



Image Segmentation Using Unsupervised Learning

Md Jawed Khan, Md Tousif Anwer, Muskan Rastogi, Rishabh Pandey, Farhan Ahmad

1. Abstract

Skin cancer, an unsettling general wellbeing issue, with over 5,000,000 recently recognized cases consistently, simply in the United States. For the most part, skin cancer growth is of two types: Benign and Malignant. Malignant also known as Melanoma. Skin cancer is a typical type of cancer growth, and early identification expands the survival rate. Lots of research has already been done in this field, the best way for the classification is using clustering algorithms. Some of the clustering algorithms are K-means, Fuzzy c means, mountain clustering, etc. But the best one is the k-means clustering algorithm. Clustering is used to identify and group a similar dataset of the image. K-means clustering is the best way to classify remotely sensed imagery.

Result

The machine learning model were built and tested on standard dataset with an accuracy of about 86.4% was observed.

Keyword: Remotely sensed imagery; Clustering; skin cancer; machine learning

2. Introduction

Cancer is one of the major healthcare burdens across the world. Global statistics suggest almost 10.0 million deaths. Skin cancer is one of the kinds of cancer growths that contaminate people and is emerging from abnormal cells. It can spread in the parts of the body on the off chance that there is no early finding on schedule. Skin cancer, including both malignant also, benign skin cancer growth (NMSC), are normal diseases in Caucasians and their frequency is on the ascent [2]. As per the US Skin Cancer Foundation, skin malignant growth influences more individuals in the United States every year than any remaining diseases joined.

Melanoma is the skin cancer with the most terrible guess. Whenever analyzed early, it very well may be treated effectively with surgeries. Be that as it may, when there is metastasis, rates of endurance are reduced altogether [4]. Conclusion of melanoma relies upon the clinical assessment and exemplary discoveries on the sore biopsy. Instances of NMSC incorporate basal cell carcinoma (NMSC) and squamous cell carcinoma.

The progress of skin cancer growth depends on early conclusion and fitting treatment. Visual assessment may not be adequate to separate harmless sores from threatening growths. The highest quality level system is histopathology assessment of the skin biopsy. The intrusive idea of the strategy related pain, and the requirement for rehashed tests in thought sores with differed introductions are a portion of the constraints for skin biopsy. Painless devices can likewise aid clinical analysis. Mastery, cost, and accessibility are the difficulties for the far reaching utilization of these instruments. A few headways in science and innovation have come about in the accessibility of various painless imaging techniques to recognize melanoma [4]. The precision of these strategies in the conclusion of melanoma and other skin diseases is as yet a point of conversation.

By and large, early identification is key for the compelling treatment and better results of skin malignant growths. Experts can precisely analyze the malignant growth, notwithstanding, thinking about their restricted numbers, there is a need to foster robotized frameworks, which can analyze

the sickness effectively to save lives and lessen wellbeing and monetary weights on the patients. Skin growths can be hard to perceive from normal harmless skin injuries, and melanoma has an especially fluctuated look. Computer based intelligence can help with the early location of skin disease, bringing down the weight of dreariness and mortality related with the sickness [6]. As well as lessening the responsibility, AI-based frameworks can likewise help by further developing skin injury diagnostics.

Artificial Intelligence (AI), a part of software engineering that utilizes machines and projects to mirror clever human way of behaving by means of a star grouping of advancements, is a key driver of the fourth modern transformation. AI (ML) is an AI strategy including measurable models and calculations that can dynamically gain from information to anticipate the attributes of new examples and play out an ideal undertaking. In this way, the complex calculations are intended to play out the errands that generally would be challenging for human cerebrums to do. K-means clustering is a kind of ML that mimics the handling of organic neurons and is the cutting edge network for design acknowledgment in clinical picture examination. Artificial intelligence is ready to acquire change medical services due to its benefits over conventional logical strategies. There is rising positive thinking with respect to uses of AI in medical care, going from help with clinical diagnostics, therapy also, regulatory help to diminish courses of events of new medication advancement. It might likewise be of advantage as an adjuvant in clinical decision making [9]. Dermatology, as an outwardly escalated field, is at the cliff of an AI unrest. The relationship for the headway of AI characterizes it as "the logical information on the systems hidden mind and insightful way of behaving and its execution in machines" [10]. Simulated intelligence utilizes PC frameworks to achieve undertakings that would commonly require human knowledge, for example, recognizing the sort of bloom or perceiving an individual's voice. To imitate the activities of the human mind, Computer based intelligence utilizes an assortment of innovations and procedures, including advanced mechanics, ML, and the web. Simulated intelligence can possibly surpass people, because of its unending handling power and capacity limit [11]. Apple's Siri, Amazon's Alexa, and Google Assistant are the most famous examples of AI as of now being used by common individuals [12].

There are three main steps for automatic analysis of dermoscopy

- Feature selection And extraction
- Image segmentation
- Feature classification.

Image segmentation plays an important role in digital image processing.

This process is organised by different steps:-
Section 2 - clarifies the relative work of different methods.

Section 3 - digital segmentation methods has been discussed.

Section 4 - provide evaluation criteria

Section 5 - all results are calculated

In final section 6 -presenting the discussion.

3. Methodology:

Figure 1 shows the overview of the proposed method and execution of data based on K means clustering . The major steps involved :(i) Dataset processing ,(ii) Pre processing and (iii) segmentation . The result of these steps is a segmented image.

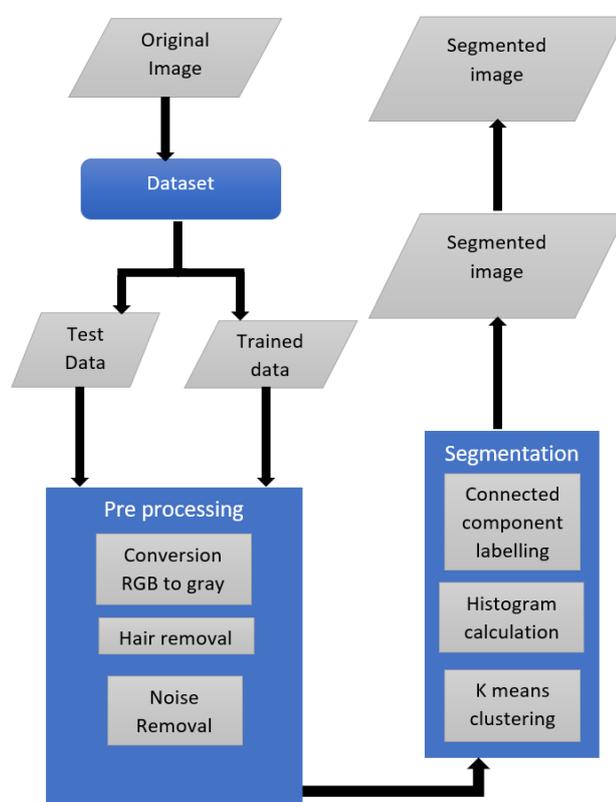


Figure 1:- Flow of the Proposed approach.

Dataset

Kaggle is a great platform containing real time data and also gives a balanced data format for the proper execution of the process. To make this project effective we use a dataset named as “Skin Cancer : Malignant Vs Benign”. This dataset contains two folders ”train” and “test” shown in figure 2.

Each folder contains two sub folders named as “Malignant” and “Benign”, which contains the images of malignant and benign skin cancer.

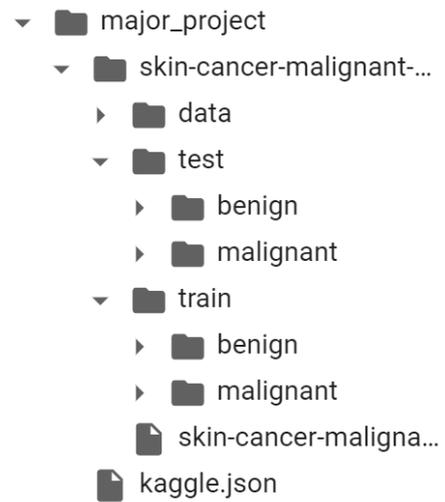


Figure :-2 “Train” and “Test” Folder in Dataset

Figure :- 3 “Malignant” and “Benign” Folders

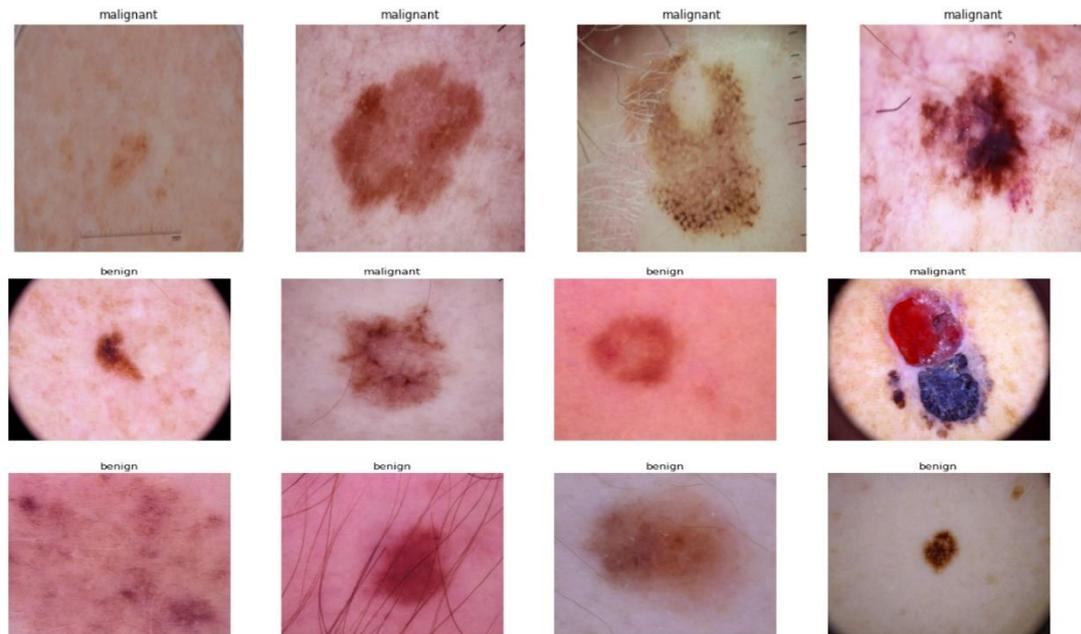


Figure :-4 Sample images from the dataset

Table 1 contains the summarised description of the dataset used for this project.

Dataset	Skin Cancer : Malignant Vs Benign
Type	Medical Images
Image size	224 pixels x 244 pixels
Number of images	3,297
Image type	JPEG (RGB)
Class labels	0: Malignant 1: Benign

Table 1 Dataset information

Pre-Processing

It consist of three main steps:

- a. Conversion of colour image into grayscale.
- b. Hair Removal
- c. Image Filtering
- d. Image Smoothing

The initial step is changing over the RGB tone picture into a grayscale picture. From that point onward, the blue shading channel from the picture is picked. It has been tentatively affirmed that the blue tone directly in dermoscopy pictures presents the best contrast among sores and the skin, along these lines getting the best outcome for division.

Conversion of colour image into grayscale

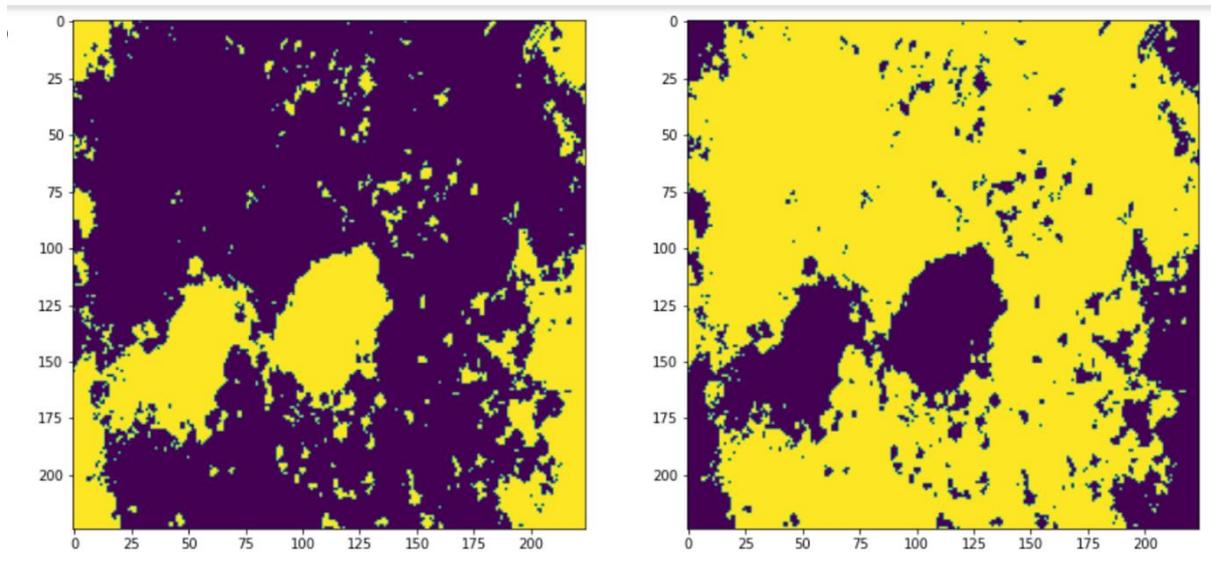


Figure :- 5 Conversion of RGB into Grey

Hair Removal

Medical pictures, for the most part, have some hair surfaces and intrinsic articles because of human nature. These influence division, accordingly we first and foremost eliminated these articles from the pictures. The morphological close separating is generally exact sifting among the rundown, this is the explanation that I picked. Morphological Close Filtering is utilised on grayscale pictures to eliminate the dim detail.

window with the mean of all the pixel values in the pixel values in the window. The kernel(window) is mostly square but can be any shape.

For Example:-

45	23	56
78	55	34
43	35	66

Unfiltered values

$$45+23+56+78+55+34+43+35+66/9=48$$

*	*	*
*	48	*
*	*	*

Filtered values

Image Filtering

Image filtering is the process of changing the apperence and removing the noise from an image by altering the colours of the pixels. As filtering is one of the important part of image processing we choose to use a mean filtering method for this project. The mean filter is a basic sliding - window spatial filter that replaces the central value in the

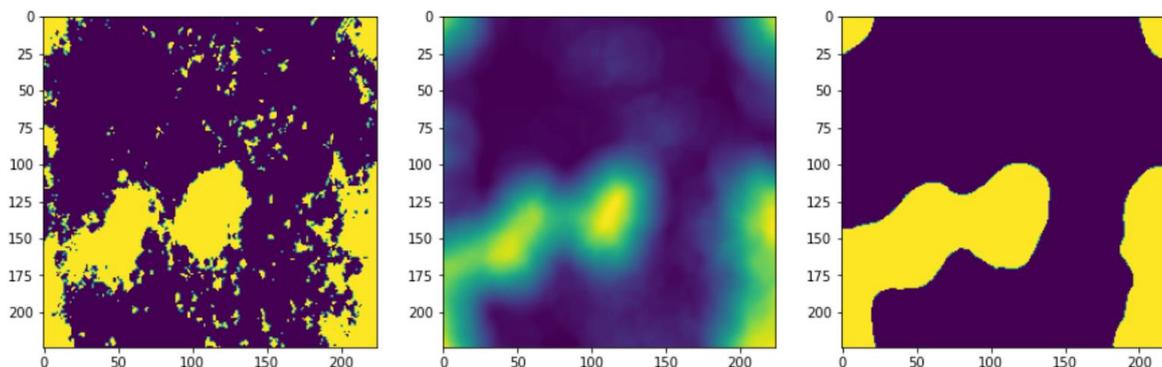


Figure :- 6 Filtration Process using mean filtering method

Image Smoothing

With the expulsion of hair from the dermoscopy picture, a few little, dim spots can stay, one reason is the hair may not be taken out totally. To resolve this issue, I utilised a middle channel to smooth the pictures. The middle channel is a non-direct smoothing strategy that replaces the first dark level pixels with the middle pixels in a predetermined region:

$$y(i,j)=\text{median} \{x(m,n),(m,n) \ 2 \ z(i,j)\} \quad (1)$$

In Equation 1, x is the info picture, y is the yield picture, and z is a region focused at picture facilitates (I, j) . This channel is valuable to decrease commotion. In our work, clamour is demonstrated by dull focuses.

4. Segmentation Method

Image Segmentation is a method that isolates a picture into disjoint areas that are comparable in certain elements, like force, shading, or surface. Every one of the districts that association should match to all pictures.

K-means Clustering

K-means clustering is a sort of unsupervised learning, which is utilised when you have unlabeled data (i.e., information without characterised classes or gatherings). The objective

of this calculation is to track down bunches in the information, with the quantity of gatherings addressed by the variable K . The calculation works iteratively to relegate every information to highlight one of K gatherings in view of the elements that are given. Information focuses are clustered in light of component compatibility.

Let us consider an image with resolution of $x \times y$ and the image has to be clustered into k numbers of clusters. Let $p(x, y)$ be an input pixel to be cluster and c_k be the cluster centres. The algorithm for k means

clustering is following as:

1. Initialise the number of cluster k and centre.
2. For each pixel of an image, calculate the Euclidean distance d , between the centre and each pixel of an image using the relation given below.

$$d = \| p(x, y) - C \|$$

3. Assign all the pixels to the nearest centre based on distance d .
4. After all pixels have been assigned, recalculate new position of the centre using the relation given below.

$$C = 1/k(\sum_{y \in C} \sum_{x \in C} p(x,y))$$

5. Repeat the process until it satisfies the tolerance or error value.
6. Reshape the clustere pixel into an image.

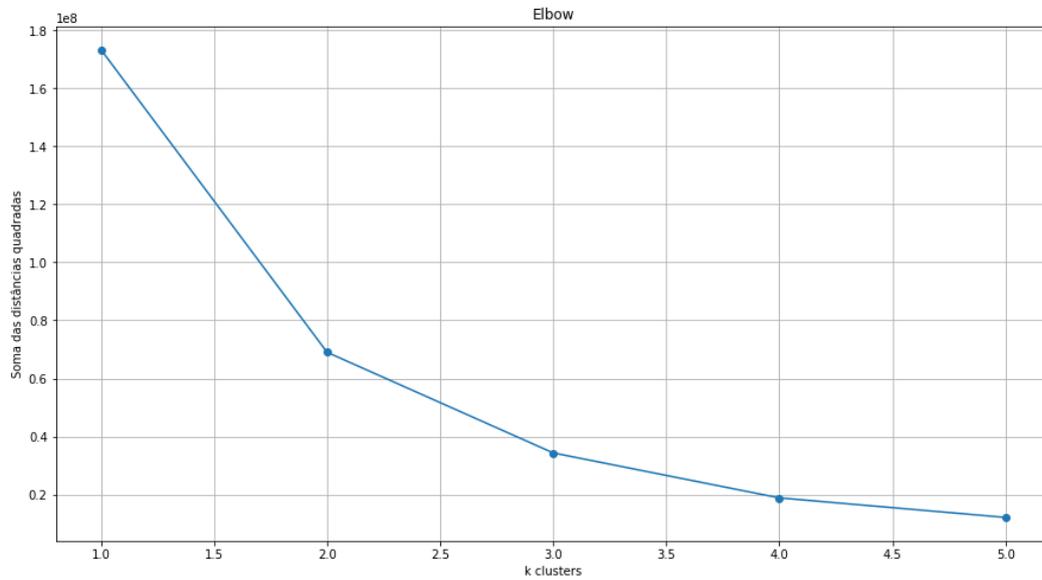


Figure :- 7 Elbow graph shows the number of clusters

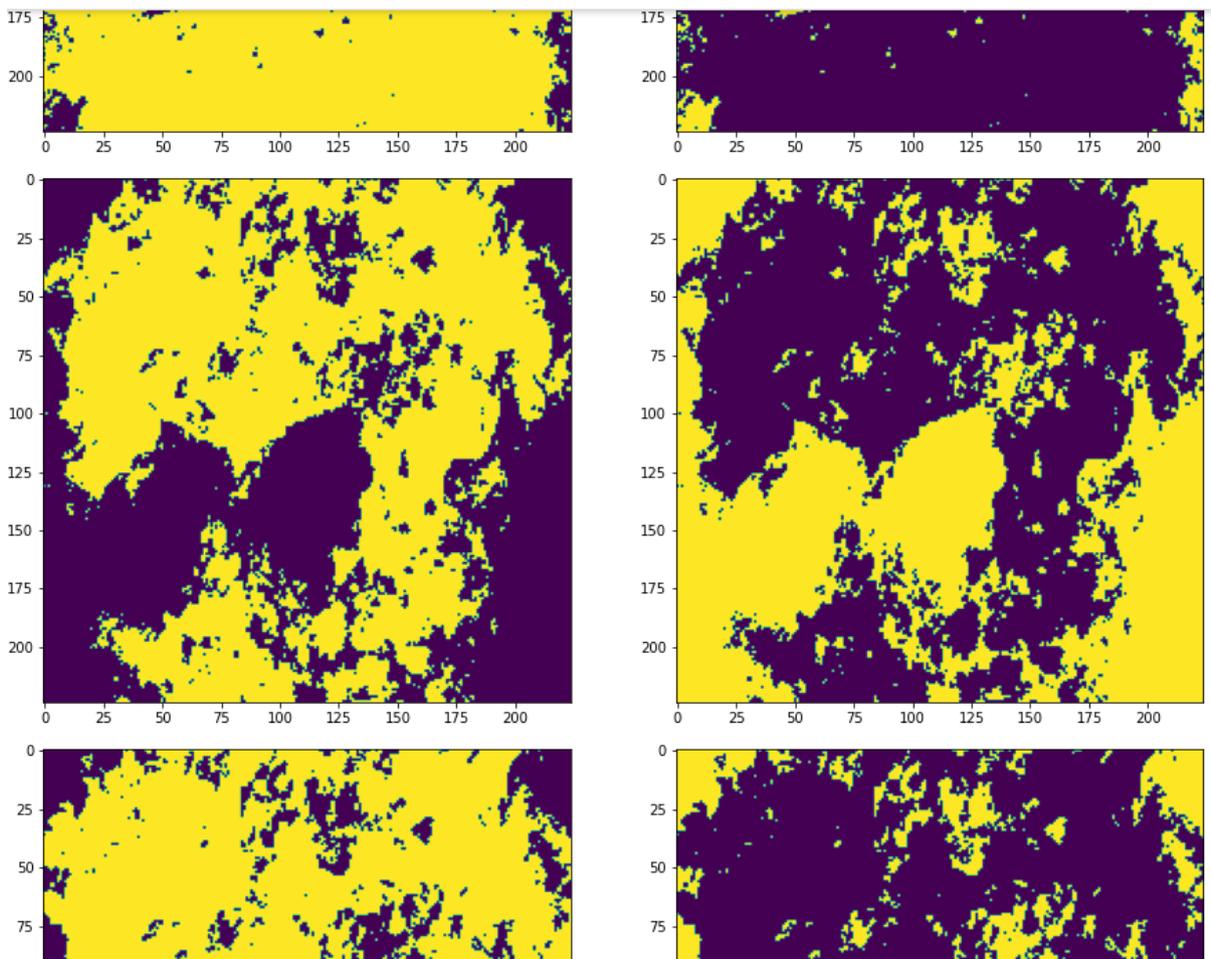


Figure :- 8 Cluster formation

Loss Function

Loss function measures how far an expected worth is from its actual worth. A loss function maps

choices to their related expenses. Misfortune capacities are not fixed, they change contingent upon the assignment close by and the objective to be met.

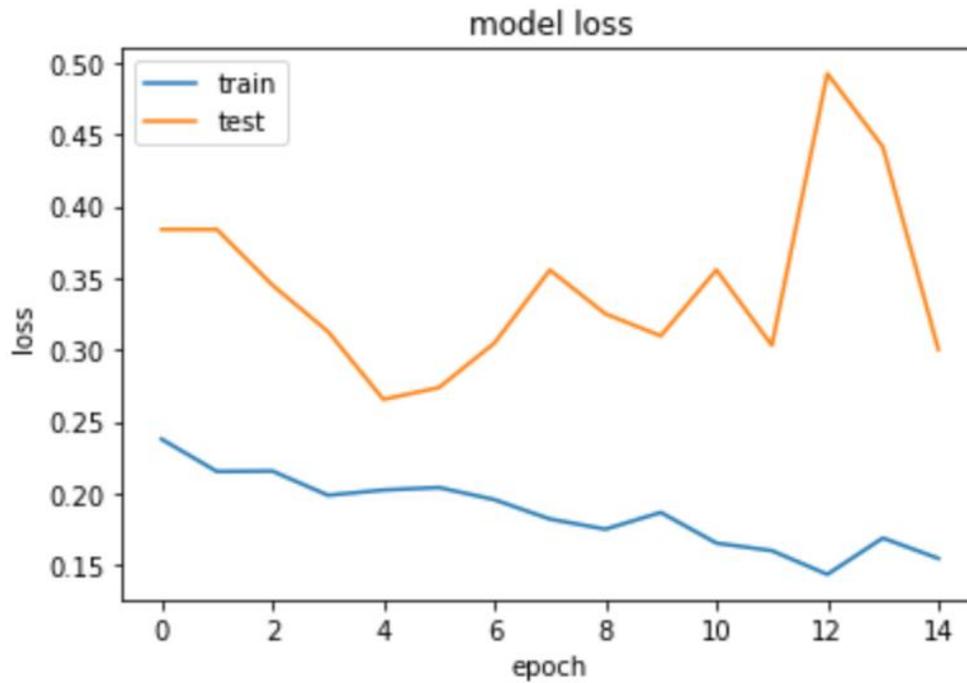


Figure :- 9 Loss curve for train and test

5. Evaluation Criteria

There are various boundaries that are utilised with the depiction of responsiveness, particularity furthermore exactness. The terms are: True Positive (TP) which alludes to the presence of the infection, the nonattendance of the illness True Negative (TN), TP and TN show a dependable outcome between the demonstrative examination and the demonstrated infection. False Negative (FN), and False Positive (FP), though each analytic examination are not right, so when the experimental outcome shows an infection that doesn't exist in the patient the experimental outcome is considered as FP. Furthermore in the event that the test neglects to demonstrate the illness that exists in the patient without a doubt, the outcome is FN. Both FP and FN show that the indicative result struggles with the genuine circumstance.

Specificity = $TN / (TN + FP)$

(Number of true negative/Number of all negative)

Accuracy

Accuracy is defined as the proportion of the samples correctly classified out of the total number of samples and can be defined as follows:

Accuracy = $(TP + TN) / (TP + TN + FP + FN)$

(Number of positive assessment/Number of all assessment)

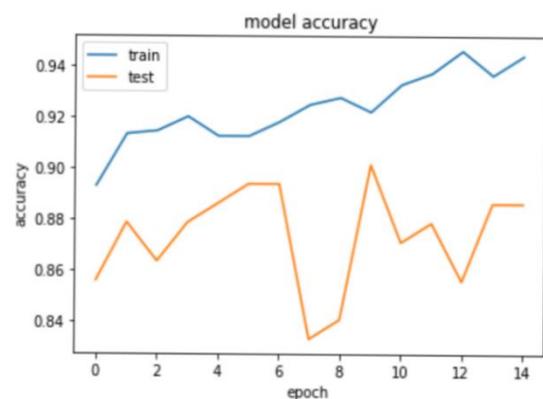


Figure:-10 Accuracy curve

5. Discussion and Comparison

A few segmentation algorithms have been recommended to apply to this issue, involving four significant kinds of strategy: thresholding, edge/contour based, region based, what's more, bunching based strategies. Numerous analysts have been chipping away at PC vision draws near to skin-cancer detection. To segment skin cancer in an information picture, existing frameworks utilize

manual, self-loader, or completely programmed techniques.

Our work to distinguish skin cancer growth is proposed. Two distinct techniques; segmentation,

also, new proposals inside this work named k-means clustering technique considering locale developing are analyzed.

157/157 - 2s - loss: 0.2379 - accuracy: 0.8930 - val_loss: 0.3839 - val_accuracy: 0.8561
Epoch 2/20
157/157 - 2s - loss: 0.2153 - accuracy: 0.9134 - val_loss: 0.3839 - val_accuracy: 0.8788
Epoch 3/20
157/157 - 2s - loss: 0.2156 - accuracy: 0.9146 - val_loss: 0.3451 - val_accuracy: 0.8636
Epoch 4/20
157/157 - 2s - loss: 0.1988 - accuracy: 0.9202 - val_loss: 0.3128 - val_accuracy: 0.8788
Epoch 5/20
157/157 - 2s - loss: 0.2024 - accuracy: 0.9126 - val_loss: 0.2655 - val_accuracy: 0.8864
Epoch 6/20
157/157 - 2s - loss: 0.2042 - accuracy: 0.9126 - val_loss: 0.2737 - val_accuracy: 0.8939
Epoch 7/20
157/157 - 2s - loss: 0.1957 - accuracy: 0.9182 - val_loss: 0.3048 - val_accuracy: 0.8939
Epoch 8/20
157/157 - 3s - loss: 0.1822 - accuracy: 0.9250 - val_loss: 0.3556 - val_accuracy: 0.8333
Epoch 9/20
157/157 - 2s - loss: 0.1751 - accuracy: 0.9277 - val_loss: 0.3251 - val_accuracy: 0.8409
Epoch 10/20
157/157 - 2s - loss: 0.1868 - accuracy: 0.9222 - val_loss: 0.3098 - val_accuracy: 0.9015
Epoch 11/20
157/157 - 3s - loss: 0.1654 - accuracy: 0.9329 - val_loss: 0.3557 - val_accuracy: 0.8712
Epoch 12/20
157/157 - 2s - loss: 0.1602 - accuracy: 0.9373 - val_loss: 0.3031 - val_accuracy: 0.8788
Epoch 13/20
157/157 - 2s - loss: 0.1436 - accuracy: 0.9461 - val_loss: 0.4925 - val_accuracy: 0.8561
Epoch 14/20
157/157 - 2s - loss: 0.1600 - accuracy: 0.9265 - val_loss: 0.4414 - val_accuracy: 0.8964

Figure :- 11 Table of Accuracy

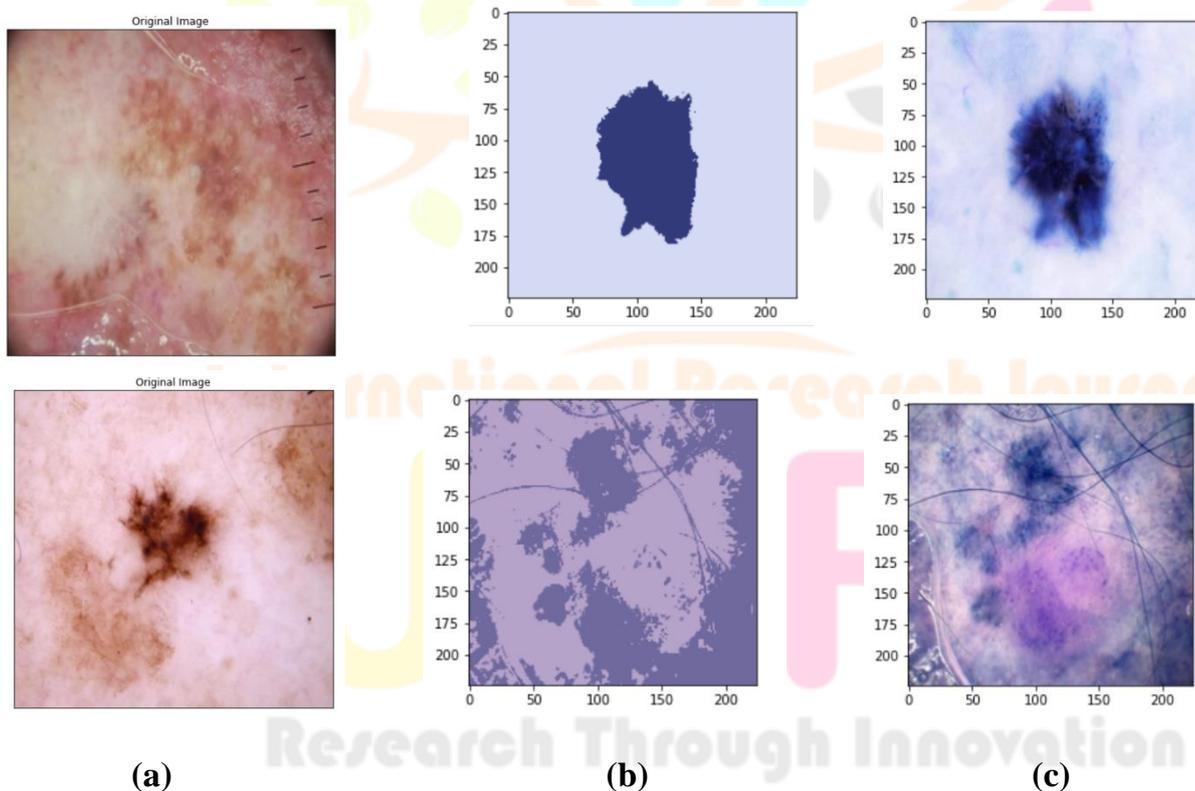


Figure :- 12 Result of the project shows three parts (a) Original image (b) the region where cancer is present (c) segmented image

6. Conclusion

Melanoma skin cancer is the most generally analyzed kind of malignant growth. As the quantity of cases develops every year, powerful, fast, and early detection of melanoma is important. If skin cancer is recognized in beginning phases, it very well might be dealt with without any problem. The removal of skin-cancer lesions in the final stages is

costly, while in beginning phases lesions are simple and affordable to treat.

To repeat, this project was fully intent on creating k-means clustering models to analyze and recognize skin cancer from sore pictures. It moreover investigated the information expansion method as a preprocessing step to reinforce the grouping strength of the k-means model. The best

model, to be specific our machine learning model, is working with an accuracy of 86.4%.

7. References

- [1] S. Salih, S.A-Rahim et al., "Comparison of skin image between segmented curve" *Journal of Theoretical and Applied Information Technology* 30th September 2018. Vol.96. No 18
- [2] Xin Zheng, Qinyi Lei, Run Yao, Yifei Gong and Qian "Image segmentation based on adaptive K-means algorithm" *EURASIP Journal on Image and Video Processing* (2018) 2018:68 <https://doi.org/10.1186/s13640-018-0309-3>.
- [3] Nameirakpam Dhanachandra*, Khumanthem Manglem and Yambem Jina Chanu "Image Segmentation using K-means Clustering Algorithm and Subtractive Clustering Algorithm" *National Institute of Technology, Manipur 795 001, India Procedia Computer Science 54 (2015) 764 – 771*.
- [4] Mohammad Naved Qureshia, Mohd Vasim Ahamadb,* ,* *Electrical Engineering Section, University Polytechnic (Boys), Aligarh Muslim University, India, Procedia Computer Science 132 (2018) 534–540*.
- [5] Mohamed A.Hamada et al., "Multi-Spectral Image Segmentation Based on the K-means Clustering" *International Journal of Innovative Technology and Exploring Engineering (IJITEE)* ISSN: 2278-3075, Volume-9 Issue-2, December 2019.
- [6] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial nets," in *Proc. Adv. Neural Inf. Process. Syst.*, 2014, pp. 2672–2680.
- [7] L. Ding, M. H. Bawany, A. E. Kuriyan, R. S. Ramchandran, C. C. Wykoff, and G. Sharma, "A novel deep learning pipeline for retinal vessel detection in fluorescein angiography," *IEEE Trans. Image Process.*, vol. 29, pp. 6561–6573, 2020, doi: 10.1109/TIP.2020.2991530.
- [8] Y. Enokiya, Y. Iwamoto, Y.-W. Chen, and X.-H. Han, "Automatic liver segmentation using U-Net with Wasserstein GANs," *J. Image Graph.*, vol. 6, no. 2, pp. 152–159, 2018.
- [9] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation," in *Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Intervent.*, 2015, pp. 234–241.
- [10] Q. Zhang, Z. Cui, X. Niu, S. Geng, and Y. Qiao, "Image segmentation with pyramid dilated convolution based on ResNet and U-Net," in *Proc. Int. Conf. Neural Inf. Process.*, 2017, pp. 364–372, doi: 10.1007/978-3-319-70096-0_38.
- [11] A. Abdollahi, B. Pradhan, and N. Shukla, "Road extraction from high-resolution orthophoto images using convolutional neural network," *J. Indian Soc. Remote Sens.*, vol. 49, pp. 1–15, Nov. 2020.
- [12] V. Mnih, "AI for airborne picture naming," Ph.D. dissertation, Dept. Comput. Sci., Univ. Toronto, Toronto, ON, Canada, 2013.
- [13] C. Henry, S. M. Azimi, and N. Merkle, "Street division in SAR satellite pictures with profound completely convolutional brain organizations," *IEEE Geosci. Remote Sens. Lett.*, vol. 15, no. 12, pp. 1867–1871, Dec. 2018.
- [14] A. Abdollahi, B. Pradhan, and A. Alamri, "VNet: An end-to-end fully convolutional neural network for road extraction from highresolution remote sensing data," *IEEE Access*, vol. 8, pp. 179424–179436, 2020.
- [15] J. Wang, J. Song, M. Chen, and Z. Yang, "Road network extraction: A brain dynamic system in view of profound learning and a limited state machine," *Int. J. Remote Sens.*, vol. 36, no. 12, pp. 3144–3169, Jun. 2015.
- [16] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, Z. Wojna, Rethinking the beginning engineering for PC vision, in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (2016)*
- [17] K. He, X. Zhang, S. Ren, J. Sun, Deep leftover learning for picture acknowledgment, in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (2016)*
- [18] C. Szegedy, S. Ioffe, V. Vanhoucke, A.A. Alemi, Inception-v4, origin ResNet and the effect of leftover associations on learning, in *31st AAAI Conference on Artificial Intelligence, AAAI 2017 (2017)*
- [19] A.G. Howard et al., *MobileNets*. arXiv Prepr. arXiv1704.04861 (2017) 18. A. Baratloo, M. Hosseini, A. Negida, G.El Ashal, Part 1: Simple Definition and Calculation of Accuracy, Sensitivity and Specificity. (Emergency, Tehran, Iran, 2015)
- [20] P. Li, Y. Zang, C. Wang, J. Li, M. Cheng, L. Luo, and Y. Yu, "Street network extraction by means of profound learning and line fundamental convolution" in *Proc. IEEE Int. Geosci. Remote Sens. Symp. (IGARSS)*, Beijing, China, Jul. 2016, pp. 1599–1602, doi: 10.1109/IGARSS.2016.7729408.
- [21] T. Panboonyuen, P. Vateekul, K. Jitkajornwanich, and S. Lawawirojwong, "An enhanced deep convolutional encoder-decoder network for road segmentation on aerial imagery," in *Proc. Int. Conf. Comput. Inf. Technol. Cham*,

Switzerland: Springer, 2017, pp. 191–201, doi: 10.1007/978-3-319-60663-7_18.

[22] Y. Wang, J. Seo, and T. Jeon, “NL-LinkNet: Toward lighter but more accurate road extraction with nonlocal operations,” *IEEE Geosci. Remote Sens. Lett.*, early access, Jan. 26, 2021, doi: 10.1109/LGRS.2021.3050477.

[23] G. Cheng, Y. Wang, S. Xu, H. Wang, S. Xiang, and C. Pan, “Programmed street discovery and centerline extraction by means of fell start to finish convolutional brain organization,” *IEEE Trans. Geosci. Remote Sens.*, vol. 55, no. 6, pp. 3322–3337, Jun. 2017.

[24] Y. Xu, Z. Xie, Y. Feng, and Z. Chen, “Road extraction from high-goal remote detecting symbolism utilizing profound learning,” *Remote Sens.*, vol. 10, no. 9, p. 1461, Sep. 2018.

[25] P. Luc, C. Couprie, S. Chintala, and J. Verbeek, “Semantic segmentation using adversarial networks,” 2016, arXiv:1611.08408. [Online]. Available:

<http://arxiv.org/abs/1611.08408>

[26] X. Zhang, X. Han, C. Li, X. Tang, H. Zhou, and L. Jiao, “Aerial image road extraction based on an improved generative adversarial network,” *Remote Sens.*, vol. 11, no. 8, p. 930, Apr. 2019.

[27] C. Yang and Z. Wang, “An ensemble Wasserstein generative adversarial network method for road extraction from high resolution remote sensing images in rural areas,” *IEEE Access*, vol. 8, pp. 174317–174324, 2020.

[28] X. Lv, D. Ming, Y. Chen, and M. Wang, “Very high goal remote detecting picture characterization with SEEDS-CNN and scale impact investigation for superpixel CNN order,” *Int. J. Remote Sens.*, vol. 40, no. 2, pp. 506–531, Jan. 2019.

[29] Y. Wei, Z. Wang, and M. Xu, “Xu, “Road structure refined CNN for street extraction in ethereal picture,” *IEEE Geosci. Remote Sens. Lett.*, vol. 14, no. 5, pp. 709–713, May 2017.

[30] Z. Hong, D. Ming, K. Zhou, Y. Guo, and T. Lu, “Street extraction from a high spatial goal remote detecting picture in light of more extravagant convolutional highlights,” *IEEE Access*, vol. 6, pp. 46988–47000, 2018, doi: 10.1109/ACCESS.2018.2867210.

[31] Aswani V.S., and Hema S. (December 2017). Progressed melanoma location utilizing

ABCD Rule. ISSN (PRINT): 2393-8374, (ONLINE): 2394-0697, VOLUME-4, ISSUE12, 2017.

[32] Jiang, Y.Q.; Xiong, J.H.; Li, H.Y.; Yang, X.H.; Yu, W.T.; Gao, M.; Zhao, X.; Ma, Y.P.; Zhang, W.; Guan, Y.F.; et al. Perceiving basal cell carcinoma on cell phone caught advanced histopathology pictures with a profound brain organization. *Br. J. Dermatol.* 2020, 182, 754–762.

[33] Cruz-Roa, A.A.; Ovalle, J.E.A.; Madabhushi, A.; Osorio, F.A.G. A deep learning design for picture portrayal, visual interpretability and mechanized basal-cell carcinoma disease identification. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*; Springer: Berlin/Heidelberg, Germany, 2013; pp. 403–410. [34] Xie, P.; Zuo, K.; Zhang, Y.; Li, F.; Yin, M.; Lu, K. Interpretable Classification from Skin Cancer Histology Slides Using Deep Learning: A Retrospective Multicenter Study. *ArXiv190406156 Cs Q-Bio* [Internet]. 12 April 2019. Available online: <http://arxiv.org/abs/1904.06156> (accessed on 22 June 2021).

[35]. Nelson, C.A.; Perez-Chada, L.M.; Creadore, A.; Li, S.J.; Lo, K.; Manjaly, P. Patient points of view on the utilization of computerized reasoning for skin malignant growth screening: A subjective report. *JAMA Dermatol.* 2020, 156, 501–512. [CrossRef]

[36] Oh, S.; Kim, J.H.; Choi, S.-W.; Lee, H.J.; Hong, J.; Kwon, S.H. Physician confidence in artificial intelligence: An online mobile survey. *J. Med. Internet Res.* 2019, 21, e12422.

[37] M.S. Mabrouk, A.Y. Sayed, H.M. Afifi, M.A. Sheha, A. Sharwy, Fully automated approach for early detection of pigmented skin lesion diagnosis using ABCD, *J. Healthc. Inf. Res.* (2020) 1–23.

[38] S. Sachdeva, Fitzpatrick skin composing: applications in dermatology, *Indian J. Dermatol. Venereol. Leprol.* 75 (1) (2009) 93–96.

[39] R.C. Gonzalez, R.E. Woods, S.L. Eddins, *Digital Image Processing Using MATLAB*, Pearson Education India, 2004.

[40] R. Dobrescu, M. Dobrescu, S. Mocanu, D. Popescu, Clinical pictures characterization for skin malignant growth conclusion in view of consolidated surface and fractal examination, *WISEAS Trans. Biol. Biomed.* 7 (3) (2010) 223–232.