

# Investigation of the training data set influence on the accuracy of the optical Laguerre-Gaussian modes recognition

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## INTRODUCTION

Information technology continues to evolve rapidly. In parallel with this, the amount of information transmitted by digital devices is significantly increasing. However, a platform to achieve all-optical signal processing remains difficult to implement due to limitations in optical communication systems [1,2]. One way to solve this problem is Gaussian beams [3]. They have great potential for increasing the throughput of optical communication and information processing in classical and quantum modes [4]. One more advantage is that they can be processed using neural networks [5] which are strongly developed and widely used for different applications [6] in the recent years. However, in real conditions, the optical signal often has distortions associated, for example, with atmospheric turbulence [7]. The purpose of this work is to study the ability of a convolutional neural network to recognize Laguerre-Gaussian optical modes with geometric distortions which are caused by receiver bias or distortion in the environment and are described by Affine transformations, as well as to study the influence of a training sample on the recognition accuracy.

## THE DATASETS GENERATION

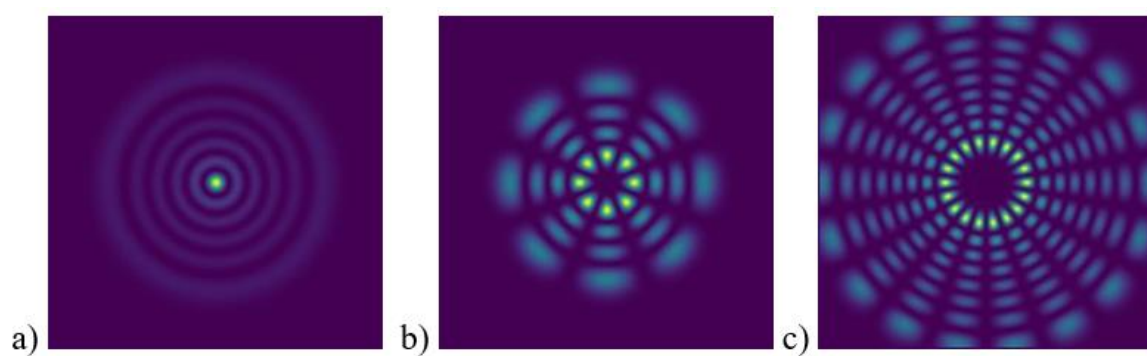


Figure 1. Images of Laguerre-Gaussian modes with the next parameters: a)  $m = 0, n = 5$ ; b)  $m = 4, n = 3$ ; c)  $m = 9, n = 7$

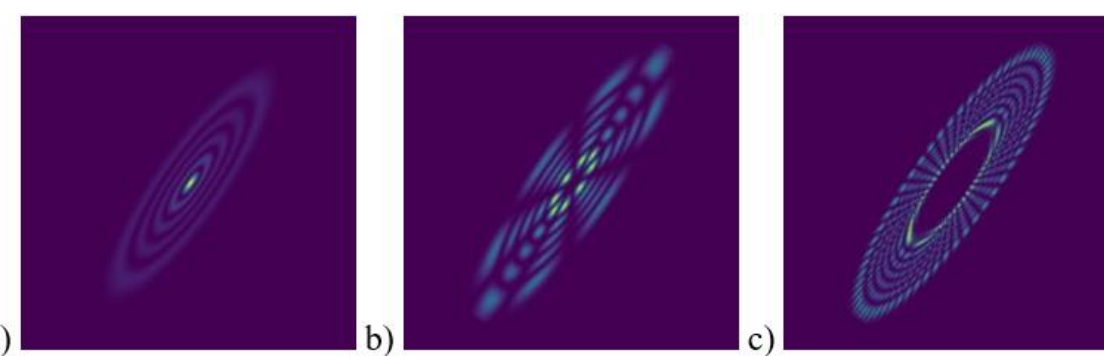


Figure 2. Images of Laguerre-Gaussian modes after Affine transformations with a rotation angle of  $\alpha = 35^\circ$  and a stretching factor of  $S = 4$  with the next parameters: a)  $m = 0, n = 5$ ; b)  $m = 4, n = 3$ ; c)  $m = 9, n = 7$

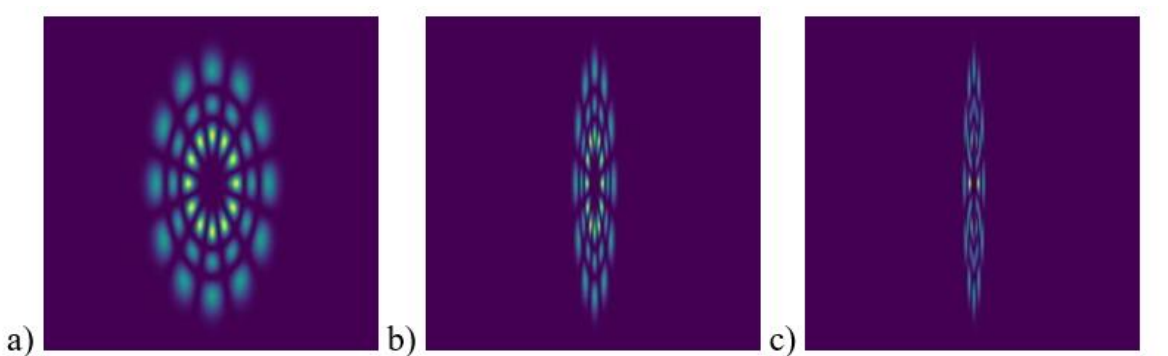


Figure 3. Images of Laguerre-Gaussian modes with  $m = 6, n = 2$  and stretched with a coefficient of: a)  $S = 2$ ; b)  $S = 6$ ; c)  $S = 12$

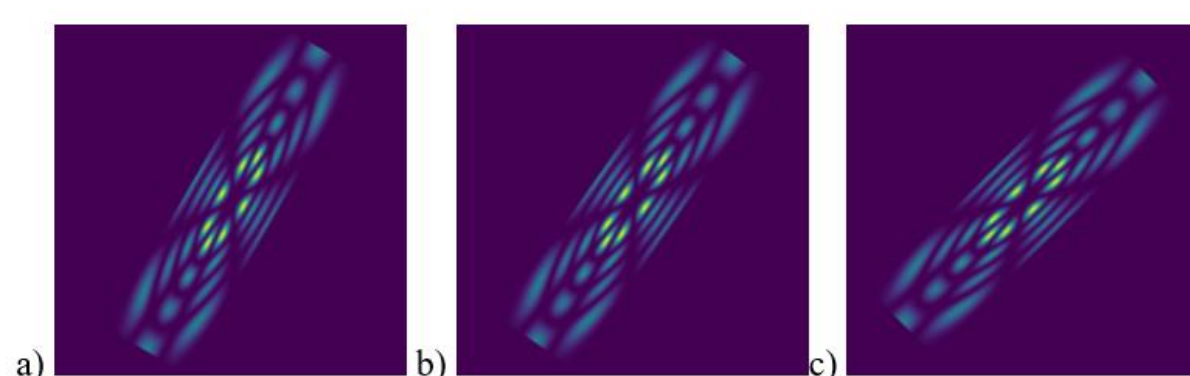


Figure 4. Examples of images of Laguerre-Gaussian modes with  $m = 4, n = 3$  stretched with a coefficient of  $S = 4$  and rotated on: a)  $\alpha = 30^\circ$ ; b)  $\alpha = 35^\circ$ ; c)  $\alpha = 45^\circ$

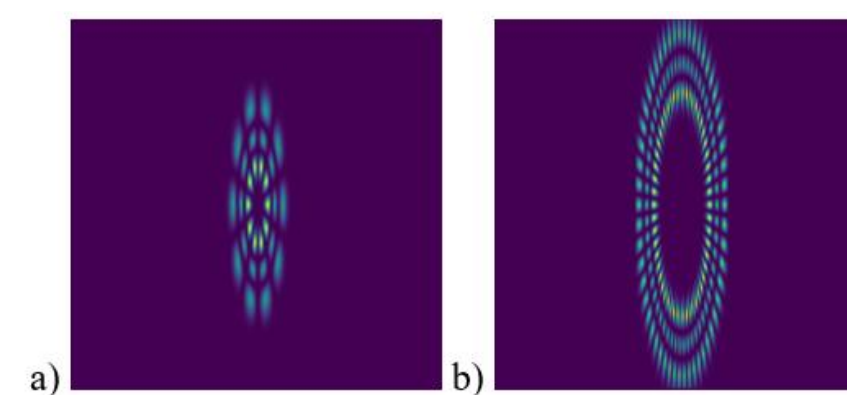


Figure 5. Examples of images of Laguerre-Gaussian modes with next parameters: a)  $m = 4, n = 3$ ; b)  $m = 23, n = 2$  and stretched with a coefficient of  $S = 4$

## CONVOLUTION NEURAL NETWORK DESIGN

To implement the recognition of optical modes, three different structures of convolutional neural networks were considered. Training and testing were carried out on datasets with only original mode images TDS-I, with only transformed images TDS-II, and with combination of both types of images TDS-III.

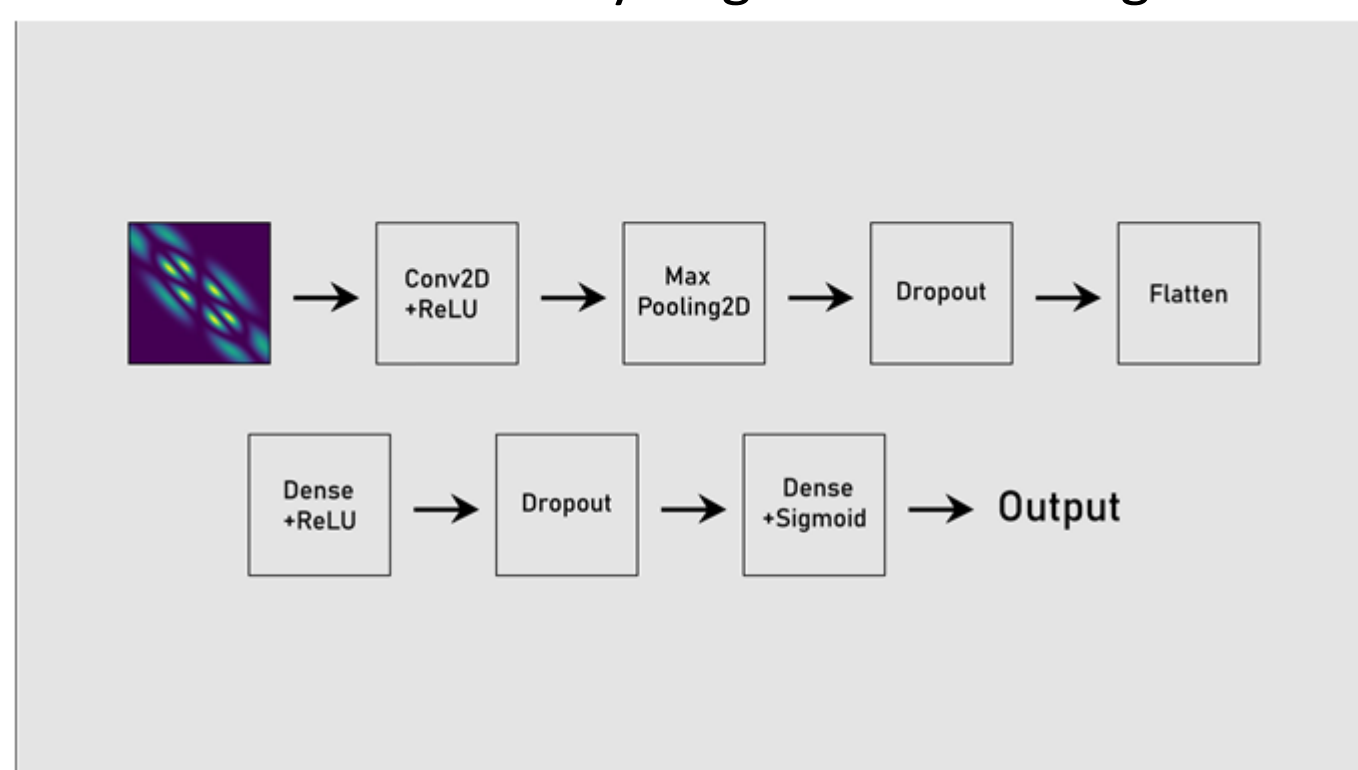


Figure 6. The structure of the CNN-I. Accuracy 89.14%, 51.34%, and 96.90

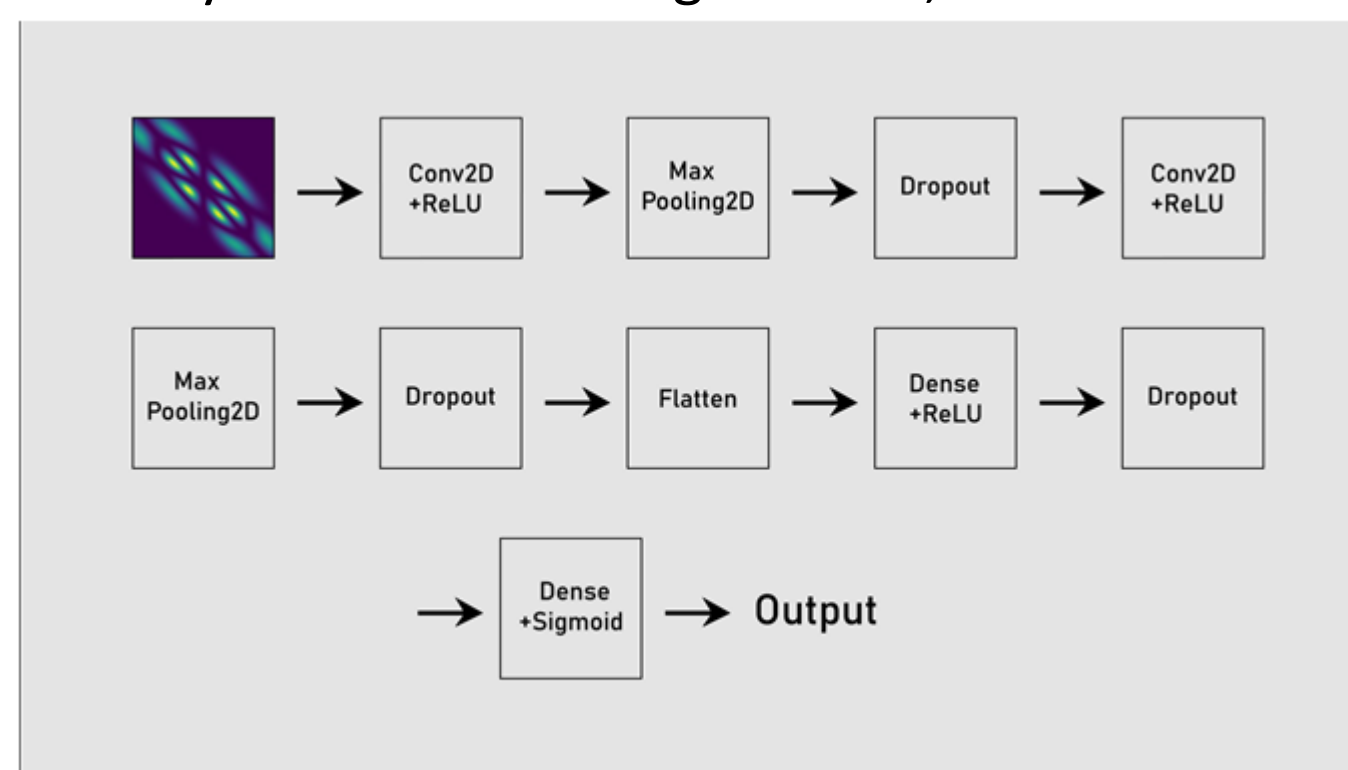


Figure 7. The structure of the CNN-II. Accuracy 99.53%, 54.17% and 97.92%

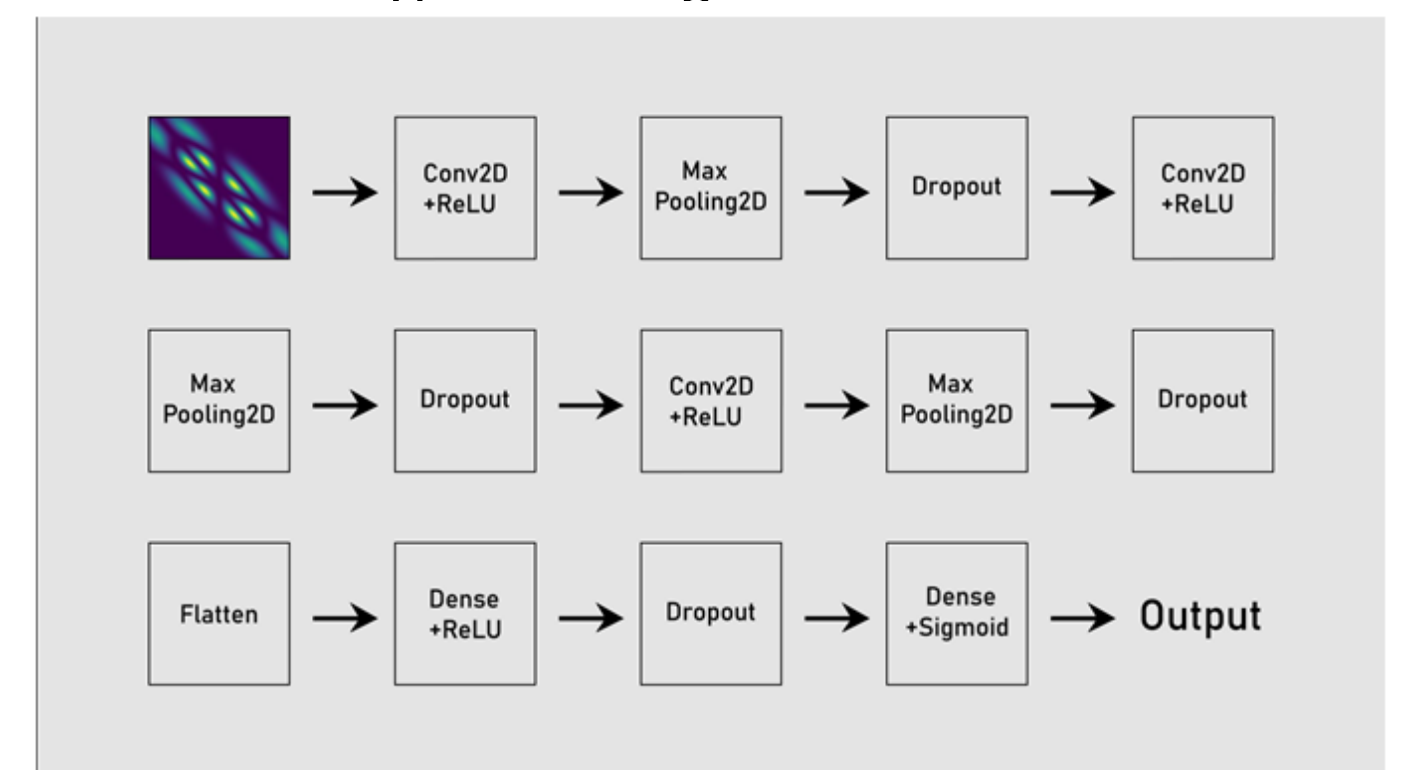


Figure 8. The structure of the CNN-III. Accuracy 97.91%, 62.69% and 89.10%

## TESTING OF RECOGNITION ACCURACY

For testing, the models of convolutional neural networks obtained using the second (Figure 7) and third structures (Figure 8) were selected, since they showed the best result. They were trained on the dataset with fixed distortions (the stretching coefficient of  $S = 4$ , rotation angle of  $\alpha = 35$ ). In tests were used datasets: with different stretching coefficient  $S = 2$  (DS\_S-I),  $S = 4$  (DS\_S-II),  $S = 6$  (DS\_S-III), and  $S = 12$  (DS\_S-IV); with different rotation angles  $\alpha = 25^\circ$  (DS\_SA-I),  $\alpha = 35^\circ$  (DS\_SA-II) and  $\alpha = 45^\circ$  (DS\_SA-III) which were applied after the stretching with coefficient of  $S = 4$ ; and the last one contained orders from 0 to 15 (DS\_M-I), and the second one contained from 16 to 31 (DS\_M-II). The degree ranged from 0 to 9 in both datasets.

TABLE II. RESULTS OF THE CNN-III TESTING FOR THE LAGERRE-GAUSSIAN MODE

	CNN-III trained on TDS-III, %	CNN-III trained on TDS-IV, %
DS_S-I ( $S = 2$ )	96.68	85.71
DS_S-III ( $S = 6$ )	88.99	81.05
DS_S-IV ( $S = 12$ )	75.50	78.03
DS_A-I ( $\alpha = 25^\circ$ )	95.29	95.88
DS_A-II ( $\alpha = 45^\circ$ )	94.99	95.04

TABLE I. TEST RESULTS OF TWO CNN

	The accuracy of the CNN-II, %	The accuracy of the CNN-III, %
Stretching ( $\alpha = 0^\circ$ )		
DS_S-I ( $S = 2$ )	78.39	89.74
DS_S-II ( $S = 4$ )	80.12	89.61
DS_S-III ( $S = 6$ )	79.10	89.41
Rotation ( $S = 4$ )		
DS_SA-I ( $\alpha = 30^\circ$ )	88.69	91.10
DS_SA-II ( $\alpha = 35^\circ$ )	90.01	90.88
DS_SA-III ( $\alpha = 45^\circ$ )	91.03	90.74
Stretching for different mode orders ( $S = 4$ )		
DS_M-I ( $m = 0, \dots, 15$ )	89.90	97.93
DS_M-II ( $m = 16, \dots, 31$ )	95.51	97.60

## CONCLUSION

In this study, the dependence of recognition accuracy on the training dataset was studied. The study was carried out for models that solve recognition problems for the Laguerre-Gaussian modes. Due to the centrosymmetry of the Laguerre-Gaussian modes, the rotation has little effect on the recognition accuracy. The stretching factor  $S$  significantly affects the recognition accuracy of modes. For example, at  $S = 12$ , the accuracy of mode recognition decreases by about 20% and 12% for neural network trained on a dataset with fixed distortions (the stretching coefficient of  $S = 4$ , rotation angle of  $\alpha = 35$ ) and on the full combination of all images, respectively. It was found that for a model trained to detect the Laguerre-Gauss mode, there is no need to use all distortion options in the training dataset. The absence of images with rotation or low values of the stretching factor in it leads to a change in accuracy by about 3%. This work can help in further research in the field of optical communication systems.

## References

- [1] Huang, Z., Wang, P., Liu, J., Xiong, W., He, Y., Xiao, J., Ye, H., Li, Y., Chen, S., Fan, D., All-Optical Signal Processing of Vortex Beams with Diffractive Deep Neural Networks, *Phys. Rev. Applied*, 2021, vol. 15, no. 1, pp. 014037.
- [2] He, Y., Wang, P., Wang, C., Liu, J., Ye, H., Zhou, X., Li, Y., Chen, S., Zhang, X., Fan, D., All-Optical Signal Processing in Structured Light Multiplexing with Dielectric Meta-Optics, *ACS Photonics*, 2020, vol. 7, no. 1, pp. 135–146.
- [3] Kotlyar, V. V., Kovalev, A. A., Porfirev, A.P. *Vortex laser beams*, CRC Press, 2018.
- [4] Sayan, Ö. F., Gerçekcioğlu, H., Baykal, Y., Hermite Gaussian beam scintillations in weak atmospheric turbulence for aerial vehicle laser communications, *Opt. Commun.*, 2020, vol. 458, pp. 124735
- [5] Bukin, D. P., Kozlova, E. S., Neural network for recognition noisy images of Laguerre-Gaussian modes, *Proc. SPIE*, 2022, vol. 12295, pp. 122950U.
- [6] Gorbachev, V. A., Krivorotov, I. A., Markelov, A. O., Kotlyarova, E. V. Semantic segmentation of satellite images of airports using convolutional neural networks, *Computer Optics*, 2020, vol. 44, no. 4, pp. 636-645.
- [7] Xia, T., Liu, D., Dong, A., Wang, G., Zhong, H., Wang, Y., Properties of partially coherent elegant Laguerre-Gaussian beam in free space and oceanic turbulence, *Optik*, 2020, vol. 201, pp. 163514.