columns in a dark brown ink on aged, yellowish paper. The script is a clear Gothic hand. There are some marginalia and small headings.</p>	 <p>This image shows a page from a medieval manuscript. The text is written in two columns in a dark brown ink on aged, yellowish paper. The script is a clear Gothic hand. There are some marginalia and small headings.</p>
block3_conv4	block4_conv2
 <p>This image shows a page from a medieval manuscript. The text is written in two columns in a dark brown ink on aged, yellowish paper. The script is a clear Gothic hand. There are some marginalia and small headings.</p>	 <p>This image shows a page from a medieval manuscript. The text is written in two columns in a dark brown ink on aged, yellowish paper. The script is a clear Gothic hand. There are some marginalia and small headings.</p>

2.4.3.8. Weight 7

2.4.3.9. Weight 8

2.5. Experiment 2

2.5.1. Content Input

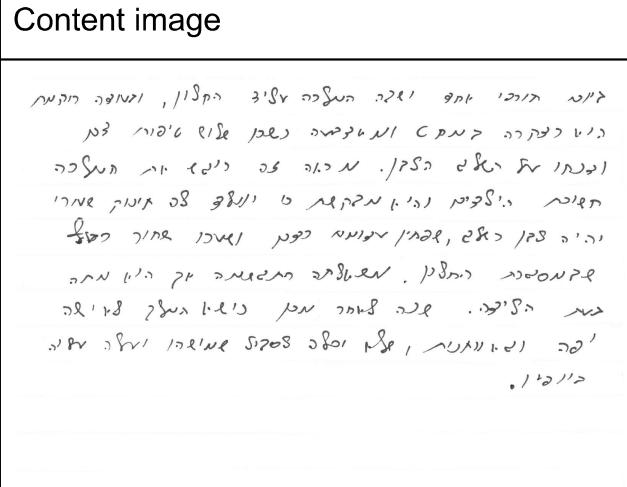
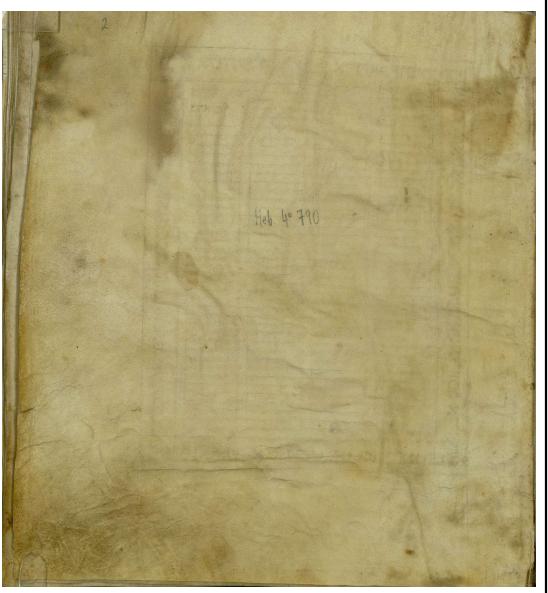
This experiment used a modern hebrew handwritten document for content.

2.5.2. Style Input

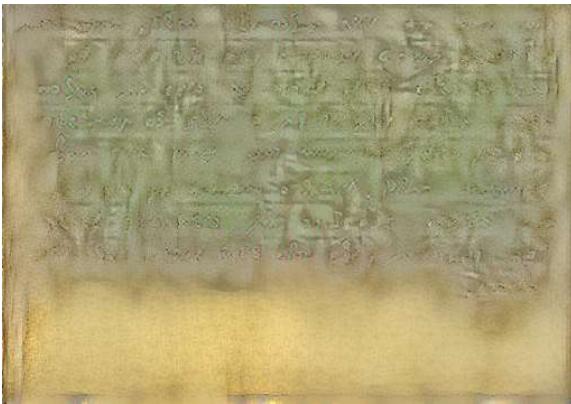
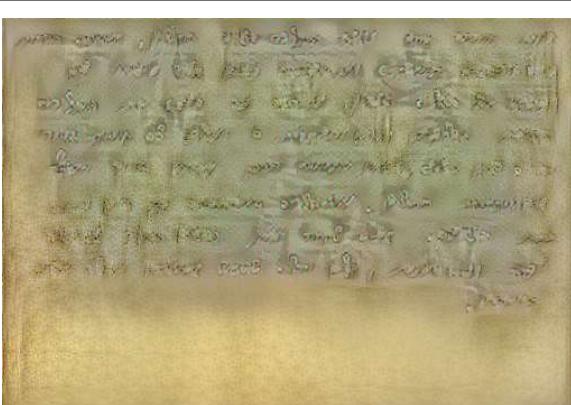
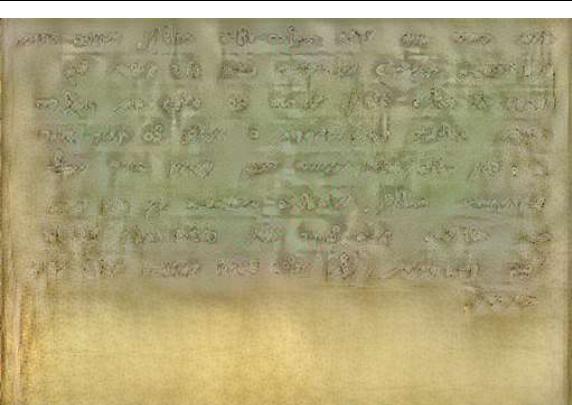
This experiment used a hebrew middle age document without text for style.

2.5.3. Results

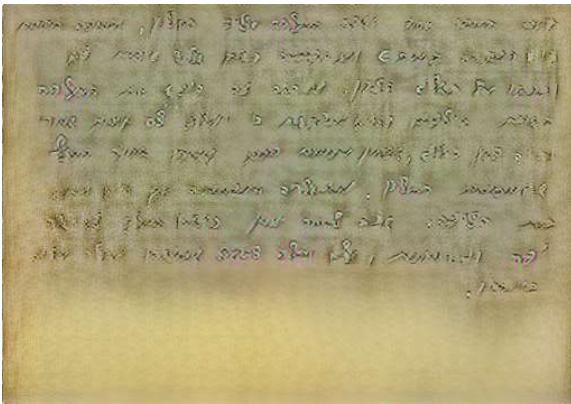
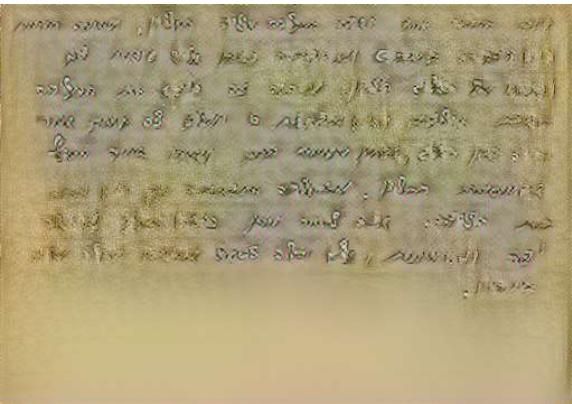
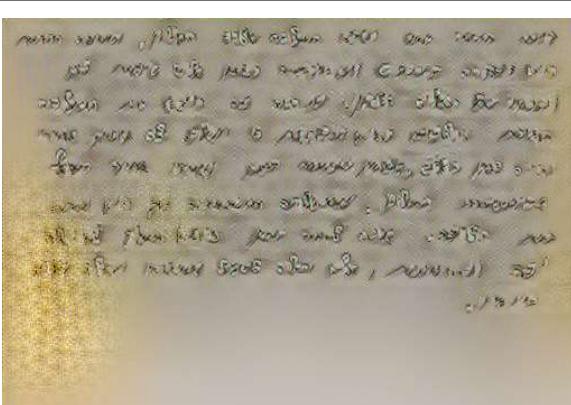
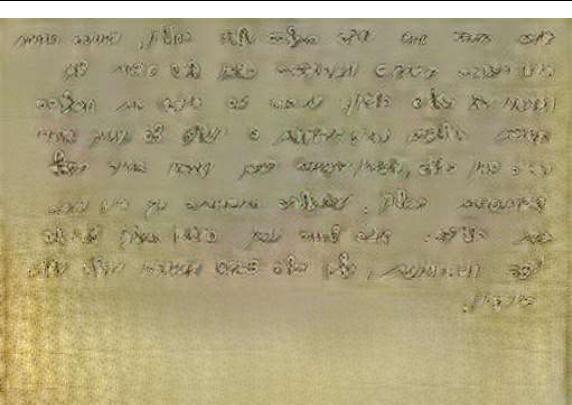
We will show samples of the results with each weight and content layer (style layers are the same).

Content image	Style image
	

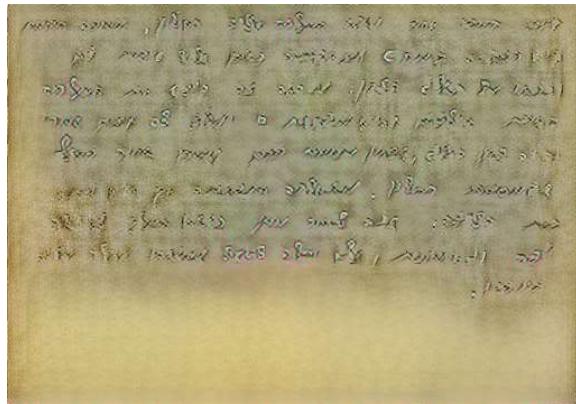
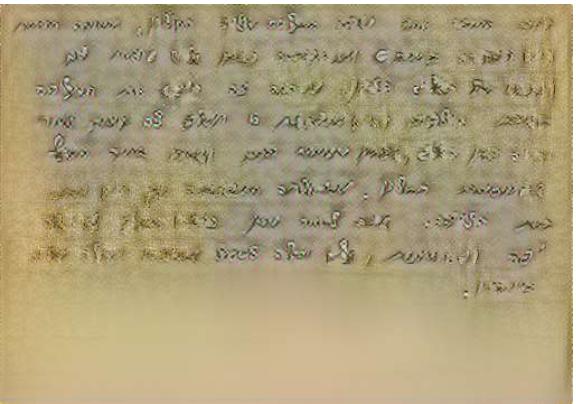
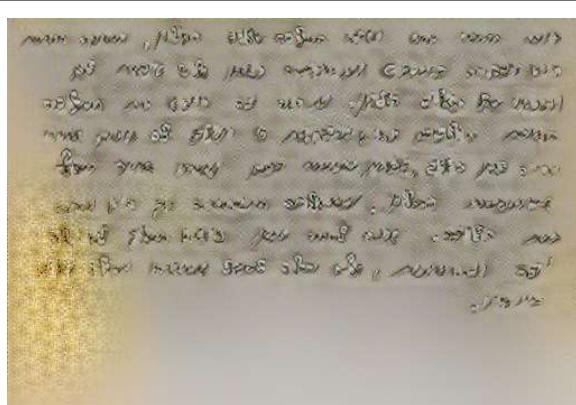
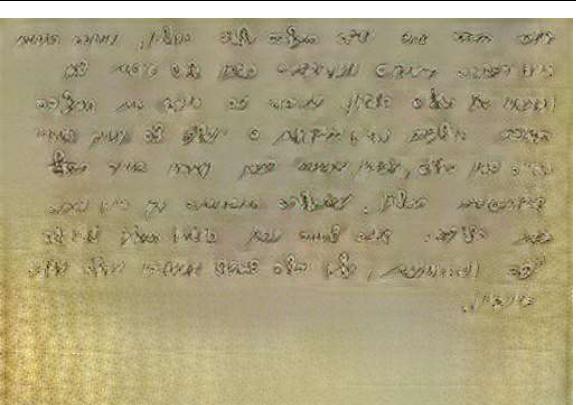
2.5.3.1. Weight 0

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

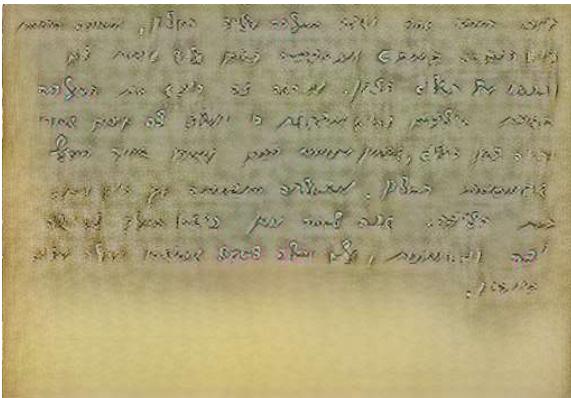
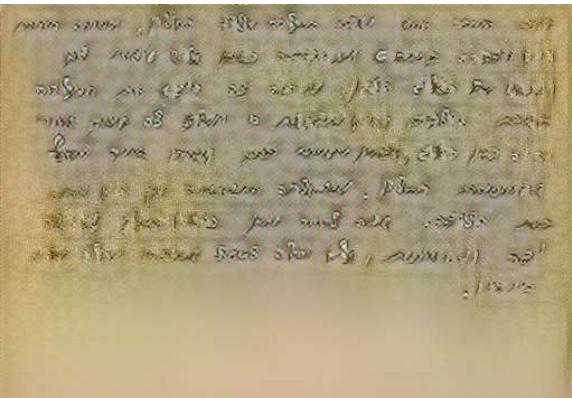
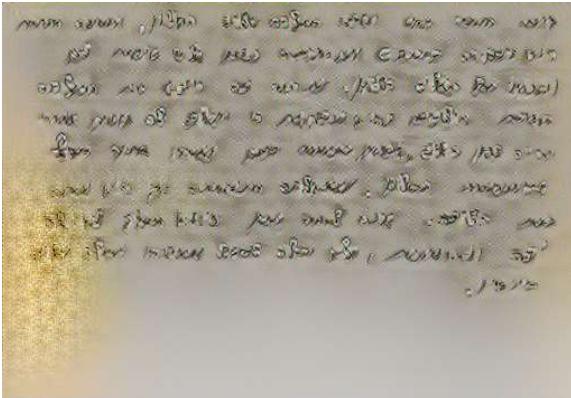
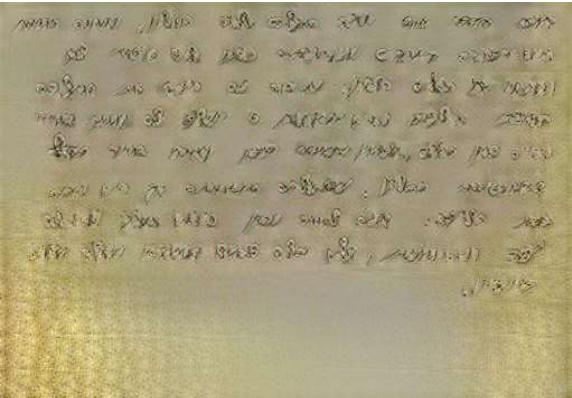
2.5.3.2. Weight 1

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

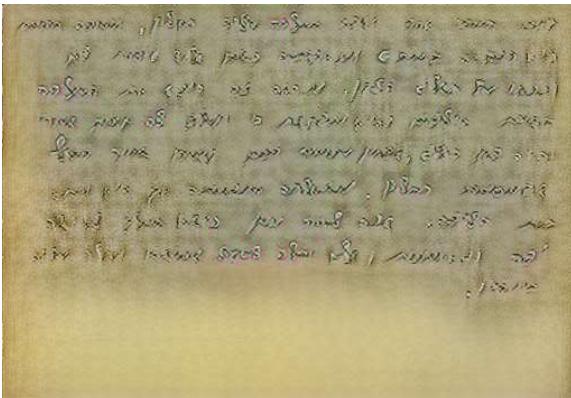
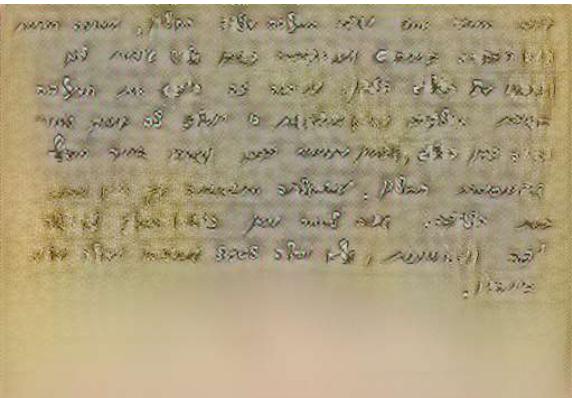
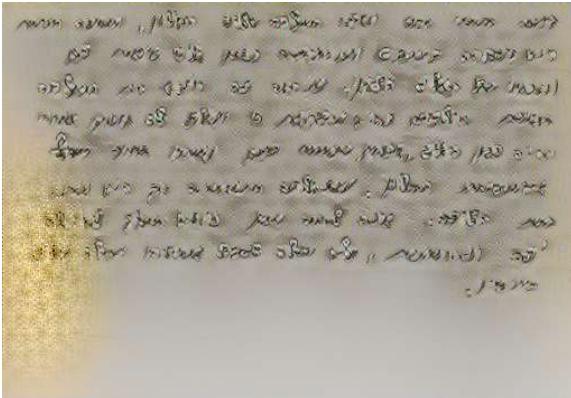
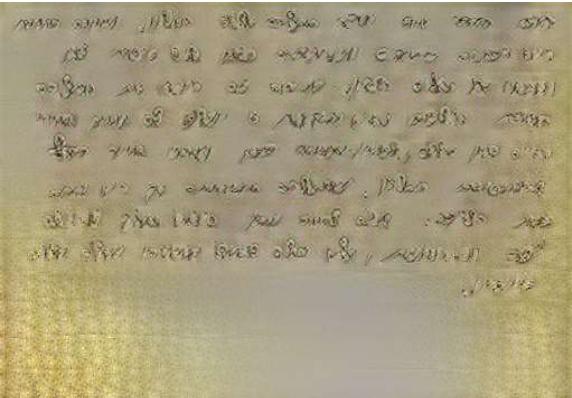
2.5.3.3. Weight 2

block3_conv2	block3_conv3
 A handwritten note in black ink on aged paper. The text is in two columns. The first column reads: "Dear Sirs, I hope this letter finds you well and that you are continuing to make progress in your studies. Please accept my best regards and kind regards for your wife, and for all the members of your family. Kind regards, [Signature]". The date at the bottom right is "1/2/12".	 A handwritten note in black ink on aged paper. The text is in two columns. The first column reads: "Dear Sirs, I hope this letter finds you well and that you are continuing to make progress in your studies. Please accept my best regards and kind regards for your wife, and for all the members of your family. Kind regards, [Signature]". The date at the bottom right is "1/2/12".
block3_conv4	block4_conv2
 A handwritten note in black ink on aged paper. The text is in two columns. The first column reads: "Dear Sirs, I hope this letter finds you well and that you are continuing to make progress in your studies. Please accept my best regards and kind regards for your wife, and for all the members of your family. Kind regards, [Signature]". The date at the bottom right is "1/2/12".	 A handwritten note in black ink on aged paper. The text is in two columns. The first column reads: "Dear Sirs, I hope this letter finds you well and that you are continuing to make progress in your studies. Please accept my best regards and kind regards for your wife, and for all the members of your family. Kind regards, [Signature]". The date at the bottom right is "1/2/12".
block5_conv2	
 A photograph of a rectangular object, likely a book or a set of documents, bound in dark green leather. The cover shows signs of age and wear.	

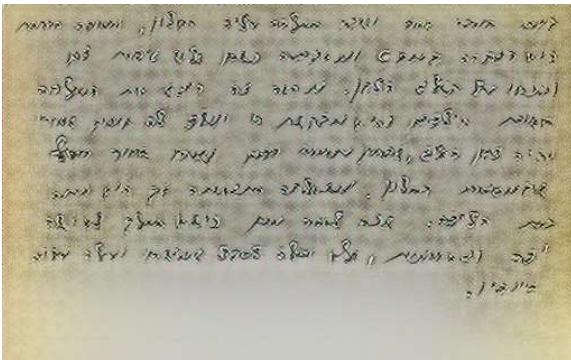
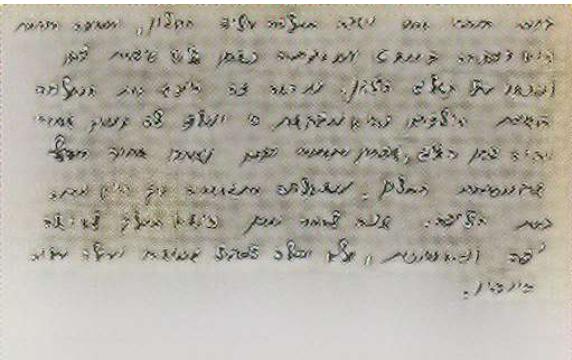
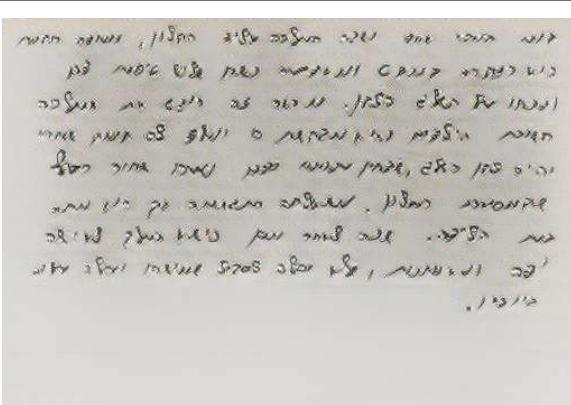
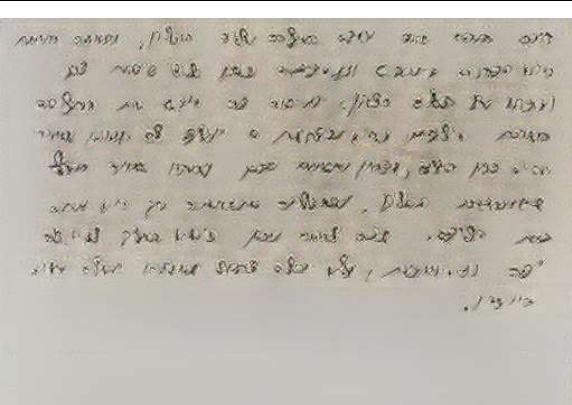
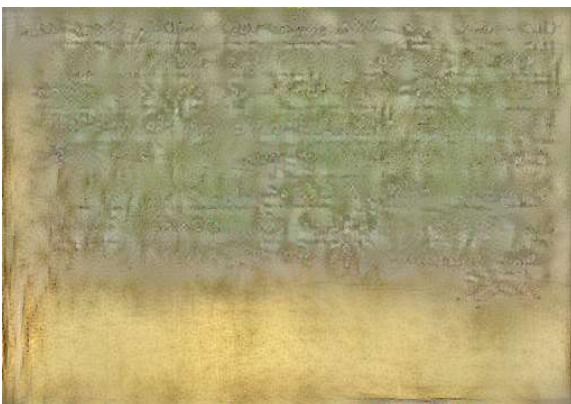
2.5.3.4. Weight 3

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

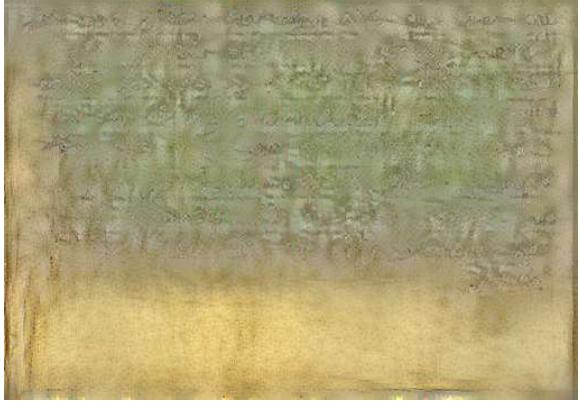
2.5.3.5. Weight 4

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.5.3.6. Weight 5

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.5.3.7. Weight 6

block3_conv2	block3_conv3
<p>num zeros: 11386 3187 unique non-zero values: 107 # of rows: 1024 # of columns: 1024 # of channels: 32 # of filters: 32 # of kernel size: 3x3 # of stride: 1x1 # of padding: 1x1 # of dilation: 1x1 # of groups: 1 # of bias: 0 # of weight: 32x1024x1024x32 # of output: 32x1024x1024x32 # of hidden: 32x1024x1024x32 # of layers: 32x1024x1024x32 # of neurons: 32x1024x1024x32 # of weights: 32x1024x1024x32 # of biases: 32x1024x1024x32 # of total: 32x1024x1024x32 . / 1024x32</p>	<p>num zeros: 11386 3187 unique non-zero values: 107 # of rows: 1024 # of columns: 1024 # of channels: 32 # of filters: 32 # of kernel size: 3x3 # of stride: 1x1 # of padding: 1x1 # of dilation: 1x1 # of groups: 1 # of bias: 0 # of weight: 32x1024x1024x32 # of output: 32x1024x1024x32 # of hidden: 32x1024x1024x32 # of layers: 32x1024x1024x32 # of neurons: 32x1024x1024x32 # of weights: 32x1024x1024x32 # of biases: 32x1024x1024x32 # of total: 32x1024x1024x32 . / 1024x32</p>
block3_conv4	block4_conv2
<p>num zeros: 11386 3187 unique non-zero values: 107 # of rows: 1024 # of columns: 1024 # of channels: 32 # of filters: 32 # of kernel size: 3x3 # of stride: 1x1 # of padding: 1x1 # of dilation: 1x1 # of groups: 1 # of bias: 0 # of weight: 32x1024x1024x32 # of output: 32x1024x1024x32 # of hidden: 32x1024x1024x32 # of layers: 32x1024x1024x32 # of neurons: 32x1024x1024x32 # of weights: 32x1024x1024x32 # of biases: 32x1024x1024x32 # of total: 32x1024x1024x32 . / 1024x32</p>	<p>num zeros: 11386 3187 unique non-zero values: 107 # of rows: 1024 # of columns: 1024 # of channels: 32 # of filters: 32 # of kernel size: 3x3 # of stride: 1x1 # of padding: 1x1 # of dilation: 1x1 # of groups: 1 # of bias: 0 # of weight: 32x1024x1024x32 # of output: 32x1024x1024x32 # of hidden: 32x1024x1024x32 # of layers: 32x1024x1024x32 # of neurons: 32x1024x1024x32 # of weights: 32x1024x1024x32 # of biases: 32x1024x1024x32 # of total: 32x1024x1024x32 . / 1024x32</p>
block5_conv2	
	

2.5.3.8. Weight 7

2.5.3.9. Weight 8

block3_conv2	block3_conv3
<p>חישוב מוקדי הנקודות המוגדרות ב-ReLU, כלומר מוקדי כינון כפלה זנודו ונקודות גלגול צפויות ב-ReLU, כלומר מוקדי הכינון דרכם של גלגולים. נזכיר ש-ReLU הוא גלגול בו מוקדי הכינון ו-ReLU מוגדר כפונקציית רצף גלגול גלגול צפוי ב-ReLU. מוקדי הנקודות המוגדרות ב-ReLU הם מוקדי גלגול צפוי ב-ReLU. מוקדי הנקודות המוגדרות ב-ReLU הם מוקדי גלגול צפוי ב-ReLU.</p>	<p>חישוב מוקדי הנקודות המוגדרות ב-ReLU, כלומר מוקדי כינון כפלה זנודו ונקודות גלגול צפויות ב-ReLU, כלומר מוקדי הכינון דרכם של גלגולים. נזכיר ש-ReLU הוא גלגול בו מוקדי הכינון ו-ReLU מוגדר כפונקציית רצף גלגול גלגול צפוי ב-ReLU. מוקדי הנקודות המוגדרות ב-ReLU הם מוקדי גלגול צפוי ב-ReLU. מוקדי הנקודות המוגדרות ב-ReLU הם מוקדי גלגול צפוי ב-ReLU.</p>
block3_conv4	block4_conv2
block5_conv2	

2.6. Experiment 3

2.6.1. Content Input

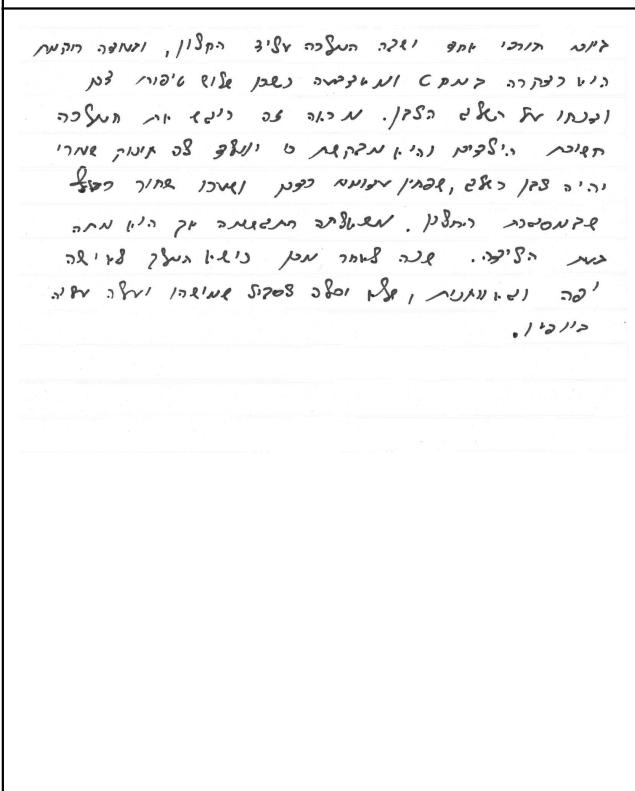
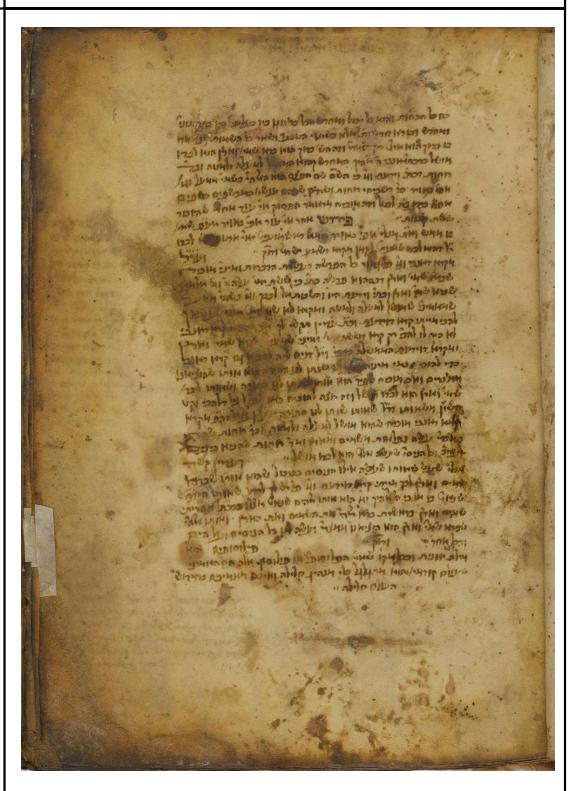
This experiment used a dilated modern hebrew handwritten document for content.

2.6.2. Style Input

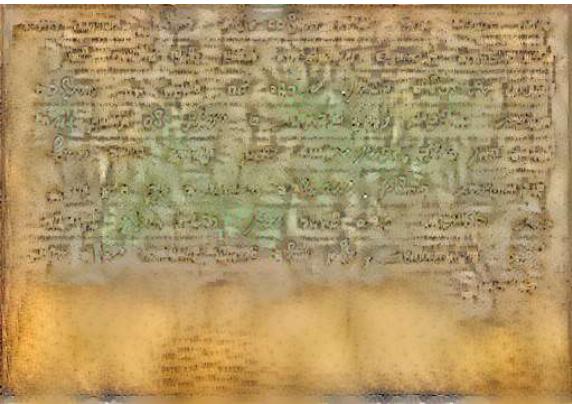
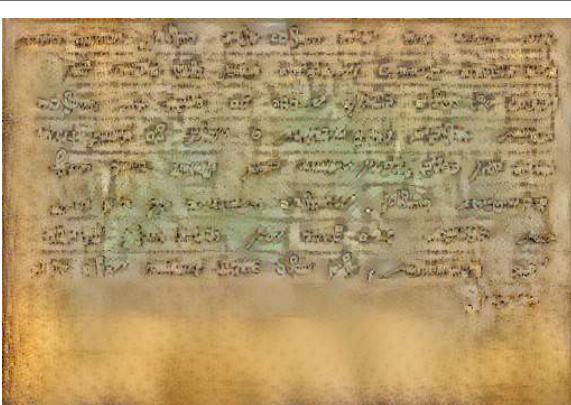
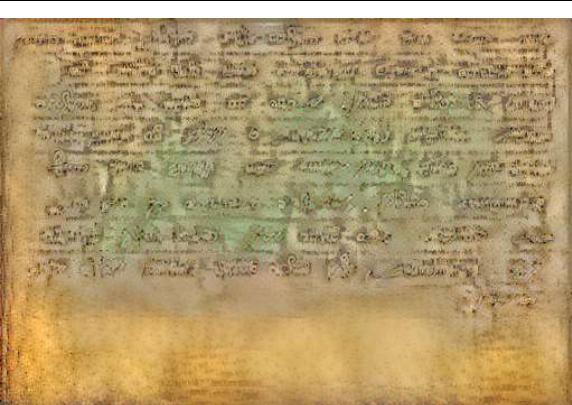
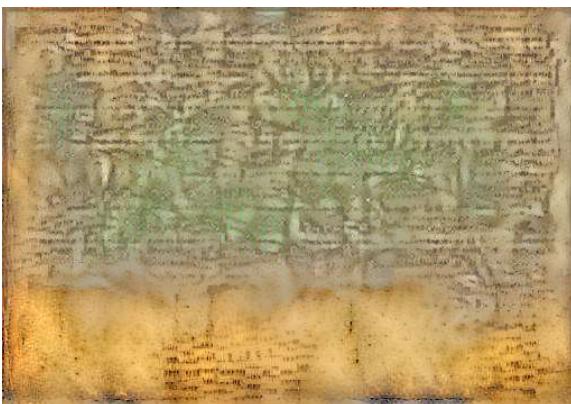
This experiment used a hebrew middle age document with text for style.

2.6.3. Results

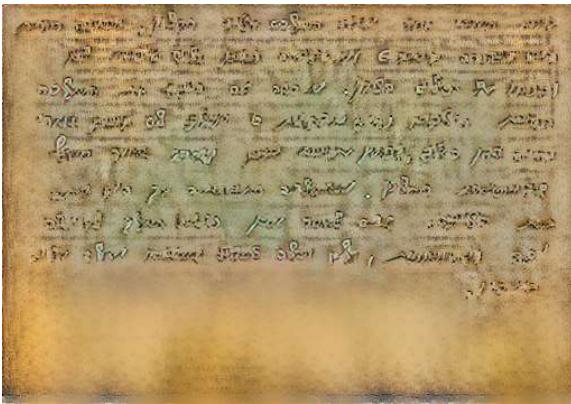
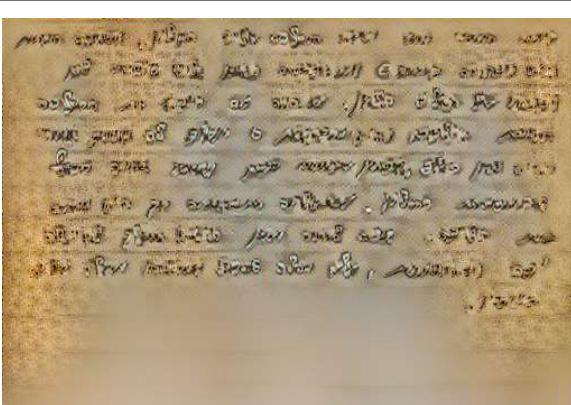
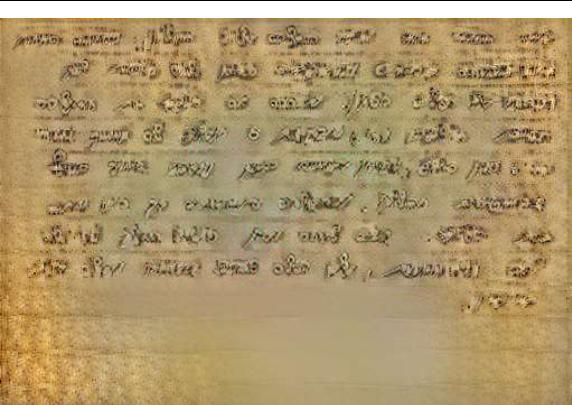
We will show samples of the results with each weight and content layer (style layers are the same).

Content image	Style image
	

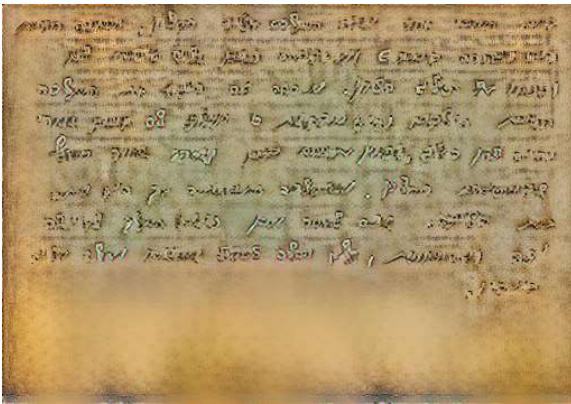
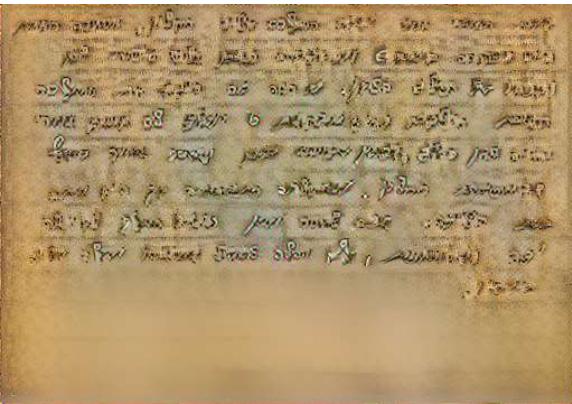
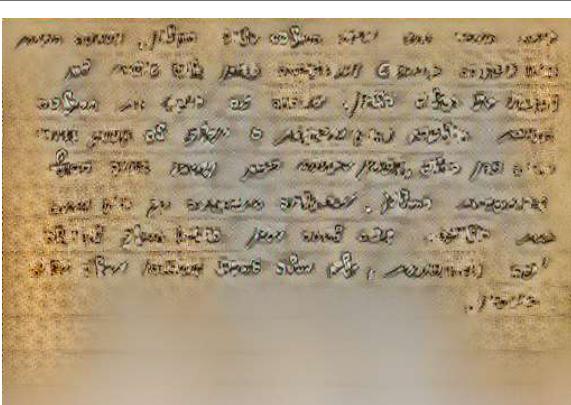
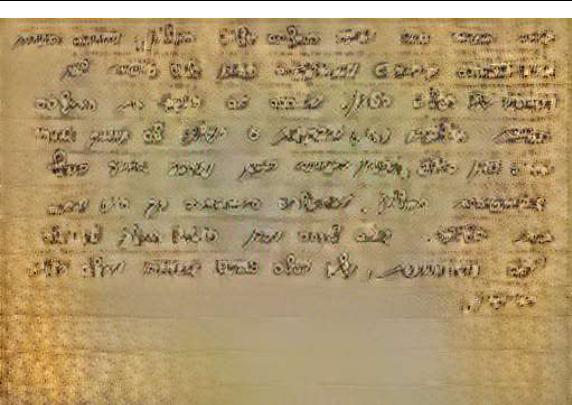
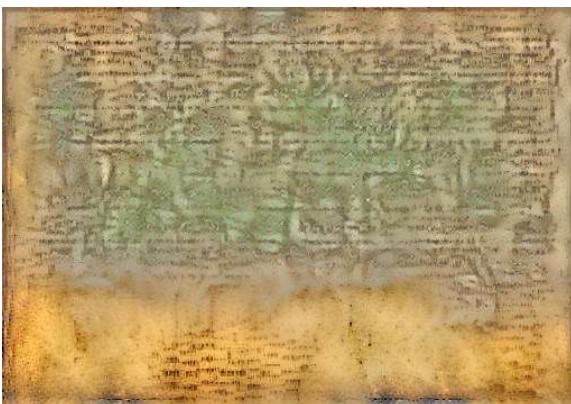
2.6.3.1. Weight 0

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

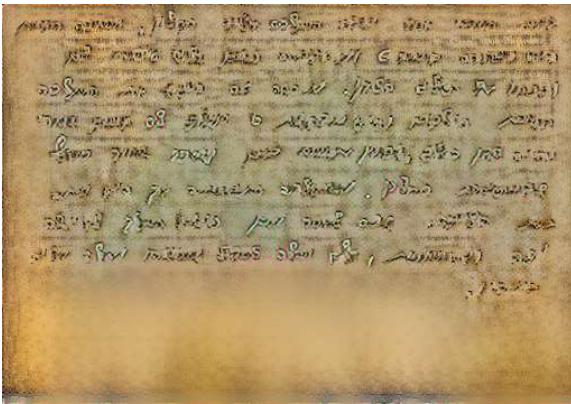
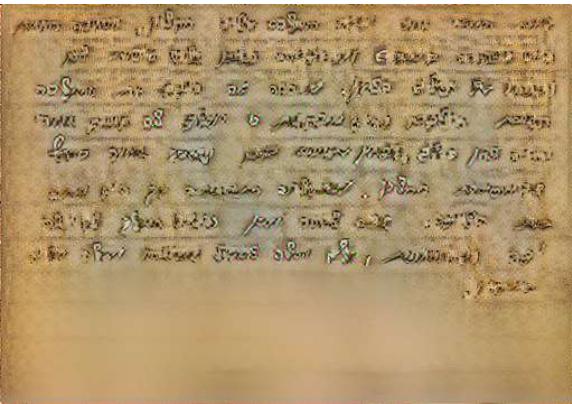
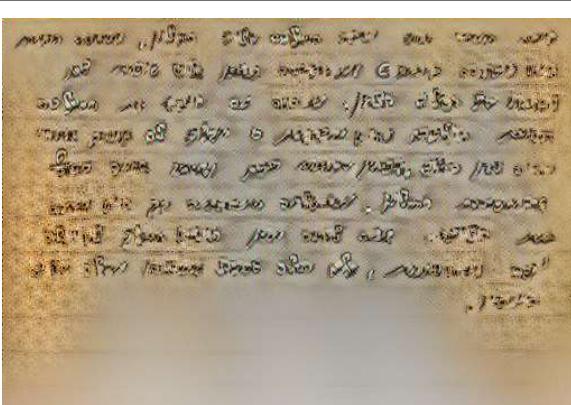
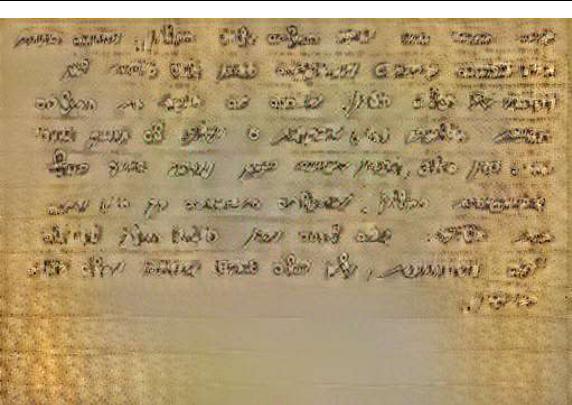
2.6.3.2. Weight 1

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

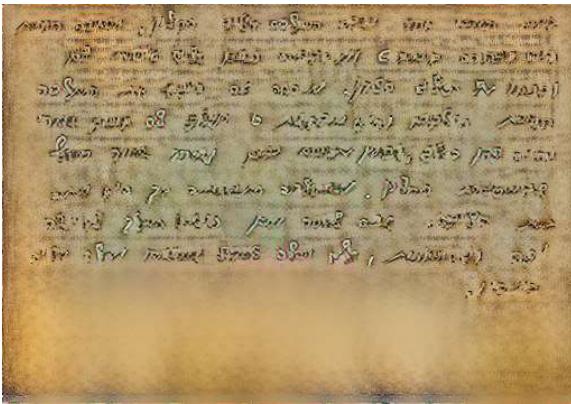
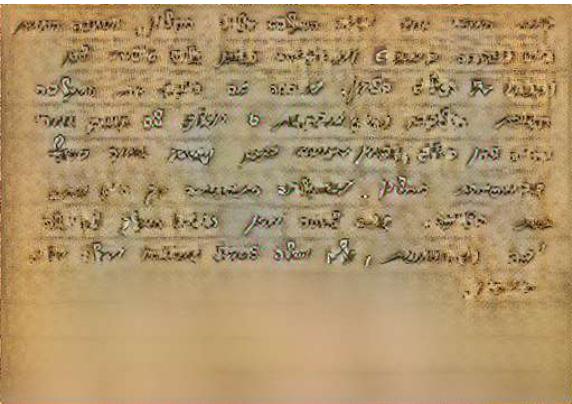
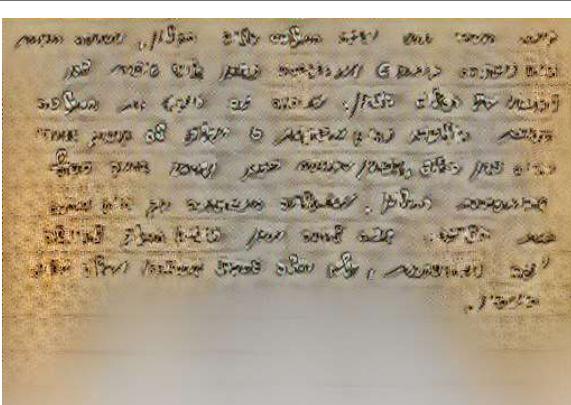
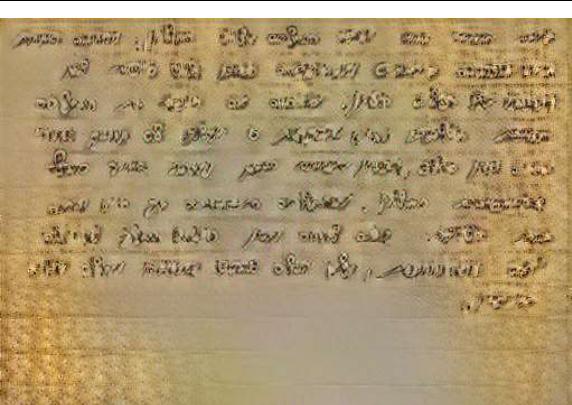
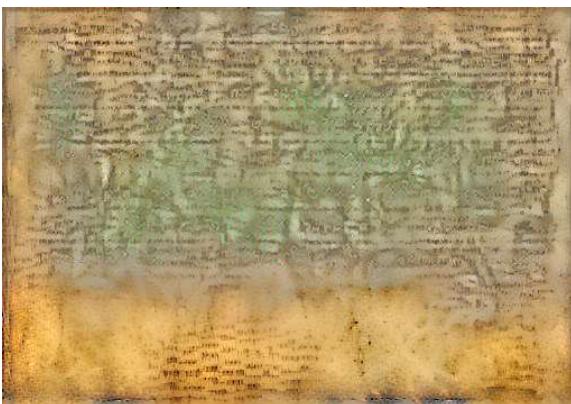
2.6.3.3. Weight 2

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.6.3.4. Weight 3

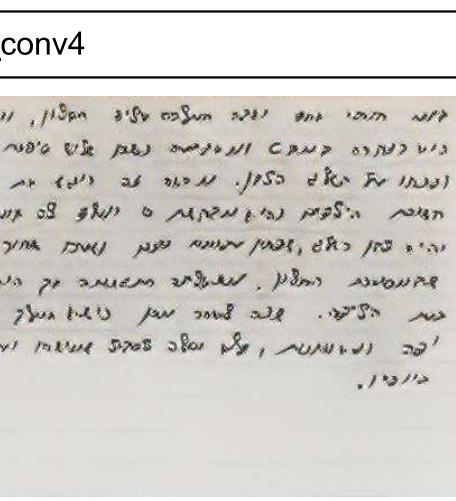
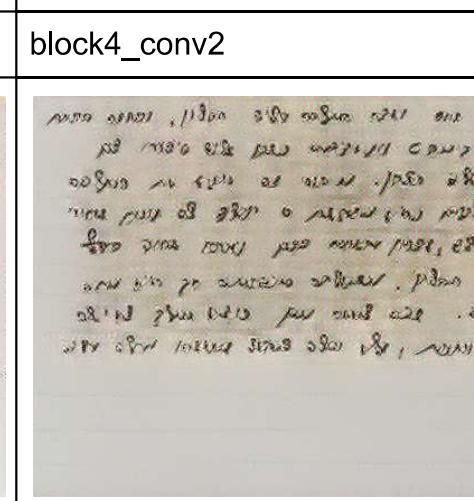
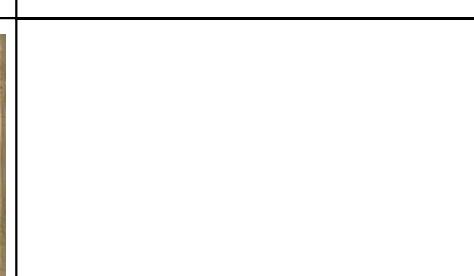
block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.6.3.5. Weight 4

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.6.3.6. Weight 5

2.6.3.7. Weight 6

block3_conv2	block3_conv3
 <p>This image shows a page from a medieval manuscript. The text is written in two columns in a Gothic script. The ink is dark brown, and the parchment appears aged and slightly yellowed at the bottom.</p>	 <p>This image shows a page from a medieval manuscript. The text is written in two columns in a Gothic script. The ink is dark brown, and the parchment appears aged and slightly yellowed at the bottom.</p>
block3_conv4	block4_conv2
 <p>This image shows a page from a medieval manuscript. The text is written in two columns in a Gothic script. The ink is dark brown, and the parchment appears aged and slightly yellowed at the bottom.</p>	 <p>This image shows a page from a medieval manuscript. The text is written in two columns in a Gothic script. The ink is dark brown, and the parchment appears aged and slightly yellowed at the bottom.</p>

2.6.3.8. Weight 7

2.6.3.9. Weight 8

block3_conv2	block3_conv3
<p>חומר ערך, וזהו מה שפ. 182 ופ. 183, יונת הילן בינה כפריה חנוך ורמאנס רכד 313 וילן פט פנור או יג'פ.-CSL. נרכז זה כפ' או מנג'ה חומר ויג'פ רוד'נווילר או יג'פ. 80 דינר עלי וה' פט. 280, 280/אלון כדור. יונת הילן כפ' בונדרס רומן. יונת הילן רם הילן מ- מן יג'פ. אלה גודל מ- 210 מ- 210 פט. 'פה (פ. 182), פ. 182 יונת סופס פט' 183: פט' ד' 11/1.</p>	<p>חומר ערך, וזהו מה שפ. 182 ופ. 183, יונת הילן בינה כפריה חנוך ורמאנס רכד 313 וילן פט פנור או יג'פ. CSL. נרכז זה כפ' או מנג'ה חומר ויג'פ רוד'נווילר או יג'פ. 80 דינר עלי וה' פט. 280, 280/אלון כדור. יונת הילן כפ' בונדרס רומן. יונת הילן רם הילן מ- מן יג'פ. אלה גודל מ- 210 מ- 210 פט. 'פה (פ. 182), פ. 182 יונת סופס פט' 183: פט' ד' 11/1.</p>
block3_conv4	block4_conv2
block5_conv2	

2.7. Experiment 4

2.7.1. Content Input

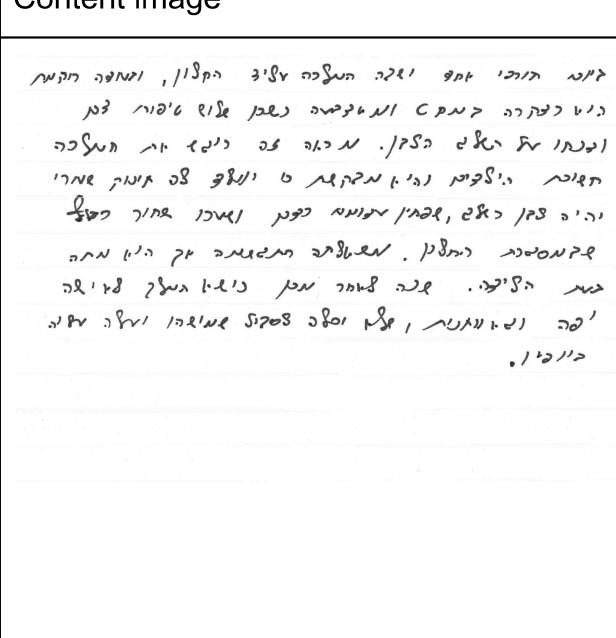
This experiment used a dilated modern hebrew handwritten document for content.

2.7.2. Style Input

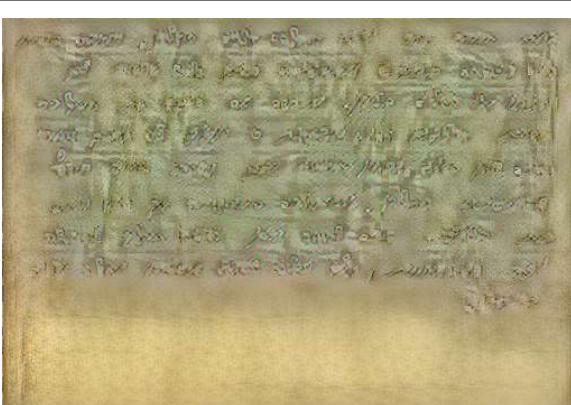
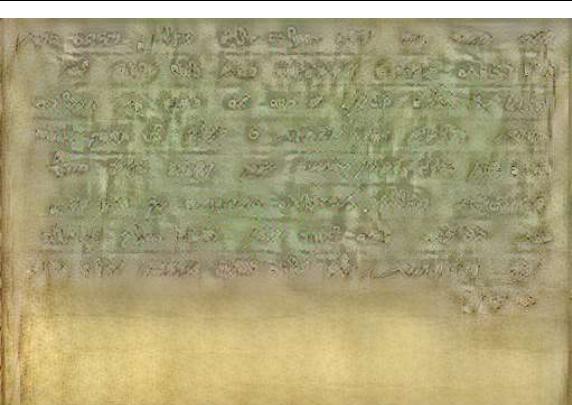
This experiment used a hebrew middle age document without text for style.

2.7.3. Results

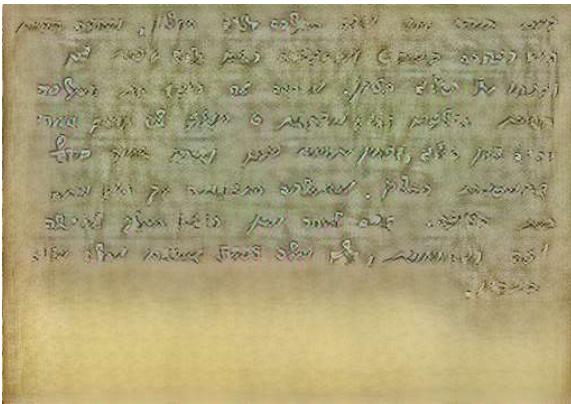
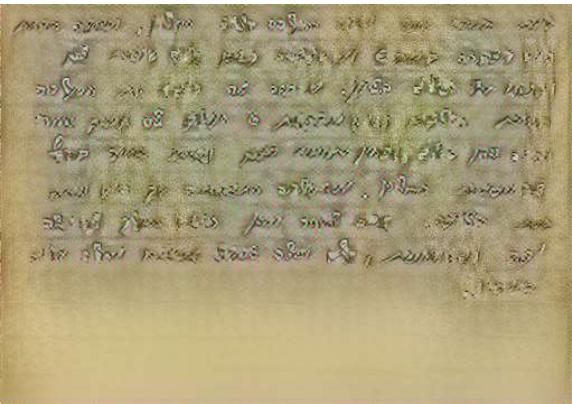
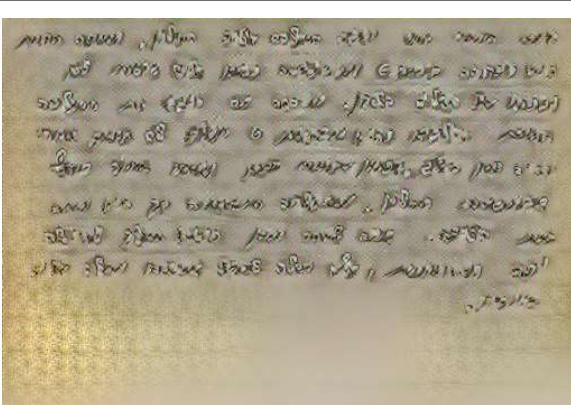
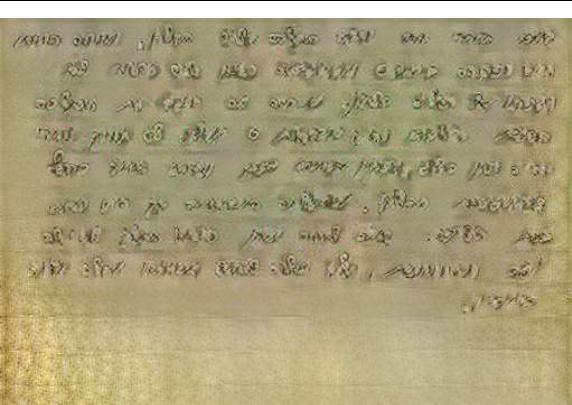
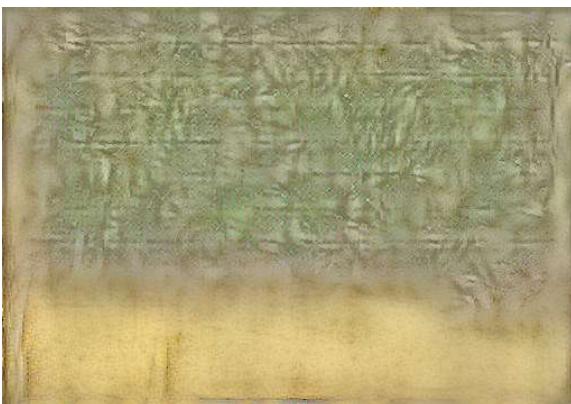
We will show samples of the results with each weight and content layer (style layers are the same).

Content image	Style image
	

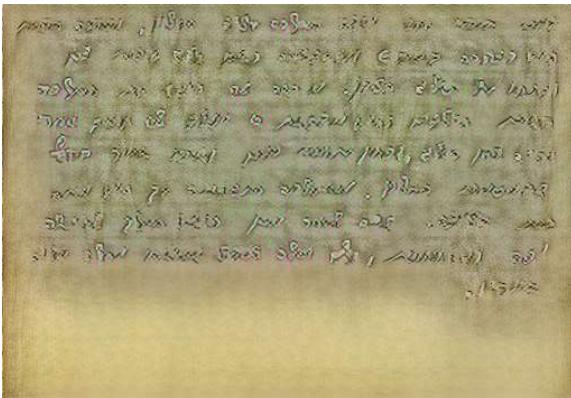
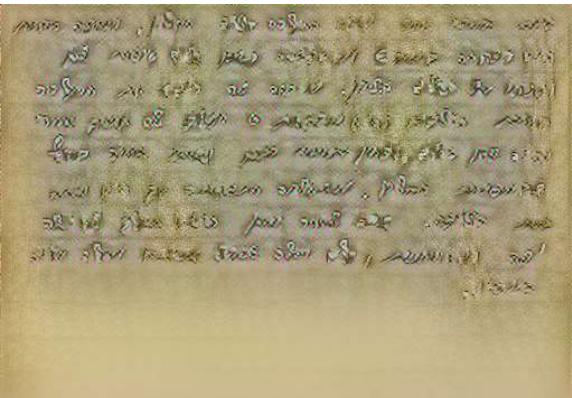
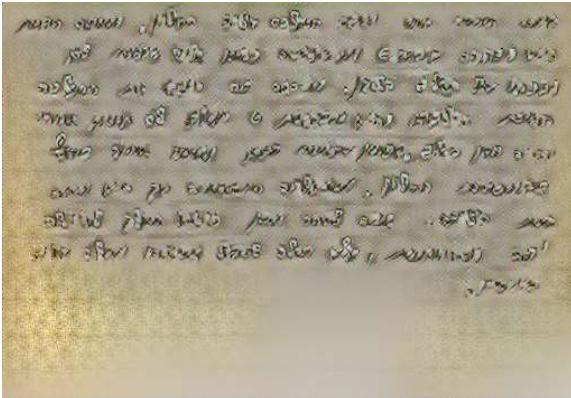
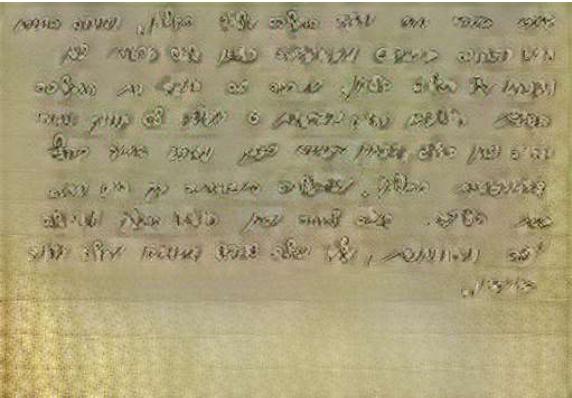
2.7.3.1. Weight 0

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

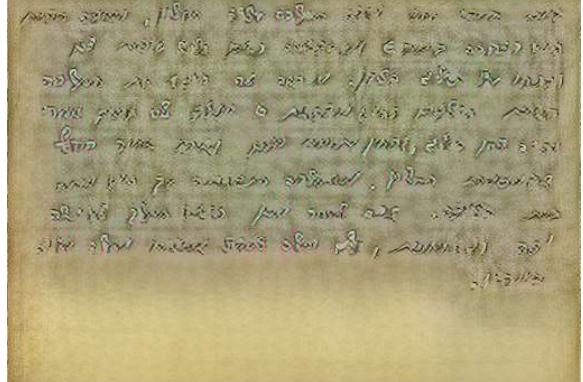
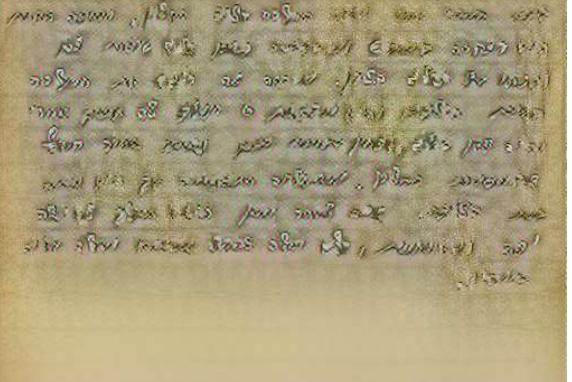
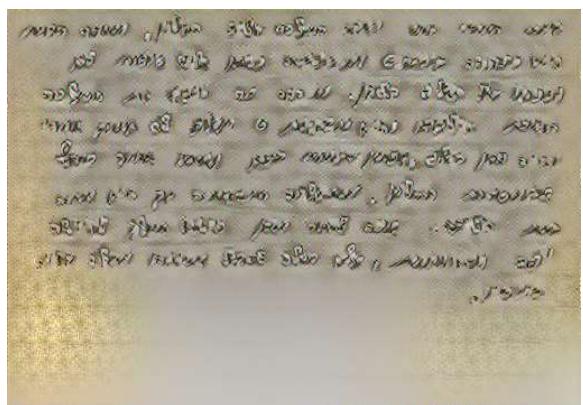
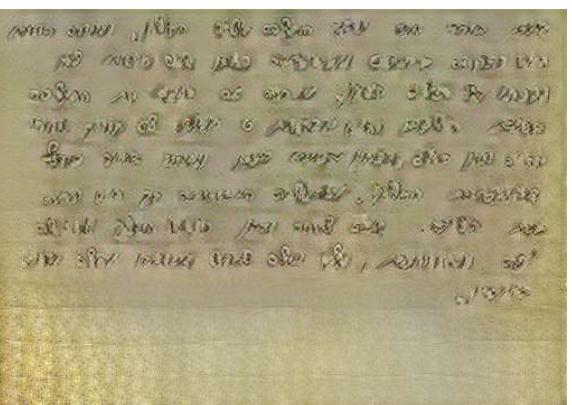
2.7.3.2. Weight 1

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

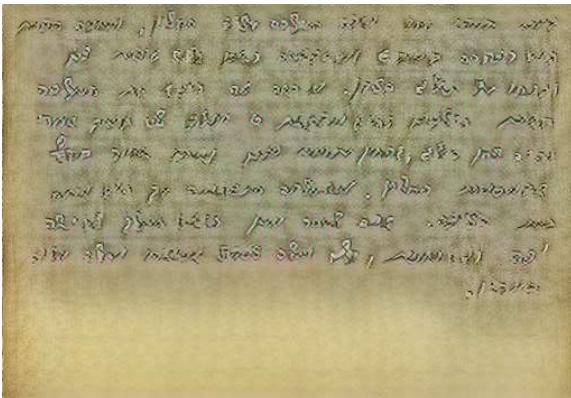
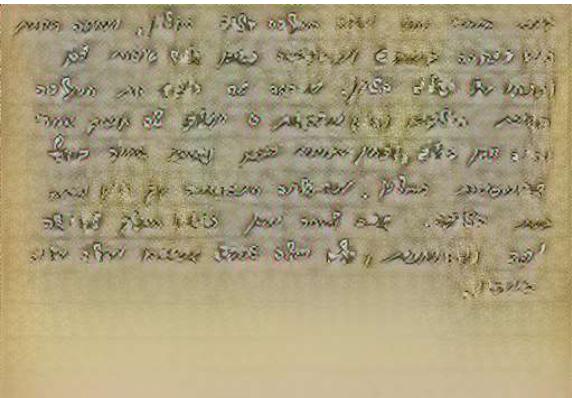
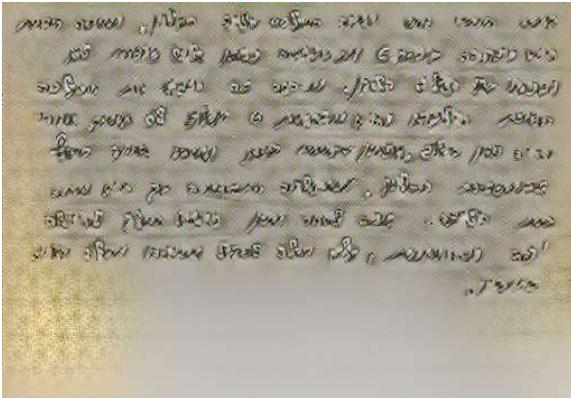
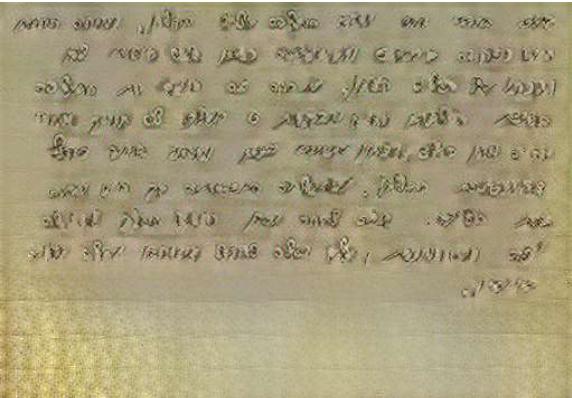
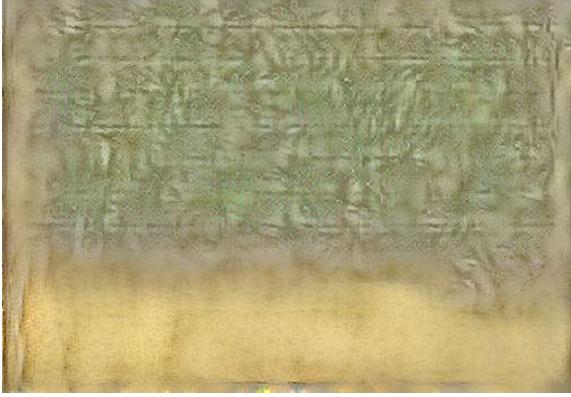
2.7.3.3. Weight 2

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

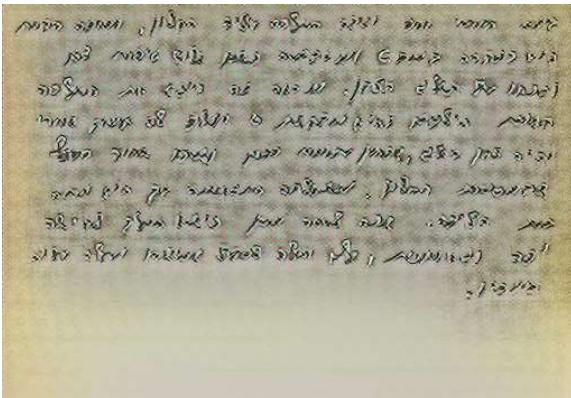
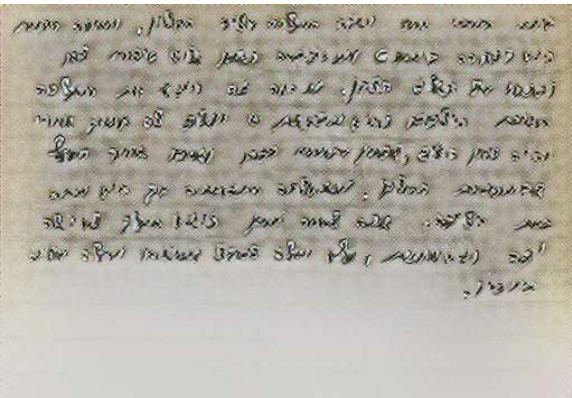
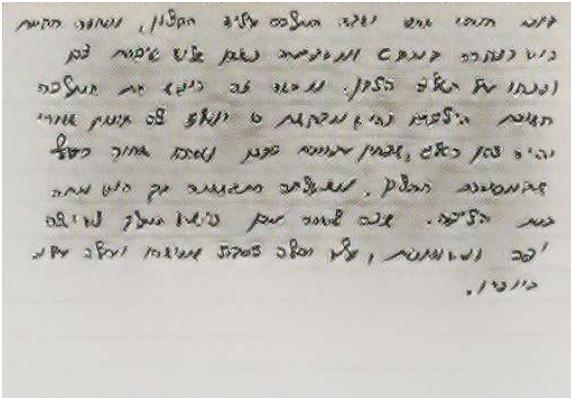
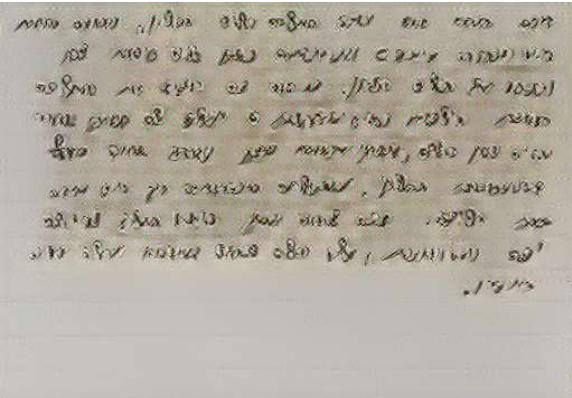
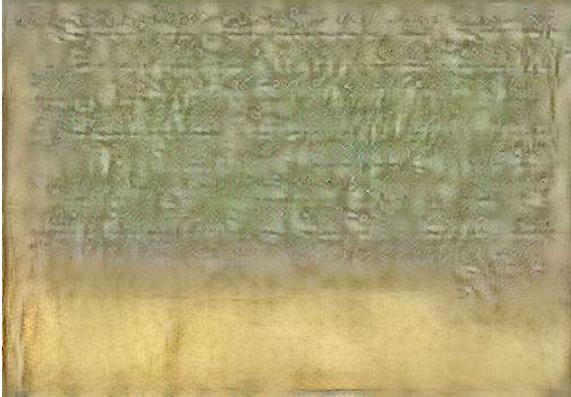
2.7.3.4. Weight 3

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

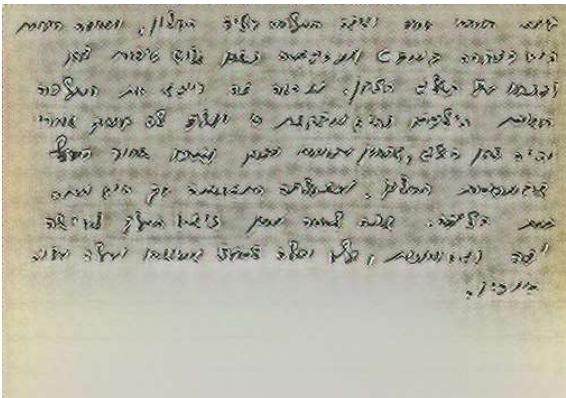
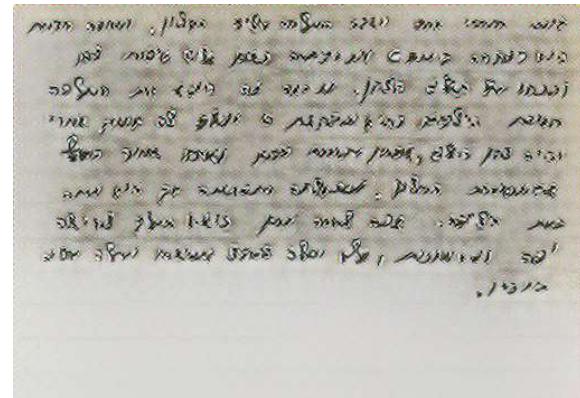
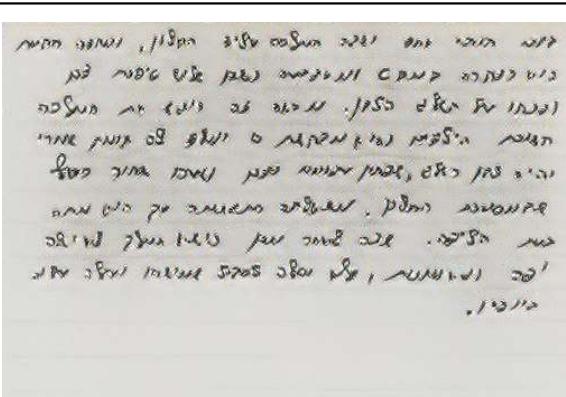
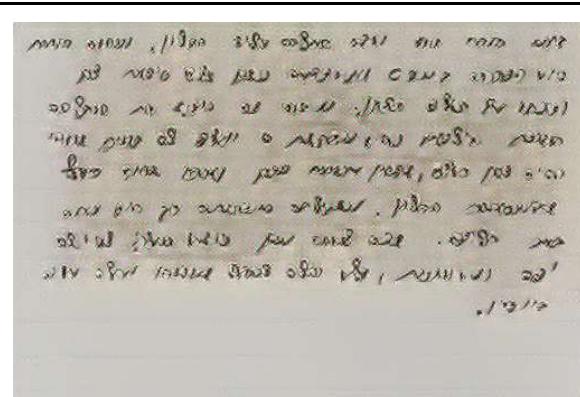
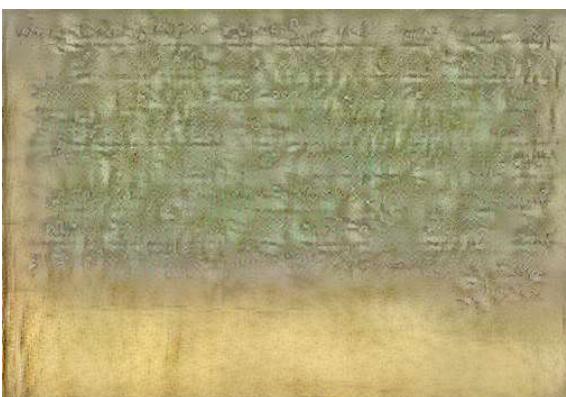
2.7.3.5. Weight 4

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.7.3.6. Weight 5

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.7.3.7. Weight 6

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.7.3.8. Weight 7

2.7.3.9. Weight 8

2.8. Experiment 5

We saw good results in experiment 3 and 4. Next we will try to apply binarization on content image to see if this can also improve experiments 1 and 2.

2.8.1. Content Input

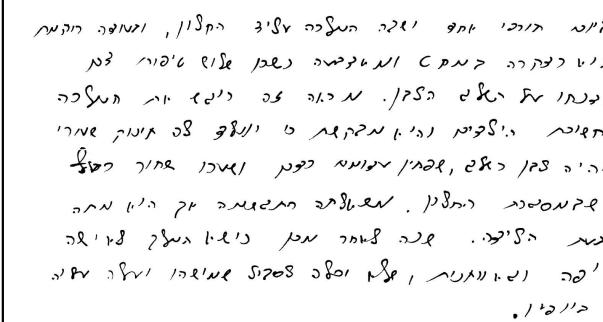
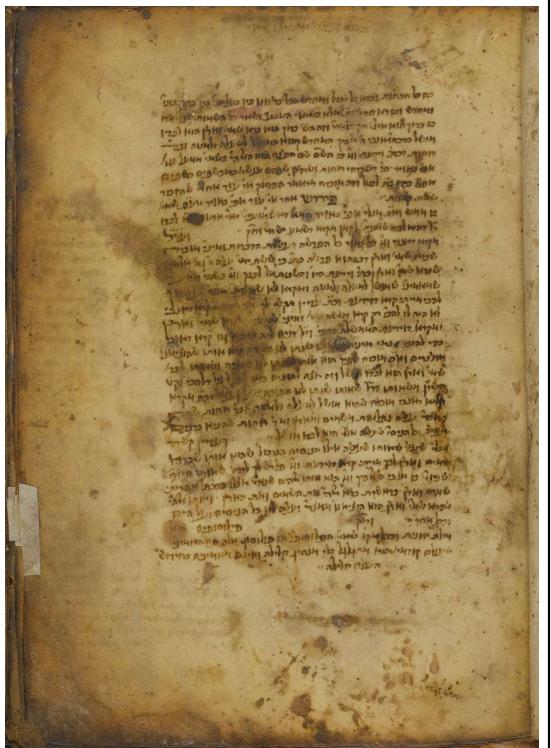
This experiment used a binary modern hebrew handwritten document for content.

2.8.2. Style Input

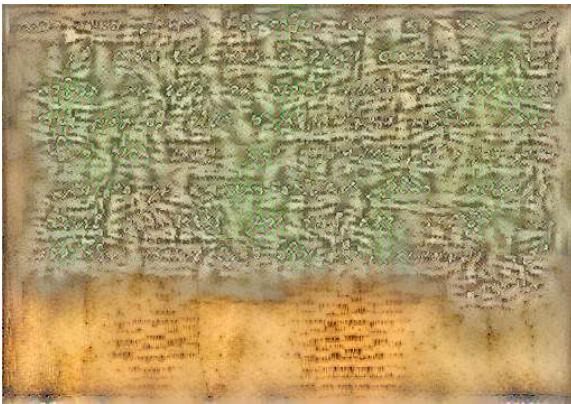
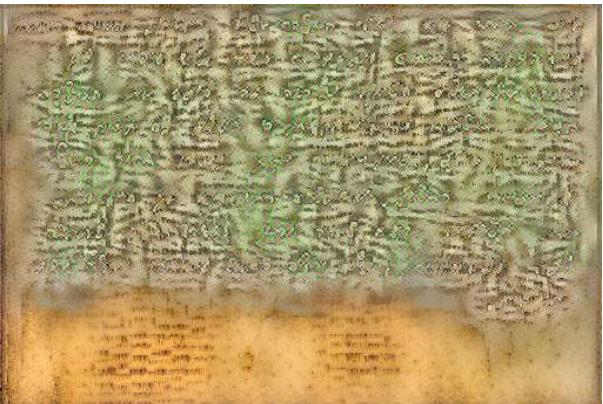
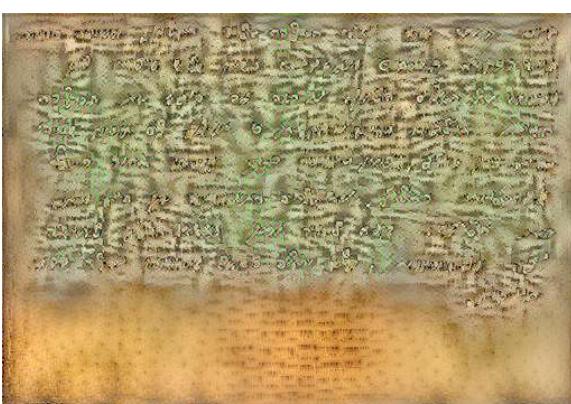
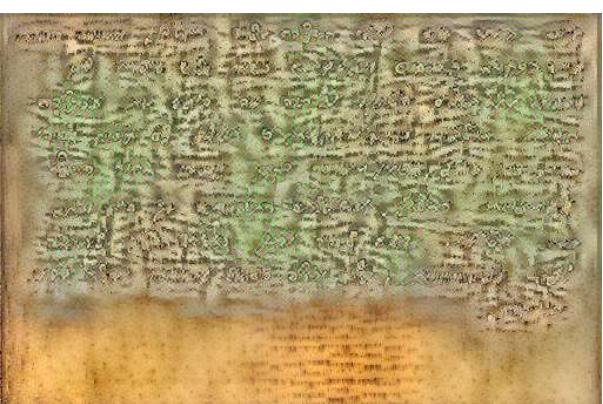
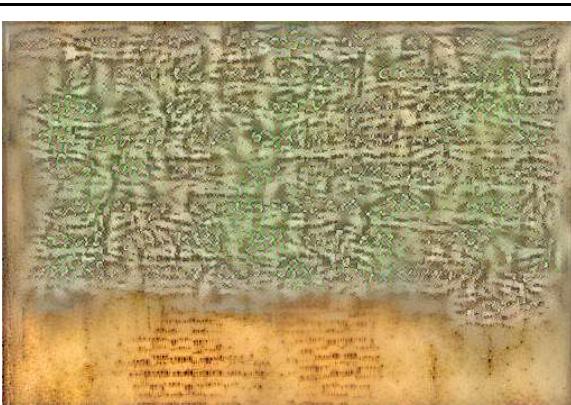
This experiment used a hebrew middle age document with text for style.

2.8.3. Results

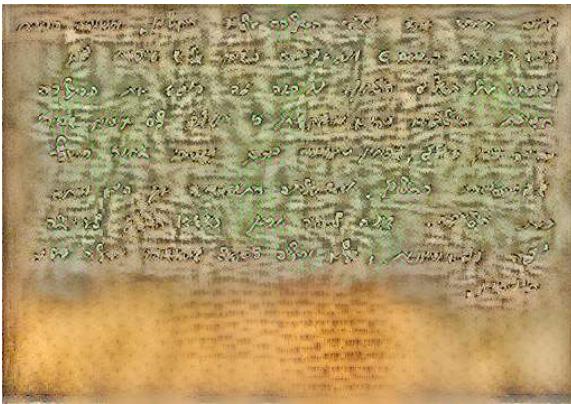
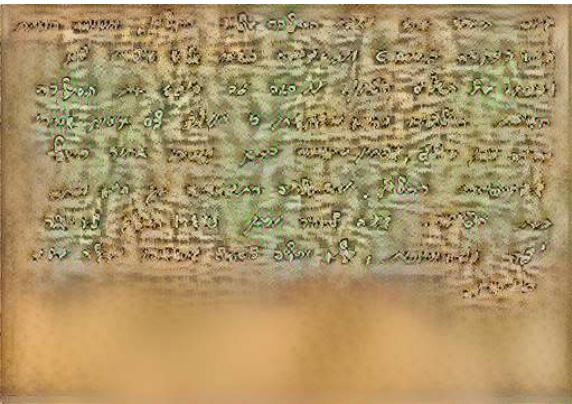
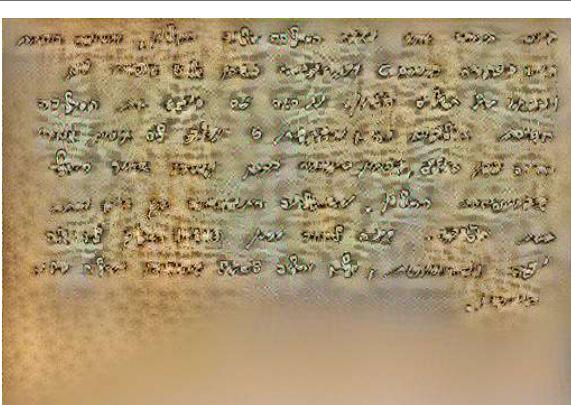
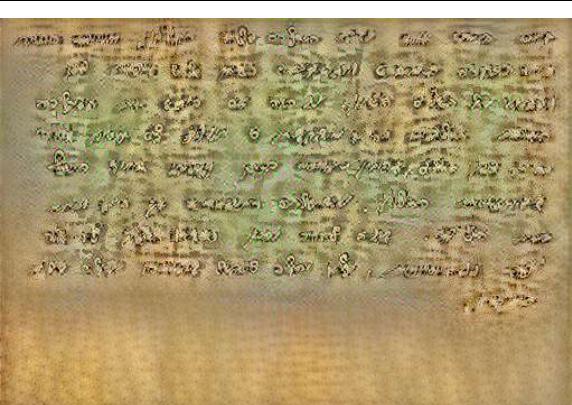
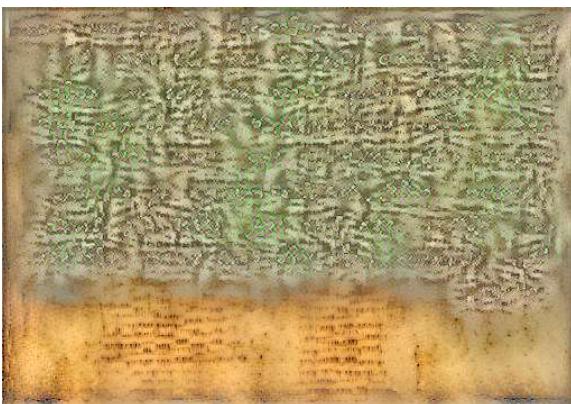
We will show samples of the results with each weight and content layer (style layers are the same).

Content image	Style image
 A binary black and white image of a modern Hebrew handwritten document. The text is in a clear, cursive script, though some strokes are thick and bold. The background is white, and the text is black. There are several lines of text, with the last line ending in a small black dot.	 A photograph of a page from a Hebrew medieval manuscript. The paper is aged and yellowed, showing significant texture and discoloration. The text is written in a dense, formal script in two columns. The parchment appears slightly uneven and stained.

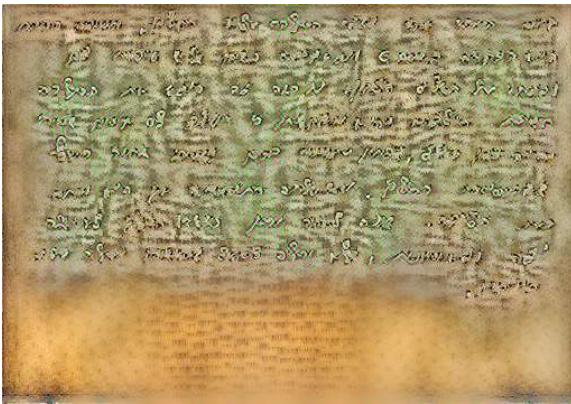
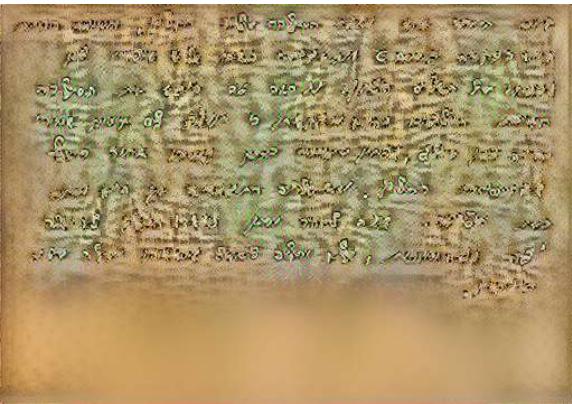
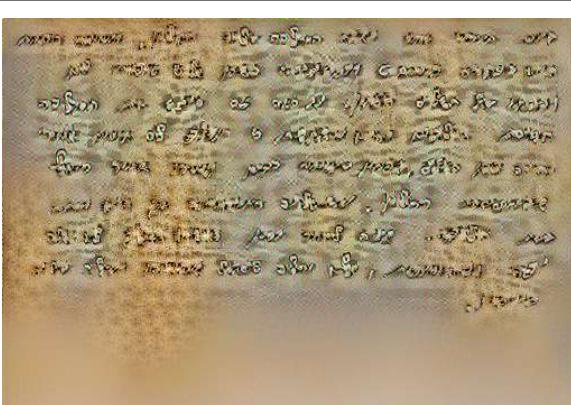
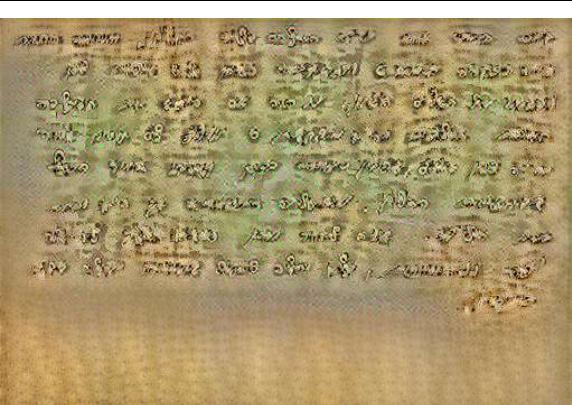
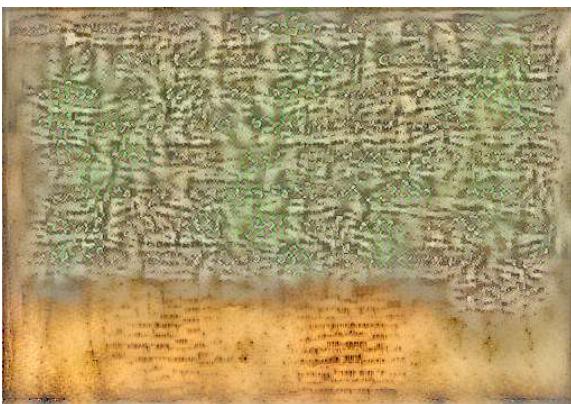
2.8.3.1. Weight 0

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

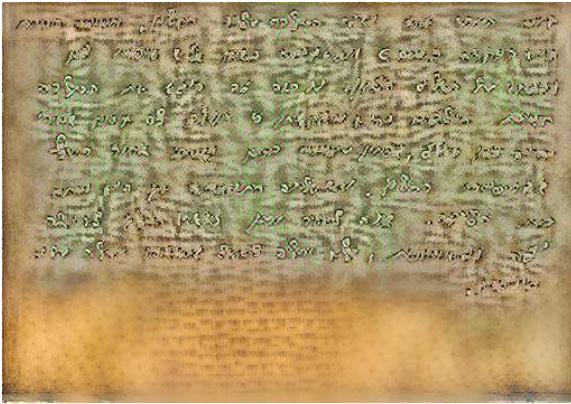
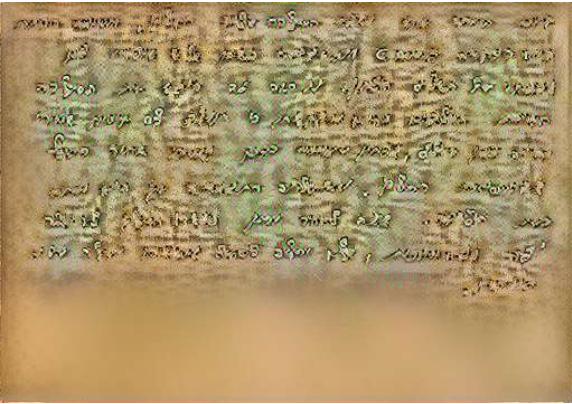
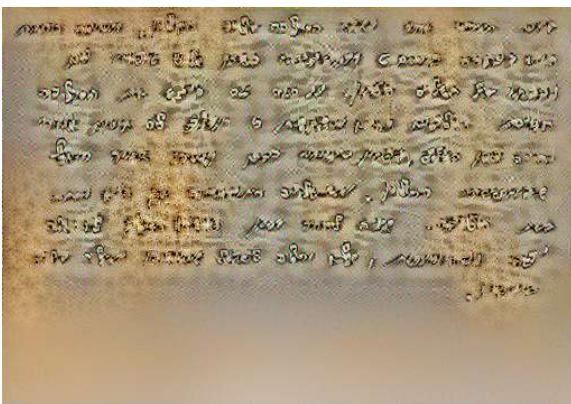
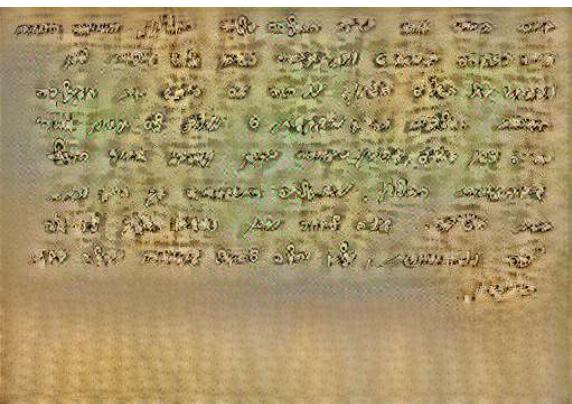
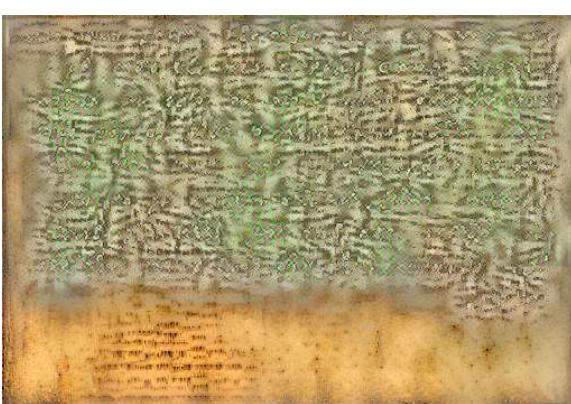
2.8.3.2. Weight 1

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

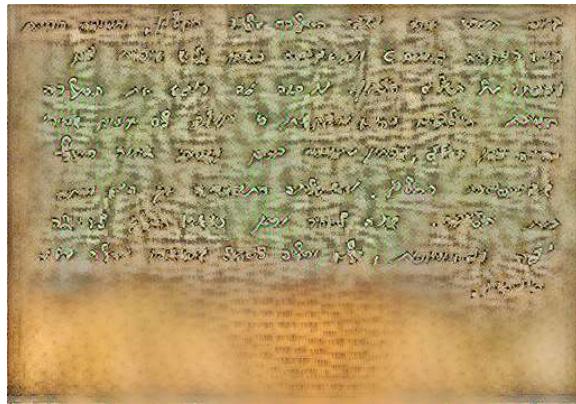
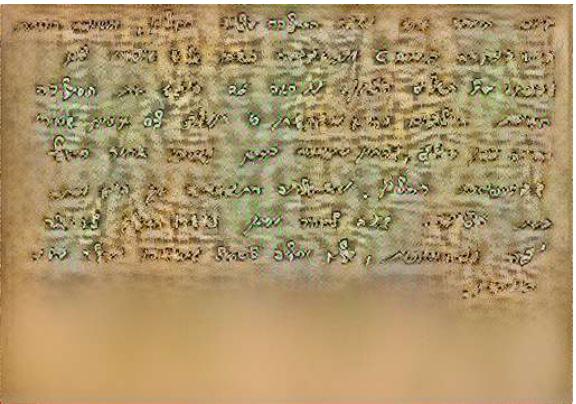
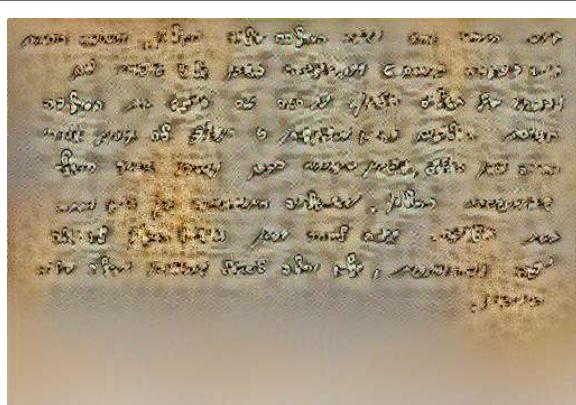
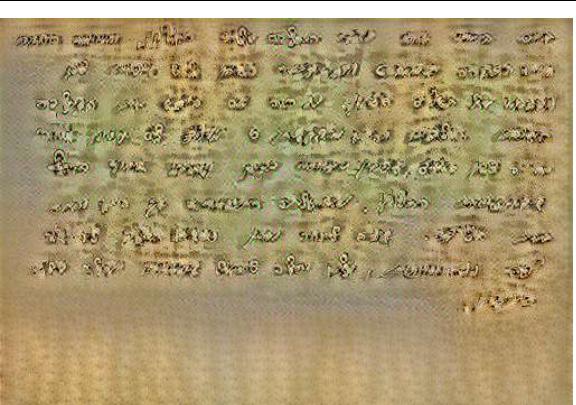
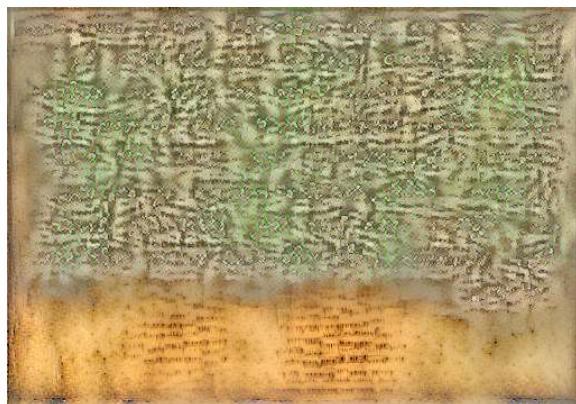
2.8.3.3. Weight 2

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

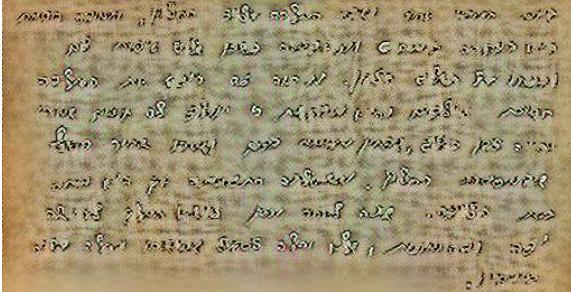
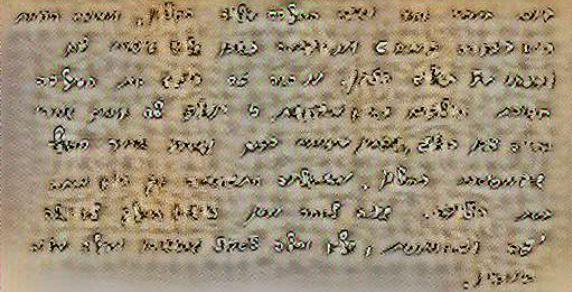
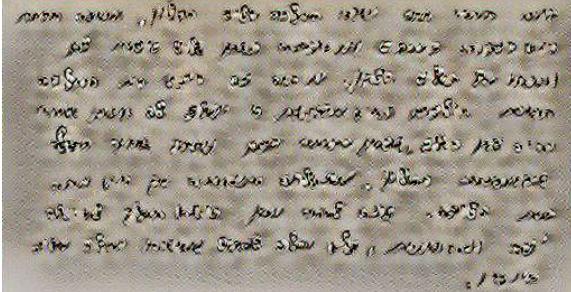
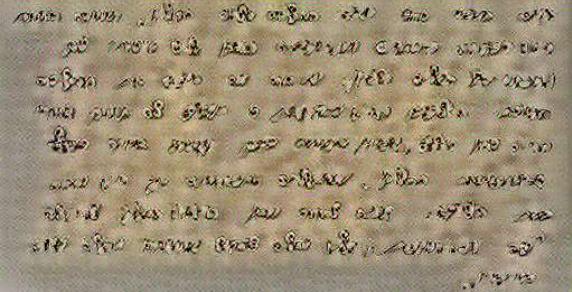
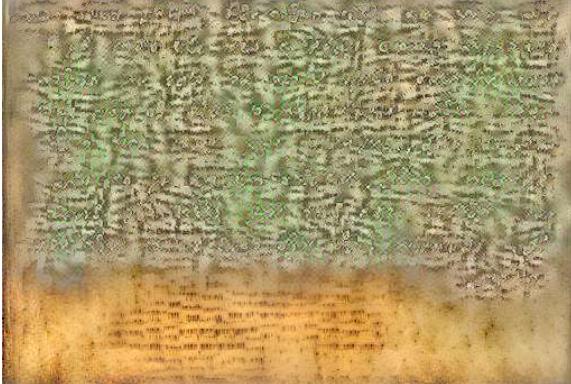
2.8.3.4. Weight 3

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

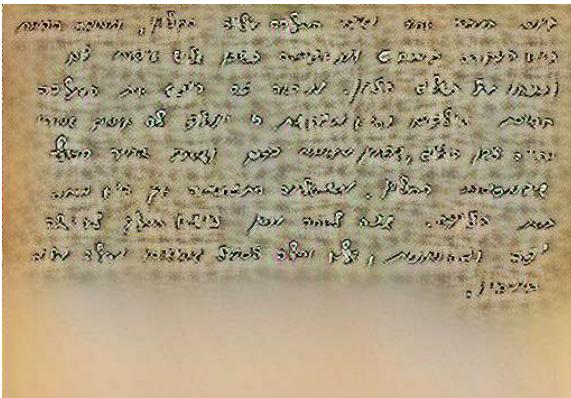
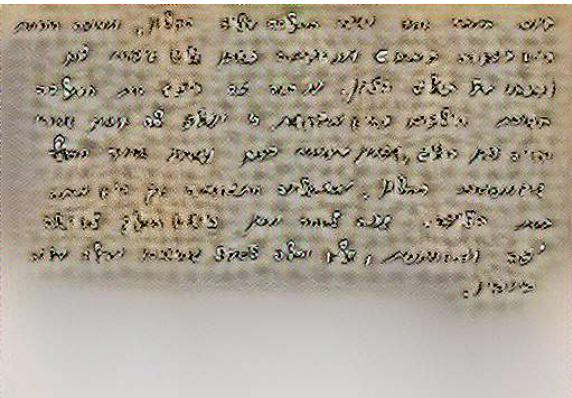
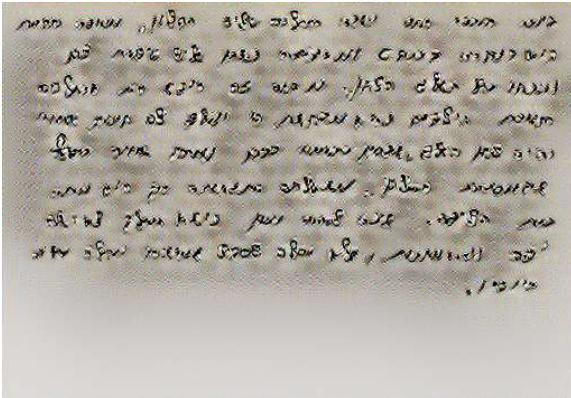
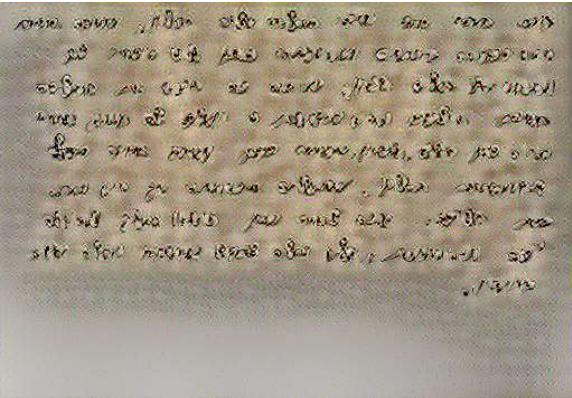
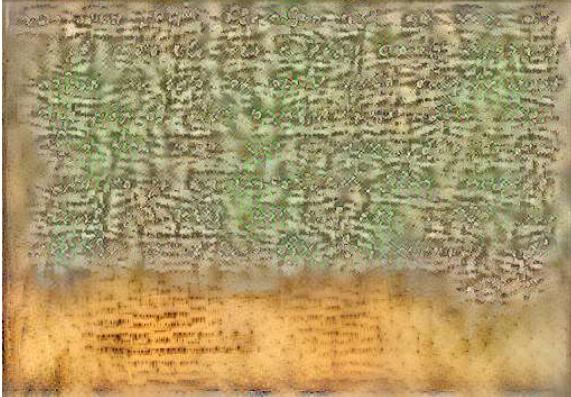
2.8.3.5. Weight 4

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.8.3.6. Weight 5

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.8.3.7. Weight 6

block3_conv2	block3_conv3
 A photograph of a handwritten note on a piece of paper. The text is in cursive and appears to be in Telugu. It discusses the need for more time to complete a task and expresses concern about the quality of work. The date '1/3/12' is at the bottom right.	 A photograph of a handwritten note on a piece of paper. The text is in cursive and appears to be in Telugu. It discusses the need for more time to complete a task and expresses concern about the quality of work. The date '1/3/12' is at the bottom right.
block3_conv4	block4_conv2
 A photograph of a handwritten note on a piece of paper. The text is in cursive and appears to be in Telugu. It discusses the need for more time to complete a task and expresses concern about the quality of work. The date '1/3/12' is at the bottom right.	 A photograph of a handwritten note on a piece of paper. The text is in cursive and appears to be in Telugu. It discusses the need for more time to complete a task and expresses concern about the quality of work. The date '1/3/12' is at the bottom right.
block5_conv2	
 A photograph of a textured surface, possibly a wall or a piece of fabric, showing a pattern of small, irregular shapes. The colors are muted greens and browns.	

2.8.3.8. Weight 7

2.8.3.9. Weight 8

block3_conv2	block3_conv3
<p>חישב ערךיו, וזה יהיה שכבת 3x3, ולבסוף תחישב כינון כפלה חנוך ונשכח הדברה גודל 3x3, וזה יתנו הערך בדרכו הגדולה. וכך זה יתנו לנו נסחה חישוב ויחסון כפלה מוקדם יותר או לאן שפונקציית היחסים 3x3, פולינומיאליות כפלה יתנו לנו גודל 3x3 בפונקציית היחסים. וזה יתנו לנו גודל 3x3 בפונקציית היחסים. וזה יתנו לנו גודל 3x3 בפונקציית היחסים. בב' פונקציית, וזה יתנו לנו גודל 3x3 בפונקציית היחסים.</p>	<p>חישב ערךיו, וזה יהיה שכבת 3x3, ולבסוף תחישב כינון כפלה חנוך ונשכח הדברה גודל 3x3, וזה יתנו הערך בדרכו הגדולה. וכך זה יתנו לנו נסחה חישוב ויחסון כפלה מוקדם יותר או לאן שפונקציית היחסים 3x3, פולינומיאליות כפלה יתנו לנו גודל 3x3 בפונקציית היחסים. וזה יתנו לנו גודל 3x3 בפונקציית היחסים. וזה יתנו לנו גודל 3x3 בפונקציית היחסים. בב' פונקציית, וזה יתנו לנו גודל 3x3 בפונקציית היחסים.</p>
block3_conv4	block4_conv2
block5_conv2	

2.9. Experiment 6

2.9.1. Content Input

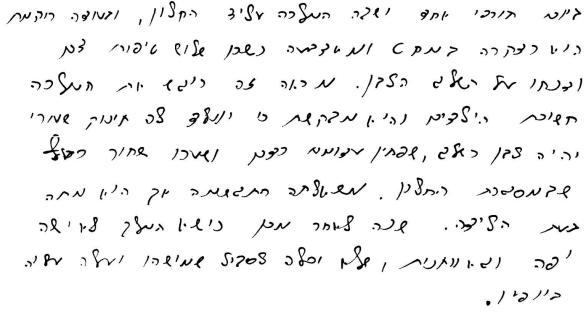
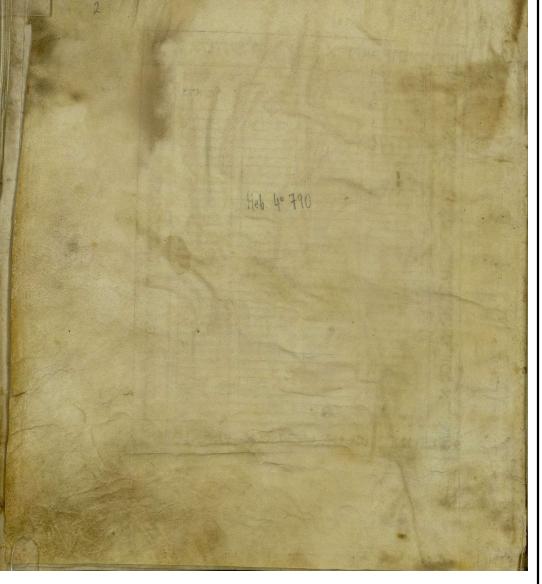
This experiment used a binary modern hebrew handwritten document for content.

2.9.2. Style Input

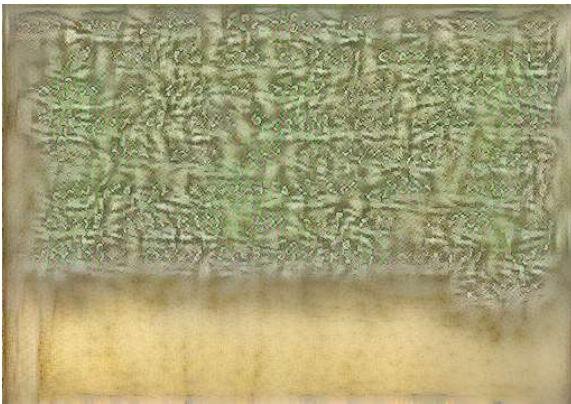
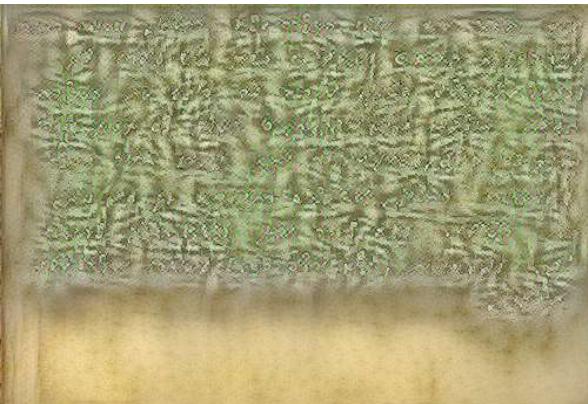
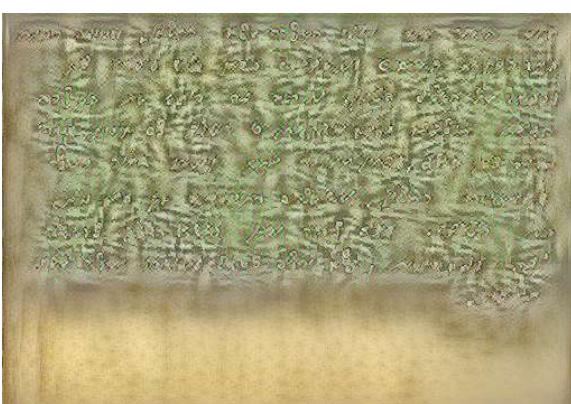
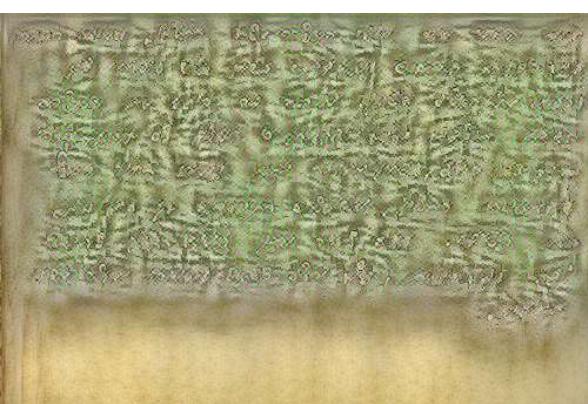
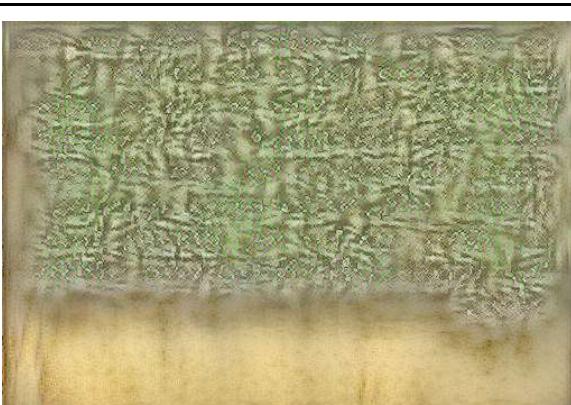
This experiment used a hebrew middle age document without text for style.

2.9.3. Results

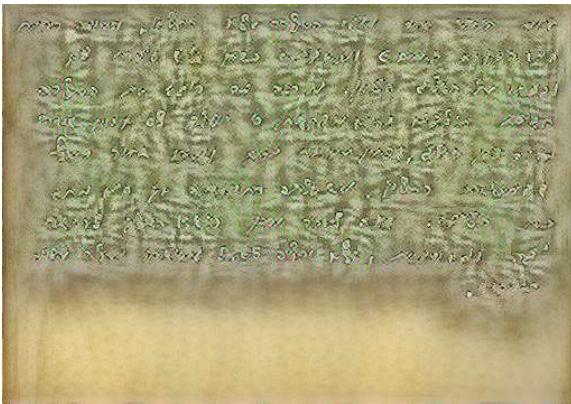
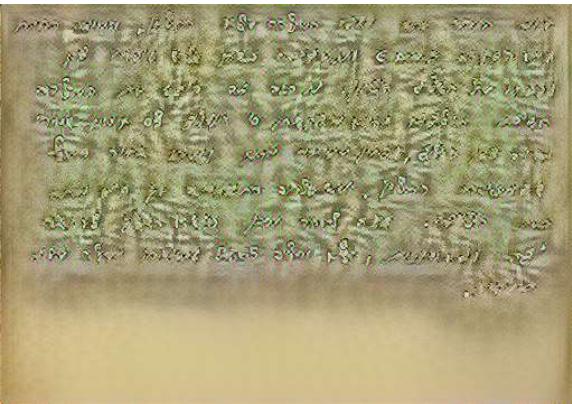
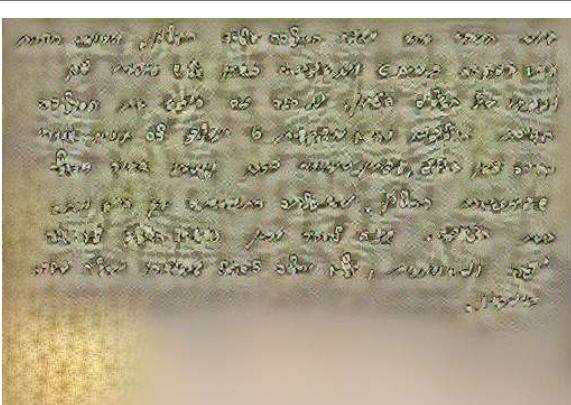
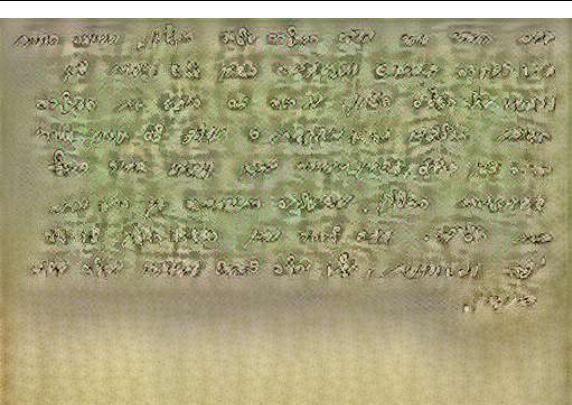
We will show samples of the results with each weight and content layer (style layers are the same).

Content image	Style image
 A binary black and white image of a page of modern Hebrew handwriting. The text is in a clear, sans-serif font, arranged in two columns. It discusses the relationship between the number of children and the quality of life in different countries.	 A photograph of a page from a Hebrew medieval manuscript. The paper is aged and yellowed, showing significant texture and some water damage. There is no text visible on this specific page.

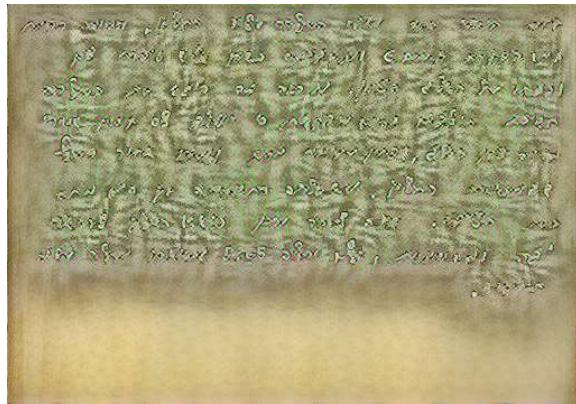
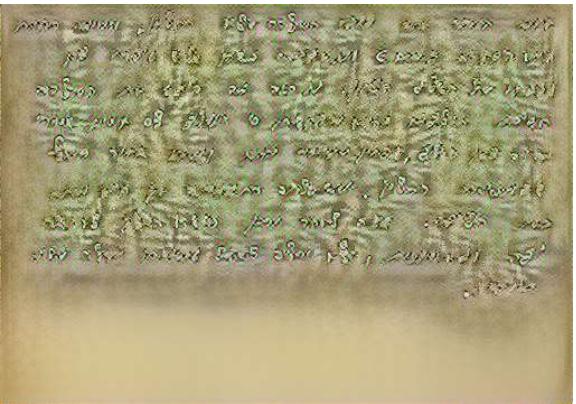
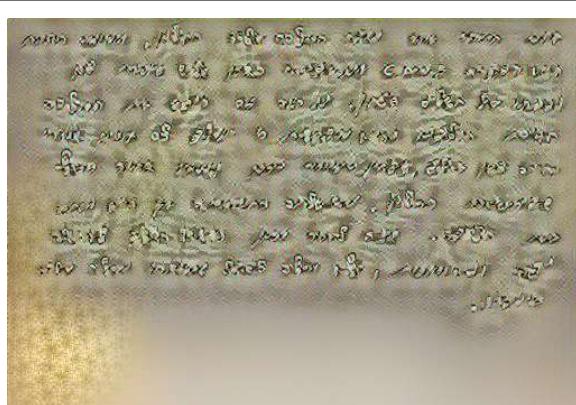
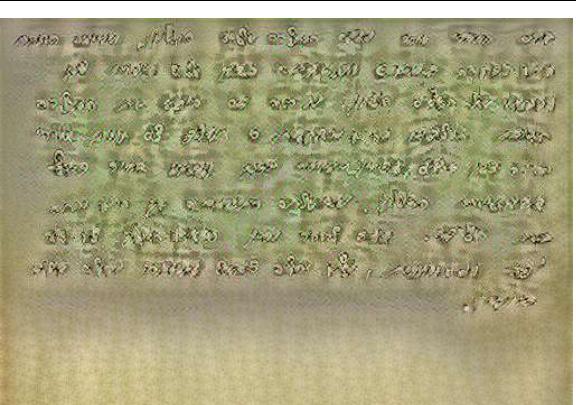
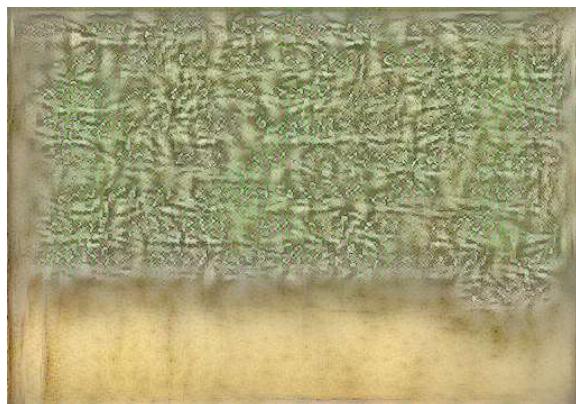
2.9.3.1. Weight 0

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

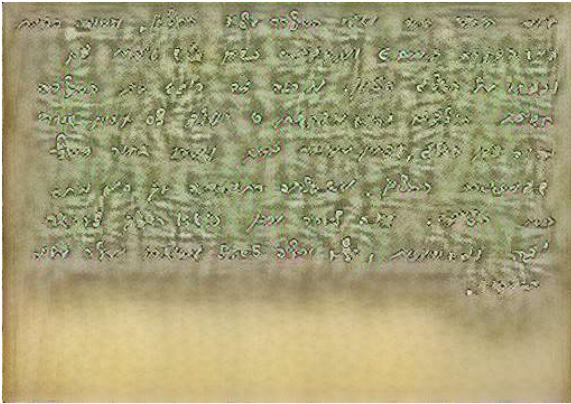
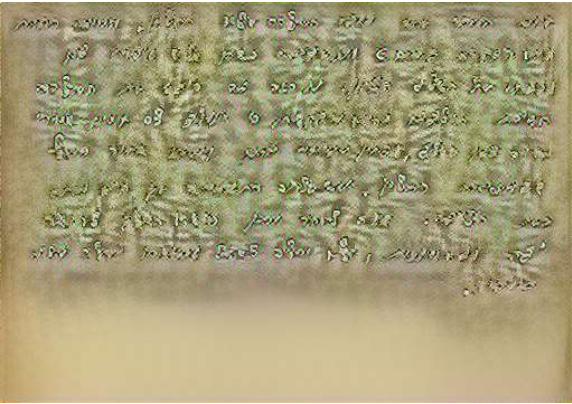
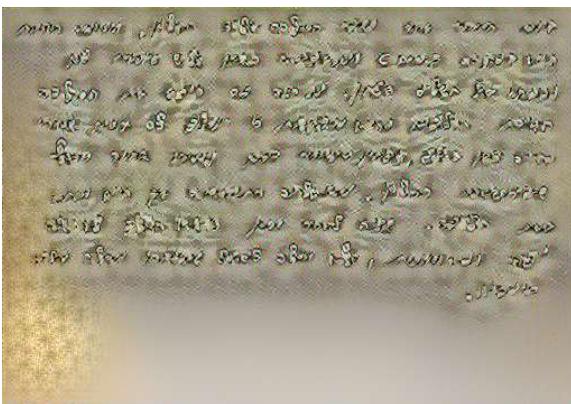
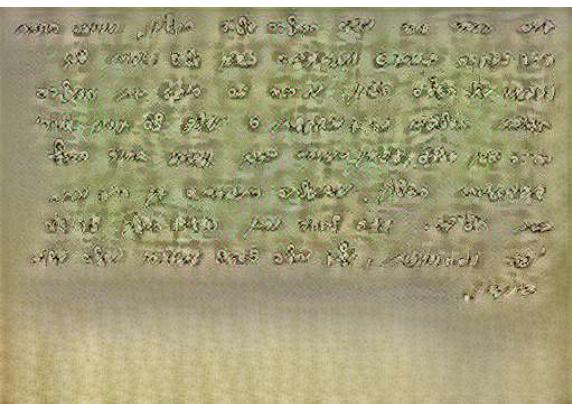
2.9.3.2. Weight 1

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

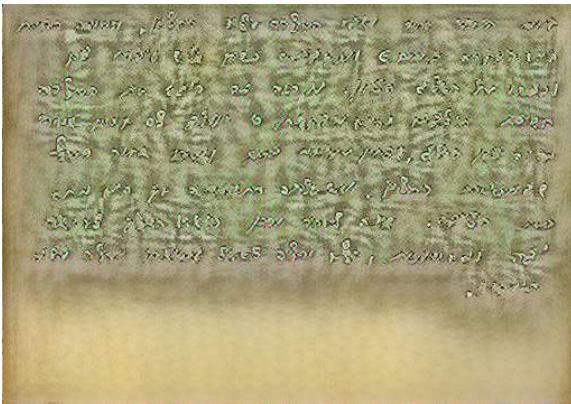
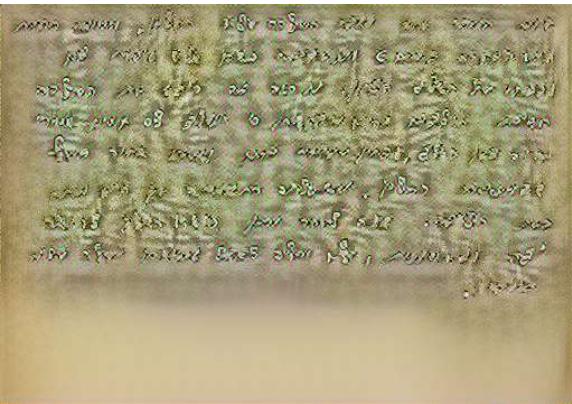
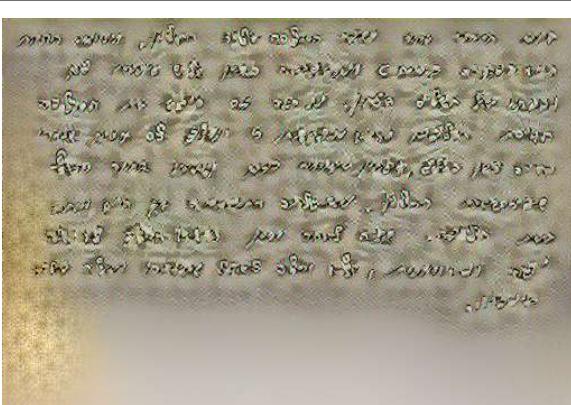
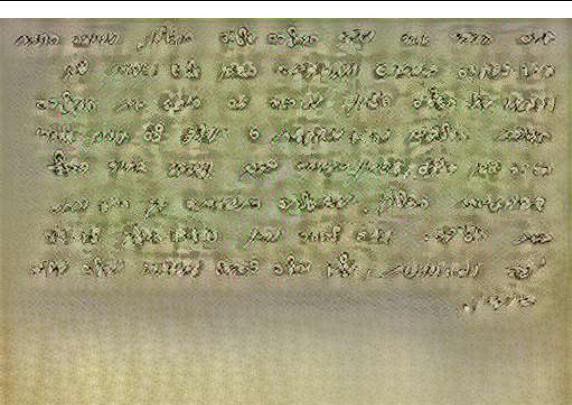
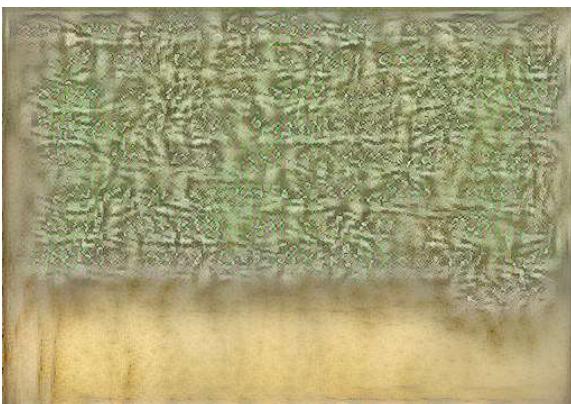
2.9.3.3. Weight 2

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

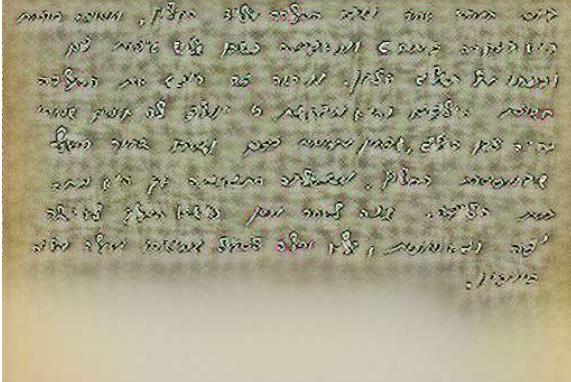
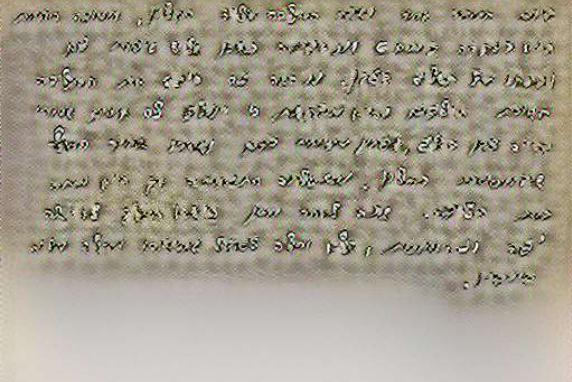
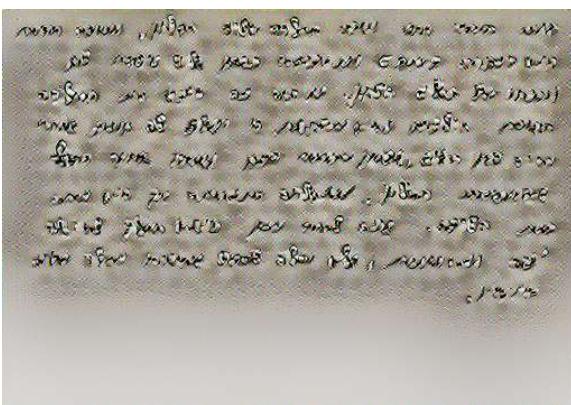
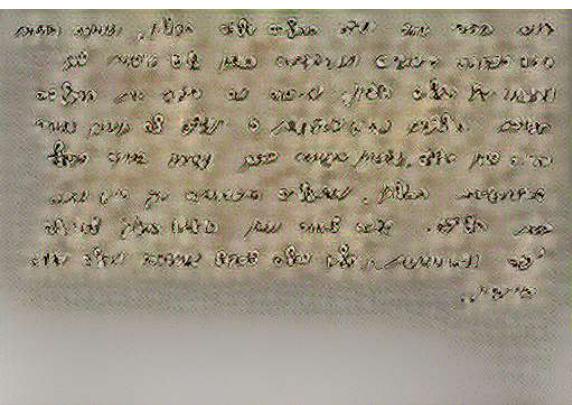
2.9.3.4. Weight 3

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

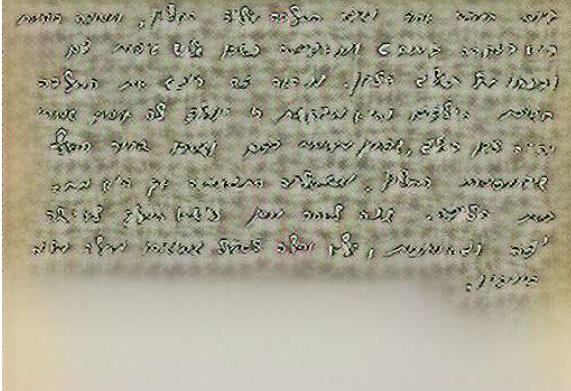
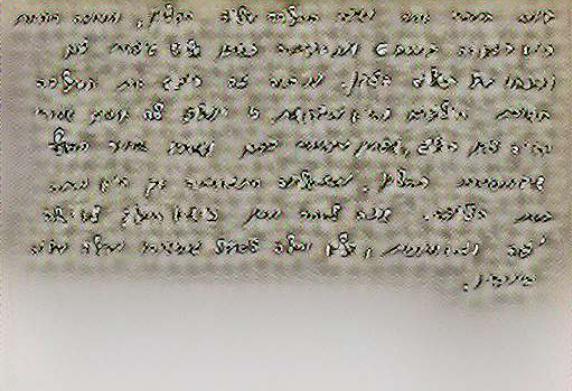
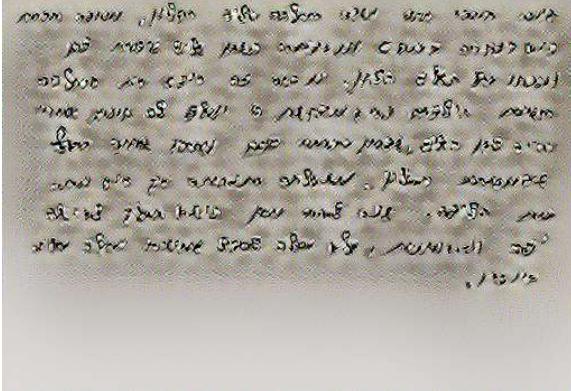
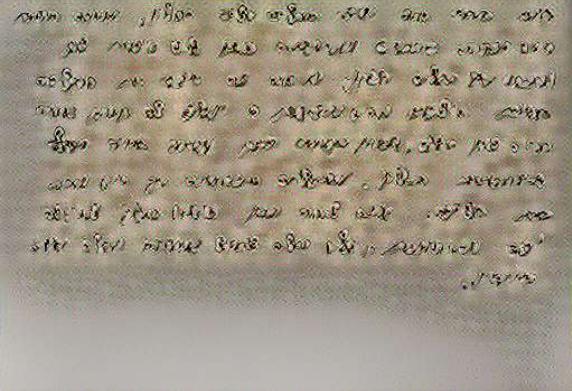
2.9.3.5. Weight 4

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.9.3.6. Weight 5

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.9.3.7. Weight 6

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.9.3.8. Weight 7

2.9.3.9. Weight 8

2.10. Experiment 7

2.10.1. Content Input

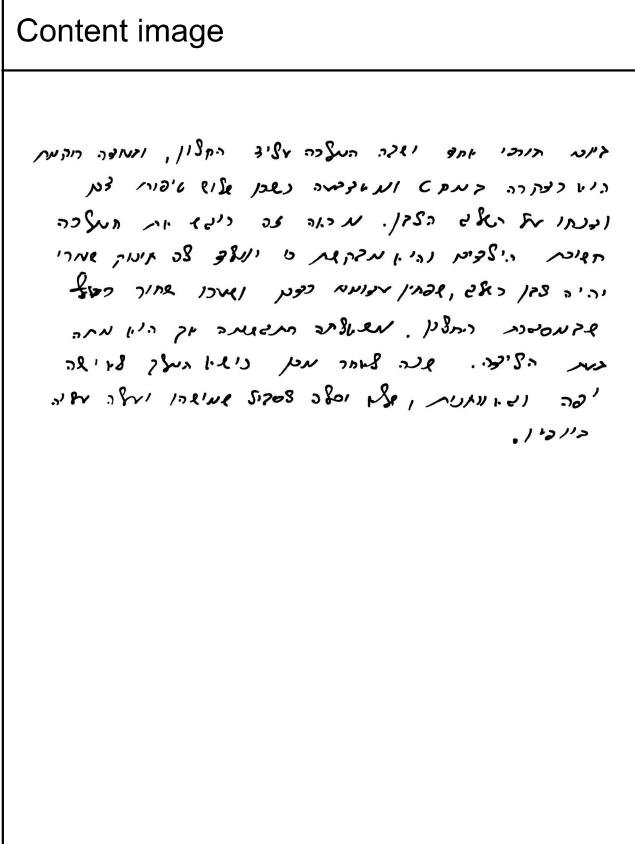
This experiment used a dilated-binary modern hebrew handwritten document for content.

2.10.2. Style Input

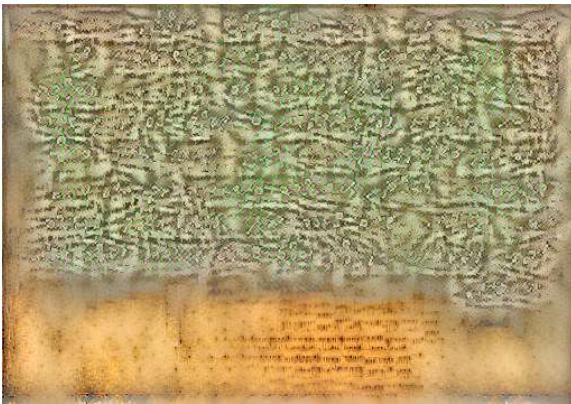
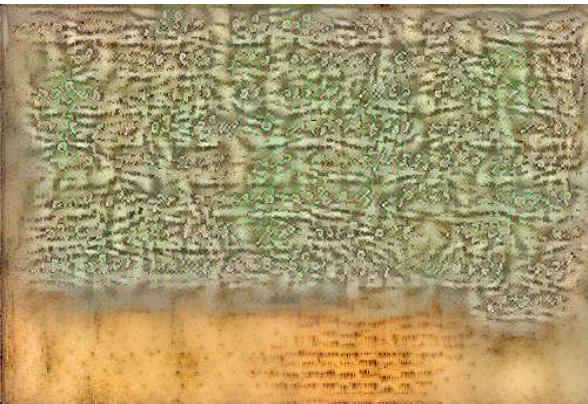
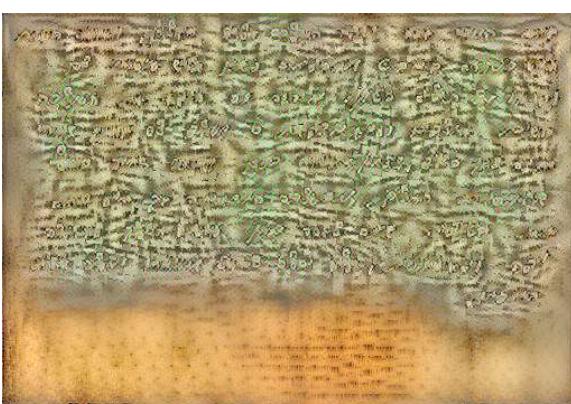
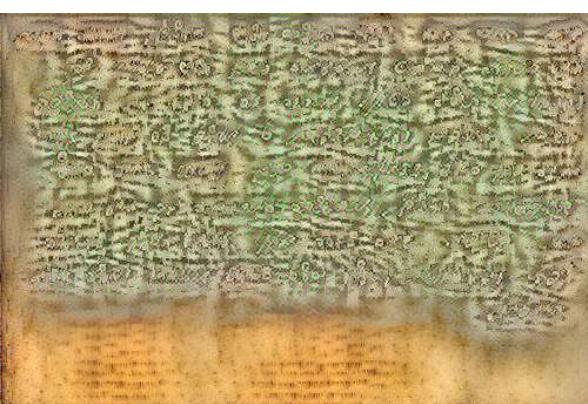
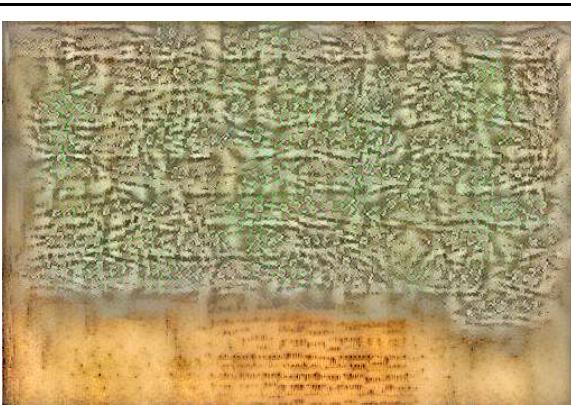
This experiment used a hebrew middle age document with text for style.

2.10.3. Results

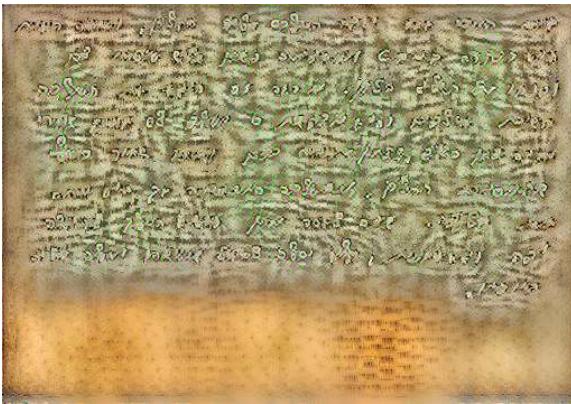
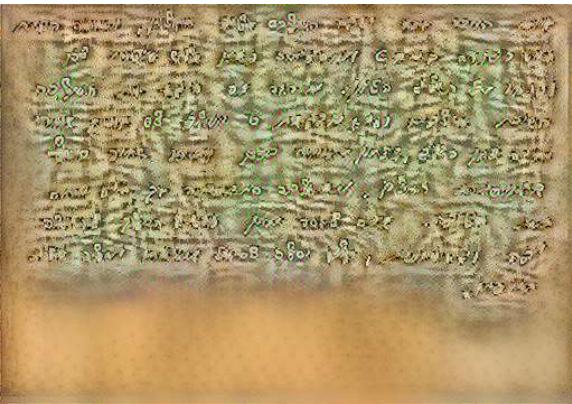
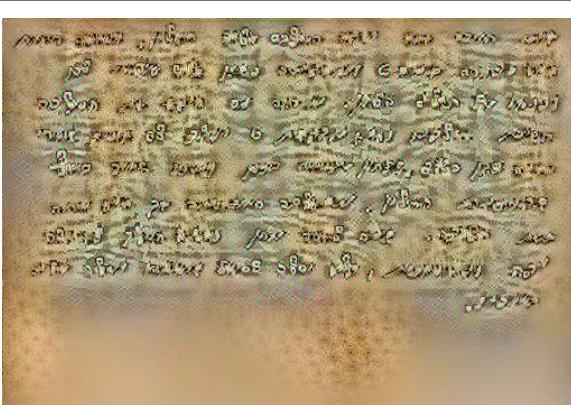
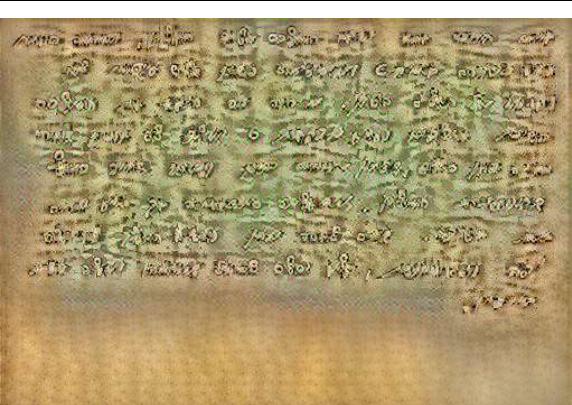
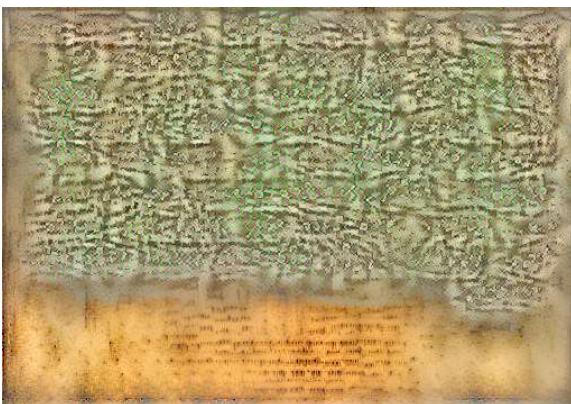
We will show samples of the results with each weight and content layer (style layers are the same).

Content image	Style image
 A rectangular image showing a block of modern Hebrew text written in black ink on a plain white background. The text is arranged in two columns of approximately 12 lines each, with a small gap between the columns.	 A rectangular image showing a block of Hebrew text from a medieval manuscript. The text is written in brown ink on a piece of aged, yellowish-brown paper. The script is a clear, cursive form of Hebrew, typical of medieval book hands. There are some minor stains and a small piece of tape visible on the paper.

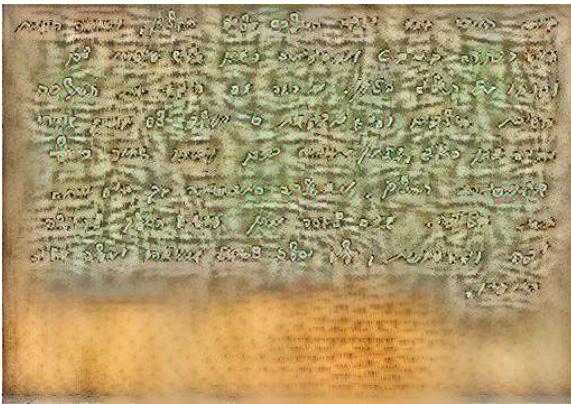
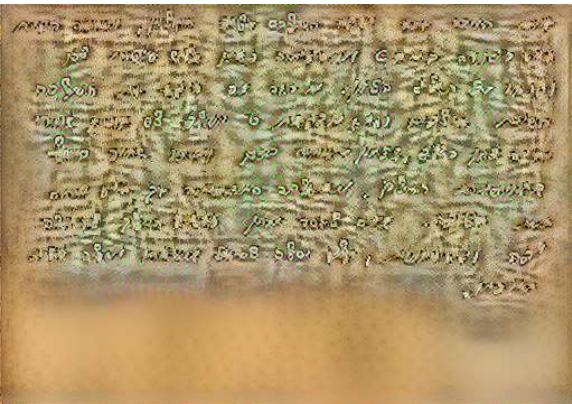
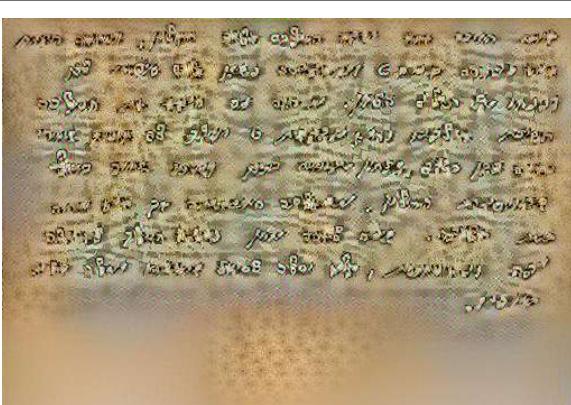
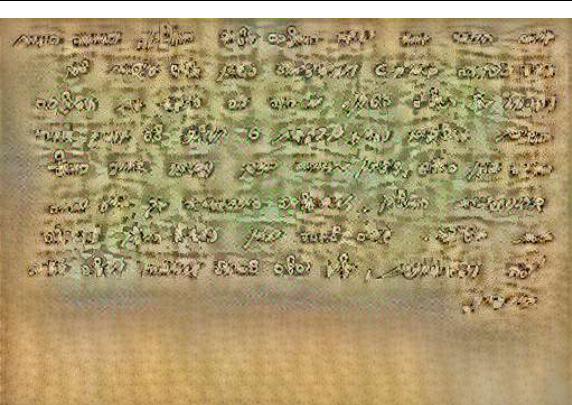
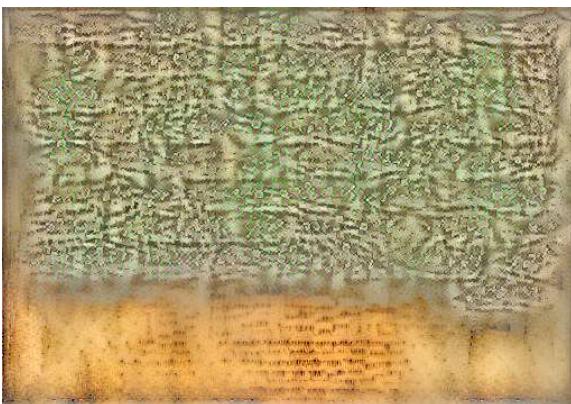
2.10.3.1. Weight 0

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

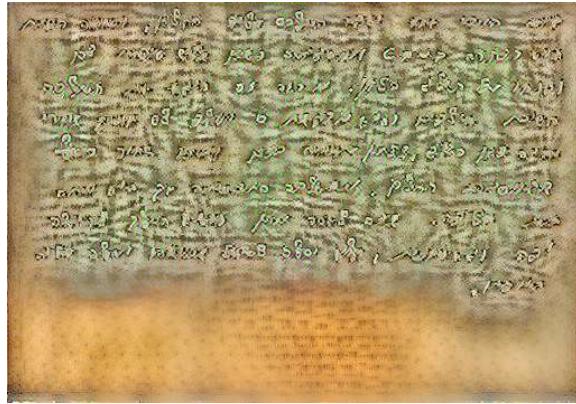
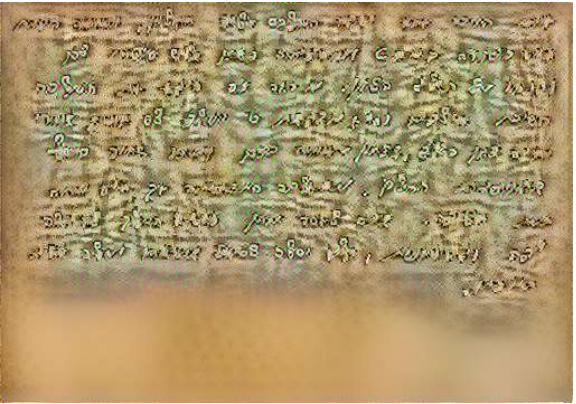
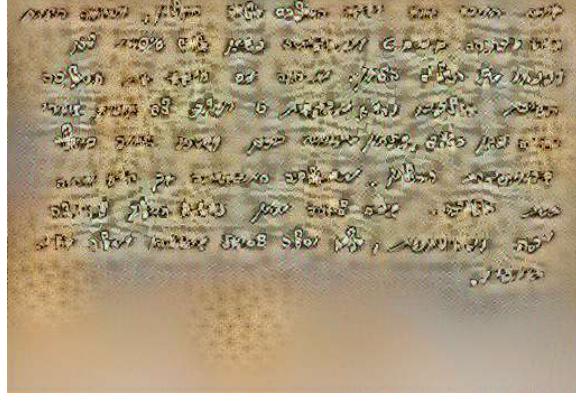
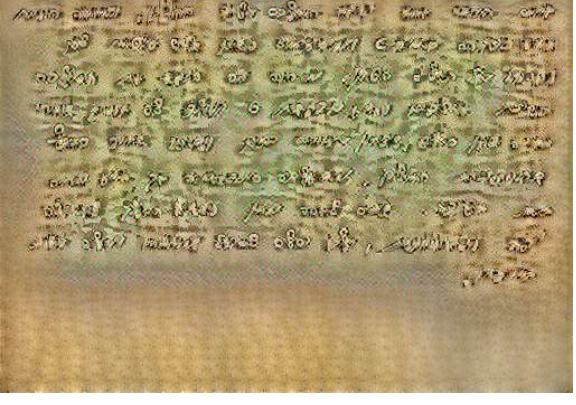
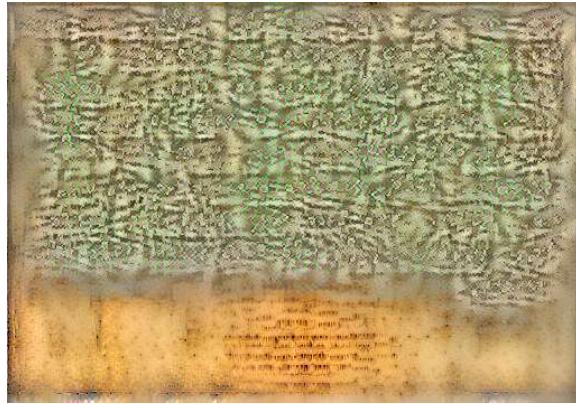
2.10.3.2. Weight 1

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

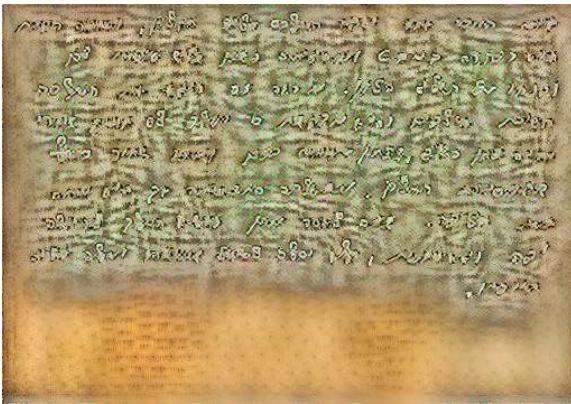
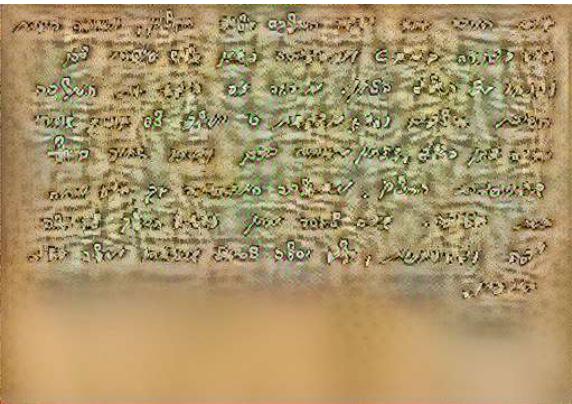
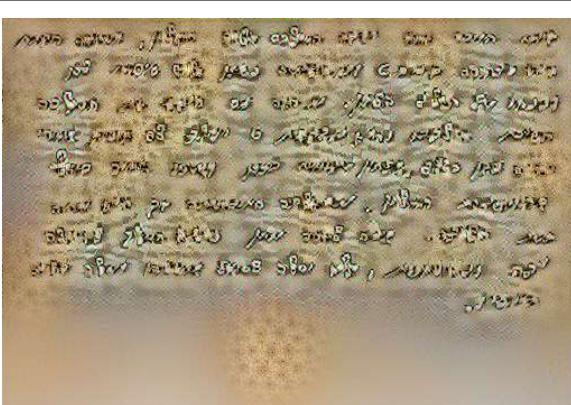
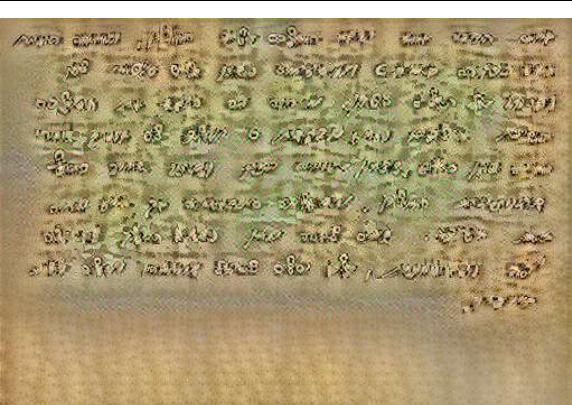
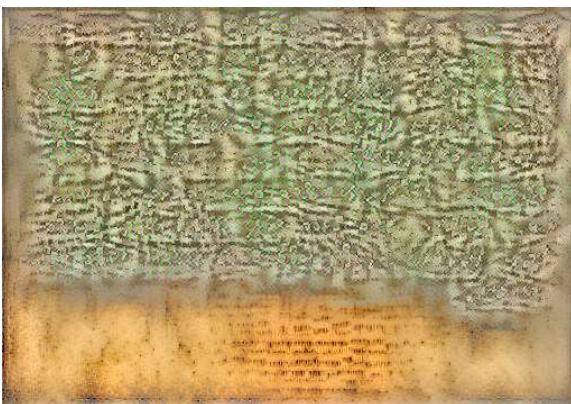
2.10.3.3. Weight 2

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

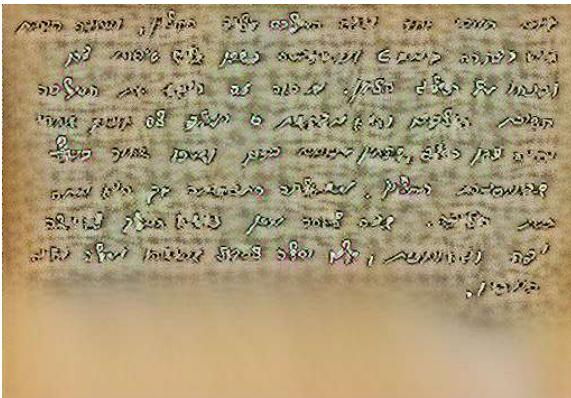
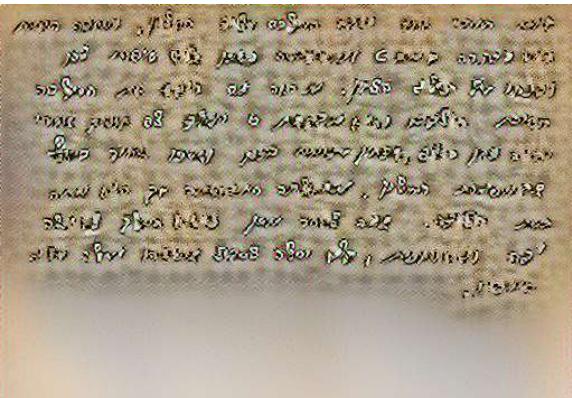
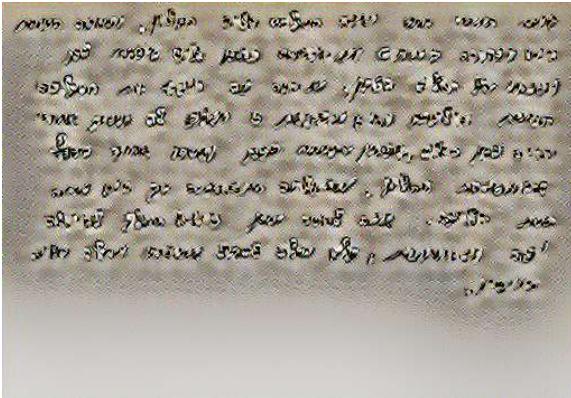
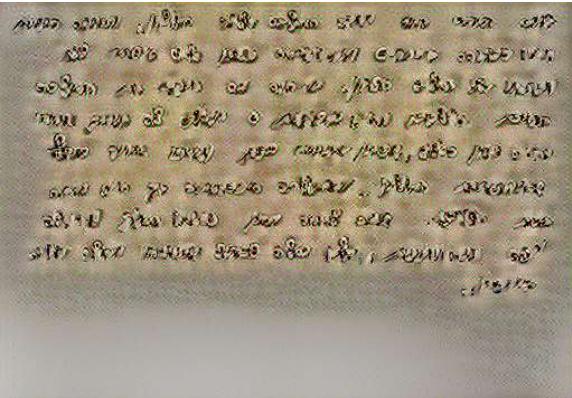
2.10.3.4. Weight 3

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

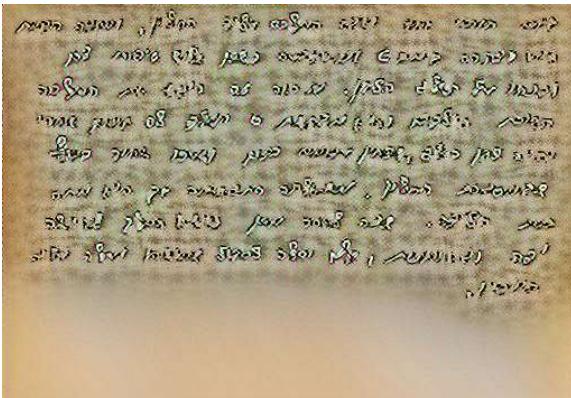
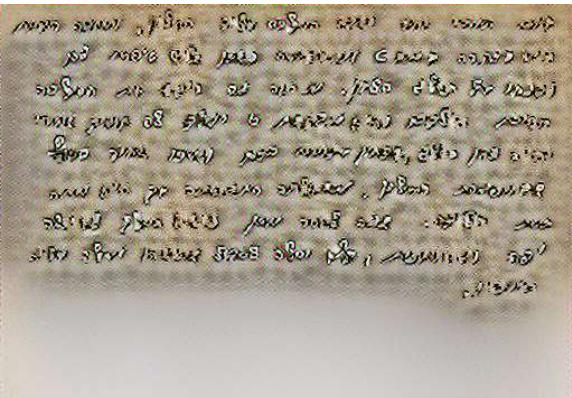
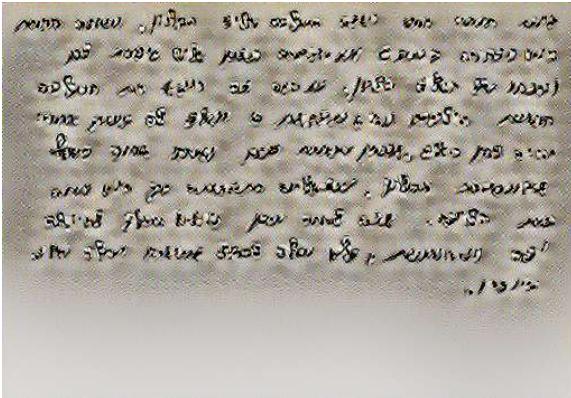
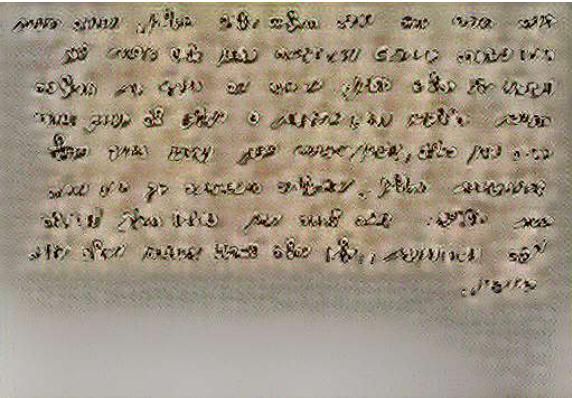
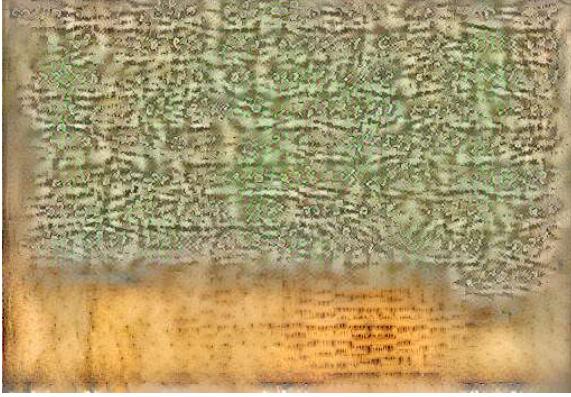
2.10.3.5. Weight 4

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.10.3.6. Weight 5

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.10.3.7. Weight 6

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.10.3.8. Weight 7

2.10.3.9. Weight 8

2.11. Experiment 8

2.11.1. Content Input

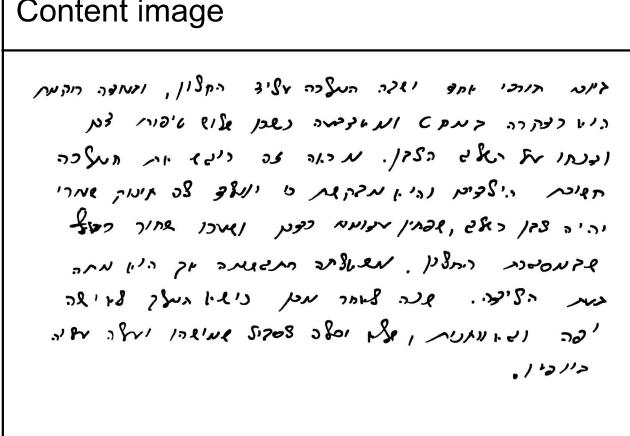
This experiment used a dilated-binary modern hebrew handwritten document for content.

2.11.2. Style Input

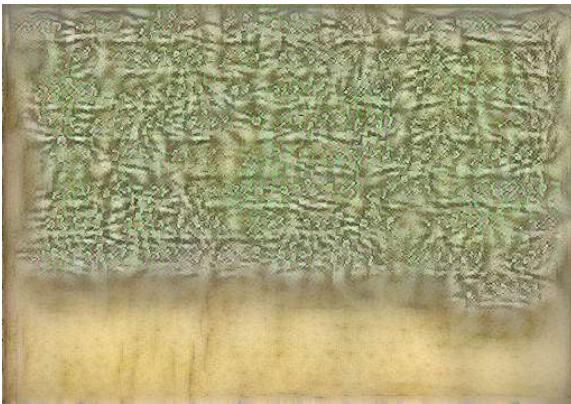
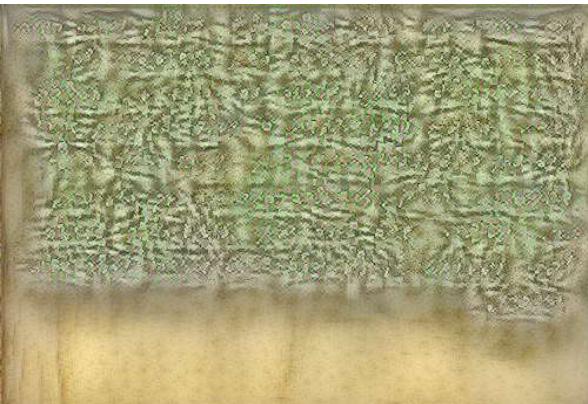
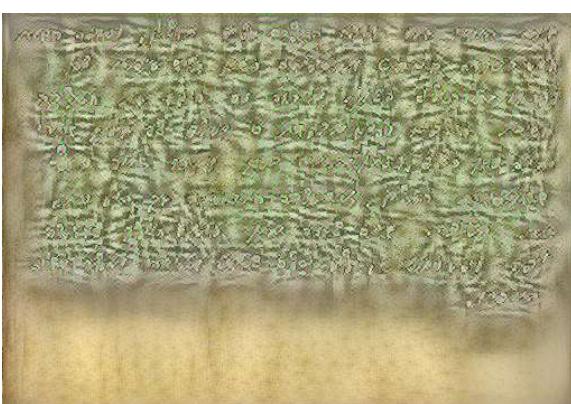
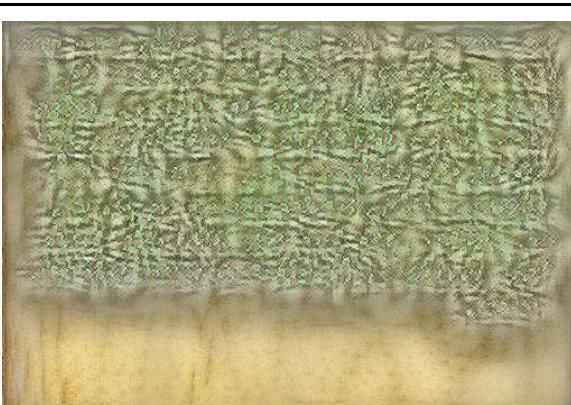
This experiment used a hebrew middle age document without text for style.

2.11.3. Results

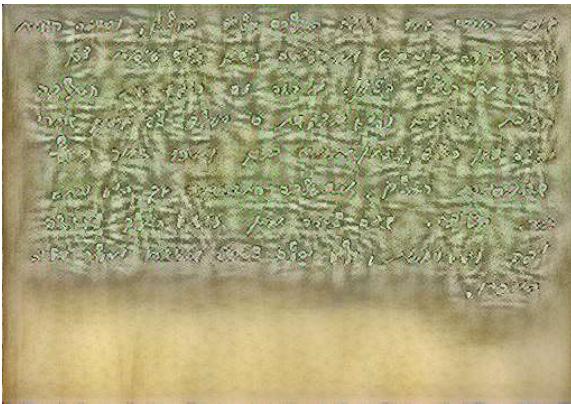
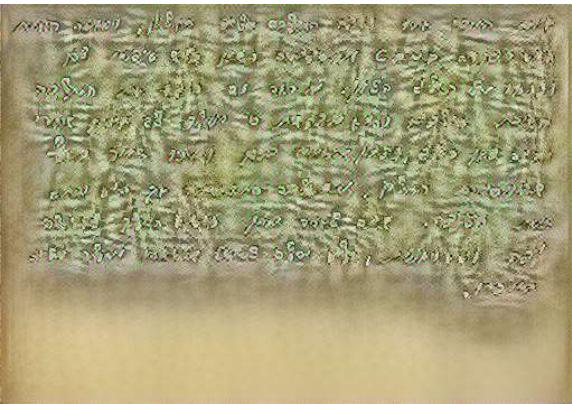
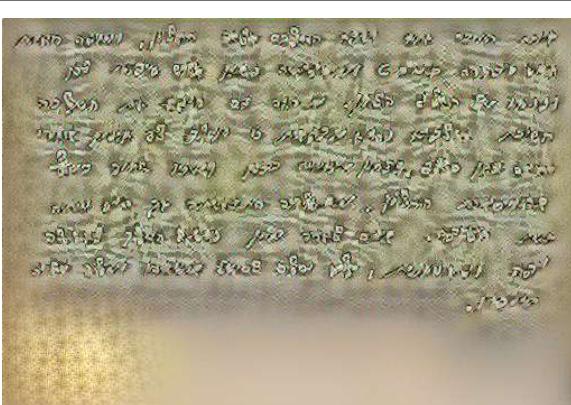
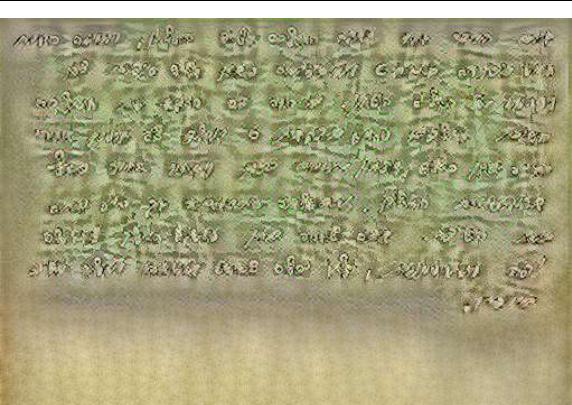
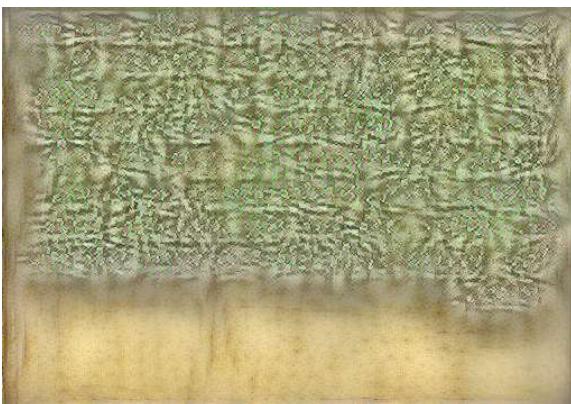
We will show samples of the results with each weight and content layer (style layers are the same).

Content image	Style image
	

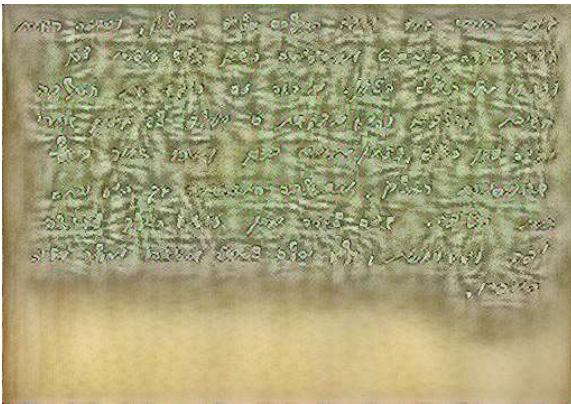
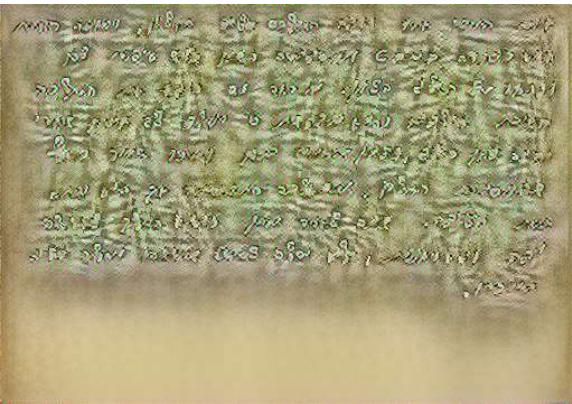
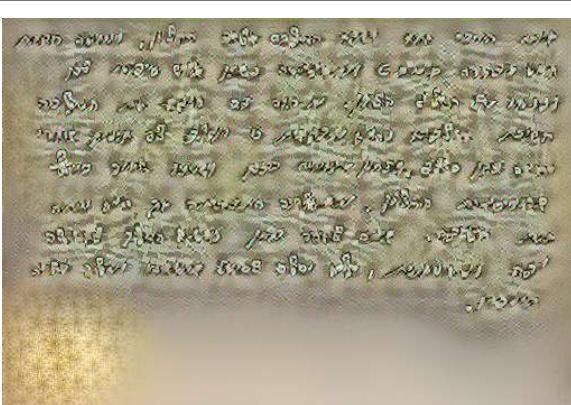
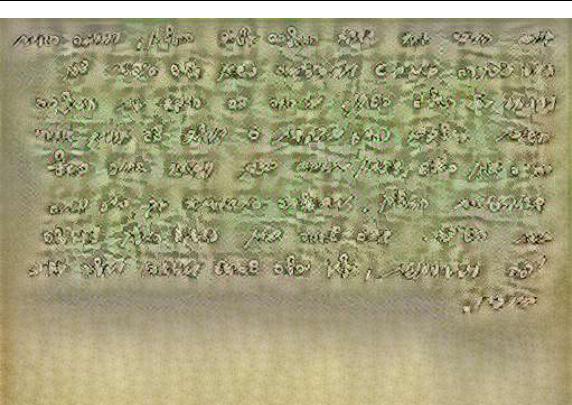
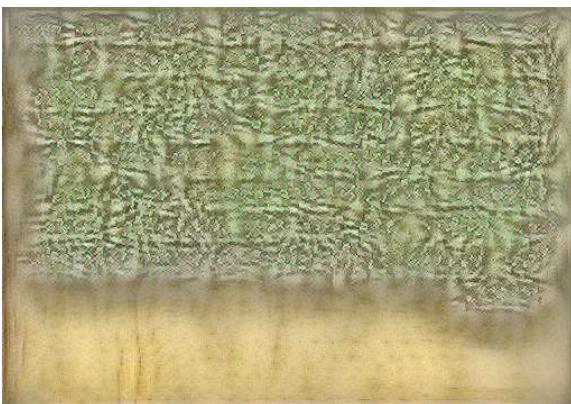
2.11.3.1. Weight 0

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.11.3.2. Weight 1

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

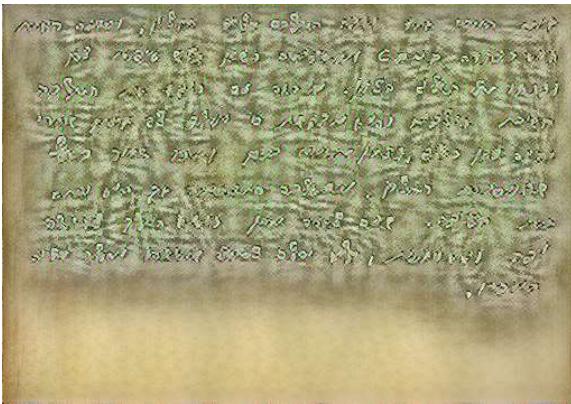
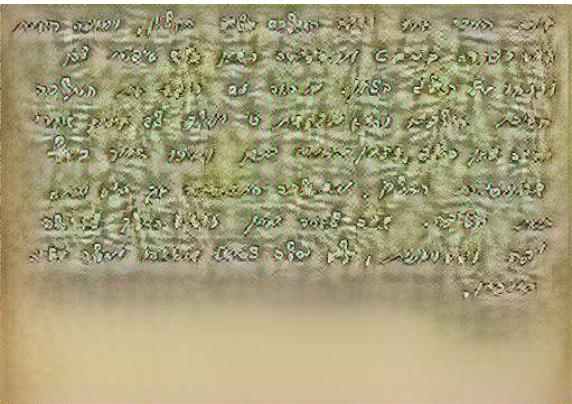
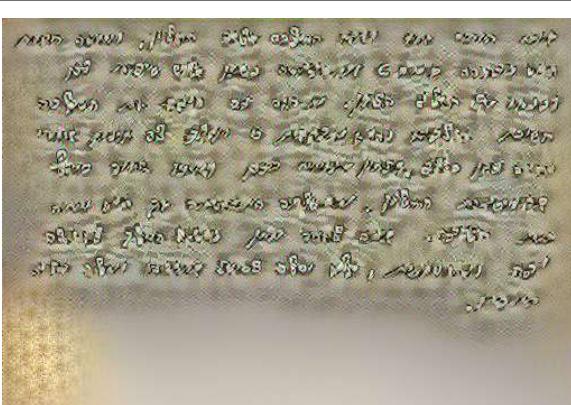
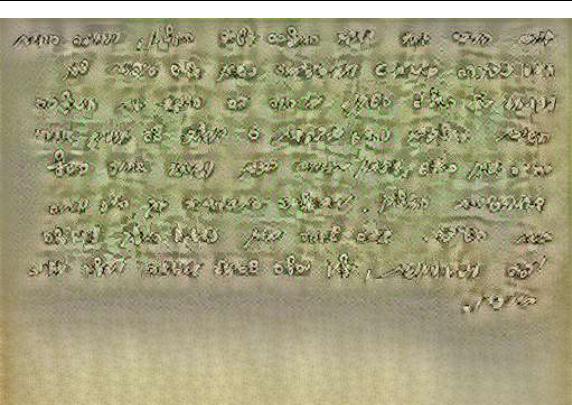
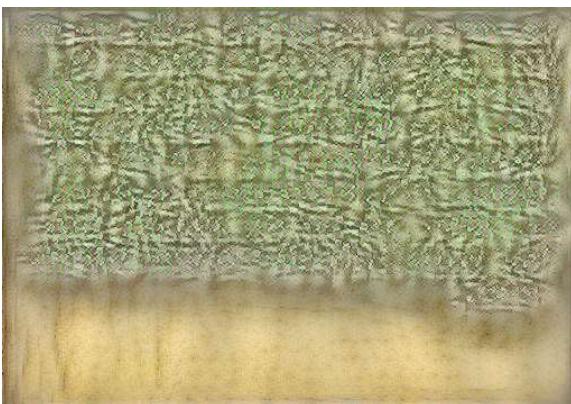
2.11.3.3. Weight 2

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

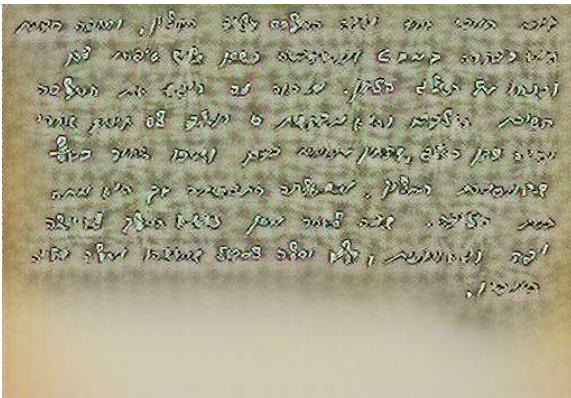
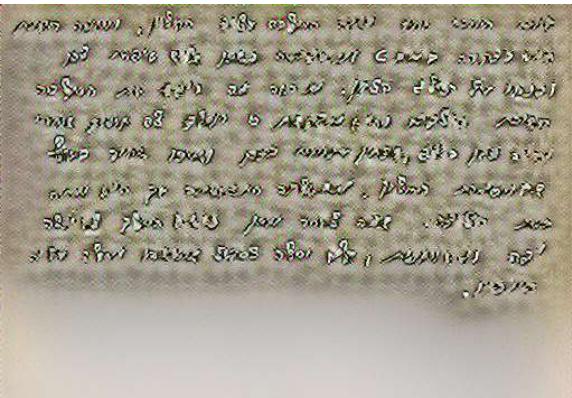
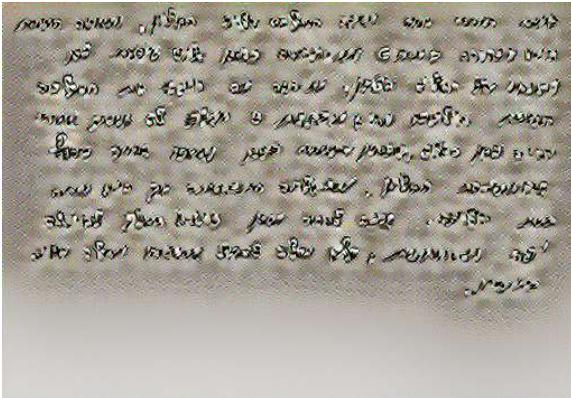
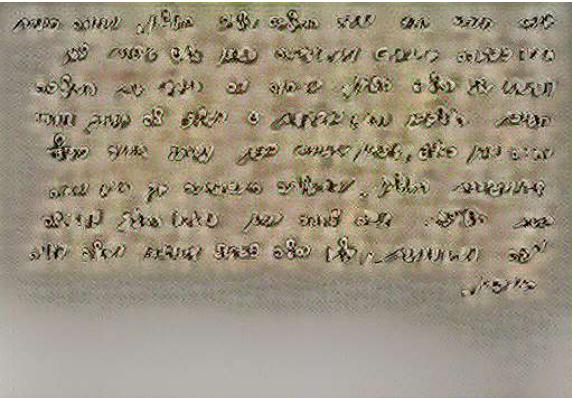
2.11.3.4. Weight 3

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	

2.11.3.5. Weight 4

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.11.3.6. Weight 5

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.11.3.7. Weight 6

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	

2.11.3.8. Weight 7

2.11.3.9. Weight 8

2.12. Experiment 9

2.12.1. Content Input

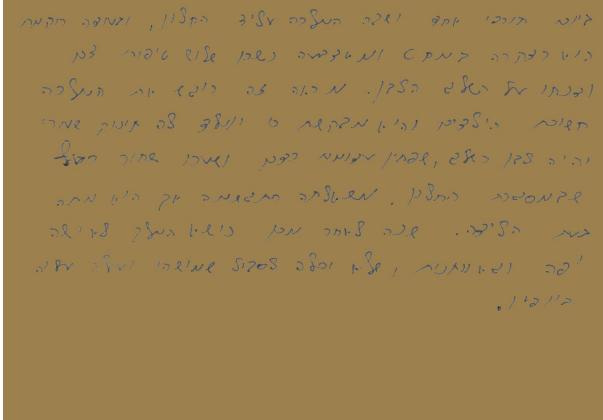
This experiment used a modern hebrew handwritten document for content, with a background created by averaging pixels color from the style document.

2.12.2. Style Input

This experiment used a hebrew middle age document with text for style.

2.12.3. Results

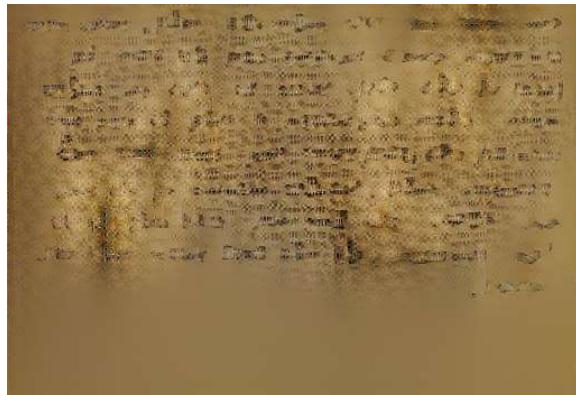
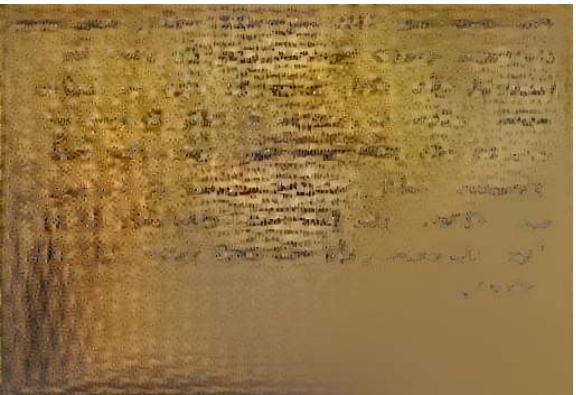
We will show samples of the results with each weight and content layer (style layers are the same).

Content image	Style image
 A rectangular image showing a single column of modern Hebrew handwritten text in black ink on a light brown background. The text is in a cursive script and appears to be a personal note or a short letter.	 A rectangular image of a page from a Hebrew medieval manuscript. The page is filled with dense, handwritten text in a formal Gothic script on aged, yellowish-brown paper. There are some small white rectangular pieces of tape or paper stuck to the left edge of the page.

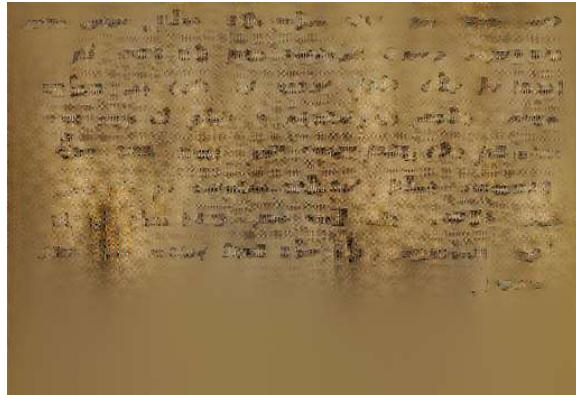
2.12.3.1. Weight 0

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.12.3.2. Weight 1

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

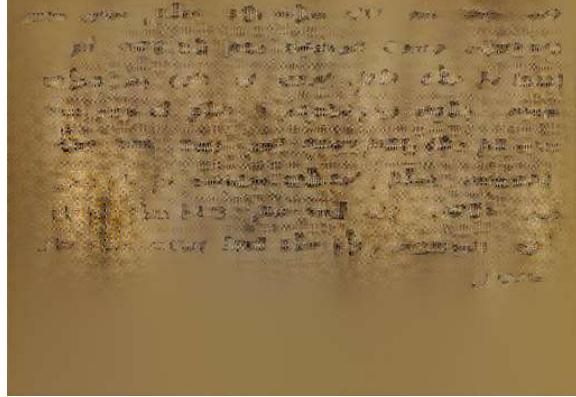
2.12.3.3. Weight 2

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.12.3.4. Weight 3

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	

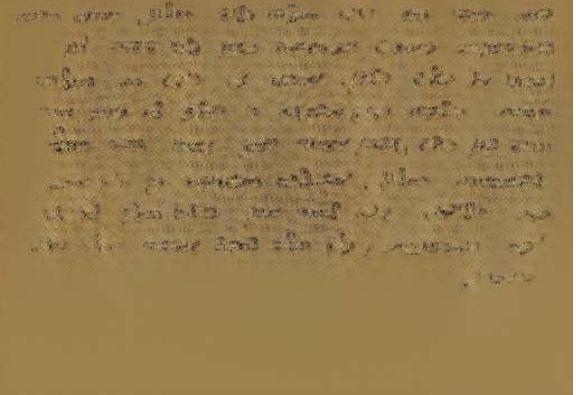
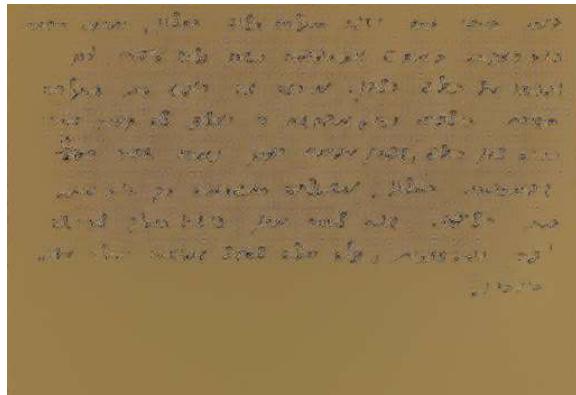
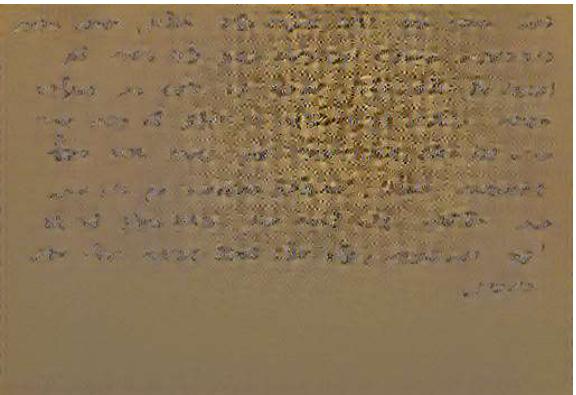
2.12.3.5. Weight 4

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.12.3.6. Weight 5

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	

2.12.3.7. Weight 6

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.12.3.8. Weight 7

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	

2.12.3.9. Weight 8

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	

2.13. Experiment 10

2.13.1. Content Input

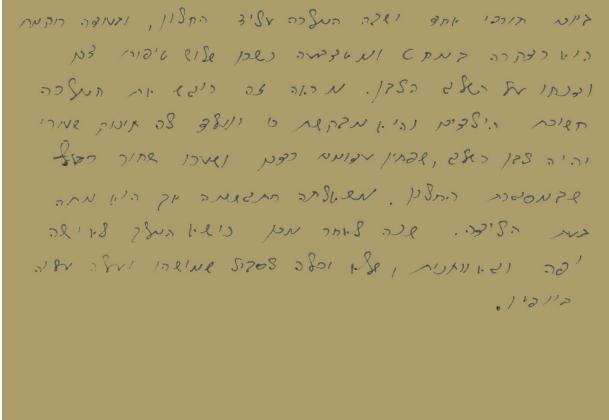
This experiment used a modern hebrew handwritten document for content, with a background created by averaging pixels color from the style document.

2.13.2. Style Input

This experiment used a hebrew middle age document without text for style.

2.13.3. Results

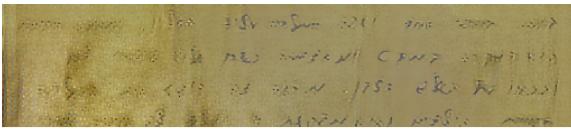
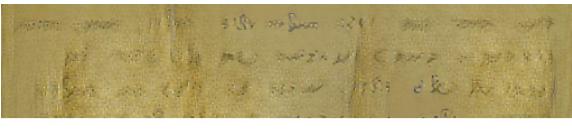
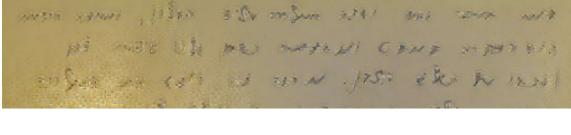
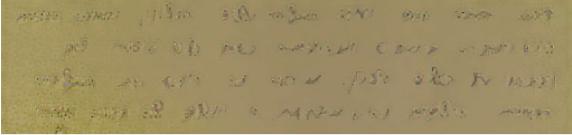
We will show samples of the results with each weight and content layer (style layers are the same).

Content image	Style image
	

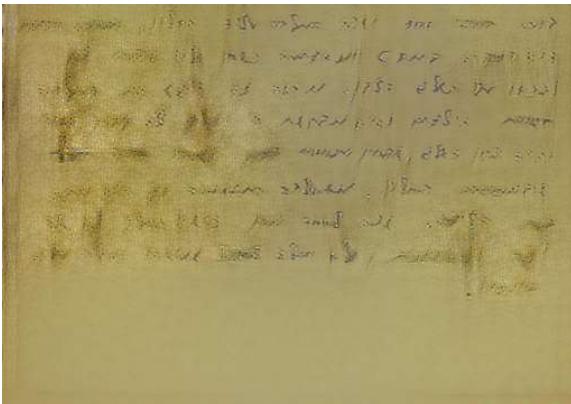
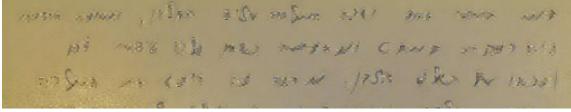
2.13.3.1. Weight 0

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	

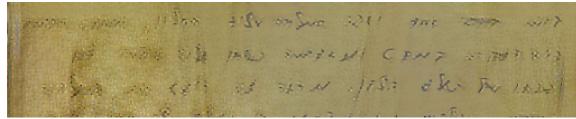
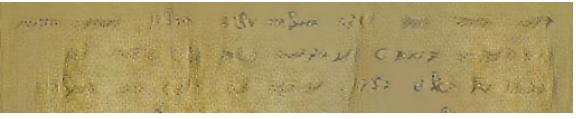
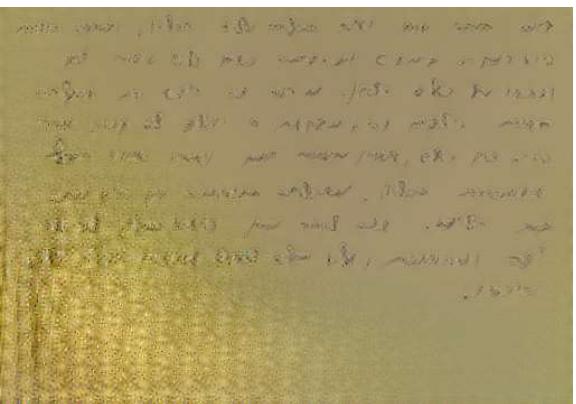
2.13.3.2. Weight 1

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

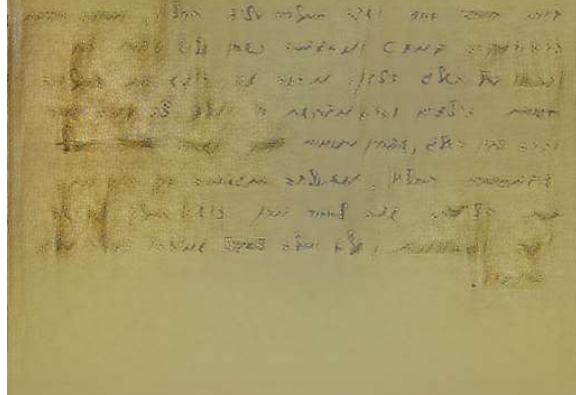
2.13.3.3. Weight 2

block3_conv2	block3_conv3
 A photograph of a handwritten note on a piece of paper. The text is in cursive and appears to be a list of items or steps, possibly related to a technical process. The handwriting is somewhat faded and difficult to read in detail.	 A photograph of a handwritten note on a piece of paper. The text is in cursive and appears to be a list of items or steps, possibly related to a technical process. The handwriting is somewhat faded and difficult to read in detail.
block3_conv4	block4_conv2
 A photograph of a handwritten note on a piece of paper. The text is in cursive and appears to be a list of items or steps, possibly related to a technical process. The handwriting is somewhat faded and difficult to read in detail.	
block5_conv2	
 A solid yellow rectangular area, likely a placeholder or a blank image within the table structure.	

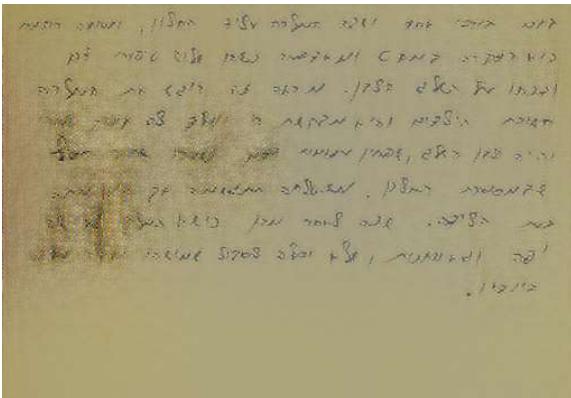
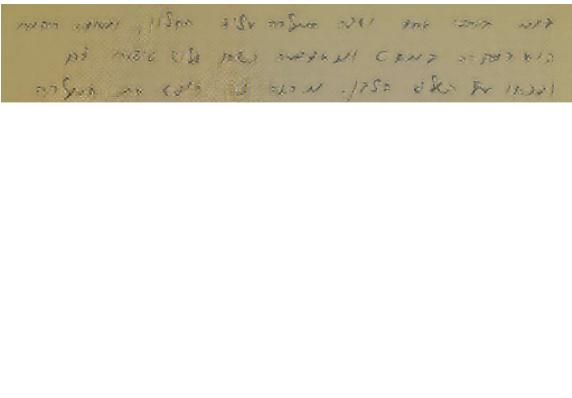
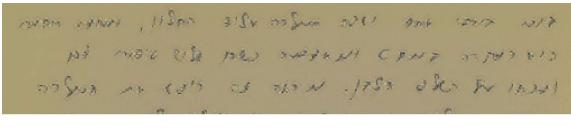
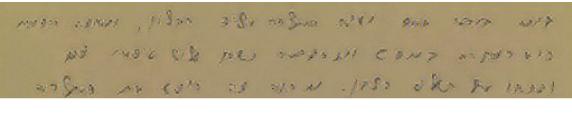
2.13.3.4. Weight 3

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	

2.13.3.5. Weight 4

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
block5_conv2	
	

2.13.3.6. Weight 5

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.13.3.7. Weight 6

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	

2.13.3.8. Weight 7

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	

2.13.3.9. Weight 8

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	

2.14. Experiment 11

2.14.1. Content Input

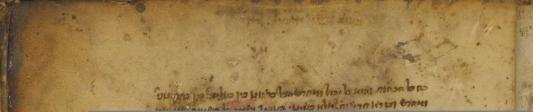
This experiment used a dilated modern hebrew handwritten document for content, with a background created by averaging a pixels color from the style document.

2.14.2. Style Input

This experiment used a hebrew middle age document with text for style.

2.14.3. Results

We will show samples of the results with each weight and content layer (style layers are the same).

Content image	Style image
	

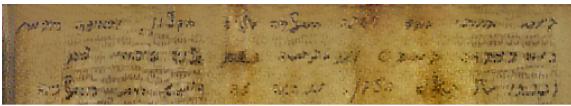
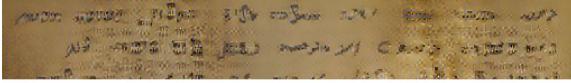
2.14.3.1. Weight 0

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

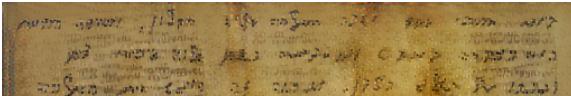
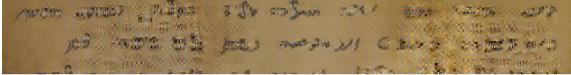
2.14.3.2. Weight 1

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	

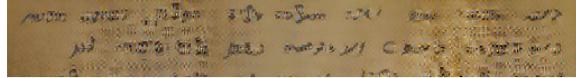
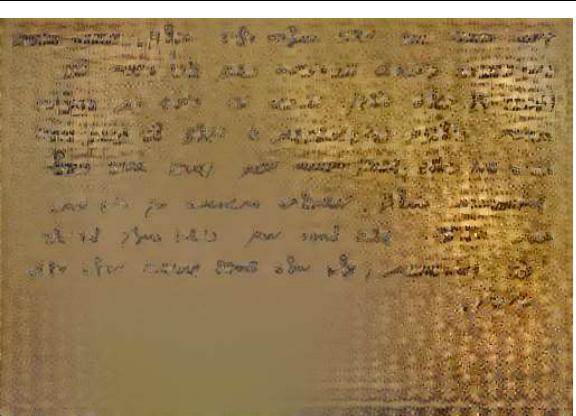
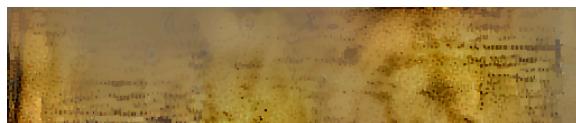
2.14.3.3. Weight 2

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

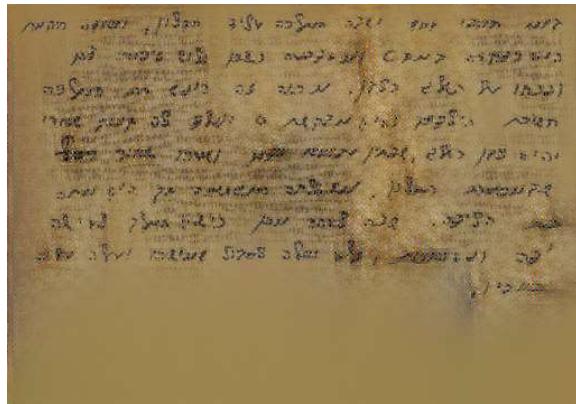
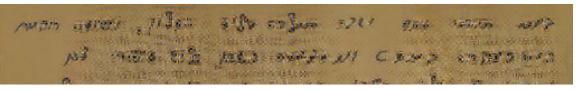
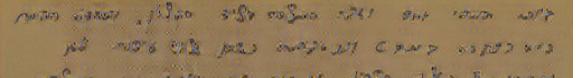
2.14.3.4. Weight 3

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

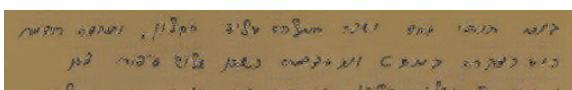
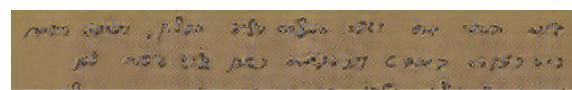
2.14.3.5. Weight 4

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.14.3.6. Weight 5

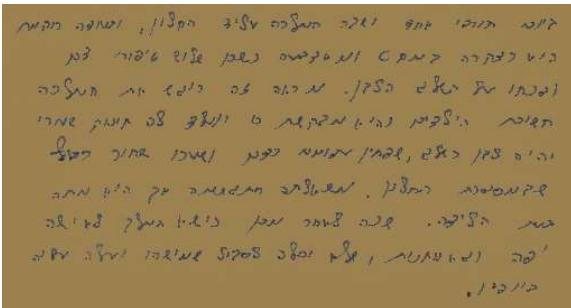
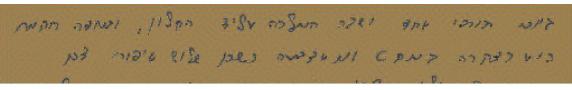
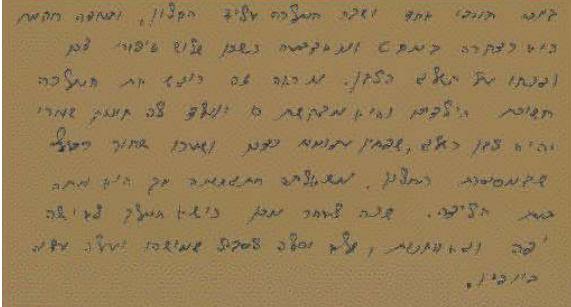
block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.14.3.7. Weight 6

block3_conv2	block3_conv3
block3_conv4	block4_conv2
	
block5_conv2	
	

2.14.3.8. Weight 7

2.14.3.9. Weight 8

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.15. Experiment 12

2.15.1. Content Input

This experiment used a dilated modern hebrew handwritten document for content, with a background created by averaging a pixels color from the style document.

2.15.2. Style Input

This experiment used a hebrew middle age document without text for style.

2.15.3. Results

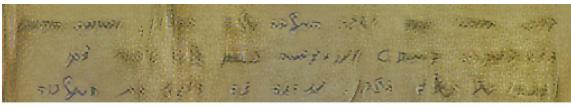
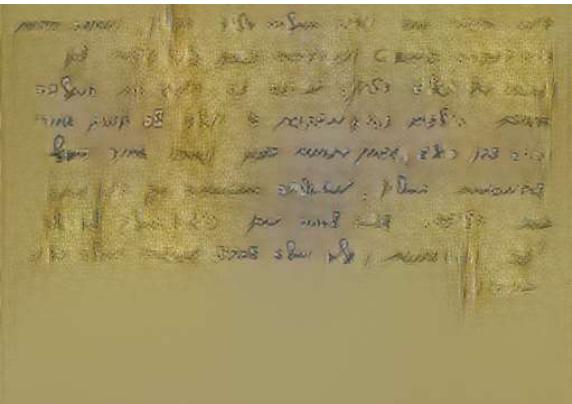
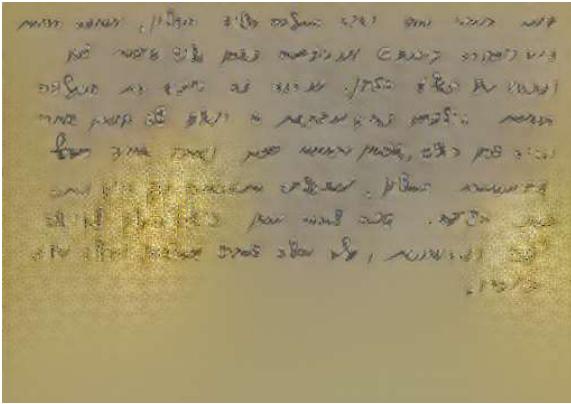
We will show samples of the results with each weight and content layer (style layers are the same).

Content image	Style image

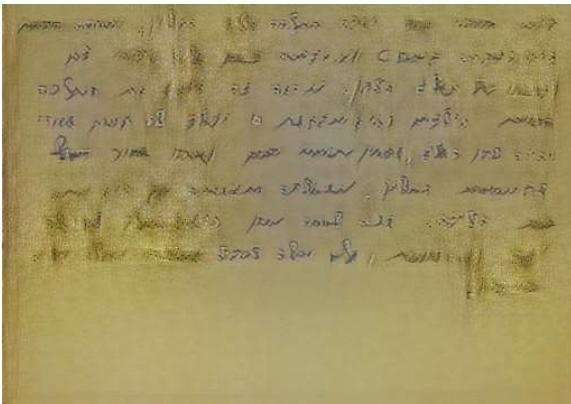
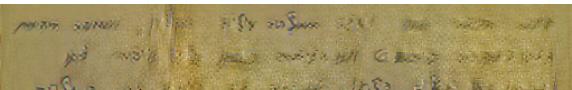
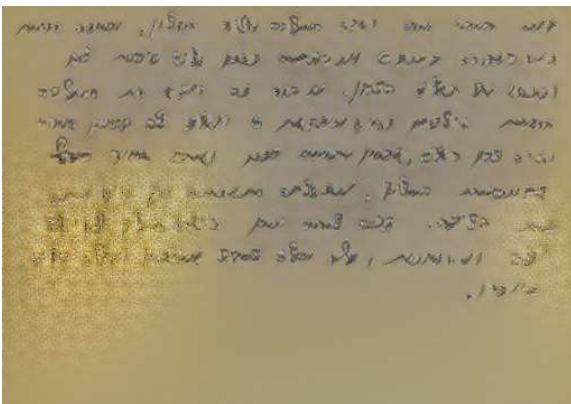
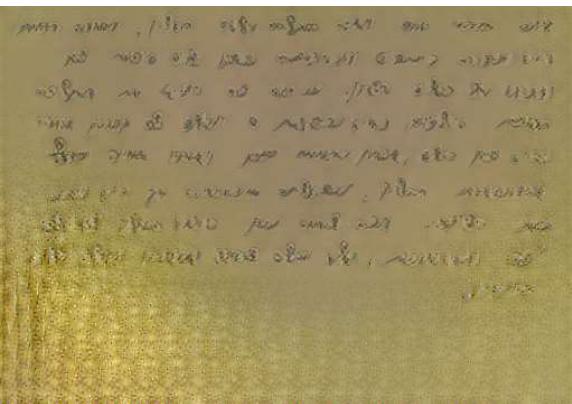
2.15.3.1. Weight 0

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	

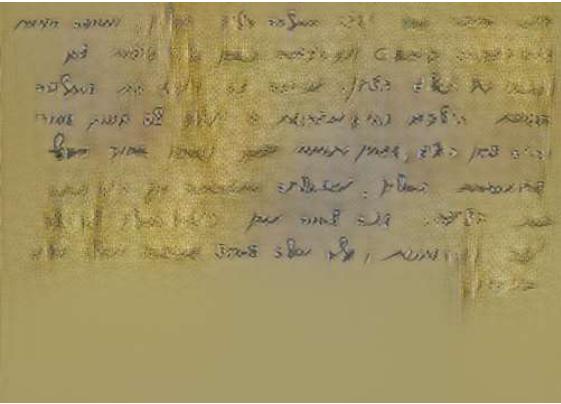
2.15.3.2. Weight 1

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

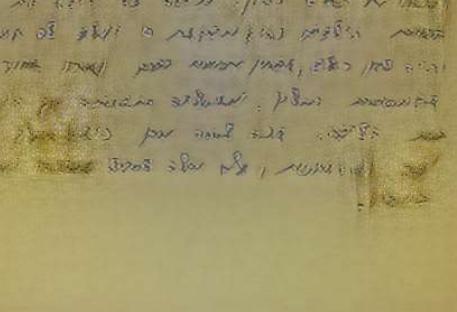
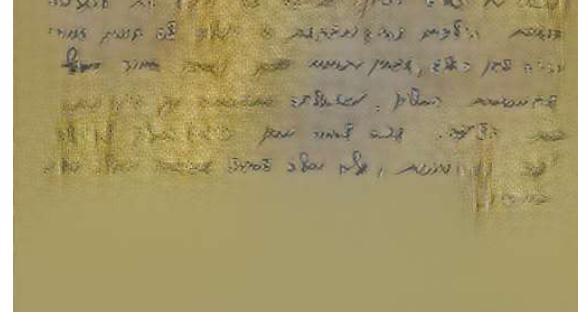
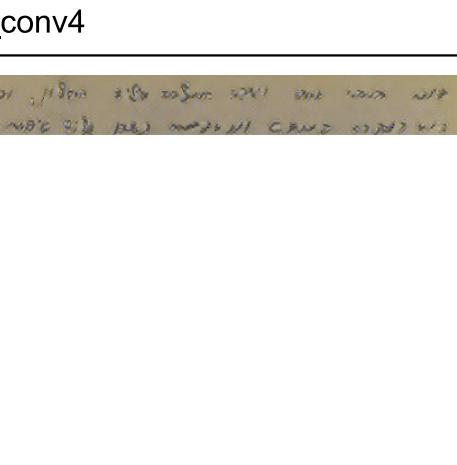
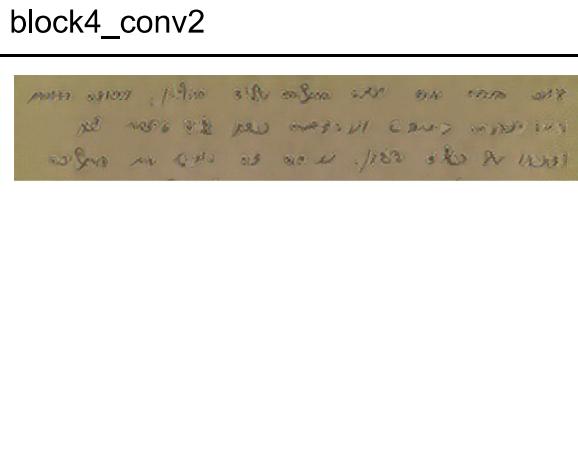
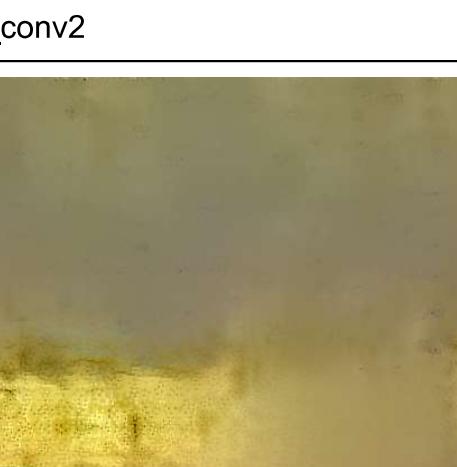
2.15.3.3. Weight 2

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.15.3.4. Weight 3

block3_conv2	block3_conv3
	 <p>Block 3 conv3 is very bad and must be replaced soon. The note is dated July 1953.</p>
block3_conv4	block4_conv2

2.15.3.5. Weight 4

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

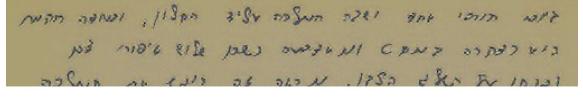
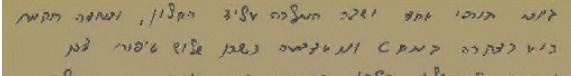
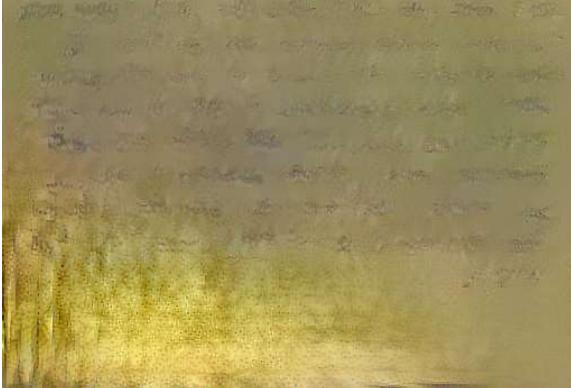
2.15.3.6. Weight 5

block3_conv2	block3_conv3
block3_conv4	block4_conv2
	<p>muon sensor, 1/1800 3184 cm² 1267 g/cm² 100% 100% muon detector 100% 1267 g/cm² 3184 cm² 100% muon detector 1267 g/cm² 3184 cm²</p>
block5_conv2	
	

2.15.3.7. Weight 6

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	

2.15.3.8. Weight 7

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	

2.15.3.9. Weight 8

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	

2.16. Experiment 13

2.16.1. Content Input

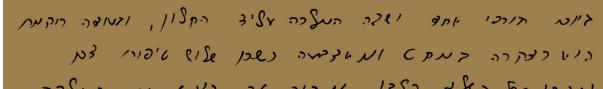
This experiment used a binary modern hebrew handwritten document for content, with a background created by averaging a pixels color from the style document.

2.16.2. Style Input

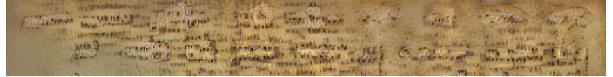
This experiment used a hebrew middle age document with text for style.

2.16.3. Results

We will show samples of the results with each weight and content layer (style layers are the same).

Content image	Style image
 A small rectangular image showing a portion of a modern Hebrew handwritten document. The text is in black ink on a white background, with some lines appearing in red ink.	 A large image of a page from a Hebrew medieval manuscript. The page is filled with dense, handwritten text in black ink on aged, yellowish-brown paper. The script is a clear, cursive form typical of medieval Hebrew writing.

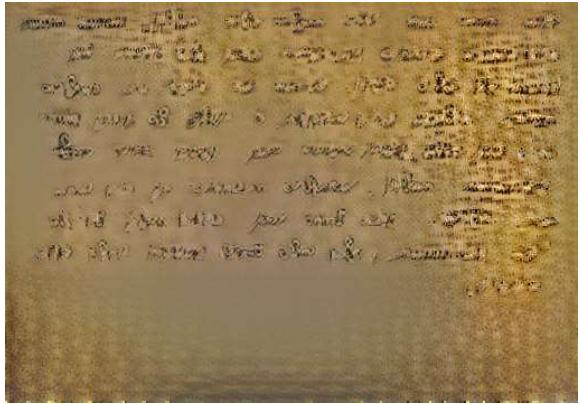
2.16.3.1. Weight 0

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.16.3.2. Weight 1

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

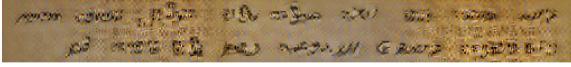
2.16.3.3. Weight 2

block3_conv2	block3_conv3
block3_conv4	block4_conv2
	
block5_conv2	
	

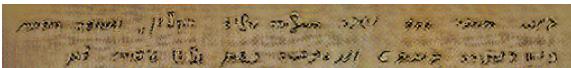
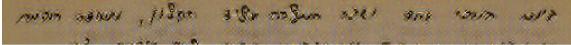
2.16.3.4. Weight 3

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	

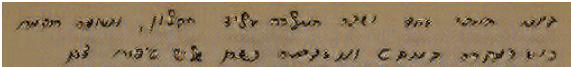
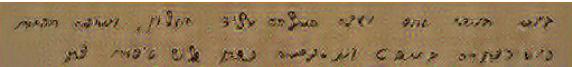
2.16.3.5. Weight 4

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

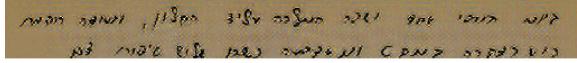
2.16.3.6. Weight 5

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.16.3.7. Weight 6

block3_conv2	block3_conv3
block3_conv4	block4_conv2
	
block5_conv2	

2.16.3.8. Weight 7

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	

2.16.3.9. Weight 8

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	

2.17. Experiment 14

2.17.1. Content Input

This experiment used a binary modern hebrew handwritten document for content, with a background created by averaging a pixels color from the style document.

2.17.2. Style Input

This experiment used a hebrew middle age document without text for style.

2.17.3. Results

We will show samples of the results with each weight and content layer (style layers are the same).

Content image	Style image
 A small rectangular image showing binary black and white handwritten Hebrew text on a light background.	 A small rectangular image showing a portion of an old, yellowed, textured document, likely parchment, with some faint markings.

2.17.3.1. Weight 0

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.17.3.2. Weight 1

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	
	

2.17.3.3. Weight 2

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.17.3.4. Weight 3

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
block5_conv2	

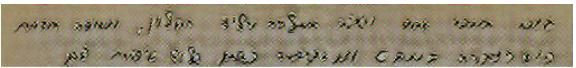
2.17.3.5. Weight 4

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	

2.17.3.6. Weight 5

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	

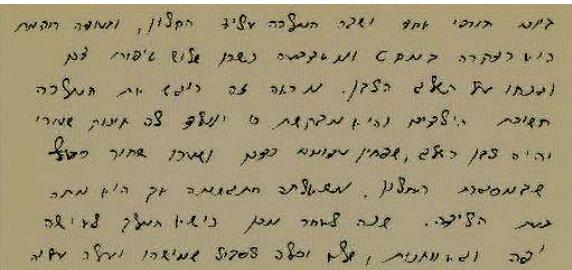
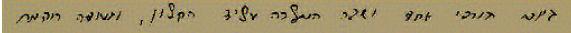
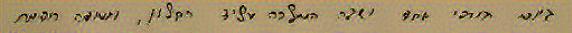
2.17.3.7. Weight 6

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.17.3.8. Weight 7

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	

2.17.3.9. Weight 8

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	
	

2.18. Experiment 15

2.18.1. Content Input

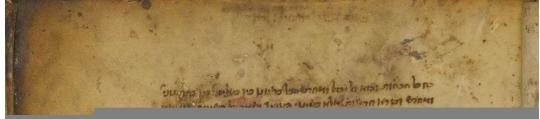
This experiment used a dilated-binary modern hebrew handwritten document for content, with a background created by averaging a pixels color from the style document.

2.18.2. Style Input

This experiment used a hebrew middle age document with text for style.

2.18.3. Results

We will show samples of the results with each weight and content layer (style layers are the same).

Content image	Style image
	

2.18.3.1. Weight 0

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
block5_conv2	
	

2.18.3.2. Weight 1

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	

2.18.3.3. Weight 2

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	

2.18.3.4. Weight 3

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
block5_conv2	
	

2.18.3.5. Weight 4

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	

2.18.3.6. Weight 5

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	
	

2.18.3.7. Weight 6

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	

2.18.3.8. Weight 7

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	

2.18.3.9. Weight 8

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	

2.19. Experiment 16

2.19.1. Content Input

This experiment used a dilated-binary modern hebrew handwritten document for content, with a background created by averaging a pixels color from the style document.

2.19.2. Style Input

This experiment used a hebrew middle age document without text for style.

2.19.3. Results

We will show samples of the results with each weight and content layer (style layers are the same).

Content image	Style image

2.19.3.1. Weight 0

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
block5_conv2	

2.19.3.2. Weight 1

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
block5_conv2	

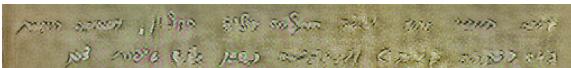
2.19.3.3. Weight 2

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	

2.19.3.4. Weight 3

block3_conv2	block3_conv3
block3_conv4	block4_conv2
	
block5_conv2	

2.19.3.5. Weight 4

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
block5_conv2	

2.19.3.6. Weight 5

block3_conv2	block3_conv3
block3_conv4	block4_conv2
	
block5_conv2	

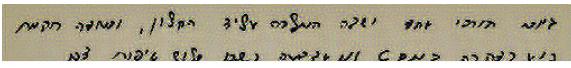
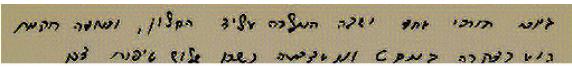
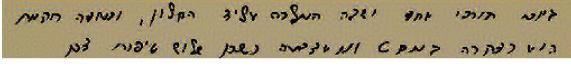
2.19.3.7. Weight 6

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	

2.19.3.8. Weight 7

block3_conv2	block3_conv3
block3_conv4	block4_conv2
block5_conv2	

2.19.3.9. Weight 8

block3_conv2	block3_conv3
	
block3_conv4	block4_conv2
	
block5_conv2	

Appendix B - Project Data

English Data

In our project there is one type of english data.

1. Modern English

Images are documents and sentences, image format is png.

Preprocess needed:

1.1. *Cropping*

Documents images need to be cropped to extract only handwriting text.

Hebrew Data

In our project there are three types of hebrew data.

1. Modern Hebrew

Images are documents in .tif format.

Preprocess needed:

1.1. *Changing Type*

Images need to be converted to .png format.

1.2. *Rotating*

Images need to be rotated 180deg to align text.

1.3. *Cropping*

Document images need to be cropped to extract only handwriting text.

1.4. *Treholding*

We need to remove yellow lines from the images.

2. Cairo Geniza Historical Hebrew

Images are documents in .tif and .png format.

No preprocess needed. This will be a hands on data preprocess by our needs.

3. Middle Ages Historical Hebrew

Images are documents in .tif and .png format.

No preprocess needed. This will be a hands on data preprocess by our needs.

Arabic Data

In our project there are two types of arabic data.

1. Modern Arab

Images are documents and sentences in .tif format.

Preprocess needed:

1.1. *Changing Type*

Images need to be converted to .png format.

2. Historical Arab

Images are documents in .jpg format.

No preprocess needed. This will be a hands on data preprocess by our needs.

Latin Data

In our project there is one type of latin data.

3. Historical Latin

Images are documents in .jpg format.

No preprocess needed. This will be a hands on data preprocess by our needs.