With the general growth of digital art popularization, it is hardly surprising that image recognition and art generation algorithms has attracted considerable attention in recent years. The main purpose of our research is to explore the field of image stylization algorithms and look into the Neural Style Transfer (NST) algorithm. NST is an example of an image stylization algorithm, a problem studied for over two decades [1] within the scope of non-photorealistic image rendering. The algorithm provided with a content picture and a style reference image (for instance, an artwork by a famous painter) at the input blends them together so the output is going to be like the content image, but “painted” in the artistic style [2]. In this paper, we present the findings of a literature review covering four journal scientific articles published in the past several years.

Gatys, Ecker, and Bethge (2016) explored new ways in the field of our research by conducting their own called "Image Style Transfer Using Convolutional Neural Networks" [3]. Their work is considered to be groundbreaking and innovative through their first NST algorithm implementation and introduction to the public. The authors are referring to some earlier studies on image stylization [4] (Efros & Free, 2001; Ashikhmin, 2003; Lee et al., 2010), which are viewed to be an underlying and crucial part as Gatys, Ecker, and Bethge are implying. The authors point out that rendering the semantic content of an image in different styles is a complicated image processing task. This paper aims at proposing an approach for applying image style transformation using a complex neural network architecture. The key finding of this study is that the representations of content and style in the Convolutional Neural Network are separable. Thus, we can manipulate both independently to produce unique, relevant images. To prove that finding, the authors provide a particular figure in the paper which illustrates a bunch of generated images that mix the content and style representation. Despite high perceptual quality and accuracy, there are still some technical limitations and drawbacks of the algorithm. The most limiting factor of such an algorithm is the resolution of the synthesized images. The speed of the image transformation heavily depends on picture resolution and computational processing power (GPU processing power and the size of the memory). The authors believed that it is likely that future improvements in deep learning will also increase the performance of this method, which indeed happened as of today.

Johnson et al. (2016) at Stanford University attempted to directly extend and enhance Gatys algorithm while developing a new approach [5]. Following the author hypothesis, high-quality images could be potentially generated by specifying and optimizing perceptual loss functions which are based on top features derived from previously trained networks. The author identifies previous implementations including Gatys' produced high-quality pictures, but they were slow while dealing with optimization issue. Thus, to overwhelm the following issue, the researchers suggested having the best of both worlds by combining the benefits of several approaches. Rather than using per-pixel loss functions, the authors have introduced perceptual loss functions instead. They proved the accuracy of their implementation and showed the results of the Image Style Transfer. Compared to the Gatys' optimization-based method, their neural network presented similar qualitative outcomes, but it was three times faster.

Another study conducted by Cui, Qi, Wang (2017) aimed at extending the technique of Fast Neural Style Transfer to multiple styles, allowing the user to transfer the contents of any input image into an aggregation of various abundant patterns [6]. For building Multiple Style Transfer the researchers used Single Image Style Transfer implementation proposed in Gatys et al. (2016) paper combined with a Fast Style Transfer algorithm. The authors stated that it is sufficiently general and can handle any variety of input images, but it was still limited to a fixed selection of style pictures to be trained on, followed by an extensive training process. Unfortunately, the proposed algorithm is also restricted to a predetermined set of parameter weights on both content and style losses, in a way that they cannot be altered afterward to see how the algorithm can transform the input photographs to be more realistic. Altogether, the built multiple style transfer resulted in reasonable blended output images of high quality within preserved context.

In their study, Yang et al. (2019) discussed the Single Image Super-Resolution (SISR) problem which could be defined as how to obtain a high-resolution output from one of the possible low-resolution image [7]. This paper aims to introduce a concise report of late deep learning techniques on SISR. It breaks down the latest studies into two classification groups such as deep architectures for imitating the SISR process itself and the algorithm optimization objectives for enhancing the whole learning procedures. The key point of presenting the proposed methodology of rendering high-resolution images is a potential use for applying in the NST algorithm. This study, however, has several potential fundamental limitations despite all the auspicious results announced. To begin with, the authors tried to recap the essential challenges by several features: the acceleration of deep models, the extensive comprehension of deep models along with assessing the criteria and metrics. Furthermore, illustrative works on overwhelming these restrictions were suggested rest on their authentic content, as well as the researcher's critical analysis on the topic, and relevant comparisons conducted. In conclusion, the scientists completed this review discussing some ongoing challenges and forthcoming tendencies in SISR that leverage deep learning algorithms.

References:

[1] Leon A. Gatys, Alexander S. Ecker, Matthias Bethge. A Neural Algorithm of Artistic Style, Aug 2015

[2] Neural Style Transfer. URL: https://en.wikipedia.org/wiki/Neural_Style_Transfer

[3] Leon A. Gatys, Alexander S. Ecker, Matthias Bethge. Image Style Transfer Using Convolutional Neural Networks. The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 2414-2423, 2016

[4] Efros A.A., Freeman W.T. Image quilting for texture synthesis and transfer. In Proceedings of the 28th annual conference on Computer graphics and interactive techniques, pp.341-346, 2001

[5] Justin Johnson, Alexandre Alahi, Li Fei-Fei . Perceptual Losses for Real-Time Style Transfer and Super-Resolution, 2016, Stanford University

[6] Brandon Cui, Calvin Qi, Aileen Wang. Multi-style Transfer: Generalizing Fast Style Transfer to Several Genres, 2017, Stanford University

[7] Wenming Yang, Xuechen Zhang, Yapeng Tian, Wei Wang, Jing-Hao Xue, Qingmin Liao. Deep Learning for Single Image Super-Resolution: A Brief Review, Jul 2019