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INNOVATIONS
AND PROSPECTS

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Authors: Oleksandr Aranivskyi, Vasyl Baranivskyi, Olena Berezinska, Oleksiy Bobko, Alla Cherep, Oleksandr Cherep, Gulasal Devanova, Larysa Duda, Tetiana Faichuk, Sergey Iepishkin, Jaroslav Karpov, Nina Korbozerova, Zoryana Koval, Petro Krul, Andrii, Krupa, Olga Kyvliuk, Halyna Lavrik, Oleksandr Lesko, Nataliia Lysenko, Maria Miroschnychenko, Ilona Myroshnichenko, Kateryna Nazaruk, Vitalina Nikitenko, Ludmila Oleynikova, Oleg Pergat, Iryna Riabinina, Oksana Romaniuk, Oleksandr Romaniuk, Dmytro Savenko, Vasyl Shakun, Tetiana Skliaruk, Sergey Skolybog, Mykyta Slyusar, Oleksiy Stakhov, Larysa Strashynska, Ihor Strashynskyi, Iryna Stohnii, Olena Sulakova, Dmytro Svitlyi, Halyna Tarasenko, Liudmyla Tkachuk, Vira Tymoshenko, Oleksandr Veremeyenko, Valentyna Voronkova, Roksolana Vynnychuk, Petro Zakharchenko, Yevhen Zavalniuk.

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Computer science

**Oleksandr ROMANIUK,**

Doctor of Technical Sciences, Professor,
Vinnytsia National Technical University
ORCID ID: 0000-0002-2245-3364

Yevhen ZAVALNIUK,

Postgraduate student,
Vinnytsia National Technical University
ORCID ID: 0009-0005-1202-4653

Oleksiy BOBKO,

Postgraduate student,
Vinnytsia National Technical University
ORCID ID: 0009-0000-1753-279X

Oleksiy STAKHOV,

Doctor of Philosophy, Senior Lecturer,
Vinnytsia National Technical University
ORCID: 0000-0002-4901-3211

Oksana ROMANIUK,

Candidate of Technical Sciences, Associate Professor,
Vinnytsia National Technical University
ORCID: 0000-0003-0235-8615
Vinnytsia, Ukraine

MACHINE LEARNING FOR ACCELERATED RENDERING

Introduction. Rendering¹ is a stage of the graphics pipeline that lies in forming the final image based on the geometric representation of the scene. Ensuring fast and efficient three-dimensional rendering is one of the main tasks of computer graphics. Rasterization and ray tracing² are traditional rendering directions that allow forming highly realistic images. However, these algorithms are characterized by high computational complexity, especially when using complex polygonal models and global illumination models.

Using the ray tracing method to simulate global illumination requires a significant number of calculations of ray intersections with object surfaces. This makes the full application of the method in real-time rendering challenging, so

1 Романюк О. Н., Романюк О. В., Чехмиструк Р. Ю. Комп'ютерна графіка. Вінниця: ВНТУ, 2023. 147 с.

2 Pharr M., Jakob W., Humphreys G. Physically Based Rendering, fourth edition: From Theory to Implementation. Cambridge: The MIT Press, 2023. 3048 p.

it is still relatively rarely used as a standalone approach even with modern GPUs (graphics processors). Rasterization methods provide faster image formation, but the possibilities of photorealistic scene visualization are limited.

The development of hardware and the increase in data volumes have led to the use of machine learning to accelerate the rendering process. The main idea is to learn, based on a dataset, an approximate representation of complex transformations used at different stages of rendering. This gives the possibility to reduce the computational costs and time of three-dimensional image visualization.

Thus, it is relevant to analyze the features of using machine learning to accelerate rendering.

Literature Analysis. The main stages of the graphics pipeline³ are characterized by shortcomings that complicate the high-performance formation of three-dimensional images.

At the stage of geometric transformations, a polygonal representation of the scene is formed, on the basis of which three-dimensional visualization is carried out. To form highly realistic images, as a rule, high-polygonal models are used, usually containing up to 100,000 polygons⁴. However, the use of detailed models for remote, peripheral areas of the scene, as well as for the representation of surfaces with slight curvature, is impractical. The optimal for accelerated rendering of images is the use of the simplest possible polygonal models⁵, in which there will be no visible losses in the quality of visualization. Determining the appropriate level of simplification is a laborious process that is carried out experimentally.

After the projection of the coordinates of the model vertices into two-dimensional space and the rasterization, the stage of the surface shading is implemented.

The shading stage⁶ is the most computationally complex stage of rendering. For each fragment, the color intensity is calculated based on the defined model of the material's reflectivity.

3 Analysis of graphics pipelines / O. Romanyuk et al. *Innovation in modern science* '2024. Karlsruhe, 2024. P. 71–80.

4 Game-Ready 3D Models: Requirements, Creation, and Export. URL: <https://threedium.io/3d-model/game-ready> (date of access: 10.03.2026).

5 Romanyuk O., Zavalniuk Y. Deep learning-based determination of optimal triangles number of graphic object's polygonal model. *IntelITSIS'2024*. Khmelnytskyi, Ukraine, 2024. P. 39–51.

6 The Concept and Means of Adaptive Shading / O. Romanyuk et al. *2022 12th International Conference on Advanced Computer Information Technologies (ACIT)*. Ruzomberok, Slovakia, 2022. P. 33–38.

The use of analytical models of reflectivity ensures the rapid formation of sufficiently realistic images. However, analytical models cannot always fully represent the reflective properties of materials. Tabular models⁷ of reflectivity allow for highly accurate reproduction of reflections on object surfaces, but are unsuitable for use in real-time systems without special optimizations.

If rendering is performed based on ray tracing instead of rasterization, the final image is more realistic. Due to the need to model multiple reflections of light from object surfaces and recursively update the color intensity of pixels, ray tracing is usually used only as a supplement to rasterization-based visualization.

The use of large ray samples further increases the computational complexity of visualization. At the same time, when using small ray samples, the image acquires significant statistical noise.

Inverse rendering methods, in contrast to direct rendering, provide the formation of photorealistic scenes from different angles based on a set of photos. In particular, the neural radiance fields (NeRF)⁸ method is well-known. Inverse rendering methods, as a rule, do not provide high speed image visualization and require optimization.

Therefore, a significant part of modern research is aimed at applying machine learning algorithms to accelerate the rendering process. The authors of existing research papers have proposed various directions of neural network approximation of complex calculations at the rendering stages.

A promising direction of work is the acceleration of the NeRF method⁹, which is used for versatile photorealistic visualization of a three-dimensional scene. Another direction of research is devoted to the use of neural models for a compact representation of measured values of the reflectivity of material surfaces.

Considerable attention has been paid by researchers to intelligently remove stochastic noise from images¹⁰ obtained using Monte Carlo ray tracing, as

7 A data-driven reflectance model / W. Matusik et al. *ACM Transactions on Graphics (TOG)*. 2003. № 3. P. 759–769.

8 NeRF: representing scenes as neural radiance fields for view synthesis / B. Mildenhall et al. *Communications of the ACM*. 2021. № 1. P. 99–106.

9 KiloNeRF: Speeding up Neural Radiance Fields with Thousands of Tiny MLPs / K. Reiser et al. *2021 IEEE/CVF International Conference on Computer Vision (ICCV)*. Montreal, Canada, 2021. P. 14315–14325; FastNeRF: High-Fidelity Neural Rendering at 200FPS / S. J. Garbin et al. *2021 IEEE/CVF International Conference on Computer Vision (ICCV)*. Montreal, Canada, 2021. P. 14326–14335; PlenOctrees for Real-time Rendering of Neural Radiance Fields / A. Yu et al. *2021 IEEE/CVF International Conference on Computer Vision (ICCV)*. Montreal, Canada, 2021. P. 5732–5741.

10 Kernel-predicting convolutional networks for denoising Monte Carlo renderings / S. Bako et al. *ACM Transactions on Graphics (TOG)*. 2017. № 4. P. 1–14.

well as to scale images¹¹ to improve frame generation performance. In addition, studies on adaptive ray sampling¹² and determining the optimal density¹³ of polygonal models are widespread.

Despite the wide possibilities for increasing the productivity of image formation, a number of disadvantages of using machine learning for accelerated rendering are identified: the complexity of training neural models, forming training datasets, and integrating neural models into visualization systems.

Main directions of using machine learning for accelerated rendering.

The use of machine learning contributes to a more effective integration of rendering algorithms into real-time applications. Such applications include computer games, virtual and augmented reality programs.

The use of machine learning algorithms at different stages of rendering is not only an auxiliary tool, but also the basis of the concept of neural rendering^{14,15}. Neural rendering is a new way of creating images and lies in a combination of classical graphics algorithms and deep learning.

The most promising areas of application of machine learning to increase rendering performance while maintaining high image quality are prediction of the level of detail of polygonal models, approximation of global illumination, application of accelerated NeRF technologies, neural models of light reflection, adaptive ray tracing, combination of small ray samples with noise removal from the image, combination of low-resolution image rendering with its subsequent intelligent scaling.

Predicting the levels of detail of scene object models provides a significant reduction in computational costs for image formation. Special neural models determine which scene objects require high-polygonal representation, and which can be visualized based on a relatively small number of polygons. To do this, the models analyze the features of the object's surface and its location in the scene.

To approximate global illumination, neural models are typically used, which allow for more efficient modeling of multiple reflections, refraction, and scat-

11 NVIDIA DLSS 4 Technology. URL: <https://www.nvidia.com/en-us/geforce/technologies/dlss/> (date of access: 10.03.2026).

12 AdaNeRF: Adaptive Sampling for Real-Time Rendering of Neural Radiance Fields / A. Kurz et al. *Computer Vision – ECCV 2022: 17th European Conference*. Tel Aviv, Israel, 2022. P. 254–270.

13 Romanyuk O., Zavalniuk Y. Deep learning-based determination of optimal triangles number of graphic object's polygonal model...P. 39–51.

14 Advances in Neural Rendering / A. Tewari et al. *Computer Graphics Forum*. 2022. № 2. P. 703–735.

15 The overview of neural rendering / Ye. K. Zavalniuk et al. *Modern Engineering And Innovative Technologies*. 2023. № 27. P. 129–134.

tering of light, as well as complex shadows. An example is the generation of images with approximated global illumination effects using the Pix2Pix model¹⁶ (one of the generative neural network architectures¹⁷).

Neural radiance fields (NeRF, Figure 1)¹⁸ are one of the most revolutionary examples of machine learning in 3D image rendering. The 3D scene is presented as a continuous function that the neural network must approximate. The neural network predicts the radiance $c(x, \vec{d})$ and volume density $\sigma(x)$ for each point x in space relative to the viewing direction $\vec{d}$. This data transformation can be expressed as the formula

$$F(x, \vec{d}) = (c, \sigma). \quad (1)$$

The predicted values are then used to generate an image from any angle using volumetric rendering expressions. An integral combining the contributions of all points along the ray $\vec{r}$ is used to determine the final pixel color intensity¹⁹

$$C(\vec{r}) = \int_{t_n}^{t_f} T(t) \sigma(\vec{r}(t)) c(\vec{r}(t), \vec{d}) dt \quad (2)$$

where $\vec{r}(t) = \vec{o} + t\vec{d}$ ($\vec{o}$ – coordinates of the beginning of the ray), transmittance coefficient $T(t) = \exp(-\int_{t_n}^t \sigma(\vec{r}(s)) ds)$.

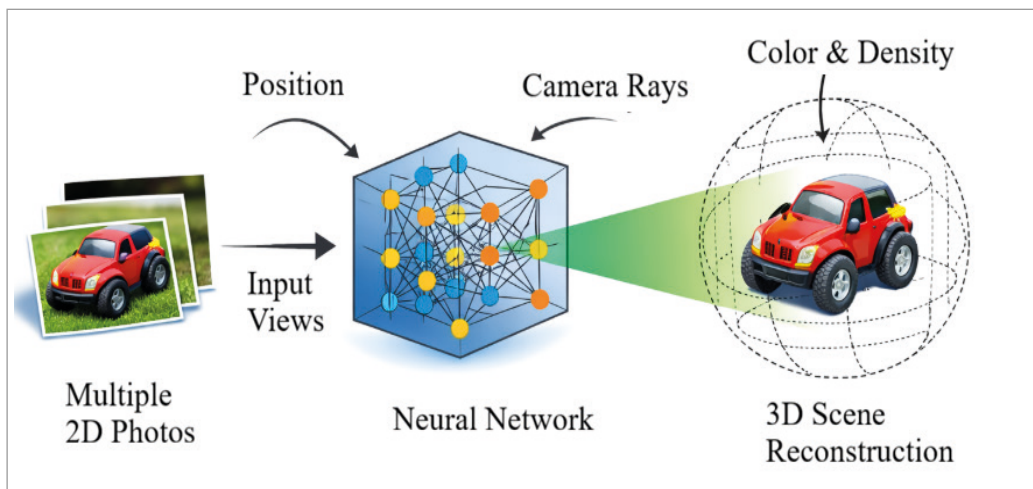


Fig. 1. NeRF Technology

16 Harris-Dewey J., Klein R. Generative Adversarial Networks for Non-Raytraced Global Illumination on Older GPU Hardware. *International Journal of Electronics and Electrical Engineering*. 2022. № 27. P. 1–6.

17 Chapter XIII. Artificial intelligence usage for the formation of graphic images / O. Romanyuk et al. *Штучний інтелект у науці: монографія*. Київ, 2025. P. 165–181.

18 NeRF: representing scenes as neural radiance fields for view synthesis / B. Mildenhall et al... P. 99–106.

19 NeRF: representing scenes as neural radiance fields for view synthesis / B. Mildenhall et al... P. 99–106.

Since using NeRF technology for scene visualization, as well as the process of training a neural model, is time-consuming, there are a number of modifications of the technology for accelerated rendering: KiloNeRF, FastNeRF, and PlenOctrees.

KiloNeRF²⁰ lies in using thousands of small neural networks in parallel instead of one large one. Each of the neural networks corresponds to a certain small area of the sphere.

Unlike NeRF, FastNeRF²¹ involves separating the data prediction process relative to the point position and viewing direction by factoring

$$F(x, \vec{d}) = \sum_{i=1} F1_i(x) \cdot F2_i(\vec{d}). \quad (3)$$

$F1_i(x)$ are calculated only once for the points of the three-dimensional scene, resulting in a cached table of values of the radiance components. $F2_i(\vec{d})$ is based on a small neural network and predicts the coefficients for the corresponding components relative to the direction $\vec{d}$. This allows one to significantly speed up the formation of images and achieve a frequency of 200 frames per second.

PlenOctrees²² lies in reading the values of spherical harmonic coefficients previously stored in the octotree during volumetric rendering for further determination of radiance. Accordingly, the neural network is no longer called at the visualization stage. The visualization frequency is 150 frames per second.

The use of machine learning for accelerated modeling of light reflection from material surfaces is promising. The most accurate reproduction of reflections on object surfaces is obtained when using tables of measured values of reflectance of materials. For example, the MERL database of measured values of reflectance is famous. However, this method is characterized by high computational complexity due to the need to interpolate measured values, as well as a large amount of tabular data. Neural models allow approximating large data tables with a relatively small set of neural network parameters.

The well-known NBRDF method²³ uses a small neural network to approximate the measured reflectance data of each material from the MERL database. Since neural networks with a small number of parameters are used, the speed of

20 KiloNeRF: Speeding up Neural Radiance Fields with Thousands of Tiny MLPs / K. Reiser et al...P. 14315–14325.

21 FastNeRF: High-Fidelity Neural Rendering at 200FPS / S. J. Garbin et al...P. 14326–14335.

22 PlenOctrees for Real-time Rendering of Neural Radiance Fields / A. Yu et al...P. 5732–5741.

23 Neural BRDF Representation and Importance Sampling / A. Sztrajman et al. *Computer Graphics Forum*. 2021. N° 6. P. 332–346.

calculating the reflectance models of materials is significantly faster than when using tables.

Machine learning allows, when implementing ray tracing, to adaptively determine²⁴, which parts of the scene require fewer ray samples and which require more.

If ray tracing is implemented based on the Monte Carlo method, the disadvantage of a formed image is the presence of stochastic noise. To remove noise²⁵ from the image, neural models based on architectures such as convolutional neural networks (CNN), transformers are used. This allows using fewer ray samples without significant loss in quality, which increases the productivity of image formation.

Neural networks allow to significantly increase the resolution and quality of image visualization. Since the image is pre-formed at a lower resolution, the computational costs for rendering the scene are lower. This provides a significant increase in the frame rate. An example of the implementation of the described technology is Nvidia DLSS²⁶ (Deep Learning Super Sampling).

Advantages and disadvantages of using machine learning for rendering.

The advantages of using machine learning algorithms at different stages of rendering include:

1. Significant acceleration of the rendering process while maintaining photo-realism. Machine learning methods provide an approximation of the application of complex rendering algorithms, such as ray tracing. In particular, the reproduction of global illumination effects is highly efficient. Neural models make it possible to obtain images that are close in quality to photo-realistic ones, but with much lower computational costs.
2. Reducing image noise without increasing the number of ray samples. Intelligent tools allow one to use a small number of ray samples during ray tracing and remove the resulting noise from the image.
3. The ability to visualize complex scenes in real time. Neural models provide a compact representation of data about complex geometric object models and complex lighting models.
4. Adaptability of neural models to different lighting conditions and materials. Since neural models can generalize learned information from training

24 AdaNeRF: Adaptive Sampling for Real-Time Rendering of Neural Radiance Fields / A. Kurz et al...P. 254–270.

25 Kernel-predicting convolutional networks for denoising Monte Carlo renderings / S. Bako et al... P. 1–14.

26 DLSS: Image Reconstruction for Real-Time Rendering With Deep Learning (Presented by NVIDIA). URL: <https://www.gdcvault.com/play/1026697> (date of access: 10.03.2026).

datasets, automatic adaptation of the rendering system to different scene geometry and lighting parameters is possible.

The disadvantages of using machine learning to render 3D images are:

1. High computational cost during the training phase of neural models. Typically, training neural networks for rendering involves processing and analyzing large volumes of complex images. This requires the use of GPUs and long computations.
2. The need for large datasets to train neural models. Training neural networks requires the generation or collection of a large number of high-quality images.
3. Possibility of artifacts in non-standard scenes. If the input parameters of the neural network differ significantly from the parameters used to train the model, the final image may contain artifacts.
4. Difficulty integrating into a traditional graphics pipeline. Integrating machine learning algorithms into a traditional graphics pipeline requires specialized software and hardware. This includes integrating intelligent software libraries into the rendering system and adapting neural models to real-time.

Using GPUs for machine learning-based rendering and hardware optimizations. The widespread use of machine learning algorithms for rendering 3D images requires the use of significant computing power. Even accelerated NeRF or CNN technologies for removing noise from images may not meet the requirements of high-performance rendering without special hardware support. Accordingly, optimization and parallelization of neural network calculations at the GPU level, applying the hardware accelerators are important.

The advantage of GPUs is the highly efficient parallelization of computational tasks. Therefore, GPUs are ideal tools for performing machine learning tasks.

Modern GPUs contain computational units (Tensor Cores)²⁷ specifically designed to perform tensor operations. These include, for example, Nvidia's RTX series GPUs. In addition, calculations are often performed on numbers in integer format (INT8) or half-precision floating-point format (FP16). This allows one to reduce the time of neural network prediction without significant computational errors.

²⁷ NVIDIA Tensor Core Programmability, Performance & Precision / S. Markidis et al. 2018 *IEEE International Parallel and Distributed Processing Symposium Workshops (IPDPSW)*. Vancouver, Canada, 2018. P. 522–531.

GPUs can also be used to parallelize the ray tracing process. This method is especially effective in combination with adaptive ray tracing and image denoising. This gives the possibility to process thousands of rays simultaneously.

Let's consider specialized hardware solutions for rendering based on machine learning.

TPU and GPU accelerators (TPU – tensor processor) were developed for optimized solutions to deep learning problems, therefore they are successfully used for neural rendering calculations. Hardware architectures such as NeuRex²⁸ use special data structures and tensor cores, which provides accelerated neural network calculations with efficient use of memory. Special integrated circuits such as FPGA and ASIC allow one to perform neural network calculations with low latency and high energy efficiency. This is most relevant for mobile rendering systems and virtual/augmented reality systems.

Let's analyze software libraries and frameworks for providing hardware acceleration of rendering based on machine learning.

AI libraries such as TensorFlow²⁹, PyTorch, JAX support optimized training and execution of neural models on GPU/TPU. In addition, facilities for differentiated rendering are provided. For example, the Tensorflow library supports automatic differentiation based on a computational graph.

OptiX³⁰ and Vulkane Compute are low-level APIs (application programming interfaces) for GPUs. They allow for optimization and parallelization of neural network computations on GPUs.

Special CUDA Kernels can accelerate the most computationally expensive stages of rendering, such as shading and ray tracing.

Additionally, there are various parallel and distributed computing strategies to accelerate machine learning-based rendering.

Data parallelization lies in the fact that neural network processing of frames or their components is carried out on separate GPUs.

Model parallelization lies in the distribution of the calculation of the components of neural models between different GPUs.

Hybrid parallelization strategies lies in a combination of the above and other existing strategies, which allows to significantly reduce the rendering

28 NeuRex: A Case for Neural Rendering Acceleration / J. Lee et al. *ISCA '23: Proceedings of the 50th Annual International Symposium on Computer Architecture*. New York, USA, 2023. Art. No. 21. P. 1–13.

29 Get started with TensorFlow. URL: <https://www.tensorflow.org/> (date of access: 10.03.2026).

30 NVIDIA OptiX™ Ray Tracing Engine. URL: <https://developer.nvidia.com/rtx/ray-tracing/optix> (date of access: 10.03.2026).

time of large scenes. The schematic examples of rendering based on model parallelization and rendering based on data parallelization are shown in Fig. 2, Fig. 3 respectively.

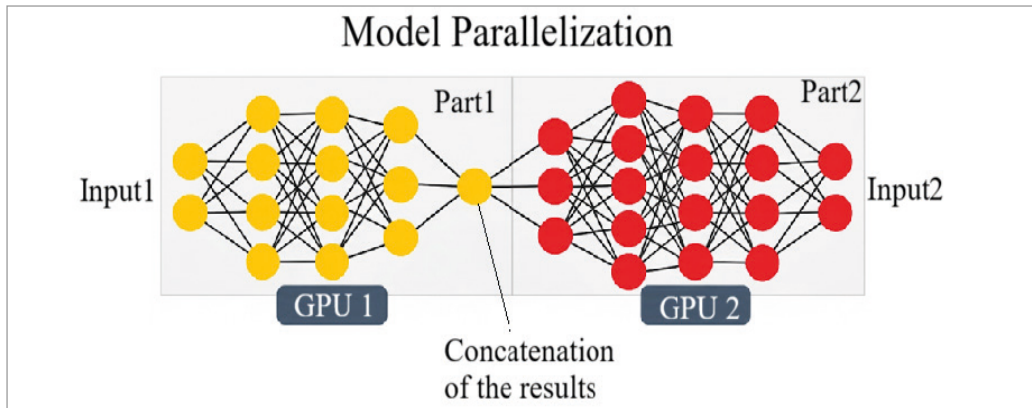


Fig. 2. Example of model parallelization for image processing

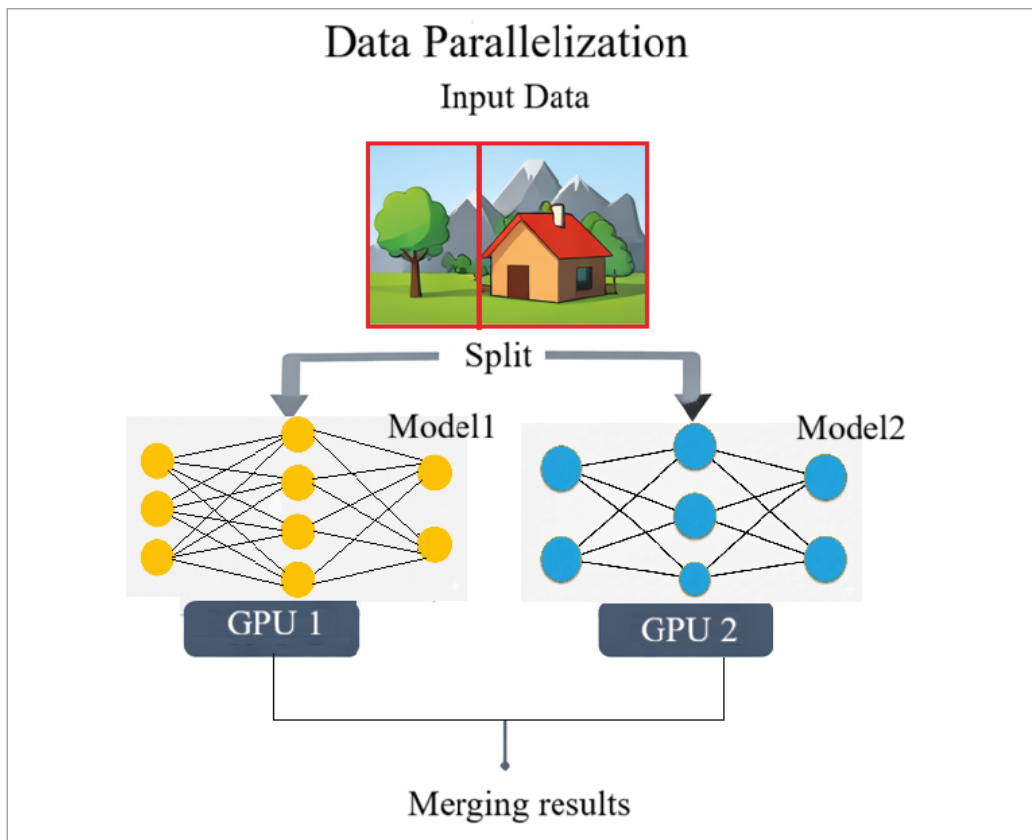


Fig. 3. Example of data parallelization for image processing

It is believed that the combination of rendering based on machine learning with special hardware allows one to speed up the time of image visualization up to 5 times³¹. Rendering of photorealistic scenes with global illumination effects in real time is provided. Also, it is possible to significantly reduce energy consumption during interactive image formation.

Thus, the combination of optimized neural networks, low-level APIs, special data structures and distributed computing tools provides fast image formation without noticeable loss in quality.

Conclusions. The paper analyzes the methods of rendering three-dimensional images based on machine learning. It is shown that neural models allow to approximate complex calculations at different stages of rendering. This allows to significantly reduce computational costs and increase the speed of image formation.

The main directions of application of machine learning methods to accelerate rendering are considered, in particular, determining the optimal number of polygons of the geometric model of the object, compact representation of the reflective properties of materials using neural models, adaptive ray tracing, image denoising to reduce the size of ray samples, neural image scaling. Additionally, such technologies as KiloNeRF, Fast-NeRF, PlenOctrees are considered, which allow to increase the performance of image formation.

The importance of using specialized hardware for machine learning-based image rendering is analyzed. Parallelization of tasks on GPUs and the use of special hardware architectures provide significant acceleration of neural network calculations.

A number of limitations are identified that are characteristic of machine learning-based rendering: high complexity of training neural models and formation of a training data set from images, complexity of integrating machine learning algorithms into traditional graphics pipelines.

Thus, machine learning is one of the most promising tools for improving traditional computer graphics algorithms. Using machine learning for rendering three-dimensional images contributes to the formation of photorealistic images in real time.

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31 New AI Speeds Computer Graphics by Up to 5x. URL: <https://spectrum.ieee.org/ai-graphics-neural-rendering-2658650804?> (date of access: 10.03.2026).