A New Deep Learning method for Automatic Ovarian Cancer Prediction & Subtype classification

Kokila. R. Kasture¹, Dilip D. Shah², Pravin N. Matte³

¹Research Scholar, E & TC Engineering, G H Raisoni University, Amravati, India
²Vice Chancellor, G H Raisoni University, Amravati, India
³ Dean - Polytechnic, E & TC Engineering, RSCOE, Pune, India
Email: kasture_kokila.ghruaphdet@ghru.edu.in¹

Article History: Received: 11 January 2021; Revised: 12 February 2021; Accepted: 27 March 2021; Published online: 23 May 2021

Abstract: Computer-aided diagnosis and other relevant biomarkers can provide valuable advice to doctors for precise diagnosis. The traditional techniques, mainly Computer Tomography (CT) & Magnetic Resonance Imaging (MRI), are costly, time-consuming, and tedious. During the literature survey, it was learned that Deep Learning outclassed traditional CNN algorithms among various image processing algorithms. In the present work, Deep Convolutional Neural Network (DCNN) is implemented for predicting ovarian cancer and classifying its subtypes with histopathological images as input. For achieving higher accuracy, a new architecture is designed and implemented from the scratch inspiring by pre-Trained AlexNet Model. The basic AlexNet architecture consists of 5 convolutional layers, 3 Maxpooling layers, and three fully-connected layers with Rectified Linear Unit (ReLU) as the activation function. We modified this by adding a Maxpooling layer after each pair of convolutional layers, four such iterations, four fully connected layers, replaced ReLU with Exponential Linear Unit (ELU), and modified architectural parameters. The original architecture considers kernel sizes of 11x11 and 5x5, which we modified to make it uniform at 3x3 as the kernel size. The network was trained using 24,742 augmented images. The accuracy of predicting Ovarian Cancer and its subtypes classification improved to 83.93% with the help of 43,94,533 parameters compared with previous studies that achieved 78%. We also trained the model with both the datasets, before and after augmentation. We concluded that the augmentation increased the accuracy from 70% to 83.93%. This new model can be considered as a benchmark.

Keywords: Ovarian Cancer; Medical Imaging; Deep Learning; Convolutional Neural Networks; AlexNet

1. Introduction

Significant causes of death around the globe are primarily due to Cancer. As per the American Cancer Society survey, around a million people would lose their lives due to different types of Cancer in the USA itself [1]. Therefore, the fight against Cancer is a huge challenge that needs to be addressed by patients, doctors, research scientists, and pathologists. Amongst women, Ovarian Cancer (OC) stands fifth, leading to deaths [2]. It is mainly characterized by minimal symptoms in the early stage and a low survival rate [1]. OC is the most recurrent and aggressive type of gynecologic cancer [2]. Primary epithelial ovarian carcinoma is classified into the following subtypes: serous, mucinous, Endometroid, and clear cell [1] [25]. The previous literature highlights that one out of fifty-four women can develop OC [1-2]. A patient diagnosed with OC has a 5-year survival rate of around 48.6% [26]. The low survival rate is mainly due to cancer detection in the advanced stage, as 72% of the cases get identified in stage III or IV [26]. Hence, early screening is imperative [2-4]. In the past, efforts have been made to detect OC in the preclinical stage, using both medical imaging and serum markers [27]. Although these biomarkers show promising results, there are several limitations like missed classification, sluggishness, and more working hours [6] [27]. Serum Carbohydrate Antigen (CA125) is widely used, but the accuracy rate is not satisfactory as it has high sensitivity [6]. Imaging modalities such as Ultrasound imaging, MRI, CT scan plays a significant role in locating and characterizing tumor[11] [20] [34]. Early prediction of any medical disorder, specifically Cancer, is integral for improving the survival rates [27] [28]. As per research, Medical Imaging is one of the effective techniques for early-stage detection, prediction of brain imaging modalities, monitoring the stages of Cancer, and follow-up procedures after the cancer treatment [7–11]. Interpreting the results manually from these medical images is tedious and prone to human errors [7–11]. Also, Computer-

Aided Diagnosis (CAD) systems are widely used for assisting clinicians & pathologists in interpreting the results from medical images with more accurate results [6] [8].

CAD-based medical imaging approach for cancer detection, machine learning techniques are leveraged [9] [11]. In the machine learning approach, feature extraction is an important step [29]. Various feature extraction methods have been reviewed and analyzed in the literature, considering different MRI, CT, and ultrasound images [29]. It can be stated that previous work focuses on developing worthy feature descriptors along with machine learning algorithms for context learning from different types of medical images [30]-[32]. These methods possess certain disadvantages limiting CAD-based techniques for medical diagnosis [6-10]. In the present research work, we emphasize representation learning instead of featuring a learning-based approach to overcome the CAD-based system's inadequacy. Deep Learning learns through hierarchical feature representation from image data, a type of representation learning technique [7] [19] [29]. It generates high-level feature representation through image data itself [7] [19] [29]. With the addition and support of substantial parallel architecture and Graphical Processing Units, the deep learning approach has achieved enormous profits and success in various applications such as image recognition, objection detection, speech processing, and many more [34]. In [7], a deep learning approach gives promising results in cancer detection as well. This paper presents a method for predicting OC and classifying its subtypes using deep convolutional neural networks. Our contribution in this research is as follows:

- 1. Augmentation of histopathological images
- 2. Designed & implemented novel DCNN architecture for OC subtype classification.
- 3. First attempt to introduced ELU as the activation function & Mean square error (MSE) rate as a cost function in medical image analysis.

The paper is systematized in the following manner: Section 1 introduces the problem statement and a brief of the solution,. Section 2 highlights the materials and methods used to build our novel architecture, and section 3 summarizes the obtained results in research work and section 4 mentions the conclusions drawn based on the experimentation followed by the future scope.

2. Materials and Methods

This section discusses the proposed and implemented Deep Convolutional Neural Network (DCNN) architecture in detail, along with dataset preparation.

2.1 Image Dataset

In the present research, a total of five hundred labeled histopathological images, of which 175 were serous, 100 mucinous, 60 endometroid, 80 clear-cell, and 85 non-cancerous, were collected from the National Cancer Institute's Genomic Data Commons data portal, TCGA-OV repository [36], and were used for training, predicting, and further analysis. The GDC Data Portal is a robust data-driven platform that allows cancer researchers and bioinformaticians to search and download cancer data for analysis. Although the portal has more images available, they are primarily of Serous type since it is a common subtype. The other three subtypes are rare, and minimal data is available for them; of course, all from the GDC data portal for these subtypes was used entirely. The validation dataset was carved out of the complete dataset and includes 10% of the complete dataset. The authors have also published this validation dataset was all categorized and labeled according to the subtypes; hence, there were no redundant images in the dataset.

2.2 Image Dataset Augmentation

In deep learning, the augmentation of data is an essential operation. Since a large amount of data is required when operating with DCNN, many images cannot always be collected; data augmentation is the solution. It eventually helps to increase the size of the database and to add uncertainty to the dataset. A small amount of training data may also lead to overfitting [7] [15]. This image manipulation or augmentation process to the images is achieved by zooming, tilting & enhancing some features. Our work rotated the original image by 90, zoomed in to capture more minor details,

did horizontal and vertical flips of the images, and increased the brightness. After augmenting the images, 24,742 image samples were obtained almost 50 times more than the original dataset. All the RGB images were digitized in JPG file format and resized with a uniform size of 227x227 pixels. Figure 1 shows various augmented techniques for increasing the training data size. We implemented two independent models, one for the original dataset and the other for the augmented image dataset, which was roughly 50 times bigger. The authors publish the code used for the data augmentation on Github at https://github.com/kokilakasture/OvarianCancerPrediction [37].

Table 1- Number of images of each class

Class	Original Images	Augmented Images
Serous	175	5640
Mucinous	100	5223
Endometroid	60	4353
Clear Cell	80	4999
Non-Cancerous	85	4527
Total	500	24742
Original Rotate 90	degrees Zoom In	
Increased Brightness Horizo	intal Flip Vertical Flip	

Figure 1. Image Augmentation of the original dataset.

3. Proposed a New DCNN Architecture

The Convolutional Neural Network architecture is like a multilayer perceptron and resembles the autonomous supervised learning approach [29] [40]. It mainly consists of three layers the input layer, hidden layer, and output layer [29] [38]. The network parameters are updated using the backpropagation algorithm [39]. The pre-trained architecture of a convolutional neural network is discussed in [6]. In the present work, a new DCNN architecture is designed and implemented from the scratch for prediction and Subtype classification of Ovarian Cancer. The SuperVision group designed the AlexNet pre-trained model in 2012 [21]. It is a well-known pre-trained model as it won first place in ImageNet Large Scale Visual Recognition Challenge 2012 with high accuracy of image classification.





In present research, A new DCNN architecture is designed and implemented from the scratch inspiring by pre-trained AlexNet Model as shown in Figure 2 & Table 2 [7]. The motivation behind using AlexNet is its fast ability to train the network. In the present work, A new DCNN Model with convolution layers, different feature maps and hyperparameters setting, as shown in Table 3.

Unlike the former research work [7], we designed the new DCNN model from scratch instead of using the pre-trained model. After careful analysis and multiple experimentations, we concluded to use eight convolutional layers, four max-pooling layers, and four dense layers as the best combination to achieve higher accuracy. ELU followed each convolutional layer as the activation function. Four max-pooling layers of size 2x2 pixels & having a stride of 1 were used to give input to the subsequent convolutional layers. The fourth and last max-pooling layer's output, 14x14x256, is flattened to 50,176 pixels and supplied to the dense layers for further processing. Three FC layers with 64 nodes each with a dropout of 0.3, over 0.5 as in [7], and the last FC layer, which is the softmax layer, does the sub-type classification, and it is set to 5, equal to the number of classes. We observed that some of the images were misclassified with the validation dataset testing, meaning the model could not generalize well, meaning that the model suffers from overfitting. In order to decrease overfitting, dropout is leveraged. Dropout is an efficient method for reducing overfitting and improving deep neural networks' performance [42].

We accomplished this implementation using Python language, Google Collaboratory (TPU) & libraries like Keras, Tensorflow. Table 2 gives a summary of the novel DCNN architecture implemented [40].

Layers	Feature Map	Size	Kernel Size	Stride	Activation Function
Input Image	1	227x227x3	-	-	-
Convolution Layer 1	32	227x227x32	3x3	1	ELU
Convolution Layer 2	32	227x227x32	3x3	1	ELU
Maxpooling Layer 1	32	113x113x32	2x2	1	ELU
Convolution Layer 3	64	113x113x64	3x3	1	ELU
Convolution Layer 4	64	113x113x64	3x3	1	ELU
Maxpooling Layer 2	64	56x56x64	2x2	1	ELU
Convolution Layer 5	128	56x56x128	3x3	1	ELU
Convolution Layer 6	128	56x56x128	3x3	1	ELU
Maxpooling Layer 3	128	28x28x128	2x2	1	ELU
Convolution Layer 7	256	28x28x256	3x3	1	ELU
Convolution Layer 8	256	28x28x256	3x3	1	ELU

Table 2.	The architecture	of the proposed	l novel DCNN	model -Summary
----------	------------------	-----------------	--------------	----------------

Maxpooling Layer 4	256	14x14x256	2x2	1	ELU
Fully Connected Layer 1	-	64	-	-	ELU
Fully Connected Layer 2		64	-	-	ELU
Fully Connected Layer 3	-	64	-	-	ELU
Fully Connected Output Layer	-	5	-	-	Softmax

4. Results & Discussions

We set the hyper-parameters for training the proposed novel DCNN model as summarized in Table 3.

Table 3 - Hyper-Parameters	of the pro	oposed novel DCNN model	l

Parameter	Value
Learning Rate	0.001
Cost function	Mean Squared Error (MSE)
Optimizer	RMSprop
Epoch Number	20
Batch Size	32
Dropout (Convolution Layer)	0.2
Dropout (Dense Layer)	0.3
Activation function	ELU

As seen from Figure 3, graph A shows the training accuracy and loss per epoch, where training accuracy increased per epoch, whereas the loss decreased. Although after ten epochs, the accuracy started to drop, and since we leveraged the early stopping technique, we terminated the training at the best-obtained result at epoch 10. Graph B shows that after epoch eight, the validation accuracy started reducing; hence the checkpoint is generated, and the CNN model is then exported in an h5 format. This configuration has been explained in subsection 3.3.



Figure 3. Training accuracy & loss versus epoch

We trained the models with the dataset before and after augmentation and achieved improved accuracy with augmentation. Table 4 shows the classification accuracy generated by the DCNN model. In the present work, 83.93% accuracy is obtained for prediction post image augmentation, whereas it was 72% before augmentation.

Table 4 -	Classification A	Accuracy of each	n class for two	models (before	and after augmentation)

Class	Original	Image	Dataset	Augmented Image Dataset	
	Accuracy			Accuracy	
Clear Cell	70%			85%	
Endometroid	79%		85.3%		
Mucinous	70%		84.45%		
Non – Cancerous	70.79%	80%			
Serous	75%	85%			

In the present work, classification accuracy on each subtype was computed along with precision, recall, and F1 score.

Class	Precision	Recall	F1-score	Testing Images
Clear Cell	0.85	0.90	0.89	100
Endometroid	0.90	0.89	0.90	98
Mucinous	0.75	0.90	0.87	100
Non-Cancerous	0.85	0.80	0.83	100
Serous	0.92	0.88	0.92	100

Table 5 - Performance Metrics of proposed novel DCNN architecture

It can be observed that the classification rates improved due to image augmentation. We observed that some images were misclassified, caused predominantly due to overfitting and insufficient learning of the model from the limited dataset size of 24,742 augmented images. Figure 4 shows the predicted results.



Figure 4. Predicted results using the proposed novel DCNN architecture

Figure 5 shows the confusion matrix obtained after the validation process is completed. In the confusion matrix, the diagonal cells are the true positive cases. For example, in the Clear cell class, 94% of images were correctly classified, 96%, 94%, 80%, and 92% for endometroid, mucinous, non-cancerous, and serous, respectively.



Figure 5. Confusion Matrix

5. Conclusion & Future Scope

This work is the first attempt at combining the prediction of ovarian cancer & also sub-type classification from histopathology images by designing and implementing a new DCNN model. The prediction and classification accuracy was improved to 83.93% compared to the previous 78% from the literature [7]. Without augmentation, we achieved only 72% accuracy, concluding that augmentation improves the accuracy of the DCNN model. Pathologists can effectively use the presented approach for classifying OC and its subtypes after the authors publish this work publicly.

As compared to traditional image classification methods, an automated system for predicting ovarian Cancer and classifying its subtype from histopathological images is implemented using DCNN architecture. These images were augmented by enhancing, rotating, zooming, and flipping them. It can be said that the Classification of the model trained by augmented data is equal to the pathologists predicting level and can be considered satisfactory [7] [16]. The authors have also published the dataset on Mendeley Data [23] and the source code on Github [37]. Without any prior pathological or biomedical knowledge, the DCNN model predicts and classifies ovarian cancer cells. The future work includes creating a user interface for pathologists to upload the image and predict. In the future, we intend to improvise the proposed novel DCNN architecture and use the same dataset on other pre-trained networks such as GoogleNet, VGG-16, VGG-19, MobileNet to analyze the prediction and classification accuracy further.

6. Acknowledgment

The authors would like to thank the entire faculty of the Electronics & Telecommunications department in GHRU, Amravati, and Smt. Kashibai Navale College of Engineering, Pune, for their constant support. Authors gratefully acknowledge the Staff members of the Medicine Department in Smt. Kashibai Navale Medical College & General Hospital allows working with them and sharing their knowledge to make this research a success.

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

7. Author Contributions

Kokila R. Kasture – Conceptualization, Methodology, Software, Validation, Formal Analysis, Writing- original and Draft, Visualization Dilip D. Shah - Conceptualization, Investigation, Resources, Supervision Pravin Matte – Conceptualization, Data Curation, project Administration

8. Data Availability

The initial dataset consisted of five hundred histopathological images in a PNG format of size 1430x550. Images of each subtype were considered for analysis and processing. The dataset contains approximately 100 labeled images of each subtype: Serous, mucinous, endometroid, clear cell, and non – cancerous. The present study's image dataset was obtained from the GDC portal of the National Cancer Institute (TCGA-OV) [36]. The direct link to the dataset is here: [23] Kasture, Kokila (2021), "OvarianCancer&Subtypes," Mendeley Data, V1, doi: 10.17632/w39zgksp6n.1 http://dx.doi.org/10.17632/w39zgksp6n.1

References

- [1] World Health Organization (WHO), Cancer Fact Sheet, 2019, https://www.who.int/news-room/fact-sheets/detail/cancer
- [2] American Cancer Society., Cancer facts, and figures. US: American Cancer Society; 2019. https://www.cancer.org/research/cancer-facts-statistics/all-cancer-facts-figures/cancer-facts-figures-2019.html

- [3] L. A. Torre, B. Trabert, C. E. DeSantis, K. D. Miller, G. Samimi, C. D. Runowicz, M. M. Gaudet, A. Jemal, and R. L. Siegel, Ovarian cancer statistics, 2018, CA: A Cancer Journal for Clinicians, vol. 68, no. 4, pp. 284–296, May 2018.
- [4]G. Chornokur, E. K. Amankwah, J. M. Schildkraut, and C. M. Phelan, Global ovarian cancer health disparities, *Gynecologic Oncology*, Vol. 129, no. 1, pp. 258–264, Apr. 2013.
- [5] Ala'a El-Nabawy, Nashwa El-Bendary, Nahla A. Belal, Epithelial Ovarian Cancer Stage Subtype Classification using Clinical and Gene Expression Integrative Approach, *Procedia Computer Science*, Volume 131, pp. 23-30, 2018.
- [6] Zhang, L., Huang, J., & Liu, L., Improved deep learning network based in combination with costsensitive learning for early detection of ovarian cancer in color ultrasound detecting system, *Journal of Medical Systems*, Vol. 43, no. 8, pp.243 – 251, 2019
- [7] Wu, M., Yan, C., Liu, H. and Liu, Q., Automatic classification of ovarian cancer types from cytological images using deep convolutional neural networks, *Bioscience Reports*, Vol. 38, no. 3, 2018.
- [8] Shibusawa M, Nakayama R, Okanami Y, Kashikura Y, Imai N, Nakamura T, et al., The usefulness of a computer-aided diagnosis scheme for improving the performance of clinicians to diagnose non-mass lesions on breast ultrasonographic images, *J Med Ultrason.*, Vol. 43, pp. 387–94, 2016.
- [9] Chen, S. J., Chang, C. Y., Chang, K. Y. et al., Classification of the thyroid nodules based on characteristic sonographic textural feature and correlated histopathology using hierarchical support vector Machines, *Ultrasound in Medicine and Biology*, Vol. 36, no.12, pp. 2018 – 2026, 2010.
- [10]Chang, C. Y., Liu, H. Y., Tseng, C. H. et al., Computer-aided diagnosis for thyroid graves' disease in ultrasound images, *Biomedical Engineering: Applications, Basis and Communications*, Vol. 22, no. 2, pp. 91–99, 2010.
- [11]Acharya, U. R., Sree, S. V., Swapna, G. et al., Effect of complex wavelet transform filter on thyroid tumor classification in three-dimensional ultrasound, *Proceedings of the Institution of Mechanical Engineers*, Part H: Journal of Engineering in Medicine, Vol. 227, no. 3, pp. 284–292, 2013.
- [12] Iakovidis, D. K., Keramidas, E. G., Maroulis, D., Fuzzy local binary patterns for ultrasound texture characterization, *Proceedings of the 5th International Conference on Image Analysis and Recognition*, Póvoa de Varzim, Portugal: Springer, pp. 750-759, 2008.
- [13]Martínez-Más J, Bueno-Crespo A, Khazendar S, Remezal-Solano M, Martínez-Cendán J-P, Jassim S, et al., Evaluation of machine learning methods with Fourier Transform features for classifying ovarian tumors based on ultrasound images, *PLoS ONE*, Vol. 14, no.7, 2019.
- [14]Tuan Zea Tan, Chai Quek, Geok See Ng, Khalil Razvi, Ovarian cancer diagnosis with complementary learning fuzzy neural network, *Artificial Intelligence in Medicine*, Volume 43, Issue 3, pp. 207-222, 2008
- [15]Wang, Shuo, et al., Deep learning provides a new computed tomography-based prognostic biomarker for recurrence prediction in high-grade serous ovarian cancer, *Radiotherapy, and Oncology*, Vo.132, pp. 171 177, 2019.
- [16]Zhang, L., Huang, J., & Liu, L., Improved deep learning network based in combination with costsensitive learning for early detection of ovarian cancer in color ultrasound detecting system, *Journal of Medical Systems*, Vol. 43, no. 8, pp.243 – 251, 2019.
- [17]Krizhevsky, A., Sutskever, I., Hinton, G. E., ImageNet classification with deep convolutional neural networks, *Proceedings of the 25th International Conference Neural Information Processing Systems*. Lake Tahoe, Nevada, pp. 1097-1105, 2012.
- [18]Xu, X., Zhou, Y., Cheng, X., Song, E., and Li, G., Ultrasound intima-media segmentation using though transform and dual snake model, *Comput. Med. Imaging Graph.* Vol. 36, No. 3, pp.248– 258, 2012.
- [19]Teramoto, A.; Tsukamoto, T.; Yamada, A.; Kiriyama, Y.; Imaizumi, K.; Saito, K.; Fujita, H. Deep learning approach to Classification of lung cytological images: Two-step training using actual and synthesized images by the progressive growth of generative adversarial networks, *PLoS ONE 2020*, 15, 0229951.

- [20]A. Masood, B. Sheng, P. Li, X. Hou, X. Wei, J. Qin, et al., Computer-assisted decision support system in pulmonary cancer detection and stage classification on CT images, *J. Biomed. Inf.*, Vol. 79, pp. 117-128, Mar. 2018.
- [21]Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S. et al., Image Net large scale visual recognition challenge, *Int J. Comput. Vis.*, Vol. 115, pp. 211–252, 2015.
- [22]http://www.gpecimage.ubc.ca/aperio/images/transcanadian/-
- [23]Kasture, Kokila (2021), "OvarianCancer&Subtypes," Mendeley Data, V1, doi: 10.17632/w39zgksp6n.1 http://dx.doi.org/10.17632/w39zgksp6n.1
- [24]http://ensc-mica-www02.ensc.sfu.ca/download/
- [25]Ehdaivand S WHO classification. PathologyOutlines.com website. https://www.pathologyoutlines.com/topic/ovarytumorwhoclassif.html. Accessed February 27th, 2021.
- [26]National Cancer Institute, Surveillance, Epidemiology, and End results Program, Cancer Stat Facts: Ovarian Cancer <u>https://seer.cancer.gov/statfacts/html/ovary.html</u>
- [27]Rauh-Hain, J. A., Krivak, T. C., Del Carmen, M. G., & Olawaiye, A. B. (2011). Ovarian cancer screening and early detection in the general population. *Reviews in obstetrics & gynecology*, 4(1), 15–21.
- [28]Bi-jun Wang, Jun-yi Chen, Yu Guan, Da-chao Liu, Zi-chuan Cao, Jin Kong, Zheng-Sheng Wu, Wen-Yong Wu; Predicted the P2RX7 rs3751143 polymorphism is associated with cancer risk: a meta-analysis and systematic review. *Biosci. Rep.* 26 February 2021; 41 (2): BSR20193877. doi: <u>https://doi.org/10.1042/BSR20193877</u>
- [29]Intisar Rizwan I Haque, Jeremiah Neubert, 2020, Deep learning approaches to biomedical image segmentation, *Informatics in Medicine Unlocked*, Volume 18, 100297, ISSN 2352-9148,https://doi.org/10.1016/j.imu.2020.100297.
- [30]Kevin M Elias, Wojciech Fendler, Konrad Stawiski, Stephen J Fiascone, Allison F Vitonis, Ross S Berkowitz, Gyorgy Frendl, Panagiotis Konstantinopoulos, Christopher P Crum Diagnostic potential for a serum miRNA neural network for detection of ovarian cancer, *Elife*, 2017 Oct 31;6:e28932. doi: 10.7554/eLife.28932.
- [31]Pegah Khosravi, Ehsan Kazemi, Marcin Imielinski, Olivier Elemento, Iman Hajirasouliha, Deep Convolutional Neural Networks Enable Discrimination of Heterogeneous Digital Pathology Images, *EBioMedicine* (2017), https://doi.org/10.1016/j.ebiom.2017.12.026
- [32]Md. Akizur Rahman, Ravie Chandren Muniyandi, Kh Tohidul Islamy, and Md. Mokhlesur Rahman, Ovarian Cancer Classification Accuracy Analysis Using 15-Neuron Artificial Neural Networks Model, 2019 IEEE Student Conference on Research and Development (SCOReD), 978-1-7281-2613-5/19/\$31.00, IEEE 2019.
- [33]Alganci, U.; Soydas, M.; Sertel, E. Comparative Research on Deep Learning Approaches for Airplane Detection from Very High-Resolution Satellite Images. *Remote Sens.* 2020, 12, 458. <u>https://doi.org/10.3390/rs12030458</u>
- [34]Kyu-Hwan Jung, Hyunho Park, Woochan Hwang, "Deep Learning for Medical Image Analysis: Applications to Computed Tomography and Magnetic Resonance Imaging," *Hanyang Med Rev* 2017;37:61-70,https://doi.org/10.7599/hmr.2017.37.2.61 pISSN 1738-429X eISSN 2234-4446 ©2017
- [35]Jose' Marti'nez-Ma's, Andre's Bueno-Crespo, Shan Khazendar, Manuel Remezal-Solano, Juan-Pedro Marti'nez-Cend'n, Sabah Jassim, Hongbo Du, Hisham Al Assam, Tom Bourne, Dirk Timmerman, Evaluation of machine learning methods with Fourier Transform features for classifying ovarian tumors based on ultrasound images, *PLOS ONE*, https://doi.org/10.1371/journal.pone.0219388, 2019.
- [36]Dataset Available: <u>https://portal.gdc.cancer.gov</u>

[37]Kasture, Kokila (2021), OvarianCancerPrediction

[38]Ismail Mebsout (2020), Convolutional Neural Networks - Part 1, https://www.ismailmebsout.com/Convolutional%20Neural%20Network%20-%20Part%201/

- [39]Piotr Skalski, 2019, Gentle Dive into Math Behind Convolutional Neural Networks, <u>https://towardsdatascience.com/gentle-dive-into-math-behind-convolutional-neural-networks-</u> 79a07dd44cf9
- [40]Tammina, Srikanth. (2019). Transfer learning using VGG-16 with Deep Convolutional Neural Network for Classifying Images. *International Journal of Scientific and Research Publications* (IJSRP). 9. p9420. 10.29322/IJSRP.9.10.2019.p9420.
- [41]Machine Learning Glossary Activation Functions (2020) https://mlcheatsheet.readthedocs.io/en/latest/activation_functions.html#elu
- [42]Deeplizard, Machine Learning & Deep Learning Fundamentals (2021) https://deeplizard.com/learn/video/DEMmkFC6IGM
- [43]Thomas Wood, What is the Softmax Function?, (2021), <u>https://deepai.org/machine-learning-glossary-and-terms/softmax-layer</u>