**LITERATURE SURVEY**

**1) ImageNet Classification with Deep Convolutional Neural Networks**

**Authors: Alex Krizhevsky, Ilya Sutskever , Geoffrey E. Hinton**

We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0%, respectively, which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully connected layers with a final 1000-way softmax. To make training faster, we used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overfitting in the fully connected layers we employed a recently developed regularization method called "dropout" that proved to be very effective. We also entered a variant of this model in the ILSVRC-2012 competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry.

**2. Going Deeper with Convolution**

**Authors: Christian Szegedy , Wei Liu , Yangqing Jia , Pierre Sermanet**

We propose a deep convolutional neural network architecture codenamed Inception that achieves the new state of the art for classification and detection in the ImageNet Large-Scale Visual Recognition Challenge 2014 (ILSVRC14). The main hallmark of this architecture is the improved utilization of the computing resources inside the network. By a carefully crafted design, we increased the depth and width of the network while keeping the computational budget constant. To optimize quality, the architectural decisions were based on the Hebbian principle and the intuition of multi-scale processing. One particular incarnation used in our submission for ILSVRC14 is called GoogLeNet, a 22 layers deep network, the quality of which is assessed in the context of classification and detection.

**3 Deep Residual Learning for Image Recognition**

**AUTHORS: Kaiming He, Xiangyu Zhang, Shaoqing Ren and Jian Sun**

Deeper neural networks are more difficult to train. We present a residual learning framework to ease the training of networks that are substantially deeper than those used previously. We explicitly reformulate the layers as learning residual functions with reference to the layer inputs, instead of learning unreferenced functions. We provide comprehensive empirical evidence showing that these residual networks are easier to optimize, and can gain accuracy from considerably increased depth. On the ImageNet dataset we evaluate residual nets with a depth of up to 152 layers - 8× deeper than VGG nets [40] but still having lower complexity. An ensemble of these residual nets achieves 3.57% error on the ImageNet test set. This result won the 1st place on the ILSVRC 2015 classification task. We also present analysis on CIFAR-10 with 100 and 1000 layers. The depth of representations is of central importance for many visual recognition tasks. Solely due to our extremely deep representations, we obtain a 28% relative improvement on the COCO object detection dataset. Deep residual nets are foundations of our submissions to ILSVRC & COCO 2015 competitions1, where we also won the 1st places on the tasks of ImageNet detection, ImageNet localization, COCO detection, and COCO segmentation.

**4. “Rethinking the Inception Architecture for Computer Vision**

**AUTHORS: Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jonathon Shlens and Zbigniew Wojna**

Convolutional networks are at the core of most state of-the-art computer vision solutions for a wide variety of tasks. Since 2014 very deep convolutional networks started to become mainstream, yielding substantial gains in various benchmarks. Although increased model size and computational cost tend to translate to immediate quality gains for most tasks (as long as enough labeled data is provided for training), computational efficiency and low parameter count are still enabling factors for various use cases such as mobile vision and big-data scenarios. Here we are exploring ways to scale up networks in ways that aim at utilizing the added computation as efficiently as possible by suitably factorized convolutions and aggressive regularization. We benchmark our methods on the ILSVRC 2012 classification challenge validation set demonstrate substantial gains over the state of the art: 21:2% top-1 and 5:6% top-5 error for single frame evaluation using a network with a computational cost of 5 billion multiply-adds per inference and with using less than 25 million parameters. With an ensemble of 4 models and multi-crop evaluation, we report 3:5% top-5 error and 17:3% top-1 error on the validation set and 3:6% top-5 error on the official test set.

**5. Brain Tumor Classification Using ResNet-101 Based Squeeze and Excitation Deep Neural Network**

**AUTHORS: Palash Ghosal, Lokesh Nandanwar, Swati Kanchan, Ashok Bhadra, Jayasree Chakraborty and Debashis Nandi**,

The brain tumor is one of the leading and most alarming cause of death with a high socio-economic impact in Occidental as well as eastern countries. Differential diagnosis and classification of tumor types (Gliomas, Meningioma, and Pituitary tumor) from MRI data are required to assist radiologists as well as to avoid the dangerous histological biopsies. In the meantime, improving the accuracy and stability of diagnosis is also one challenging task. Many methods have been proposed for this purpose till now. In this work, an automatic tool for classification of brain tumor from MRI data is presented where the image slice samples are passed into a Squeeze and Excitation ResNet model based on Convolutional Neural Network (CNN). The use of zero-centering and normalization of intensity for smooth variation of the intensity over the tissues was also investigated as a preprocessing step which together with data augmentation proved to be very effective. A relative study had been done to prove the efficacy of the proposed CNN model in free tumor database. Experimental evaluation shows that the proposed CNN archives an overall accuracy rate of 89.93% without data augmentation. Addition of data augmentation has further improved the accuracies up to 98.67%, 91.81% and 91.03% for Glioma, Meningioma and Pituitary tumor respectively with an overall accuracy of 93.83%. Promising improvement with reference to sensitivity and specificity compared with some of the state-of-the-art methods was also observed.