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| **Title:** ImageNet Classification with Deep CNNs  **Main author:** Alex Krizhevsky  **Year:** 2012  **Link:**<https://www.researchgate.net/publication/267960550_ImageNet_Classification_with_Deep_Convolutional_Neural_Networks> |
| **Journal:**  Advances in Neural Information Processing Systems  **Citations:** 37,920  **Pages:** 9 |
| **Structure of the paper**   1. Abstract 2. Introduction 3. The Dataset 4. The Architecture    * ReLU Nonlinearity    * Training on multiple GPUs    * Local Response Normalization    * Overlapping Pooling    * Overall architecture 5. Reducing Over fitting.    * Data Augmentation    * Dropout 6. Details of learning 7. Results    * Quantitative Evaluations 8. Discussions |
| **Detail of figures and plots**  **Regarding Activation Functions.**   1. Graph of Activation functions: Explains the learning efficiency of ReLU over other functions.   **Regarding Overall architecture**   1. Figure: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs.   **Related to convolutional filters**   1. 96 convolutional filters and their impact   **Related to dataset.**   1. Eight ILSVRC-2010 test images and the five labels considered most probable by our model |
| **Experimental setup and experimentation**   * **Experiment-1:** ILSVRC-2010 Dataset   + **Compared with:** State of the art CNNs   + **Outputs:** Error rates.   + **Output structure:** Tabular and plots * **Experiment-2:** ILSVRC-2012 competition   + **Compared with:** State of the art   + **Outputs:** Error rates   + **Output structure:** Tabular and plots |
| **A brief summary of the proposed work [one paragraph]**  The convolutional neural networks used to classify images. In this paper the researchers have used a large amount of image data to train their neural networks. The huge amount of data proved to be very useful in classification. Although the number of tunable parameters were about 60 million but the accuracy outperforms any other state of the art CNN. These convolutional Neural Networks were trained on multiple GPUs to make the training process faster and efficient. Such a complex CNN can easily get over fitted during the training process, to overcome this problem used two very powerful techniques to reduce the over fitting in the CNN one **data augmentation** and the other was **dropout**. Non-saturated neurons were used to increase the accuracy of the prediction. |
| **Critical review**  They have used **five** convBlocks in the experiments reducing the number of convBlocks reduces the efficiency they have stated that in the paper. Why they haven’t used more than **five** convBlocks will it increase the efficiency or decrease |
| **Any idea to upgrade the concept** |
| **Name five papers from references, you’d like to read next**   1. R.M. Bell and Y. Koren. Lessons from the netflix prize challenge. ACM SIGKDD Explorations Newsletter, 9(2):75–79, 2007. 2. A. Berg, J. Deng, and L. Fei-Fei. Large scale visual recognition challenge 2010. www.imagenet.org/challenges. 2010. 3. D. Cire¸san, U. Meier, and J. Schmidhuber. Multi-column deep neural networks for image classification. Arxiv preprint arXiv:1202.2745, 2012 4. V. Nair and G. E. Hinton. Rectified linear units improve restricted boltzmann machines. In Proc. 27th International Conference on Machine Learning, 2010 5. P.Y. Simard, D. Steinkraus, and J.C. Platt. Best practices for convolutional neural networks applied to visual document analysis. In Proceedings of the Seventh International Conference on Document Analysis and Recognition, volume 2, pages 958–962, 2003. 6. S.C. Turaga, J.F. Murray, V. Jain, F. Roth, M. Helmstaedter, K. Briggman, W. Denk, and H.S. Seung. Convolutional networks can learn to generate affinity graphs for image segmentation. Neural Computation, 22(2):511–538, 2010. |
| **Name five papers from citations, you’d like to read next** |