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FEATURE-OPTIMIZED DEEP LEARNING MODEL FOR LIVER CT SCANS VIA SOCIAL SPIDER OPTIMIZATION

Dr. P. Nagendra Kumar, K. Sai Likith, K. Tanmay, K. Avinash, K. Yashwanth Kumar
Department of Computer Science and Engineering (AI&ML), Geetanjali Institute of Science and Technology, Nellore, Andhra Pradesh, India.

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ABSTRACT
Liver diseases such as fatty liver, cirrhosis, and hepatitis are becoming increasingly widespread due to factors like poor diet, excessive alcohol consumption, and sedentary lifestyles. Given the liver’s vital role in human physiology, early detection of such conditions is critical to reducing the high mortality rates associated with liver dysfunction. Traditional diagnostic techniques, including biopsy, X-ray, CT, and MRI scans, aid in the early identification of liver-related abnormalities. This research introduces an advanced framework for liver disease detection utilizing artificial intelligence (AI) and pre-trained deep learning models. The study primarily focuses on CT scan images for liver disease classification. To enhance computational efficiency and improve model accuracy, the Social Spider Optimization (SSO) algorithm is implemented for feature selection and dimensionality reduction from the CT images. Following feature extraction and reduction via SSO, three established Convolutional Neural Networks (CNNs) are employed to classify the liver images. These CNN models are trained and fine-tuned using the optimized feature sets produced by the SSO algorithm. A publicly accessible liver CT image dataset is used to assess the performance of the proposed models through various evaluation metrics. This structured approach enables an in-depth analysis of the influence of feature reduction on classification outcomes. By integrating SSO-based feature optimization with powerful pre-trained CNN architectures, the proposed method demonstrates the potential of AI-enhanced tools in medical imaging and accurate liver disease diagnosis.

Keywords: Liver Disease Detection, CT Scan Analysis, Deep Learning, Social Spider Optimization

1. INTRODUCTION

Waste management has emerged as one of the most pressing environmental and public health challenges in India, particularly in the context of rapid urbanization and population growth. The escalating volume of municipal solid waste, especially in urban centers, places immense pressure on existing waste disposal systems. As of 2022, Indian cities collectively generate around 150,000 metric tons of solid waste per day, with states like Maharashtra contributing significantly to this burden. Rural regions, too, are witnessing a surge in waste generation—estimated between 0.3 to 0.4 million metric tons daily—driven by increasing consumerism and population density.

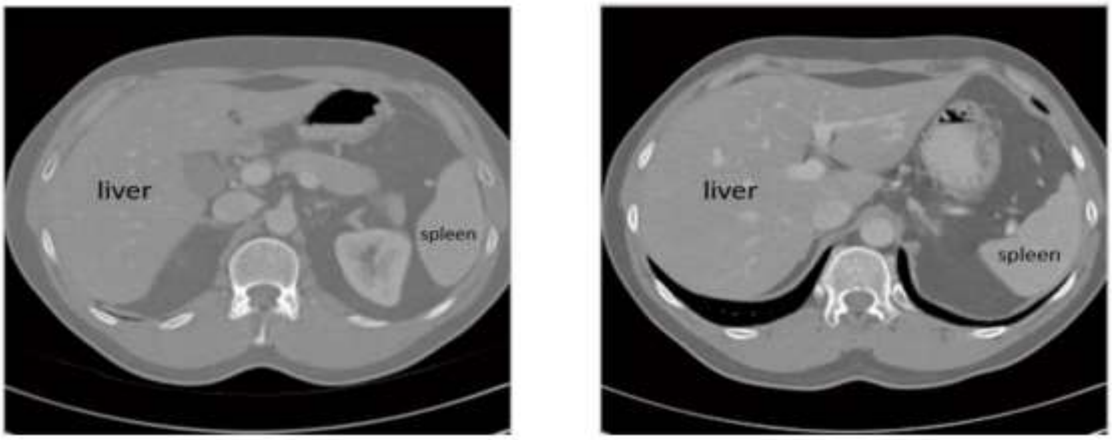


Fig 1: Liver Segmentation in CT Scan.

Improper handling and disposal of waste, including hazardous and biomedical materials, can have devastating health implications, such as respiratory disorders, infections, and chronic diseases. Traditional practices like open dumping and burning of waste further exacerbate environmental degradation, releasing toxic pollutants into the air and soil.

In response to these challenges, India has made considerable efforts to strengthen its waste management infrastructure by establishing solid waste treatment plants and e-waste collection centers. While these initiatives represent a step in the right direction, their success heavily relies on effective waste segregation at the source. This highlights the urgent need for intelligent, automated solutions to enhance sorting accuracy and operational efficiency.

Automated trash classification, driven by artificial intelligence (AI) and machine learning (ML), presents a promising avenue for transforming waste management practices. These technologies enable the precise identification and segregation of various waste types, minimizing manual intervention, reducing exposure to harmful substances, and improving overall recycling rates. By integrating automated classification systems, India can not only optimize its waste processing capabilities but also advance toward a cleaner, healthier, and more sustainable future.

2. LITERATURE SURVEY

In recent years, various machine-learning techniques have been utilized to segment the liver and tumors in medical images [4]. Additionally, Song and coauthors introduced an adaptive algorithm based on the fast marching method (FMM) for fully automatic liver segmentation. Their method dynamically adjusts parameters by considering the intensity statistics within the potential liver region, as detailed in their research [5]. Researchers have developed methods for identifying liver tumors in systems by using deep learning models, such as CNNs. They classified sets of functions into predefined or undefined classes using both supervised and unsupervised methods. Training and test data are needed to train and assess a classifier's output [6].

Regarding medical image analysis, professionals who label a set of objects—differentiating between normal and diseased cells—usually provide training data. In this study, 79 HE-stained tissue samples were used; 48 of these samples were HCC tissue, and the remaining 31 were normal tissue. The researchers aimed to distinguish between malignant and normal hepatocellular carcinoma (HCC) liver tissues and proposed a method to identify it. Deep learning approaches have been found to have good learning capacities for detecting liver tumors [7]. To detect liver tumors, several deep learning models, "including stacked autoencoders (SAEs), convolutional neural networks (CNNs), deep Boltzmann machines (DBMs) and deep belief networks, have been used" [3,4,5,6,7,8]. Various CNN architectures [9,10] have been used; however, some studies have used the VGG16 architecture, while others have used a two-dimensional (2D) UNet [3,11,12,13,14] architecture, which is frequently employed for segmenting medical images [15]. The liver and its surrounding organs have low contrast intensities, challenging liver segmentation from CT images.

3. PROPOSED METHODOLOGY

The proposed system leverages Social Spider Optimization (SSO) and artificial intelligence (AI) pretrained models to enhance the accuracy and efficiency of liver disease detection. Traditional diagnostic methods often suffer from limitations such as human error, prolonged evaluation time, and suboptimal feature selection. To overcome these challenges, the system integrates bio-inspired optimization techniques with deep learning-based classification for improved diagnostic precision.

The process begins with data preprocessing, where liver function test results and medical records are cleaned and optimized. Feature selection is performed using SSO, which mimics the social behavior of spiders to extract the most relevant attributes, thereby reducing computational complexity and improving prediction accuracy. Once optimal features are identified, AI-based classification is applied using pretrained deep learning models, such as Convolutional Neural Networks (CNNs) and Transformer-based architectures. These models, fine-tuned through transfer learning, analyze medical data to detect patterns associated with liver disease.

Convolution Neural Network (CNN) is used for feature extraction and classification, especially when working with medical images such as ultrasound, CT, or MRI scans. A typical CNN architecture consists of the following layers as shown in Figure 4.6.

Input Layer: Takes liver disease images as input, typically in the form of grayscale or RGB images with a fixed size (e.g., 224×224×3 for RGB).

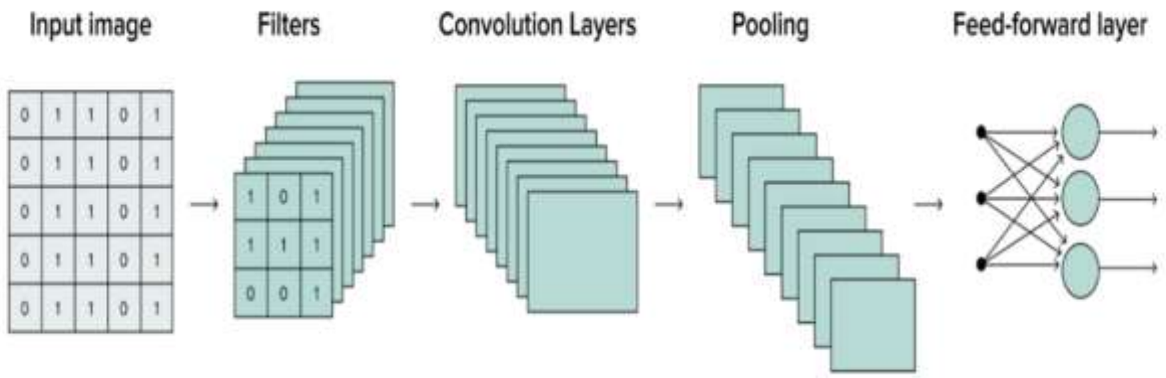


Fig 2. Proposed CNN Classifier.

Convolution Layers: These layers apply filters (kernels) to extract important features such as edges, textures, and patterns from liver images. Each filter slides over the image, performing dot product operations to create a feature map that highlights specific features. Activation functions like ReLU (Rectified Linear Unit) are used to introduce non-linearity and improve learning.

Pooling Layers: These layers reduce the spatial dimensions of feature maps while retaining important information. Max Pooling selects the maximum value from a feature region, while Average Pooling computes the average value. This helps in reducing computational cost and prevents overfitting.

Batch Normalization: This layer normalizes activations to improve training stability and speed. It helps the network converge faster and enhances generalization.

Fully Connected Layers: The extracted features are flattened into a 1D vector and passed through fully connected (dense) layers for classification. A Softmax activation function is used in the final layer to classify the image into different categories (e.g., healthy liver vs. diseased liver).

3.1 Convolution Layer

The convolutional layer is the core building block of a CNN, and it is where the majority of computation occurs. It requires a few components, which are input data, a filter, and a feature map.

Let's assume that the input will be a color image, which is made up of a matrix of pixels in 3D. This means that the input will have three dimensions a height, width, and depth—which correspond to RGB in an image. We also have a feature detector, also known as a kernel or a filter, which will move across the receptive fields of the image, checking if the feature is present. This process is known as a convolution.

The feature detector is a two-dimensional (2-D) array of weights, which represents part of the image. While they can vary in size, the filter size istypically a 3x3 matrix; this also determines the size of the receptive field. The filter is then applied to an area of the image, and a dot product is calculated between the input pixels and the filter. This dot product is then fed into an output array. Afterwards, the filter shifts by a stride, repeating the process until the kernel has swept across the entire image. The final output from the series of dot products from the input and the filter is known as a feature map, activation map, or a convolved feature.

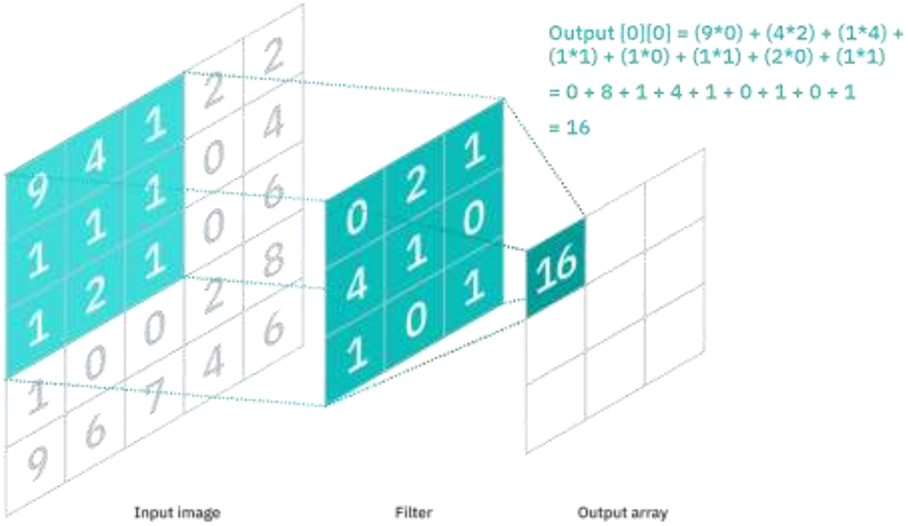


Fig 3. Convolution Layer.

The **number of filters** affects the depth of the output. For example, three distinct filters would yield three different feature maps, creating a depth of three.

Stride is the distance, or number of pixels, that the kernel moves over the input matrix. While stride values of two or greater is rare, a larger stride yields a smaller output.

Zero-padding is usually used when the filters do not fit the input image. This sets all elements that fall outside of the input matrix to zero, producing a larger or equally sized output. There are three types of padding:

Valid padding: This is also known as no padding. In this case, the last convolution is dropped if dimensions do not align.

Same padding: This padding ensures that the output layer has the same size as the input layer

Full padding: This type of padding increases the size of the output by adding zeros to the border of the input.

CNN Advantages

Convolutional Neural Networks (CNNs)are highly effective in analyzing medical images such as ultrasound, CT scans, and MRI scans for liver disease detection. CNNs offer several advantages over traditional machine learning methods:

Automatic Feature Extraction: CNNs eliminate the need for manual feature extraction, as they automatically learn important patterns such as lesions, fibrosis, and abnormalities in liver images. This improves accuracy and efficiency compared to handcrafted features used in traditional methods.

Spatial Hierarchy of Features: CNNs detect low-level features (edges, textures) in early layers and high-level features (disease patterns) in deeper layers. This hierarchical approach enhances detection accuracy for liver diseases.

Translation Invariance: CNNs recognize patterns regardless of their position in the image, ensuring robustness against variations in medical scans. This is especially useful in liver disease detection, where abnormalities may appear in different regions.

Improved Accuracy and Sensitivity: CNN-based models achieve higher accuracy, sensitivity, and specificity in liver disease classification compared to traditional methods. They outperform older techniques like SVM or Random Forest when analyzing complex medical images.

4. RESULTS AND DISCUSSION

The confusion matrix for the proposed model highlights its classification performance for three liver diseases: liver cirrhosis, hepatocellular carcinoma, and fatty liver. The model correctly identifies all 38 cases of liver cirrhosis without any false positives or false negatives, indicating high precision and recall for this class. Similarly, hepatocellular carcinoma is accurately classified with 43 true positives and no misclassifications, demonstrating strong performance. Fatty liver also achieves high accuracy, with 44 true positives and no false classifications. The model maintains a perfect false positive rate across all categories, suggesting it does not mistakenly classify instances into incorrect categories. Additionally, the true negative values remain consistently high, further indicating the model's robustness. This performance suggests the model is highly reliable for detecting liver diseases with minimal errors. However, continued validation with larger datasets may be necessary to confirm its generalizability. The results indicate a well-optimized model that effectively distinguishes between these liver diseases.

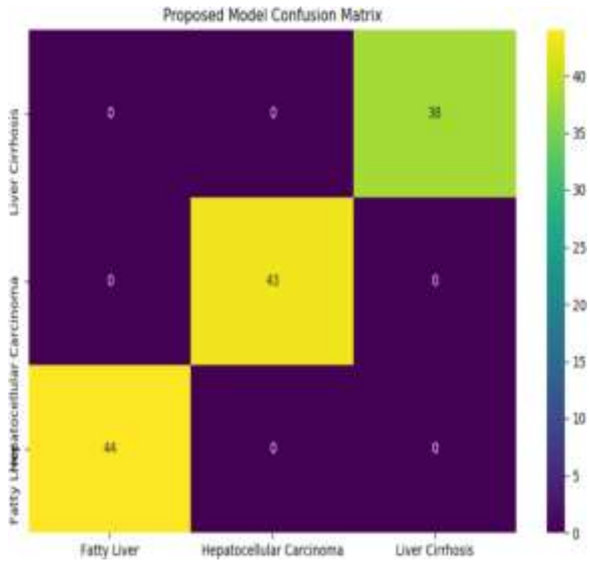
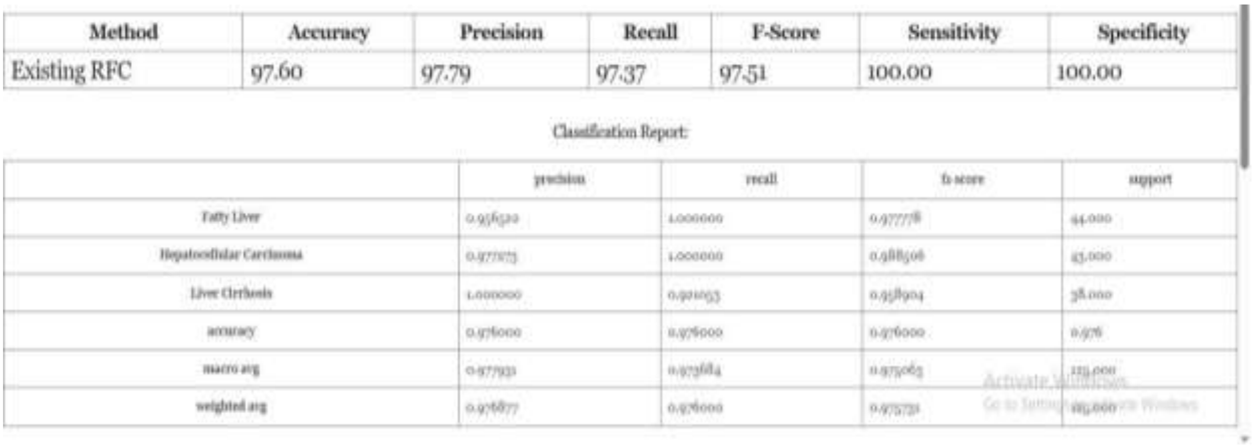


Fig 4. Confusion Matrix of Proposed DLCNN with SSO.

The image Fig 5. Existing Random Forest Classifier" presents the performance evaluation metrics of a Random Forest Classifier (RFC) model applied to a liver disease classification task. The classifier was tested on three liver conditions: Fatty Liver, Hepatocellular Carcinoma, and Liver Cirrhosis. Here's a detailed description of the image contents:



Method	Accuracy	Precision	Recall	F-Score	Sensitivity	Specificity
Existing RFC	97.60	97.79	97.37	97.51	100.00	100.00

Classification Report:

	precision	recall	f1-score	support
Fatty Liver	0.956520	1.000000	0.977778	44.000
Hepatocellular Carcinoma	0.977273	1.000000	0.988506	43.000
Liver Cirrhosis	1.000000	0.921053	0.958904	38.000
accuracy	0.976000	0.976000	0.976000	0.976
macro avg	0.977931	0.973684	0.975063	125.000
weighted avg	0.976877	0.976000	0.975731	125.000

Fig 5. Existing Random Forest Classifier

The averaged classification metrics highlight the strong overall performance of the model across all disease categories, while accounting for class imbalance. The macro average scores are: precision at 0.9779, recall at 0.9737, and F1-score at 0.9751, indicating consistent performance across each class without considering class frequency. The weighted average scores—precision at 0.9769, recall at 0.9760, and F1-score at 0.9757—further reinforce the model's robustness, as they take into account the support (number of instances) of each class. Together, these metrics reflect the model's high accuracy and reliability in multi-class classification tasks.

5. CONCLUSION

Liver disease detection integrates deep learning with an optimization technique to enhance classification accuracy and computational efficiency. By leveraging CT scan images, the proposed method utilizes the Social Spider Optimization (SSO) for feature selection, effectively reducing computational complexity while preserving critical diagnostic information. The optimized feature set obtained through SSO significantly enhances the training process of Convolutional Neural Networks (CNNs), resulting in improved classification performance. The experimental evaluation demonstrates that the SSA-based feature selection, combined with Random Forest Classifier (RFC) leads to superior accuracy compared to conventional approaches. By effectively balancing exploration and exploitation, SSA ensures optimal feature representation, facilitating better generalization in liver disease classification. The results highlight the potential of integrating nature-inspired optimization techniques with deep learning models for medical imaging applications. This AI-driven approach provides a reliable and efficient solution for liver disease detection, with the potential to aid clinical diagnosis and improve patient outcomes.

REFERENCES

[1] World Health Organization; Çelikgün, S.; Koc, T.; Arslan, E.; Gonca, K.; Yildiz, F.; Emine, G.; Gultop, F.; Argon, M.; Tekin, S.; et al. Cancer. Son. Erişim. Tarihi 2021, 24. Available online: https://www.who.int/news-room/factsheets/detail/cancer (accessed on 3 February 2022).

[2] Li, Q.; Cao, M.; Lei, L.; Yang, F.; Li, H.; Yan, X.; He, S.; Zhang, S.; Teng, Y.; Xia, C.; et al. Burden of liver cancer: From epidemiology to prevention. Chin. J. Cancer Res. 2022, 34, 554.

[3] Christ, P.F.; Elshaer, M.E.A.; Ettlinger, F.; Tatavarty, S.; Bickel, M.; Bilic, P.; Rempfler, M.; Armbruster, M.; Hofmann, F.; D'Anastasi, M.; et al. Automatic liver and lesion segmentation in CT using cascaded fully convolutional neural networks and 3D conditional random fields. In Proceedings of the International Conference on Medical Image Computing and Computer-assisted Intervention, Athens, Greece, 17–21 October 2016; Springer: Berlin/Heidelberg, Germany, 2016; pp. 415–423.

[4] Li, D.; Liu, L.; Chen, J.; Li, H.; Yin, Y. A multistep liver segmentation strategy by combining level set based method with texture analysis for CT images. In Proceedings of the 2014 International Conference on Orange Technologies, Xi'an, China, 20–23 September 2014; IEEE: Piscataway, NJ, USA, 2014; pp. 109–112.

[5] Song, X.; Cheng, M.; Wang, B.; Huang, S.; Huang, X.; Yang, J. Adaptive fast marching method for automatic liver segmentation from CT images. Med. Phys. 2013, 40, 091917.

[6] Wen, Y.; Chen, L.; Deng, Y.; Zhou, C. Rethinking pretraining on medical imaging. J. Vis. Commun. Image Represent. 2021, 78, 103145.

[7] Li, X.; Chen, H.; Qi, X.; Dou, Q.; Fu, C.W.; Heng, P.A. H-DenseUNet: Hybrid densely connected UNet for liver and tumor segmentation from CT volumes. IEEE Trans. Med. Imaging 2018, 37, 2663–2674.

[8] Meraj, T.; Rauf, H.T.; Zahoor, S.; Hassan, A.; Lali, M.I.; Ali, L.; Bukhari, S.A.C.; Shoaib, U. Lung nodules detection nusing semantic segmentation and classification with optimal features. Neural Comput. Appl. 2021, 33, 10737–10750.

[9] Yang, D.; Xu, D.; Zhou, S.K.; Georgescu, B.; Chen, M.; Grbic, S.; Metaxas, D.; Comaniciu, D. Automatic liver segmentation using an adversarial image-to-image network. In Medical Image Computing and Computer Assisted Intervention—MICCAI 2017, Proceedings of the 20th International Conference, Quebec City, QC, Canada, 11–13 September 2017; Proceedings, Part III 20; Springer: Berlin/Heidelberg, Germany, 2017; pp. 507–515.

[10] Shafaey, M.A.; Salem, M.A.M.; Ebied, H.M.; Al-Berry, M.N.; Tolba, M.F. Deep learning for satellite image classification. In Proceedings of the International Conference on Advanced Intelligent Systems and Informatics, Cairo, Egypt, 1–3 September 2018; Springer: Berlin/Heidelberg, Germany, 2019; pp. 383–391.

[11] Peng, J.; Dong, F.; Chen, Y.; Kong, D. A region-appearance-based adaptive variational model for 3D liver segmentation. Med. Phys. 2014, 41, 043502.

[12] Pan, F.; Huang, Q.; Li, X. Classification of liver tumors with CEUS based on 3D-CNN. In Proceedings of the 2019 IEEE 4th international conference on advanced robotics and mechatronics (ICARM), Toyonaka, Japan, 3–5 July 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 845–849.

[13] Yasaka, K.; Akai, H.; Abe, O.; Kiryu, S. Deep learning with convolutional neural network for differentiation of liver masses at dynamic contrast-enhanced CT: A preliminary study. Radiology 2018, 286, 887–896.

[14] Wen, Y.; Chen, L.; Deng, Y.; Ning, J.; Zhou, C. Toward better semantic consistency of 2D medical image segmentation. J. Vis. Commun. Image Represent. 2021, 80, 103311.

[15] Krizhevsky, A.; Sutskever, I.; Hinton, G.E. Imagenet classification with deep convolutional neural networks. Commun. ACM 2017, 60, 84–90