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Predictive Identification of Malignant Melanoma from Fractional Differentiation-based Image Enhancement

Abstract: - Recent advancements in computer vision and artificial intelligence allow for the automatic detection of some abnormalities in medical photographs. One of these is a skin lesion, and prompt and accurate detection of these conditions substantially aids in treatment. When image processing is combined with the fundamental edge detection technique, there has been potential demonstrated in the automatic identification and delineation of boundaries inside skin lesions. In this work, we investigate how to improve edge-detection in photos using fractional differentiation. We present a fractional differential filter based method for edge detection in images of skin lesions. The original photos are then improved with the help of the derived images. During acquisition, acquired images are classified using deep learning models. In the experiments, a well-researched dataset of HAM10000 is employed. The outcomes demonstrate how well these filters work to cut through noise and pick up minute edge characteristics that can provide useful information while performing recognition tasks.

Keywords: Fractional Calculus, Skin Lesion, Deep Learning, Melanoma, Fractional Differentiator, Grunwald Letnikov, Melanoma, Edge Detection.

I. INTRODUCTION

Research in the ever-evolving field of digital image processing is connected to human perception, computing, mathematics, and image manipulation, among other academic fields. A vast number of disciplines, including biology, medicine, geology, astronomy, and archaeology, are now able to employ mathematical methodologies thanks to technological advancements in programming languages and hardware. A crucial step in image processing is edge detection, which entails locating the borders between areas of an image with different gray scale values. These edges aid with tasks like object recognition and region segmentation by offering useful information about objects. First-order differential algorithms are among the many mathematical techniques that have been developed for edge identification. As an illustration, [7] employed the edge detection technique to eliminate speckle noise from images while maintaining diagnostic information, while [8] employed the Canny and Sobel algorithms. Radar remote sensing images were analyzed using the Sobel edge detection technique in [9], and gray scale and color images were subjected to the Roberts edge detector in [10]. These methods, however, may result in thick edges with subpar detection quality.

The history of fractional differentiation, sometimes referred to as non-integer differentiation, dates back to the work of physicists and mathematicians like Letnikov, Riemann, Cauchy, and Liouville in the 19th century. Since then, a large number of mathematicians and physicists have studied fractional-order linear differentiation equations, or more accurately, fractional differentiation equations. The mathematical analysis of these equations is

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covered in a number of papers, including [11, 12, 13, 14]. Fractional differentiation has gained importance recently in a variety of domains, including biology, chemistry, and control theory, robotics, and mechanical engineering, modeling, and system identification in the time and frequency domain [13, 15]. Fractal image compression was also utilized in this work [16, 17, 18, 19, 20, 21].

In this work, we use the HAM10000 dataset of dermoscopic images to assess the classification performance of the EfficientNetv2s [22, 23]. There are 10015 images in the collection, representing seven distinct forms of skin cancer: akiec, bcc, bkl, df, mel, nv, and vasc. Using Image Net pre-trained weights, CNN fine-tuning and transfer learning were carried out for the HAM10000 dataset. The essay's remaining sections are arranged as follows. The HAM10000 dataset distribution is included in the Dataset section. The methodology section provides an illustration of the research strategy. Information about the training and execution of EfficientNetv2 is included in the Implementation section. The part containing the performance assessment metrics for CNN adjustments can be found there. The results and discussion section provides an explanation of the study's conclusions. The article ends with the conclusion section.

Detected edges are widely used in computer vision and image processing to improve images. Edge detection, which includes determining the borders or direction changes between several sections of a picture, is an essential stage in image analysis. These borders often correspond with discernible color or intensity differences, which can provide important information about the shapes and boundaries of the items in the picture. Once the edges are located, they can be used in a variety of ways to enhance the quality of the image, which will impact the process of detecting.

Table 1: The HAM10000 dataset's class.

Investigative classification	Quantity of images
nv	6807
mel	1112
bkl	1090
bcc	520
akiec	380
vasc	150
df	120
Total	**10,179**

II. INSPIRATION

Although each pixel in a color image has three components (red, green, and blue) that make up its vector definition, edge identification in color images is more difficult than in gray scale ones. In gray scale photographs, an intensity discontinuity is called edges; in color images, however, it is not as well well-defined. If the intensity of one of the channels in a color image discontinues, it might be regarded as an edge.

Textural variability is a major obstacle to edge recognition, which makes it difficult for algorithms for edge detection to precisely identify the margins of lesions [1, 2]. Skin lesions can have a broad color spectrum, which makes it challenging for edge detection techniques to pinpoint the lesion's edge [3]. The edge recognition method may be hampered by the presence of high noise in the background in skin lesion images, such as the hair, lines and wrinkles, and various non-lesion structures [4, 5]. Furthermore, variations in lighting can impact how skin lesions appear in images, which makes it challenging for edge recognition algorithms to precisely locate the lesion boundary [6].

Edges are important in image processing because they hold important information and features. By removing unnecessary information, edge detection helps to shrink an image without sacrificing its structural integrity. In addition to being able to identify edges, edge detectors also need to be fast and accurate, robust against noise, sensitive to orientation, and able to locate edges precisely.

The concept of employing the non-integer differential Grunwald-Letnikov definition to identify edges is the driving force behind the intriguing topic of edge detection in image processing. Many academics are currently researching the unique applications of non-integer differences in image processing, particularly edge detection, in an attempt to improve and explore new areas and advance current image processing techniques. The simplicity of the algorithms and the ease with which the order of derivation can be changed to improve edge detection results are two benefits of employing edge detection with non-integer differentials. This work aims to demonstrate that, while satisfying these requirements, the Grunwald-Letnikov definition offers even additional advantages for edge identification.

III. LITERATURE SURVEY

The calculus of variations was used in the development of the canny edge detector, which aims to provide accurate localization and effective edge detection with little response. The optimal function, which is a combination of four exponential terms, is found by optimization a given functional. Nonetheless, a Gaussian initial derivative can be used to approximate this ideal function roughly [24].

The gradient of the image's intensity at each pixel is approximated using the Sobel operator. At that specific pixel, the Sobel operator can generate either the gradient vector or the image vector's magnitude. Because it applies a small, separable, integer-valued filter in the vertical (y) and horizontal (x) axes to the picture to accomplish a convolution operation, the Sobel operator is computationally inexpensive. But this leads to somewhat coarse approximations of the gradient, especially when the frequency of the image fluctuates a lot [25].

The gradient brightness of an image can be ascertained using the Prewitt edge detector, a discrete differentiation operator. It functions by using convolution to apply a tiny, distinct, integer-valued filter to an image in the vertical as well as horizontal directions. Although it works best with highly contrasted, noiseless images, this operator is effective and quick at detecting edges [26]. The filter defines the gradient of light intensity in each pixel of the image and provides information about the direction and speed of the biggest brightness shift. The outcome indicates sharp variations in the image's brightness to imply the most likely edges. This strategy is reliable, doable, and easy to put into practice. The first derivative of the image must be computed in order to use the Roberts edge detector [27].

An image's second derivative is examined for zero crossings using the unique Marr & Hildreth operator for digital images. There are two methods available for carrying out these calculations: convolution of the image using a mask generated through the Laplacian of Gaussian (LoG) function, or convolution of the picture employing a Gaussian kernel and approximations of the next derivative (Laplacian approach) using 3x3 masks. Recursive Gaussian filters can also be used to accomplish the latter [28]. The image must be convolved, and then the method must be applied in two steps: finding the places in the filtered image where there are zero crossovers. A LoG kernel either a Gaussian kernel accompanied by a Laplacian operator can be used to further divide the picture convolution step. The Marr-Hildreth algorithm requires the convolving of an image with a kernel using a 2-D mask, a Laplacian of Gaussian kernel, as well as a Gaussian kernel. The idea of the input image's convolution serves as the foundation for the Gaussian as well as the Laplacian of the Gaussian kernel.

The Haralick operator searches the 2nd derivative of an image for zero crossing points, just like the Marr-Hildreth operator does. However, by employing a local bi-cubic polynomial approximation, the Haralick operator offers a decent approximation of the input image. In order to determine the zeros of a polynomial function's second derivative given its parameters, an analogous expression must be used in this analytical process [29].

The goal of edge detection is to locate important details in an image, including abrupt shifts in the gray scale values. Roberts [30] created the Roberts cross operator, one of the first techniques for edge detection. Introducing two kernels to the photograph using convolution, the Prewitt operator enables the estimation of derivatives in the horizontal as well as vertical directions [31]. An image's intensity gradient can be roughly calculated using a discrete differentiation operator known as the Sobel operator [32, 33]. In addition, image data can be shrunk to a size appropriate for edge detection research [34]. However, noise reduction is essential to preserve picture eminence and preclude surprising results because edge information is required for edge recognition tasks to perform [35, 36].

IV. SPECIFICS OF THE DATASET

This section covers the geographical breakdown of the HAM10000 dataset for testing and training.

4.1 HAM10000 dataset

The HAM10000 dataset, which was made available by Tschandl et al. in 2018 [37], was employed in our experimental investigation to address issues with dermoscopic picture classification. The Cliff Rosendahl in Queensland, Australia, and the Department of Dermatology at the Medical University of Vienna, Austria, are the two medical sources from which the dataset's 10015 RGB images were gathered over a 20-year period. The images are stored in the JPEG format and have a 600x450 pixel resolution. The dataset contains a large variety of vascular lesions, such as angiomas and angiokeratomas, as well as pigmented lesions, such as akiec, bcc, bkl, df, mel, and nv. It is comprehensive in terms of the classifications of diagnosis it represents.

The HAM10000 dataset's representative and well-organized nature have led to its widespread use in the field. It is presently a component of the ISIC 2019 challenge and served as the foundation for the data for the ISIC 2018 classification task. Table 1 lists how many images there are in each class.

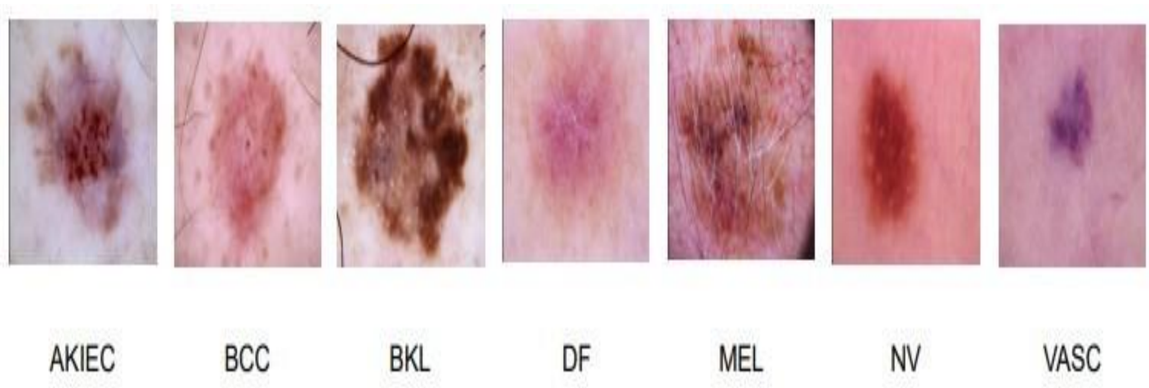


Figure 1: Skin lesion sample from the HAM10000 dataset [37].

4.2 Distribution of datasets

The HAM10000 dataset was divided into two parts: testing (10%) and training (90%). It was simpler to evaluate our trained models' performance thanks to the Testing set. We made verified that the Training and Testing collections had no duplicate photos. The distribution of the data of the HAM10000 dataset in two categories, broken down by class, is shown in Table 2.

Table 2: The information about HAM10000 dataset is distributed according to class.

Investigative classification	Training	Testing
nv	6132	675
mel	992	120
bkl	940	150
bcc	460	60

akiec	340	40
vasc	130	20
df	105	15
Total	9099	1080

V. RESEARCH METHODOLOGY

The suggested technique creates a fractional-order filter for edge identification in color images using fractional calculus. The gradient of the supplied image is ascertained using the filter. Our suggested method is predicated on the identification of both row and column edges. The report also covers the transfer-learning methodology that was utilised for learning the HAM10000 dataset employing Image Net's pre-trained weights, and the model architecture changes made to the Efficient Net model.

CNN scaling can lead to an increase in accuracy. It needed to be manually adjusted iteratively, either by using a higher input image resolution or by adjusting the CNN's depth or breadth in an arbitrary way. The Efficient Net family of architectures, developed by [38], seeks to determine a workable method for scaling CNNs for better-quality efficiency (i.e., typical parameters) and accuracy (i.e., model performance).

5.1 System Overview

Typically, pictures are obtained, processed to a standard gray scale image level, and then conventional edge detection methods are used to assess how well different edge detection algorithms work. Six distinct algorithms—rlr, rlc, glr, glc, sobel, and canny—are used in this study.

5.2 Definition for Fractional-Order

Digital image processing most commonly uses the descriptions of fractional calculus provided by Riemann-Liouville (R-L) as well as Grunwald-Letnikov (G-L), every one of which presented a version. The G-L definition is as follows: [39].

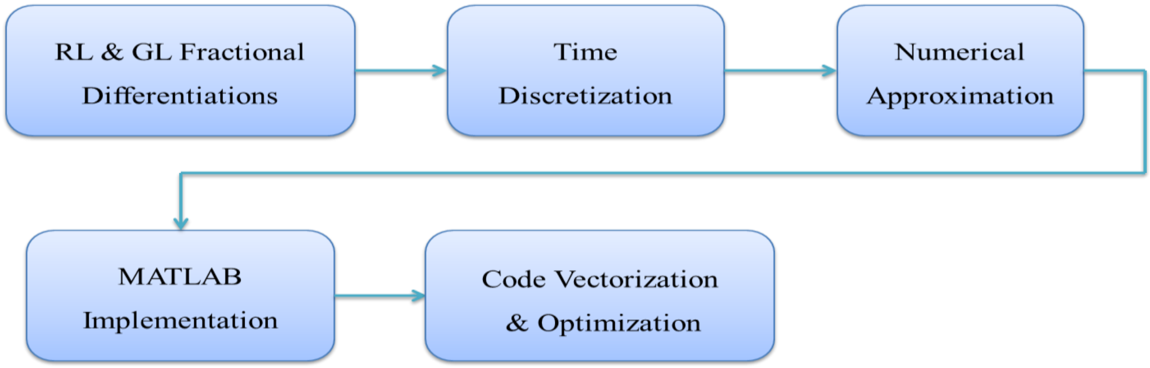
VI. RECOMMENDED EDGE DETECTION TECHNIQUE

A. Fractional Engine

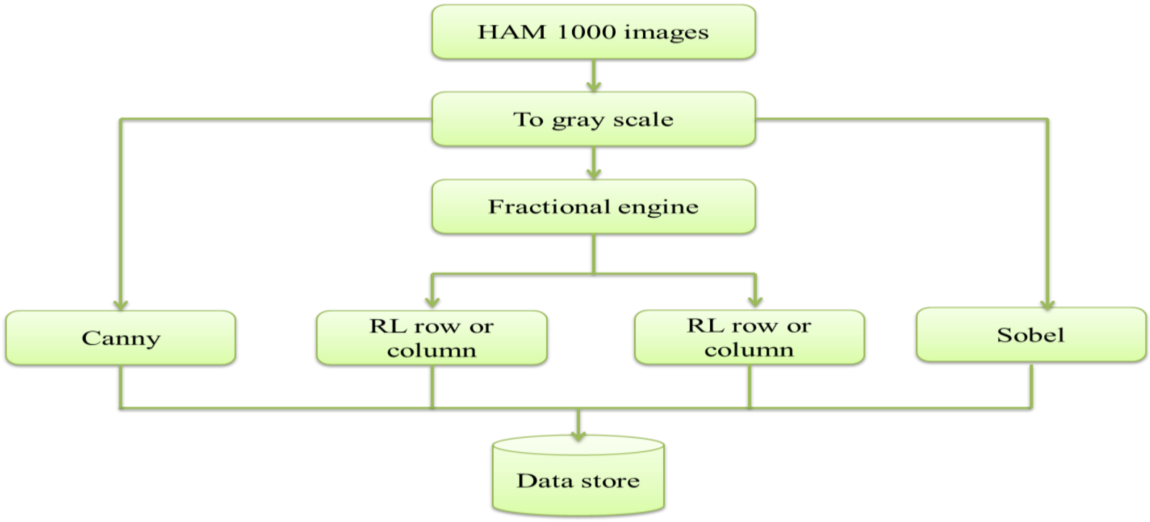
Identifying the differential equation to be solved is the first step. In our case, the image is indicated by I in the formula ( ) =^ ( ), and the fractional order is represented by α. We numerically approximated a discrete solution because our input is digital. The RL and GL procedures for the row and column processes were then put into practice and optimized. This fractional engine will handle all image processing operations.

B. Processing HAM10000

We have scanned and gray scaled ten thousand HAM photographs. Next, we use our Fractional Engine to generate Row and Column operation results for RL and GL at $\alpha = 0.5$. Additionally, we use Sobel and canny filters, storing the outcomes in our data store. Every filter is applied using its factory settings.



(A): Fractional Engine



(B): Pre-Processing HAM10000

Figure 2: Block schematics illustrating the techniques used.

VII. EXPERIMENTAL PERFORMANCE AND ANALYSIS

To conduct and test the experiment, skin cancer images were used, and the clean edges map was obtained by using the fractional differentiator. To recognize and extract edges, a range of tests have been carried out both in and out of a noisy environment. The results of applying several edge detection techniques to the initial photograph after 0.5 differentiations between the column as well as row directions are shown in Figure 2.

VIII. ALGORITHM FOR NETWORK MODERNIZATION EDGE DETECTION

An example of a feed-forward neural network is CNN. Its artificial neurons can react to nearby components of a complete coverage, recreate network designs like these in an effort to achieve accuracy and speed, and operate brilliantly for large-scale image processing. Its artificial neurons, like EfficientNetV2S, are good at processing large images, mimic network structures to seek accuracy and speed, and can respond to units nearby in a partial coverage [41].

In this work, we applied an EfficientNetV2S neural network to the task of classifying skin cancer photos. Modern feature extractors, such as EfficientNetV2S, are trained using the Image Net dataset. The architecture and principal elements of the suggested method are delineated in Figure 4 below.

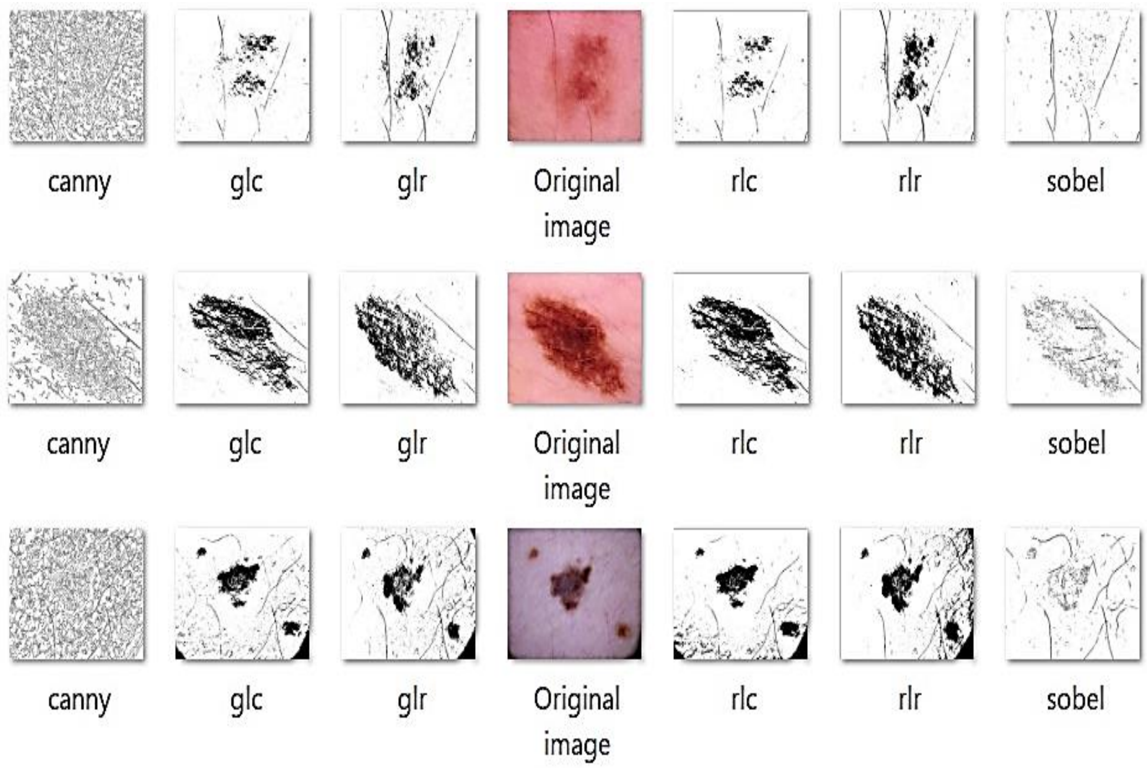


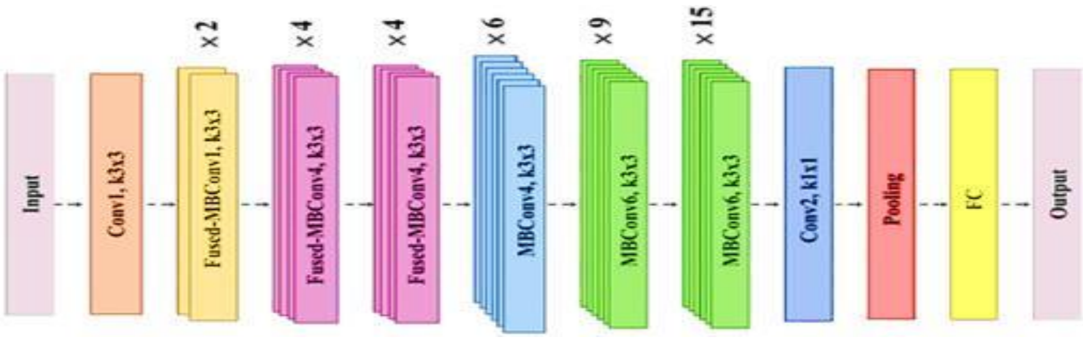
Figure 3: Sample images are used and obtained via fractional differentiation.

IX. EFFECTIVENETV2S INFRASTRUCTURE

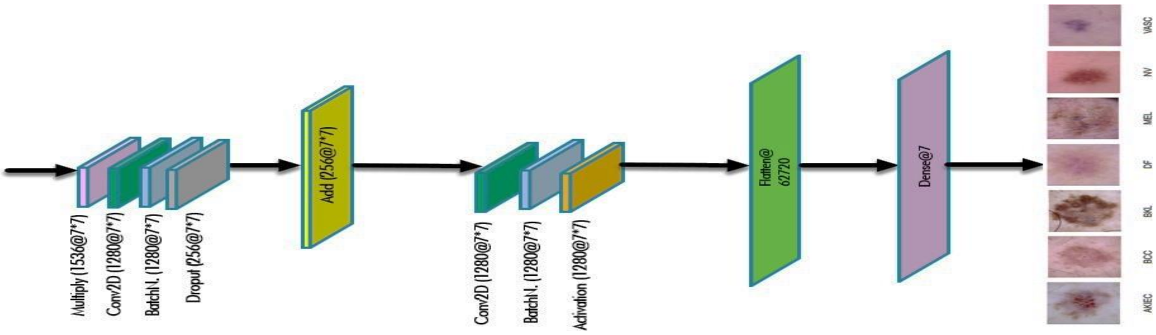
Due to its growing prevalence and potentially fatal outcome if neglected, skin cancer is a significant global health concern. Early detection is directly associated with higher survival rates and less load on healthcare systems. Identification of skin cancer is one of the many medical image processing applications where deep learning models have demonstrated promise.

We explore the possibilities of transfer learning for skin cancer diagnosis using the EfficientNetV2S architecture. Through transfer learning, performance on smaller target datasets can be enhanced and training periods shortened by utilizing the knowledge obtained from pre-training on large datasets. Our goal is to improve the overall classification accuracy as well as the minority class finding through the application of class weights techniques and EfficientNetV2S optimization on the HAM10000 dataset.

Our method is based on the EfficientNetV2S architecture, which has proven to perform exceptionally well in a range of computer vision applications. Transfer learning can be employed by using weights that were trained on the Image Net dataset first, and then fine-tuned on the HAM10000 dataset. We use class weighting strategies to compensate for the data imbalance by giving minority classes more weights during model training. This approach improves the model's ability to identify skin cancer across all classes by giving the underrepresented classes more weight [40].



(A)



(B)

Figure 4 (A) and (B): Block diagrams pertaining to the suggested approach.

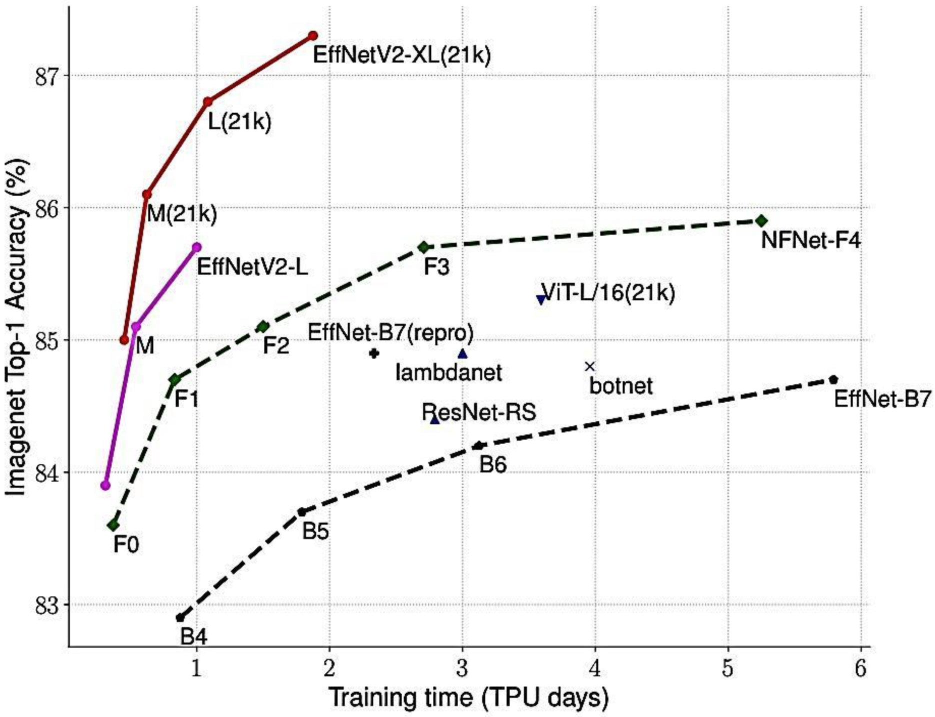


Figure 5: Demonstrates the connection between Image Net ILSVRC2012's top-1 accuracy and training duration and parameter values [40].

Table 3: Displays the F1 score, Test loss, Test accuracy, Training loss, and Test accuracy for the results of several edge detection techniques on noise- and noise-free skin cancer image sets.

image_type	Training loss	Training Accuracy	Test loss	Test Accuracy	F1 score
(Sobel, 0.5, original_image, 0.5)	0.3085	0.3096	8.5855	0.8500	0,76
(Canny, 0.5, original_image, 0.5)	0.4875	0.9033	5.5592	0.7500	0.77
Glr + GLc	0.4690	0.9325	7.5650	0.7800	0,78

RLr + RLc	0.7832	0.9143	6.4855	0.7933	0,78
Original Image	0.3350	0.9505	8.4677	0.7779	0,79
(Weighted Sum (total, 0.5)					
‘glc +glr+ 'rlc +rlr+ Original Image '	0.3814	0.9858	7.2477	0.7844	0,80
(Weighted Sum (total, 0.2, original_image, 0.8)					
‘glc +glr+ 'rlc +rlr+ Original Image '	0.2458	0.9721	5.3441	0.8204	0,82

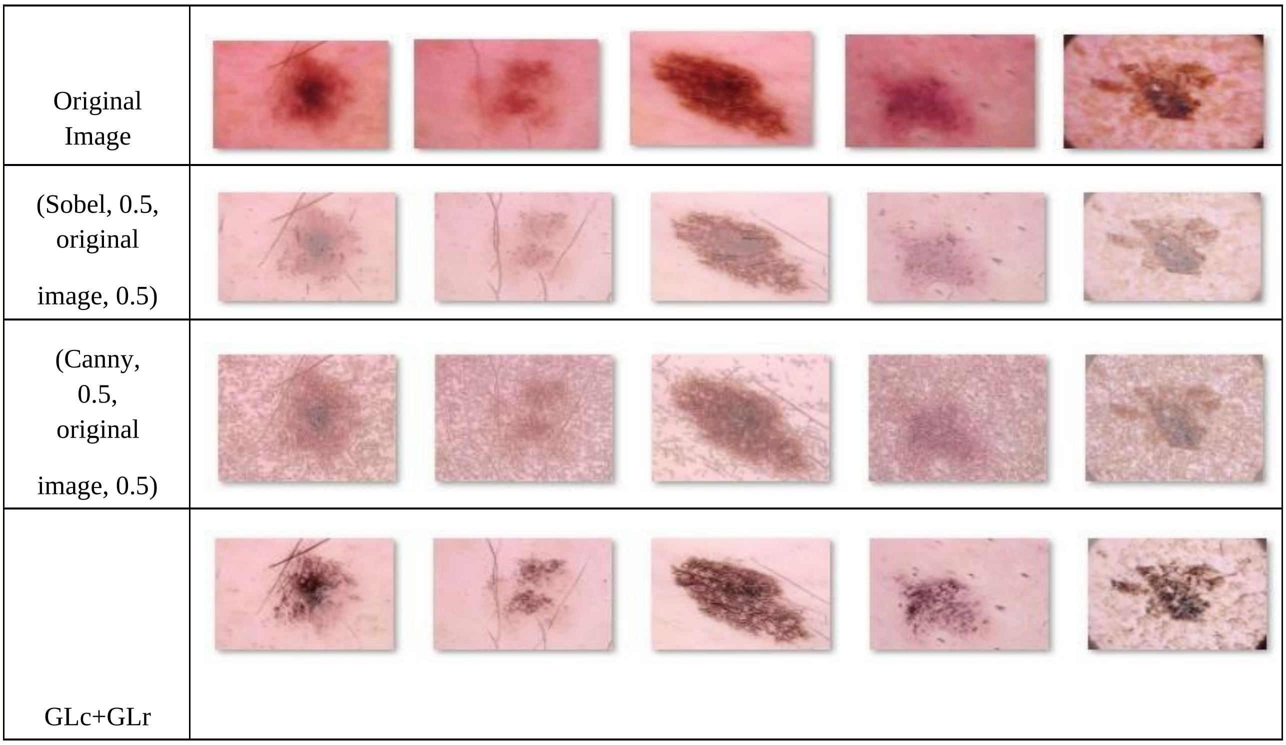
X. LINEAR BLENDING (WEIGHTED SUM)

A mathematical technique known as a "weighted sum" combines an image's pixel values according to predetermined weights. It is frequently employed in a variety of filtering and image enhancing methods. The weighted sum procedure entails multiplying the value of each pixel in the image by its associated weight before adding together all of the weighted values. Each pixel's weight indicates how much of an impact it has on the outcome [42].

The weights of the horizontal and vertical edge detectors, RL and GL, were added together to generate a total matrix of all four edge detectors. Furthermore, as table 3 illustrates, we created a weighted sum using varying addition factors (degrees of blending) between the entire matrix and the original image.

XI. RESULTS AND TESTS CONDUCTED IN EXPERIMENTS

The HAM10000 dataset is used as the basis for experiments that compare fractional differentiation based on picture analysis. The experiment's original image and the visual results of using several edge detection methods are shown in Figure 3.



RLc+RLr	
Original Image (0.5), Total (0.5)	
Original Image (0.2), Total (0.8)	

Figure 5: Original Skin Cancer Image with (Sobel, original image), (Canny, original image) and with the Fractional Calculus (GLc, GLr), (RLc, RLr) and (GLc, GLr+ RLc, RLr) by apply 0.5 differentiation in both directions (row and column).

For both GL and RL, the weighted sum with an alpha of 0.5 has been applied, multiplying the values of the two edge pixels that were detected. Next, we apply another weighted sum and multiply the pixels in the original image by 0.8 and the pixels in the total image by 0.2. Finally, we apply a weighted sum between the original and total images with alpha equal to 0.5 for both the original and total images.

The outcomes of several weighted sums are displayed in the following figure. Figure 5 illustrates that the suggested method yields photos that are similar to those from prior investigations. A comprehensive investigation employing several image processing methodologies is carried out, utilizing the primary image of a skin cancer abrasion as its important point. Because the Sobel edge detection operator displays the precise borders and contours of the lesion, it facilitates the identification of aberrant areas in the original image. In parallel, the original image's canny edge detection algorithm highlights its edges while reducing noise interference, enhancing the structural attributes' clarity.

With a fractional order of 0.5 across both the row as well as the column directions, enhanced image edge detection surpasses the limitations of traditional methods by implementing these concepts individually as (GLc, GLr) and (RLc, RLr), subsequently in combination as (GLc, GLr+ RLc, RLr). Firstly, the fractional derivatives of the sophisticated mathematical devices Grünwald-Letnikov (G-L) and Riemann-Liouville (R-L) are studied. The picture analysis is able to overcome the constraints of conventional techniques by using these concepts as (GLc, GLr) and (RLc, RLr) separately, and then combined them as (GLc, GLr+ RLc, RLr), resulting in a proportionate order of 0.5 in both the row as well as the column directions. Better visual quality can be achieved by using the suggested strategy, as demonstrated by the positive results in this section.

XII. CONCLUSION

The growing combination of computational vision, image processing, and machine learning has led to the widespread use of edge detectors in daily technology for the purpose of extracting as well as detecting features. Since edge detectors provide a variety of information on the geometry of the objects in the image, they are more significant. The detection abilities are also improved by the modifications to highlight the quality of edges in a picture. Here, the usage of fractional derivatives is suggested by the paper. This term deals with edge detection as a non-integer differentiation based on the Grunwald-Letnikov definition; two approaches that make use of this idea are developed and evaluated. The primary advantage of the two devised approaches is that the equation is derived at the given order of derivative by applying the descriptions of Riemann-Liouville (R-L) as well as Grunwald-Letnikov (G-L). The derivatives are then added to the original photos to improve them. Moreover, the improved photos are classified by the deep learner. A recent issue in medical imaging is automatic diagnosis of malignant melanoma, to which the suggested technology is tailored. The outcomes demonstrate that the suggested technique produces encouraging outcomes and is amenable to future advancements.

REFERENCES

[1] Vesal, Sulaiman, Nishant Ravikumar, and Andreas Maier. "SkinNet: A deep learning framework for skin lesion segmentation." In 2018 IEEE Nuclear Science Symposium and Medical Imaging Conference Proceedings (NSS/MIC), pp. 1-3. IEEE, 2018.

[2] Xie, Yutong, Jianpeng Zhang, Yong Xia, and Chunhua Shen. "A mutual bootstrapping model for automated skin lesion segmentation and classification." IEEE transactions on medical imaging 39, no. 7 (2020): 2482-2493.

[3] Joshi, Aparna, Rupali Bagate, Yogita Hambir, Ashwini Sapkal, Nilesh P. Sable, and Mahesh Lonare. "System for Detection of Specific Learning Disabilities Based on Assessment." International Journal of Intelligent Systems and Applications in Engineering 12, no. 9s (2024): 362-368.

[4] Rajesh, A. "Classification of malignant melanoma and Benign Skin Lesion by using back propagation neural network and ABCD rule." In 2017 IEEE International Conference on Electrical, Instrumentation and Communication Engineering (ICEICE), pp. 1-8. IEEE, 2017.

[5] Mutkule, Prasad Raghunath, Nilesh P. Sable, Parikshit N. Mahalle, and Gitanjali R. Shinde. "Predictive Analytics Algorithm for Early Prevention of Brain Tumor using Explainable Artificial Intelli-gence (XAI): A Systematic Review of the State-of-the-Art." Industry 4.0 Convergence with AI, IoT, Big Data and Cloud Computing: Fundamentals, Challenges and Applications (2023): 69.

[6] Celebi, M. Emre, Q. U. A. N. Wen, H. I. T. O. S. H. I. Iyatomi, K. O. U. H. E. I. Shimizu, Huiyu Zhou, and Gerald Schaefer. "A state-of-the-art survey on lesion border detection in dermoscopy images." Dermoscopy image analysis 10, no. 1 (2015): 97-129.

[7] Baig, Ramsha, Maryam Bibi, Anmol Hamid, Sumaira Kausar, and Shahzad Khalid. "Deep learning approaches towards skin lesion segmentation and classification from dermoscopic images-a review." Current Medical Imaging 16, no. 5 (2020): 513-533.

[8] Sable, Nilesh P., Vijay U. Rathod, Mangesh D. Salunke, Hemantkumar B. Jadhav, Ravindra S. Tambe, and Suhas R. Kothavle. "Enhancing Routing Performance in Software-Defined Wireless Sensor Networks through Reinforcement Learning." International Journal of Intelligent Systems and Applications in Engineering 11, no. 10s (2023): 73-83.

[9] Kaymak, Ruya, Cagri Kaymak, and Aysegul Ucar. "Skin lesion segmentation using fully convolutional networks: A comparative experimental study." Expert Systems with Applications 161 (2020): 113742.

[10] Kumar, M. Ravi, J. Lakshmi Prasanna, Varanasi Sri Harsha Vardhan, M. B. V. Swamulu, G. K. Kumar, S. Cheerla, and C. Santhosh. "Image enhancement for ultrasound images using Sobel edge detection." Journal of Critical Reviews 7, no. 13 (2020): 390-394.

[11] Shafiabadi, Mina, Abolghasem Kamkar-Rouhani, Seyed Reza Ghavami Riabi, Amin Roshandel Kahoo, and Behzad Tokhmechi. "Identification of reservoir fractures on FMI image logs using Canny and Sobel edge detection algorithms." Oil & Gas Science and Technology–Revue d'IFP Energies nouvelles 76 (2021): 10.

[12] Gawali, Piyush P., Parikshit N. Mahalle, Gitanjali R. Shinde, Nilesh P. Sable, Dattatray G. Takale, and Janki Barot. "Quantum Key Distribution and Blockchain Based Secure Authentication in Medical Cyber-Physical Systems." In International Conference on ICT for Sustainable Development, pp. 607-622. Singapore: Springer Nature Singapore, 2023.

[13] Chen, Guobin, Zhiyong Jiang, and M. M. Kamruzzaman. "Radar remote sensing image retrieval algorithm based on improved Sobel operator." Journal of Visual Communication and Image Representation 71 (2020): 102720.

[14] Prasantha, H. S. "Edge detection algorithms on digital signal processor DM642." International Journal of Creative Research Thoughts 8, no. 9 (2020): 1-6.

[15] Sable, Nilesh P., and Vijay U. Rathod. "Rethinking Blockchain and Machine Learning for Resource-Constrained WSN." In AI, IoT, Big Data and Cloud Computing for Industry 4.0, pp. 303-318. Cham: Springer International Publishing, 2023.

[16] Miller, Kenneth S., and Bertram Ross. "An introduction to the fractional calculus and fractional differential equations." (No Title) (1993).

[17] Vesal, Sulaiman, Nishant Ravikumar, and Andreas Maier. "SkinNet: A deep learning framework for skin lesion segmentation." In 2018 IEEE Nuclear Science Symposium and Medical Imaging Conference Proceedings (NSS/MIC), pp. 1-3. IEEE, 2018.

[18] Xie, Yutong, Jianpeng Zhang, Yong Xia, and Chunhua Shen. "A mutual bootstrapping model for automated skin lesion segmentation and classification." IEEE transactions on medical imaging 39, no. 7 (2020): 2482-2493.

[19] Wang, Jiacheng, Lan Wei, Liansheng Wang, Qichao Zhou, Lei Zhu, and Jing Qin. "Boundary-aware transformers for skin lesion segmentation." In Medical Image Computing and Computer Assisted Intervention–MICCAI 2021: 24th International Conference, Strasbourg, France, September 27–October 1, 2021, Proceedings, Part I 24, pp. 206-216. Springer International Publishing, 2021.

[20] Song, Lei, Jianzhe Lin, Z. Jane Wang, and Haoqian Wang. "An end-to-end multi-task deep learning framework for skin lesion analysis." IEEE journal of biomedical and health informatics 24, no. 10 (2020): 2912-2921.

[21] Zafar, Kashan, Syed Omer Gilani, Asim Waris, Ali Ahmed, Mohsin Jamil, Muhammad Nasir Khan, and Amer Sohail Kashif. "Skin lesion segmentation from dermoscopic images using convolutional neural network." Sensors 20, no. 6 (2020): 1601.

[22] Kharate, Namrata, Sanket Patil, Pallavi Shelke, Gitanjali Shinde, Parikshit Mahalle, Nilesh Sable, and Pranali G. Chavhan. "Unveiling the Resilience of Image Captioning Models and the Influence of Pre-trained Models on Deep Learning Performance." International Journal of Intelligent Systems and Applications in Engineering 11, no. 9s (2023): 01-07.
[23] Chaikan, Panyayot, and Somsak Mitatha. "Improving the Addweighted Function in OpenCV 3.0 Using SSE and AVX Intrinsics." International Journal of Engineering and Technology 9, no. 1 (2017): 45.
[24] Yamashita, Rikiya, Mizuho Nishio, Richard Kinh Gian Do, and Kaori Togashi. "Convolutional neural networks: an overview and application in radiology." Insights into imaging 9 (2018): 611-629.
[25] Sable, Nilesh P., Ratnmala Bhimanpallewar, Raj Mehta, Sara Shaikh, Anay Indani, and Soham Jadhav. "A Machine Learning approach for Early Detection and Prevention of Obesity and Overweight." In 2023 IEEE 8th International Conference for Convergence in Technology (I2CT), pp. 1-5. IEEE, 2023.
[26] Tan, Mingxing, and Quoc Le. "Efficientnetv2: Smaller models and faster training." In International conference on machine learning, pp. 10096-10106. PMLR, 2021.
[27] Li, Na, Jiameng Xue, Sibo Wu, Kunde Qin, and Na Liu. "Research on Coal and Gangue Recognition Model Based on CAM-Hardswish with EfficientNetV2." Applied Sciences 13, no. 15 (2023): 8887.
[28] Devi, R. S., V. R. Kumar, and P. Sivakumar. "EfficientNetV2 Model for Plant Disease Classification and Pest Recognition." Computer Systems Science & Engineering 45, no. 2 (2023).
[29] Sable, Nilesh P., Mangesh D. Salunke, Vijay U. Rathod, and Prashant Dhotre. "Network for Cross-Disease Attention to the Severity of Diabetic Macular Edema and Joint Retinopathy." In 2022 International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON), pp. 1-7. IEEE, 2022.
[30] Rathod, Vijay U., and Shyamrao V. Gumaste. "Effect of Deep Channel to Improve Performance on Mobile Ad-Hoc Networks." Journal of Optoelectronics Laser 41, no. 7 (2022): 754-756.
[31] Railkar, P. N., P. N. Mahalle, G. R. Shinde, and N. P. Sable. "Policy-Aware Distributed and Dynamic Trust Based Access Control Scheme for Internet of Things." International Journal on Recent and Innovation Trends in Computing and Communication 10, no. 1s (2022): 155-6.
[32] Tschandl, Philipp, Cliff Rosendahl, and Harald Kittler. "The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions." Scientific data 5, no. 1 (2018): 1-9.
[33] Tschandl, Philipp, Cliff Rosendahl, and Harald Kittler. "The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions. Scientific Data. 2018; 5: 180161." Search in 2 (2018).
[34] Maji, Suman Kumar, Hussein M. Yahia, and Hicham Badri. "Reconstructing an image from its edge representation." Digital Signal Processing 23, no. 6 (2013): 1867-1876.
[35] Sobel, Irwin, and Gary Feldman. "A 3x3 isotropic gradient operator for image processing." a talk at the Stanford Artificial Project in (1968): 271-272.
[36] Sobel, Irwin Edward. Camera models and machine perception. stanford university, 1970.
[37] Codella, Noel CF, David Gutman, M. Emre Celebi, Brian Helba, Michael A. Marchetti, Stephen W. Dusza, Aadi Kalloo et al. "Skin lesion analysis toward melanoma detection: A challenge at the 2017 international symposium on biomedical imaging (isbi), hosted by the international skin imaging collaboration (isic)." In 2018 IEEE 15th international symposium on biomedical imaging (ISBI 2018), pp. 168-172. IEEE, 2018.
[38] Codella, Noel, Veronica Rotemberg, Philipp Tschandl, M. Emre Celebi, Stephen Dusza, David Gutman, Brian Helba et al. "Skin lesion analysis toward melanoma detection 2018: A challenge hosted by the international skin imaging collaboration (isic)." arXiv preprint arXiv:1902.03368 (2019).
[39] Milton, Md Ashraful Alam. "Automated skin lesion classification using ensemble of deep neural networks in isic 2018: Skin lesion analysis towards melanoma detection challenge." arXiv preprint arXiv:1901.10802 (2019).
[40] Adegun, Adekanmi, and Serestina Viriri. "Deep learning techniques for skin lesion analysis and melanoma cancer detection: a survey of state-of-the-art." Artificial Intelligence Review 54 (2021): 811-841.
[41] Kamble, Vipin Milind, Pallavi Parlewar, Avinash G. Keskar, and Kishor M. Bhurchandi. "Performance evaluation of wavelet, ridgelet, curvelet and contourlet transforms based techniques for digital image denoising." Artificial Intelligence Review 45 (2016): 509-533.
[42] Jagtap, Vandana, Uma Pujeri, Pallavi Parlewar, Someshwar Landge, Aniket Ghorpade, Abhilash Alshi, and Hitesh Khutade. "Biometric face recognition system using deep dream and CNN." International Journal of Intelligent Systems and Applications in Engineering 11, no. 10s (2023): 145-154.