JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

QUALITY OF THE IMAGE OF EXISTING IMAGE SCALING ALGORITHMS

MANICHITHRA PS[1], DR. SANJAY KUMAR TIWARI[2]

[1]Research Scholar, Sunrise University, Alwar

[2]Associate Professor, Sunrise University, Alwar

ABSTRACT

When resizing a digital picture, the process is known as "image scaling," and special algorithms are used to accomplish this task. In this research, both adaptive and non-adaptive techniques are described to produce visually distinct resized versions of the original picture. The phrase "Image Interpolation" describes the method used to transform an image from one coordinate system (dimension) to another without compromising its visual quality. A picture may gain blank pixels when enlarged using interpolation methods. Color is mathematically calculated to fill these pixels depending on the values of the pixels around it. It is usually exceedingly challenging to create a perfect replica of an original picture after using image interpolation methods. As we compute additional pixels during a resize operation, the picture quality of the scaled image will always vary from the original. During the process of resizing a picture, artefacts such as jaggies, blurring, ringing, and edge halo may become visible.

Keywords: Image Scaling, Interpolation, Bilinear, Bicubic, Cubic B-Spline, Catmull-Rom and Quality

INTRODUCTION

When talking about computer graphics and digital photography, the term "image scaling" is used to describe the process of adjusting the size of a digital photo. Upscaling, also known as resolution improvement, is a technique used in the video industry to increase the size of digital files. Images created using vector graphics may be scaled using geometric transformations without any noticeable degradation in picture quality, since this does not affect the underlying visual primitives. To increase or decrease the size of a pixel in a raster graphics picture, a new image must be created. Reducing the number of pixels (known as "scaling down") often causes a noticeable degradation in image quality. From the perspective of digital signal processing, raster image scaling is an example of sample-rate conversion, the act of transforming a discrete signal from one sampling rate (here, the local sampling rate) to another.

Picture scaling works by increasing the number of pixels in an image, thereby transforming a low-resolution image into a high-resolution one. The final appearance of a picture may be affected by the scaling technique used, which is one of several. It is thus preferable if the quality, or the discernible distinction for each pixel, is maintained throughout the interpolation process. Convolution operation, which is used to execute interpolation function, entails several arithmetic and multiplication operations. As a result, one must strike a balance between the amount of work involved in the calculation and the quality of the resulting interpolated picture.

There are a few different names for the process of enlarging or decreasing the size of a digital picture, but they all refer to the same thing: image scaling. Numerous algorithms exist now for adjusting the dimensions of digital photos. Most of them make an effort to create an exact visual copy of the original. These days, people are seeing photos, videos, and other visual data on a broad range of items, from TVs to computer displays to a wide selection of hand-held devices, thanks to the widespread adoption of multimedia in recent years. When a picture gets blown up, you can't see any more details than what's already there, and the quality of the image degrades. There are, however, a variety of ways to increase the number of pixels in a picture without altering its quality. Sometimes referred to as "image interpolation algorithms," these techniques approximate a given picture.

Picture down-scaling, also known as down sampling, is the process of interpolating an image from a higher resolution to a lower resolution. Picture up-scaling or up-sampling is the process of interpolating an image from a lower resolution to a higher one. Scaling up pictures for HDTV or medical image displays, or scaling down images to suit mini-size LCD screen in portable equipment are just two examples of the many uses for image interpolation in the fields of computer graphics, digital image editing, and medical image reconstruction. A large number of commercial image editing programmers and freeware graphic viewers, including Adobe Photoshop CS2 software, IrfanView, Fast Stone Photo Resizer, Photo PosPro, Xn Convert, etc., also provide this feature.

LITERATURE REVIEW

Akinsola J E T (2017) Finding algorithms that can infer broad hypotheses from data provided by an outside source in order to make predictions about new data is the goal of supervised machine learning (SML). Intelligent systems typically perform tasks like supervised categorization. Based on the data set, the number of instances, and the variables, this article presents and analyses several Supervised Machine Learning (ML) classification strategies and identifies the most effective classification algorithm (features). The Waikato Environment for Knowledge Analysis (WEKA) was used to evaluate seven distinct machine learning algorithms, including Decision Table, Random Forest (RF), Naive Bayes (NB), Support Vector Machine (SVM), Neural Networks (Perceptron), JRip, and Decision Tree (J48). The methods were used to a classification problem on the Diabetes data set, which had 786 occurrences and eight characteristics (seven of which were employed as independent variables and one as a dependent). Based on the findings, SVM was identified as the most accurate and precise algorithm.

Anand Narasimhamurthy (2017) Specifically, machine learning has become more popular for application in the interpretation of medical images. The goal of this chapter is to offer an overview of current work using machine learning methods to medical imaging challenges. No previous experience of machine learning is expected, and the intended audience consists of practitioners, engineers, students, and researchers engaged in medical picture analysis. While the primary focus will be on medical imaging issues, the use of machine learning in several nearby fields will be briefly discussed. The field of health informatics is a new one that focuses on extracting meaning from massive datasets. We will quickly discuss some of the most widespread difficulties in health informatics, as well as detail some of the related initiatives that have been made.

Andreas Maier, Christopher Syben, Tobias Lasser, and Christian Riess (2019) The purpose of this study is to provide a comprehensive overview of deep learning (DL) based medical image registration techniques. We gathered together recent advances and implementations of DL-based registration approaches in the medical industry. According to their purposes, user bases, and other characteristics, these strategies were placed into one of seven groups. Each section was discussed in length, with notable advancements and difficulties highlighted. After a thorough examination of each subfield, a concise evaluation of its accomplishments and possibilities was provided. Using standard datasets, we compared several DL-based approaches to lung and brain registration in detail. Finally, we reviewed all the referenced studies' data from several angles, which shed light on the current state and future trajectory of DL-based medical picture registration.

Apama, R. R. M, and Shanmugavadivu P. (2017) By automating processes and making better use of available resources, IoT technology in healthcare applications helps improve treatment quality while reducing costs. By automatically assessing the characteristics of the imaging equipment, IoT in medical imaging allows instant detection and the implementation of remedial actions. As digitization spreads, it's allowing for better monitoring and administration of medical equipment; for example, the use of the internet of things in medical imaging might minimise patient and doctor wait times and alleviate frustration. In light of the importance of the internet of things in medical imaging technology, this article provides an overview of such technology as it pertains to healthcare applications.

hoi J, Shin K, Jung J, Bae H J, Kim D H, Byeon J S, and Kim N (2020) The field of artificial intelligence has made great strides recently. In the 1950s, scientists developed the first artificial neural network. However, overfitting and vanishing gradient difficulties for training deep networks plagued artificial neural networks due to the limited computer power and datasets available at the time. Increases in big data processing capacity, computing power with parallel processing units, and new algorithms for deep neural networks have made this idea more appealing. These advancements have piqued the interest of researchers in many fields, including computer vision, speech recognition, and natural language processing. Recent research in this area is promising for use in healthcare and medicine, particularly in endoscopic imaging. An examination of deep learning's origins, evolution, potential, and stumbling blocks is presented here.

IMPLEMENTATION OF IMAGE SCALING ALGORITHMS

ImageJ, a piece of image processing software, was used to build eight different methods for resizing images. Users may write their own plugins for ImageJ, which need the opening of a picture or stack of images before they can do their intended processing. ImageJ has described two distinct interface types that may be used with these plugins. The "PlugIn" protocol may be used to start a user-defined plugin without ever opening a picture, whereas the "PlugInFilter" interface needs the opened image to be supplied as an input. The "Image Interpolator" model for scaling images is implemented as a PlugInFilter since it needs to have an image open before it can be processed. The "Image Interpolator" plugin model is seen in Figure 1.

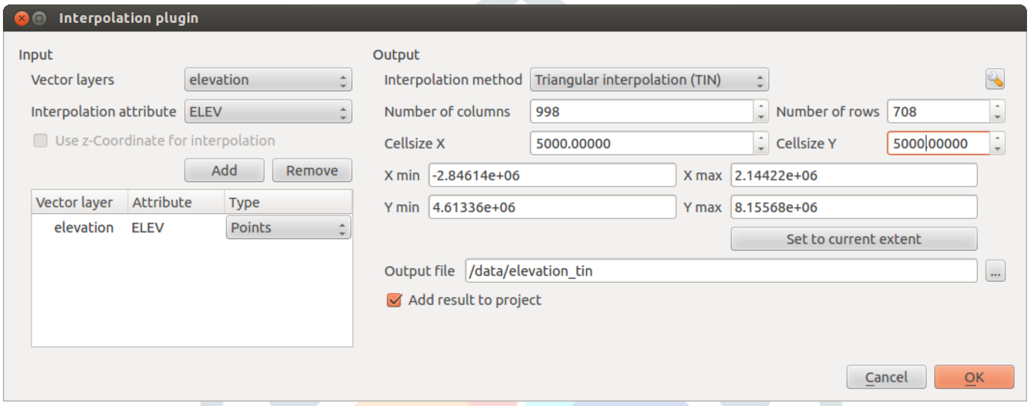

Figure 1 Image Interpolator Plugin

When resizing a picture, the model's graphical user interface (GUI) gives users a selection of eight algorithms, including Nearest Neighbor, Bilinear, Bicubic, Catmull-Rom, Cubic B-Spline, Lanczos order 2, Lanczos order 3, and the suggested "Optimal Enhanced Cubic B-Spline" (OE-CBS). Scaling parameters, shown in Figure 2 as x-scale and y-scale in number of pixels, must be entered in order to create a new picture.

Figure 2 The GUI of the Image Interpolator model

The computational time complexity of picture scaling techniques was determined across three different hardware setups. These are the hardware setups:

CPU: Intel® Core i3 CPU @ 2.40 GHz

RAM: 2 GB DDR3.

Hard Disk: 500 GB.

Graphics: 1 GB of inbuit Radeon Graphics card

OS: Windows 8 Pro

CPU: Intel® Core i5 CPU @ 2.50 GHz

RAM: 4 GB DDR3.

Hard Disk: 500 GB.

Graphics: 2 GB of inbuit NVIDIA GeForce GTX card

OS: Windows 10 Home

CPU: Intel® Core i7 CPU @ 2.70 GHz

RAM: 8 GB DDR3.

Hard Disk: 2 GB.

Graphics: 2 GB of inbuit NVIDIA GeForce GTX card

OS: Windows 10 Home

IMPLEMENTATION OF IMAGE SCALING ALGORITHMS ON CLUSTER COMPUTING

Modern cluster computing is used to realise the suggested concept. The term "cluster computing" refers to a method of using several computers as if they were one. This method requires the machines to be in close proximity to one another across a network. Networked computers act as if they were a single entity since they all run the same software at the same time. Each of the nodes in the cluster is a computer, and they share a quick LAN connection with one another (LAN). Simple cluster computing is seen in Figure 3.

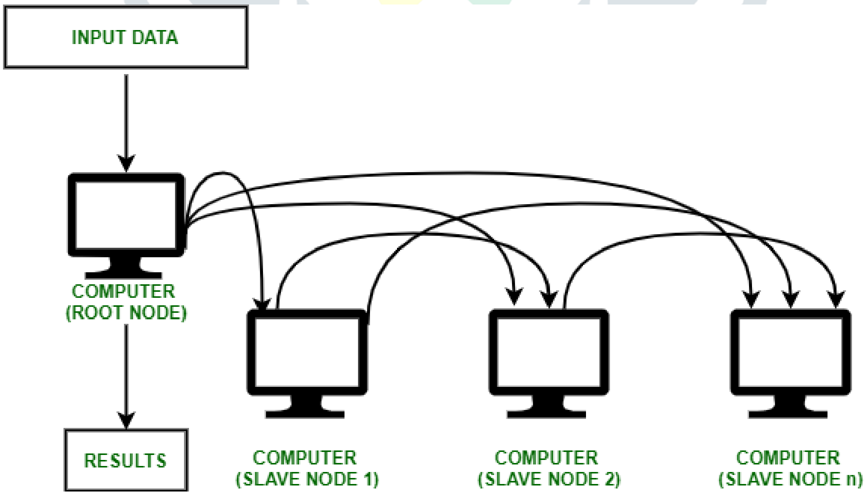

Figure 3 Layout of Simple Cluster Computing

For cluster computing, the "Image Interpolator" model makes use of the XAMPP server. The model is deployed on a small, in-house cluster computing setup consisting of a single server and four nodes. We compared the computational time complexity of each technique by using a master-slave setup to scale a picture of varying sizes.

The computational time is measured for various picture operations on a cluster, such as slicing time, scaling time with uploading and downloading time, stitching time, and total time required for each scaled image. This is done using the hardware configurations indicated in Figure 4.

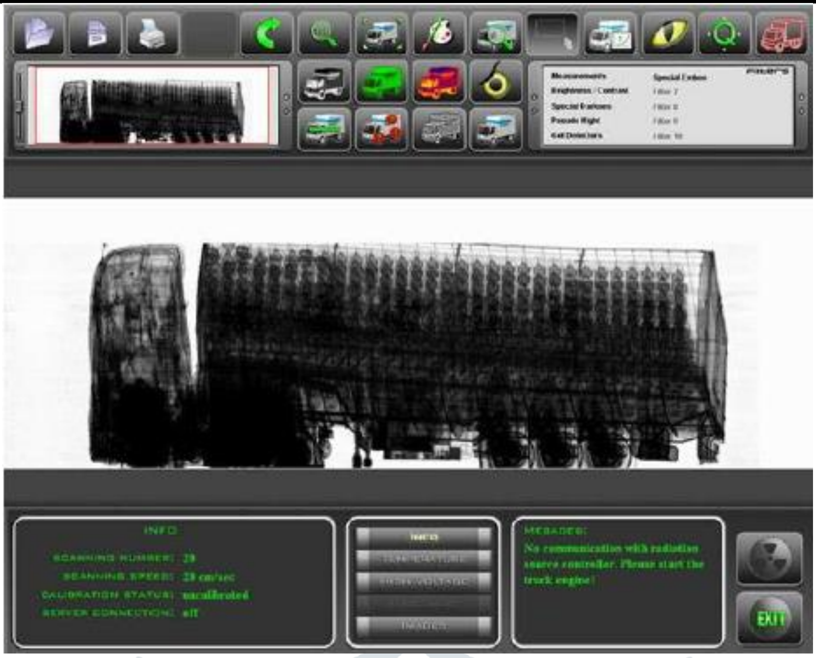

Figure 4 Computational Time taken to scale an image using Cluster Computing

To perform the image scaling using this cluster, the ImageJ macros are implemented on master and slave nodes. The model loads an image that requires scaling. This image needs to slice into four different images so that it can be sent to the individual slave nodes. The master node split the images into tiles and distributes each tile to each slave node for processing. Slave nodes receive their own tile of image and perform scaling operation by executing a “Scale.ijm” macro. The scaled image is saved temporarily on the slave node and send the result back to the master node. Once the scaled images from all slave nodes are received, the master node will stitch back these images to form the final image. Figure 5 shows the overall steps required to scale an image using cluster computing.

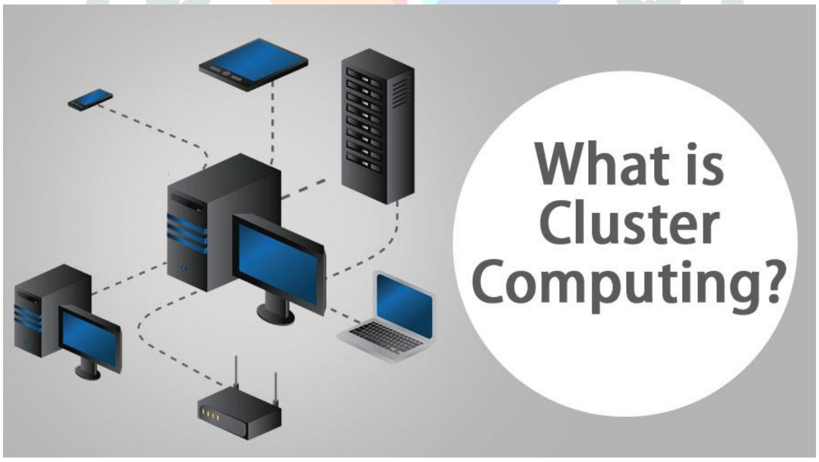

Figure 5 Image Scaling using Cluster Computing

RESULT ANALYSIS AND DISCUSSION

The computational time complexity is evaluated across three hardware setups using the "Image Interpolator" model. Seven already-existing algorithms for resizing images have been included into the model, along with a new one called OE-CBS. For our study, we obtained a 256 × 256-pixel colour picture from the USC-SIPI Image Database and reduced its resolution to 128 x 128 pixels. Eight image scaling algorithms (Nearest neighbour, Bilinear, Bicubic, Cubic B-Spline, Catmull-Rom, Lanczos order 2, Lanczos order 3, and OE-CBS) are used to generate corresponding images of the input image at sizes of 256 by 256 (2X), 512 by 512 (4X), 1024 by 1024 (8X), 1280 by 1280 (10X), 2560 by 2560 (20X), and 6400 by Intel® Core i3, i5, and i7 processor-based computers are used in the experiment to determine the computational time complexity. Tables 1, 5.2, and 5.3 show the amount of time, in seconds, required to resize photos on three different computers.

Table 1. Computational Time in seconds using Intel® Core i3 CPU @ 2.40 GHz

Algorithms	2X	4X	8X	10X	20X	50X
Nearest Neighbor	0.015	0.028	0.062	0.094	0.312	1.469
Bilinear	0.031	0.047	0.125	0.218	0.797	3.329
Bicubic	0.047	0.172	0.64	0.969	3.922	22.735
Catmill-Rom	0.063	0.218	0.906	1.422	5.516	33.829
Cubic B-Spline	0.068	0.235	0.922	1.438	5.766	34.658
Lanczos 2	0.359	1.813	8.125	13.188	51.112	324.031
Lanczos 3	0.891	4.109	18.048	28.861	112.114	706.799
OE-CBS	0.061	0.214	0.882	1.372	5.464	33.796

Table 2. Computational Time in seconds using Intel® Core i5 CPU @ 2.50 GHz

Algorithms	2X	4X	8X	10X	20X	50X
Nearest Neighbor	0.011	0.023	0.045	0.068	0.218	1.282
Bilinear	0.023	0.036	0.094	0.156	0.531	2.814
Bicubic	0.039	0.156	0.442	0.687	2.712	19.023
Catmull-Rom	0.049	0.234	0.536	0.826	3.323	19.612
Cubic B-Spline	0.051	0.256	0.547	0.849	3.368	20.819
Lanczos 2	0.314	1.134	5.853	9.432	42.817	245.275
Lanczos 3	0.608	2.902	12.492	19.926	81.373	515.078
OE-CBS	0.047	0.226	0.519	0.806	3.267	19.536

Table 3. Computational Time in seconds using Intel® Core i7 CPU @ 2.70 GHz

Algorithms	2X	4X	8X	10X	20X	50X
Nearest Neighbor	0.008	0.013	0.031	0.046	0.187	0.875
Bilinear	0.015	0.019	0.077	0.093	0.375	2.391
Bicubic	0.028	0.078	0.359	0.562	2.203	13.853
Catmull-Rom	0.033	0.109	0.427	0.667	2.766	17.406
Cubic B-Spline	0.039	0.152	0.462	0.688	2.797	17.456
Lanczos 2	0.203	1.063	4.86	7.886	32.835	203.204

Lanczos 3	0.484	2.375	10.44	16.637	69.514	439.577
OE-CBS	0.031	0.102	0.412	0.646	2.734	17.210

Tables 1, 2, and 3 show that the processing time of the relevant method increases as the picture size increases from 256 x 256 (2X) to 6400 x 6400 (50X) pixels. The experimental result demonstrates that the computing time required by the appropriate approach increases as the number of pixels to be calculated from the original picture increases. Experiments conducted on three distinct hardware setups reveal, without a shadow of a doubt, that a faster CPU and more memory result in less processing time needed by the most powerful processor.

Image Quality Assessment

When utilizing interpolation methods for picture scaling, image quality degrades. Sometimes when a picture is blown up, artefacts like jaggies, ringing, blurring, and edge halos arise. A number of Picture Quality Assessment (IQA) methods may be used to evaluate how much of the original image detail is preserved following a scaling procedure.

Table 4 displays the generated result based on PSNR and UIQI values for Lena, Girl, and Peppers photos.

Table 4 Image Quality Assessment using PSNR and UIQI for Lena, Girl, and Peppers images

Algorithms	Lena		Girl		Peppers	
	PSNR	UIQI	PSNR	UIQI	PSNR	UIQI
Nearest	27.1291	0.71642	27.8073	0.64005	23.8676	0.68856
Bilinear	31.9785	0.81806	31.5117	0.73768	26.0415	0.78541
Bicubic	31.9722	0.81774	31.3207	0.73343	25.7992	0.77711
Catmull-Rom	32.3811	0.83445	31.6477	0.74549	26.0045	0.78634
Cubic B-Spline	30.6273	0.7546	30.3735	0.67888	25.902	0.77003
Lanczos 2	31.2455	0.76508	31.3658	0.74017	26.3081	0.74832
Lanczos 3	32.3135	0.82971	31.4145	0.73399	25.7603	0.77672
OE-CBS	32.4232	0.83744	31.5664	0.74537	26.3198	0.78928

For Nearest Neighbor interpolation, the Lena, Girl, and Pepper pictures had the lowest PSNR (27.1291 dB), UIQI (0.64005), and IQE (0.68856) values, as shown in Table 4 Scaling a picture led to jagged or blocky patterns, while Closest Neighbor interpolation approaches simply duplicate the nearest pixel value. As a result, the Nearest Neighbor algorithm does not provide satisfactory results when used to create pictures.

CONCLUSION

Scaling images is an essential component of many computer graphics programmers and is therefore an essential picture operation in the field of image processing. Picture Interpolator, a paradigm for scaling images that was developed to make non-adaptive image scaling techniques in ImageJ more practical. The model may run on both dedicated machines and in a cluster environment. The primary goal is to improve upon existing methods of picture enlargement by creating a novel image scaling algorithm. Larger photos need more computing time to reconstruct an image from the original, since image processing techniques are resource-intensive processes. These methods have also been implemented by the researchers on cluster hardware. We evaluate the relative efficiency of standalone and cluster computing by measuring the time required to perform image scaling operations on pictures of varying sizes.

REFERENCE

1. Akinsola J E T (2017): Supervised Machine Learning Algorithms: classification and comparison, international journal of computer trends and technology, vol. No: 48, pp. 128-138.

2. Anand narasimhamurthy (2017): an overview of machine learning in medical image analysis: trends in health informatics, pp. 36-58.

3. Andreas maier, christopher syben, tobias lasser, and christian riess (2019): a gentle introduction to deep learning in medical image processing, zeitschrift für medizinische physik, vol. No: 29(2), pp. 86-101.

4. Apama, r. R. M, and shanmugavadivu p. (2017): a literature review on medical imaging transfer, international conference on iot in social, mobile, analytics and cloud), palladam, pp. 284- 288.

5. Choi j, shin k, jung j, bae h j, kim d h, byeon j s, and kim n (2020): convolutional neural network technology in endoscopic imaging: artificial intelligence for endoscopy, clinical endoscopy, vol. No. 53(2), pp. 117–126.

6. De lange t, halvorsen p, and riegler m (2018): methodology to develop machine-learning algorithms to improve performance in gastrointestinal endoscopy, world journal of gastroenterology, vol. No. 24(45), pp. 5057–5062.

7. Crowley c, guitron s, son j, and pianykh os (2020): modeling workflows: identifying the most predictive features in healthcare operational processes, plos one, vol. No. 15(6).

8. Choi j, shin k, jung j, bae h j, kim d h, byeon j s, and kim n (2020): convolutional neural network technology in endoscopic imaging: artificial intelligence for endoscopy, clinical endoscopy, vol. No. 53(2), pp. 117–126.

9. Tziortziotis, i.; laskaratos, f.-m.; coda, s. Role of artificial intelligence in video capsule endoscopy. Diagnostics 2021, 11, 1192. Https://doi.org/10.3390/ diagnostics11071192

10. Choi j, shin k, jung j, bae h j, kim d h, byeon j s, and kim n (2020): convolutional neural network technology in endoscopic imaging: artificial intelligence for endoscopy, clinical endoscopy, vol. No. 53(2), pp. 117–126.

11. Chengfan li, lan liu, xiankun sun, junjuan zhao, and jingyuan yin (2019): image segmentation based on fuzzy clustering with cellular automata and features weighting, eurasip journal on image and video processing, article no: 37.

12. Chandrakumar, t, and kathirvel, r (2016): classifying diabetic retinopathy using deep learning architecture, international journal of engineering research and technology, vol. No: 5(6), pp. 19-24.

13. Borgli hanna, vajira smedsrud, and pia hicks (2020): a comprehensive multi-class image and video dataset for gastrointestinal endoscopy, scientific data, vol. No. 7.

14. Bolon canedo v, and remeseiro b (2020): feature selection in image analysis: a survey, artificial intelligence review, vol. No. 53, pp. 2905–2931.

15. Birkfellner wolfgang (2019): applied medical image processing, taylor & francis inc., printed book.