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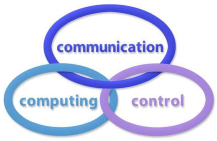

CCC Publications

Residual Generative Adversarial Adaptation Network for the Classification of Melanoma

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Abstract

The capability of recognising skin cancer in its earliest stages has the potential to be a component that saves lives. It is of the utmost importance to devise an autonomous technique that can be relied upon for accurate melanoma detection using image analysis. In this paper, Generative adversarial network (GAN) with suitable preprocessing is used to classify the labels for the detection of melanoma skin types. The simulation is run to evaluate the effectiveness of the model about several performance measures, such as accuracy, precision, recall, f-measure, percentage error, Dice coefficient, and Jaccard index. These are all performance measures that are taken into consideration. These metrics for measuring achievement are as follows: The results of the simulations make it exceedingly clear that the proposed TE-SAAGAN is more effective than the existing GAN protocols when it comes to recognising the test images.
***Keywords*:** Melanoma, Adversarial Network, Skin Cancer, Classificaiton

1 Introduction

Cancer of the skin is one of the forms of the disease that is identified with greater frequency than any other type (Ahmad, B, 2021). Given that the skin is the largest organ in the body, it should not come as a surprise that skin cancer is the most prevalent form of the disease in humans. (Ahmed, N, 2022) Melanoma and nonmelanoma are the two principal types of skin diseases (Codella, N. C, 2018., Joson, N, 2022) that can develop. Melanoma is the more dangerous of the two.

Melanoma, a severe form of skin cancer that is exceedingly uncommon but almost always results in mortality, is incurable, which means that there is no treatment that can be given to treat it. Melanoma is a type of skin cancer that only makes up 1% of all cases of skin cancer, but it has a greater death rate than any other type of skin cancer (Kumar, A. S, 2021). Melanoma accounts for only 1% of all cases of skin cancer. Melanocytes are

the cells that are targeted by melanoma the vast majority of the time when it does this. The process begins when a cancerous mass is created since an abnormal growth of melanocytes that are otherwise functioning normally. This growth results in the melanocytes becoming larger than normal. Targeting any part of a person physique is not considered inappropriate.
Melanoma is a form of cancer that is the only kind that can be cured if it is found in its early stages; otherwise, it will metastasize and lead to a painful death(Maiti, A, 2021). Melanoma can only be treated if it is discovered in its early stages. Melanoma is a sort of skin cancer, and there are several subtypes of melanoma, including nodular melanoma, surface spreading melanoma, acral lentiginous, and lentigo maligna (Rawat, V, 2022). Nodular melanoma is the most common subtype of melanoma. These cancer cells do not pose much of a threat to the spread of the disease to other organs or tissues throughout the body. Because cancers that are not caused by melanomas are simpler to treat than melanomas, the incidence of these cancers is much higher (Saeed, J, 2021). Deep learning is a technique that has only been around for a short while, but it has already made a significant contribution to the field of machine learning in the past few years. Its primary focus is on elaborate techniques for artificial neural networks, which places it at the forefront of the artificial intelligence and machine learning fields (Teodoro, A. A, 2022). The results that deep learning systems have achieved in these disciplines are remarkable, particularly when compared to the results that more traditional machine learning methods have achieved. In the previous years, several deep learning strategies have been incorporated into software that detects for skin cancer (Zhou, Y, 2023). The Data Mining Techniques for Patients Healthcare Analysis by (Poloju et al. 2022) focuses on the application of data mining techniques for analyzing healthcare data during the COVID-19 pandemic. (Kalaivani, K et al. (2023)) investigate the effectiveness of deep learning models in analyzing and predicting these signals, potentially offering valuable insights for medical diagnostics and treatment. (Indira, D et al. (2022)) explores the application of an artificial neural network architecture for the diagnosis of brain cancer cells. The technique focuses on incorporating state order dataset estimation techniques to enhance the accuracy of the neural network.
In this research, it discuss the background and concept of GANs, they do not explicitly compare or contrast it with other methods. However, the authors provide their motivation for using GANs as follows:
• GANs have shown promising results in image-to-image translation tasks, which is essential for accurately classifying melanoma images.
• By using GANs, the authors aim to enhance the feature extraction capabilities of the network, allowing for more robust classification performance.
• The authors also note that GANs can be used for data augmentation, which can address the issue of imbalanced and limited melanoma datasets.
Therefore, the authors' motivation for using GANs in their proposed method is to improve the accuracy and robustness of melanoma classification, as well as to address issues related to imbalanced and limited datasets.
Overall, it may not have extensively discussed other methods in the introduction, they do provide a clear motivation for why they chose to use GANs in their proposed approach for melanoma classification.In this paper, we propose a novel autonomous Texture Enhanced - Self-Attention Adaptation Generative Adversarial Network (TE-SAAGAN), which is a modified version of Generative Adversarial Network and is used as a medical imaging technique to generate and classify melanoma images.

2 Background of GAN

GANs, which stands for generative adversarial networks, are an example of a type of deep learning architecture that is finding increasing application in the field of medical imaging. Because of the limited size of the dataset that is presently available, the use of GAN is required to generate fictitious images of lesions that give the impression of being realistic. When looking at public datasets, the distribution of skin lesions is highly skewed due to the prevalence of each type of skin lesion among individuals.
This results in a highly skewed distribution of skin lesions and it leads to a highly asymmetrical distribution of cutaneous lesions. The Merkel cell carcinoma (MCC), Kaposi sarcoma, and sebaceous carcinoma are not included in any of the existing imaging databases, it is possible to generate images of these rare or underrepresented lesion types using GAN. This can help make up for the fact that these kinds of tumours are not included in any of the other imaging databases.
In addition to the networks that are used for data categorization and the networks that segment images, there is a subset of neural networks known as generative networks. These networks are a type of neural network that generates new information. They are not capable of identifying images in the same manner as image classification and image segmentation networks are.
The formation of visual representations is accomplished by means of generative networks. The use of GANs has seen an exponential increase in prevalence ever since their introduction. Many researchers have proposed a variety of enhancements and modifications to this extensively applied method. Although GANs can generate

any kind of data, the field of imaging has been the most common application for them so far.
Alternating the processing of one image of interest from the training set and one image that was generated by the generator is a necessary component of a network that possesses the ability to differentiate. A network that is responsible for producing a realistic image based on arbitrary inputs is referred to as a generator, and the term generator applies to this network. Neural networks are used by this system to analyse images to determine whether they are authentic.
The training of both the generator networks and the categorization networks occurs at the same time. It is the job of the discriminant network, which can tell one image apart from another, to carry out this function. On the other hand, the discriminating network is tricked by the generative network, which attempts to deceive it by producing more realistic images. The discriminating network is tricked by the generative network.
When development of the system is complete, the discriminating network will be unable to tell the difference between real images and those produced by the generating network. Because the training process for the GAN is carried out without supervision and the discriminant is not responsible for carrying out classification, it is not essential to label the images that will be generated in advance. GANs are being utilised in this research endeavour to generate images of skin lesions, which include both benign and malignant varieties.
Style-based GAN, Conditional GAN (CGAN), etc. are utilised to generate images of skin lesions based on generative adversarial network models, as described in the works that were cited previously. The images of skin lesions were generated using these models, which were used.
In this study, we create images by synthesising them with the help of an algorithm that is based on a style-based general additive network architecture. The generation of an equal amount of image examples across all classes is one of our primary objectives. When it comes to the creation of high-resolution images, this method is by far the most effective strategy. Throughout the course of training, it generates final images of an incrementally better quality, and it opens the door to incorporating randomness and style transfer into the creation process.

3 Methodology

In this section, the research discusses the GAN as well as the attention models to classify the melanoma images. GAN is used in place of CNN in the technique that is being proposed so that the recognition process can be completed in a more manageable manner.

3.1 Pre-processing

In this study, the research combines several different established datasets on skin lesions to create a realistic situation that contains a substantial amount of training images. The images that were used to compile the Kaggle dataset came from a wide variety of sources, which is why the dataset includes such a wide variety of image sizes.
Processing was required to recalculate the values of the observations, which was a direct consequence of the fact that this occurred. A central cut was made in WxW for each image, where W is the shortest dimension; this resulted in the production of square images. When it came to the measurements of the images, a central cut was made in WxW for each image.
By employing a method known as bicubic interpolation, the dimensions of the image were shrunk down to 256 pixels on each side. Because it is unlikely that the original image is square, merely resizing it in the application will cause the measurements to be distorted; as a result, it is necessary to crop the image in the centre. Cropping the image in the centre will ensure that the measurements are accurate. A reduced training set can be used to train GANs and CNNs, so the original image is downsampled. The time required to run the algorithm that gets rid of hair is getting shorter and shorter as the scale of the image gets smaller and smaller.
As soon as the appropriate conclusion was reached, the processing was carried out to get rid of the stray threads that had been left over. Because these lesions can appear anywhere on the skin, hair in the affected region can sometimes get in the way and obscure the true appearance of the pigmented scar. This happens because these lesions can appear anywhere on the skin.
A method for the removal of hair was developed to find a solution to this issue. This algorithm is made up of two primary components: one of them is an object detector, and the other is a technique for inpainting. Both components work together to create the algorithm. These two components share the ability to manipulate colour images in their respective workflows. When it comes to identifying objects, a combination of shifts and subtle colour are used.
There are a total of eight distinct modifications that can be made, and each one of them will rotate the parameters of the filters that are currently being utilised. Following the completion of these steps, the research then perform a subtraction by first selecting the set that is applied to the image after the hairs have been located to remove them completely. This step occurs after the hairs have been located.

3.2 Generative Adversarial Network

The dataset that was used for the purpose of skin lesion classification is not representative of the population. To training a GAN, fresh data specifically pertaining to melanoma were developed. The only images of melanoma-type skin cancers that were used for this cohort came from the original dataset, and they were used for this cohort specifically.

A greater number of images in the training collection leads to higher-quality outcomes from the GAN, during the training process of a GAN, there should not be any images that are left unused, and this is because there should be no unused images. Because there are fewer image examples in the melanoma class, the original dataset is supplemented with synthetic images using the one and only melanoma dataset.

The only melanoma dataset has fewer than 10,000 images, which makes it a very limited dataset. Melanoma is a type of skin cancer. Melanoma is a subtype of the cancer that affects the epidermis. to find a solution to this problem, the writers of this study employ a Differentiable Augmentation network in addition to a TE-SAGAAN network. Since this body of work, it has been proposed that data augmentation strategies be used to generate additional images for the GAN generating and discriminating networks.

It was determined to use a GAN that had already been trained for facial imaging as a seed to advance the training process much more quickly. This was done by using a GAN that had been trained for facial imaging. When contrasted with a GAN learned with random weights, the training process for a network that detects skin lesions begins with face synthesis. This guarantees that subtleties such as skin colour and texture are reused, which in turn reduces the amount of time that is required to complete a particular metric.

When the GAN had finished processing 3 million images at a resolution of 256x256 pixels and a batch size of 8 for both the input and output images, the training phase of the GAN was considered to be complete. Following the completion of GAN training phase, the algorithm that produces fictitious images of skin diseases could then be put into action.

The only component of the GAN algorithm that is utilised in the process of creating synthetic images of skin lesions is the generation element of the GAN. A total of 48,247 images were taken to maintain a balance between the number of melanoma cases and the number of instances that did not involve melanoma. The inclusion of such many additional images ensures that the information is distributed reasonably evenly between the various kinds of cases, including melanoma.

Texture Enhancement – SAGAAN A GAN-based network architecture known as a discriminator network and another network architecture known as a generator network are both suggested as potential components in this piece of research. The functionality of the feature extraction module of the generator network is characterised by the function G(ILR;G), in which the values G and (wL,bL) represent the weights and biases of the layer that contains the neural network. In other words, the function G(ILR;G) describes the functionality of the feature extraction module. The following steps were performed to produce a network that had received comprehensive training:

$$I_{HR} = G\theta G(I_{LR}) \tag{1}$$

where

IHR – higher image resolution, and

ILR – lower image resolution.

The parameters of the training network need to be optimised in such a way that guarantees the IHR will be as close to the sample distribution of IHR as is practically feasible. This is something that needs to be done to guarantee the accuracy of the IHR.

$$\theta G = argminN - 1 \sum (ILR, IHR) \tag{2}$$

where

L(IHR,ILR) - reconstruction error

The discriminator D parameters are defined as D. the training parameters are converted into LR-HR image as follows:

$$minGmaxDV(D\theta D, G\theta G) = E_{IHR}\ P_{data}(I_{HR})[logD\theta G(I_{HR})] + E_{ILR}\ pG(I_{LR})[log(1 - D(G\theta G(I_{LR})))] \tag{3}$$

The equation that was just mentioned is an expression of the core concept that, within the framework of a GAN, the generator network G is adequately trained (Figure 1).

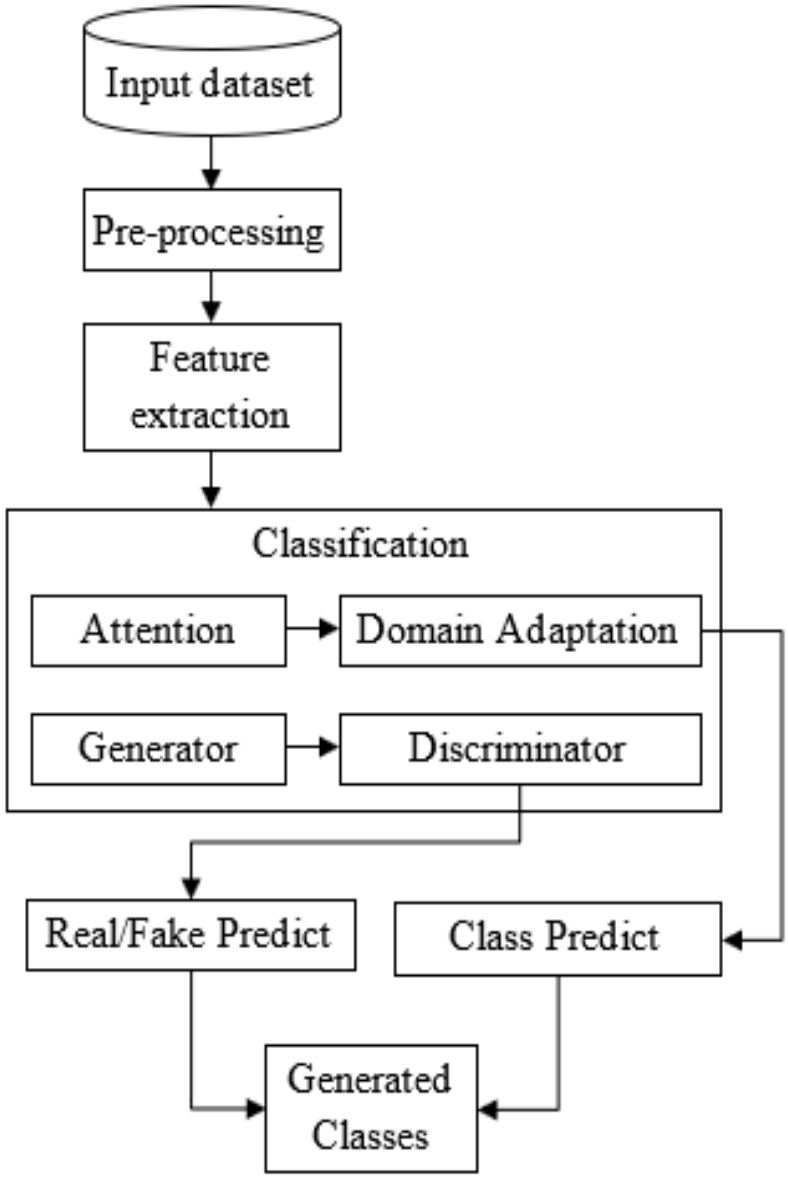


Figure 1: TE-SAGAAN

A discriminator network referred to as D is responsible for performing analysis on the incoming images received from the remote sensing system. It is the responsibility of this network to determine which of the images are authentic and which are fabricated. to reduce the likelihood that the discriminator will error the ILR sample for a false one, the generator, during the latter part of the process, simulates the ILR sample by making use of Pdata, which is the actual sample. This is done so that the probability of the discriminator mistaking the ILR sample for a false one is reduced x. There is continuous surveillance, in addition to the iterative adjustments that are made to the configuration settings of the network.

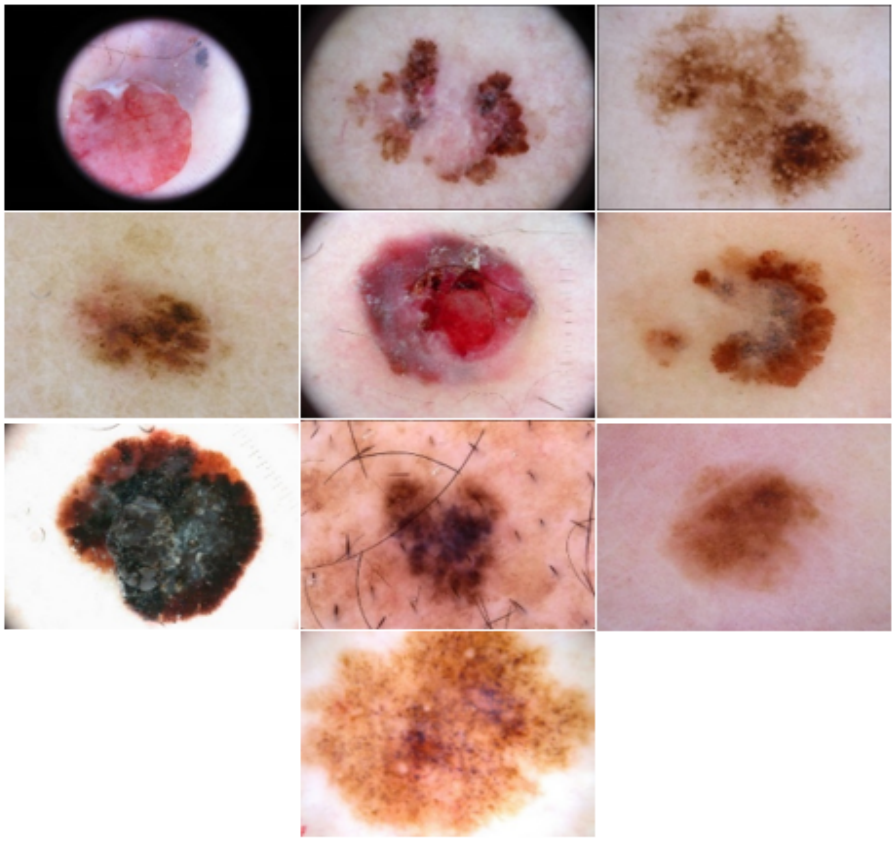
The discriminator has a difficult time determining whether the input samples can be depended upon because the generator capacity to accommodate the simulation is continuously being improved. Models that have been properly trained are able to generate novel data sources of a high quality and make inferences about the underlying probability distributions of the samples. Generator of TE-SAGAN

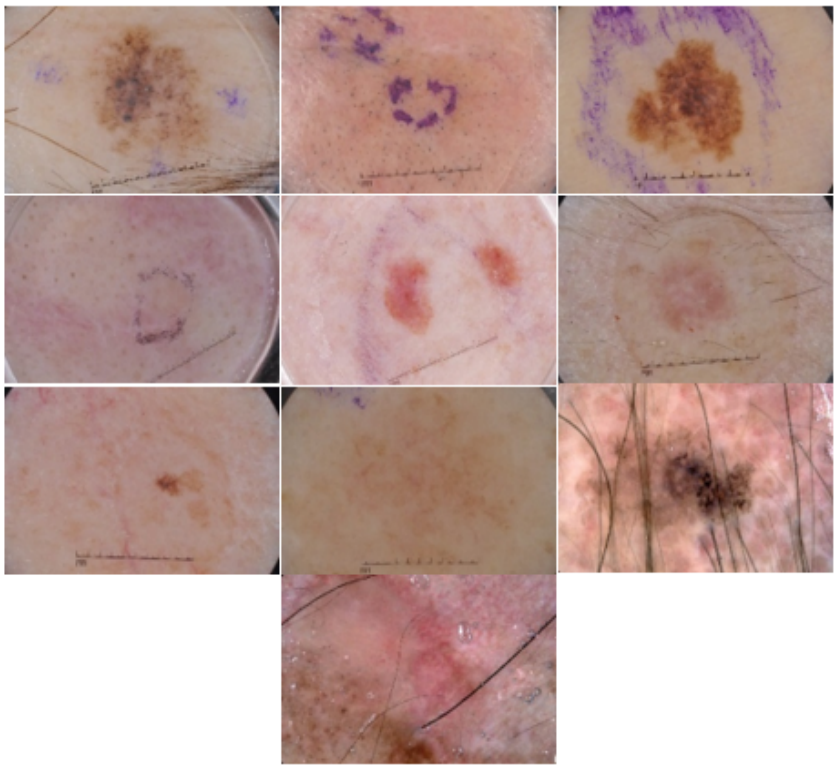
One of the limitations of the existing convolution modules is referred to as local perception, and it prohibits them from making use of global information that is located at great distances. This implies that HR imagery acquired through remote sensing cannot be used. TE-generator SAGAN was designed with a low-frequency feature extractor, a deep residual dense block, a self-attention module, and WN to improve the border and global information extraction from remote sensing images. One of the driving forces behind the creation of the self-attention component of the network was the capacity of the network to extract more generalised characteristics from the objects it was analysing. This research utilised WN as an alternate method to the more common batch normalisation (BN) procedure that is carried out in neural networks. This research aimed to eradicate image artefacts and stabilise network training as its two primary objectives.

In the generator network, a convolution layer is utilised, and then a WxN layer comes after it. This is done so that the low-frequency characteristics can be retrieved. This convolution layer utilises a three-three as its kernel. Because of its tightly connected ensemble as well as its ability to pass over residuals, the RRDB sticks out as a top-tier module when it comes to the process of extracting nonlinear features. RRDB can learn both shallow and deep semantic features, which enables it to enhance low-level feature extraction and allows it to learn both types of features. The output of the RRDB feature-flow was combined with the residual layer that was present before it. It is fed into the SAM component, which is where it was used to generate worldwide context maps.

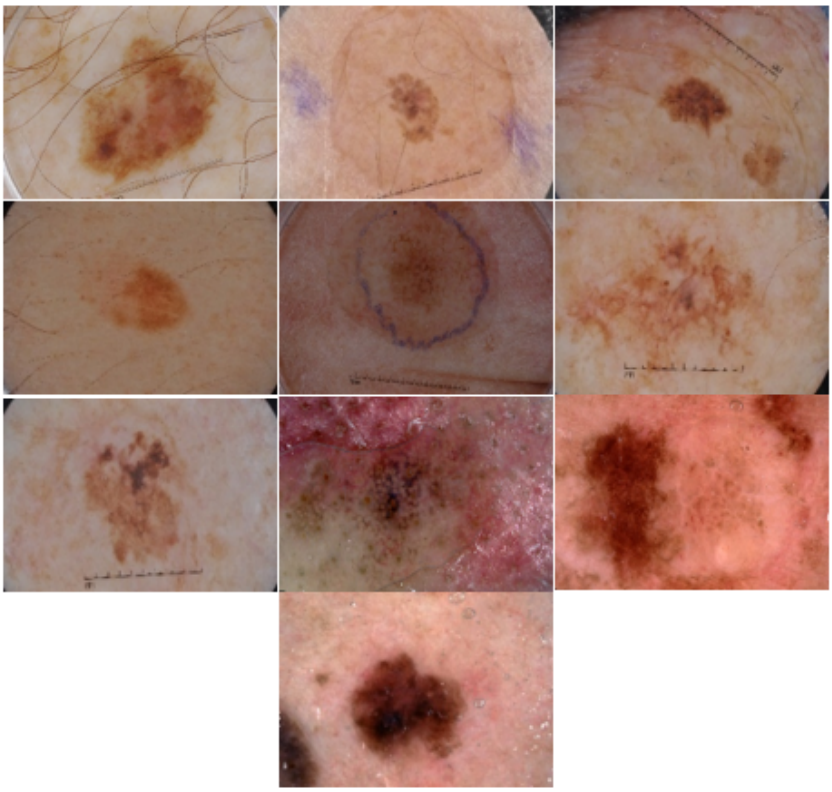
4 Results and Discussions

In this section, we will compare the model that we have proposed to some models that have already been developed. The coding is done in Python version 3.8 with the TensorFlow version 2.0.0 library, and the tests are performed on an Intel i7-6850 processor with an Nvidia GTX 1080 graphics processing unit (GPU). The Melanoma Detection Dataset is utilised to evaluate and validate not only the proposed model but also other methods that are currently in use datasets. Figure 2 shows the final products of the illustrations for all the models. It illustrate the degree of accuracy achieved by each model prediction for a variety of categories. We make use of a total of 1,000 images, dividing them up as follows: 900 for instruction and 200 for evaluation. These model results are used to determine the values of accuracy, precision, recall, f-measure, the dice coefficient, and the Jaccard index (JI).





(b) Test



(c) Validaiton

Figure 2: Datasets for training/testing/validation

Table 1: Training Results

Image	Accuracy	Precision	Recall	Dice	Jaccard
1	0.9628	0.9157	0.9878	0.9489	0.9101
2	0.8949	0.9892	0.8121	0.8977	0.8197
3	0.9661	0.9596	0.9698	0.9567	0.9248
4	0.9729	0.9494	0.9828	0.9598	0.9300
5	0.9882	0.9704	0.9903	0.9743	0.9573
6	0.9743	0.9127	0.9472	0.9503	0.9127
7	0.8946	0.7539	0.9766	0.8568	0.7539
8	0.9814	0.9643	0.9854	0.9657	0.9417
9	0.9356	0.9272	0.9198	0.8790	0.7893
10	0.9809	0.9906	0.9798	0.9419	0.8969
11	0.9819	0.9703	0.9846	0.9659	0.9414
12	0.9849	0.9812	0.9853	0.9612	0.9332
13	0.9681	0.9757	0.9667	0.9219	0.8617
14	0.9602	0.9696	0.9577	0.9194	0.8568
15	0.9078	0.9803	0.8798	0.8483	0.7409

Table 2: Testing Results

Image	Accuracy	Precision	Recall	Dice	Jaccard
1	0.9610	0.9139	0.9860	0.9471	0.9083
2	0.8939	0.9882	0.8110	0.8967	0.8187
3	0.9646	0.9581	0.9683	0.9552	0.9234
4	0.9721	0.9486	0.9820	0.9589	0.9292
5	0.9863	0.9685	0.9883	0.9724	0.9554
6	0.9726	0.9110	0.9455	0.9487	0.9110
7	0.8925	0.7520	0.9744	0.8548	0.7520
8	0.9806	0.9635	0.9846	0.9649	0.9409
9	0.9348	0.9263	0.9190	0.8782	0.7884
10	0.9790	0.9887	0.9779	0.9401	0.8951
11	0.9807	0.9691	0.9834	0.9647	0.9402
12	0.9846	0.9808	0.9850	0.9609	0.9328
13	0.9658	0.9733	0.9644	0.9196	0.8594
14	0.9590	0.9684	0.9565	0.9182	0.8556
15	0.9060	0.9785	0.8781	0.8466	0.7392

Table 3: Validation Results

Image	Accuracy	Precision	Recall	Dice	Jaccard
1	0.9594	0.9123	0.9844	0.9455	0.9068
2	0.8933	0.9876	0.8105	0.8961	0.8182
3	0.9651	0.9586	0.9688	0.9557	0.9238
4	0.9707	0.9472	0.9806	0.9576	0.9279
5	0.9838	0.9661	0.9859	0.9700	0.9530
6	0.9732	0.9116	0.9461	0.9492	0.9116
7	0.8917	0.7513	0.9737	0.8540	0.7513
8	0.9794	0.9623	0.9834	0.9637	0.9397
9	0.9339	0.9255	0.9181	0.8774	0.7876
10	0.9784	0.9881	0.9773	0.9395	0.8945
11	0.9783	0.9667	0.9810	0.9622	0.9378
12	0.9840	0.9802	0.9844	0.9603	0.9322
13	0.9672	0.9748	0.9658	0.9210	0.8607
14	0.9586	0.9680	0.9561	0.9178	0.8552
15	0.9039	0.9762	0.8760	0.8446	0.7375

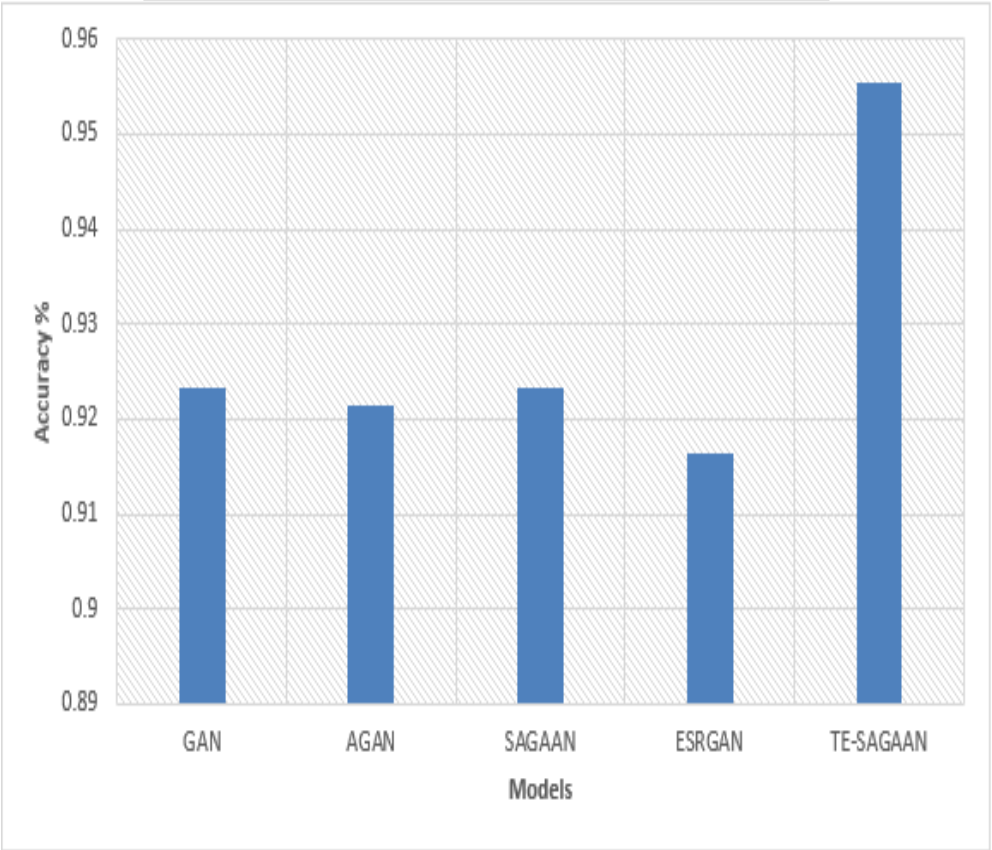


Figure 3: Accuracy

Table 1-3 and Figure 3 illustrates the accuracy is found when comparing the recently proposed TE-SAAGAN to the already existing GAN, AGAN, SAGAAN, and ESRGAN. The results of simulations conducted on a variety of subtypes of melanoma show that the proposed method is superior to the methods that are currently considered state-of-the-art. Following the successful extraction of the labels, TE-SAAGAN enables categorization. The results of the simulation provide evidence that the approach that was proposed is effective. The conclusion that can be drawn from this is that the proposed model has a higher true positive rate than any combination of the true negative rate, the false positive rate, and the false positive rate.

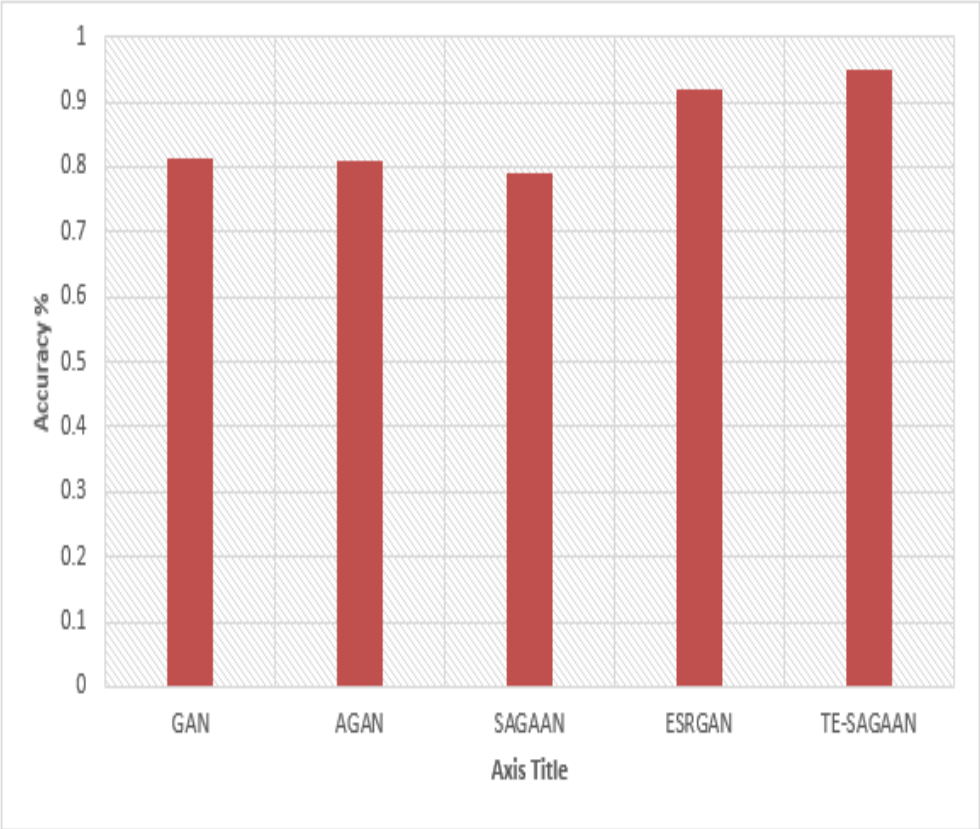


Figure 4: Precision

Figure 4 presents the results of a comparison between the precision measurements obtained by the proposed TE-SAAGAN and those obtained by the existing GAN, AGAN, SAGAAN, and ESRGAN. The results of simulations performed on various types of melanomas show that the proposed technique can achieve a higher precision rate than the methods that are currently in use. Following the accurate extraction of labels, TE-SAAGAN is the tool that makes classification feasible. There is a distinct exam for each topic covered in the course. The result of this is that the true-positive rate of the proposed model is higher than the sum of its true-positive rate and its false-positive rate.

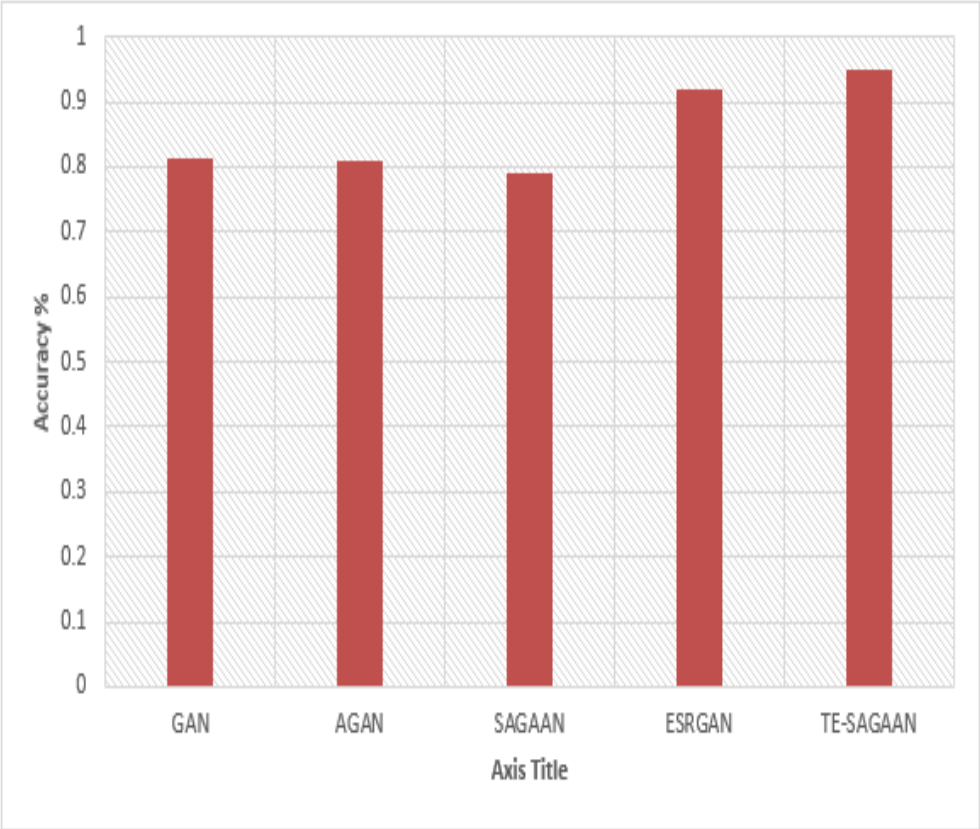


Figure 5: Recall

According to the results of simulations involving multiple types of melanomas, it is abundantly obvious that the proposed method offers an improvement over the state-of-the-art in terms of recall. In Figure 5, we can see a comparison of the memory findings for the existing GAN, AGAN, SAGAAN, and ESRGAN with the recall findings for the proposed TE-SAAGAN. Separate examinations are conducted on the various courses. As a result, the proposed model has a true-positive rate that is higher than the sum of its true-positive rate and its false-negative rate.

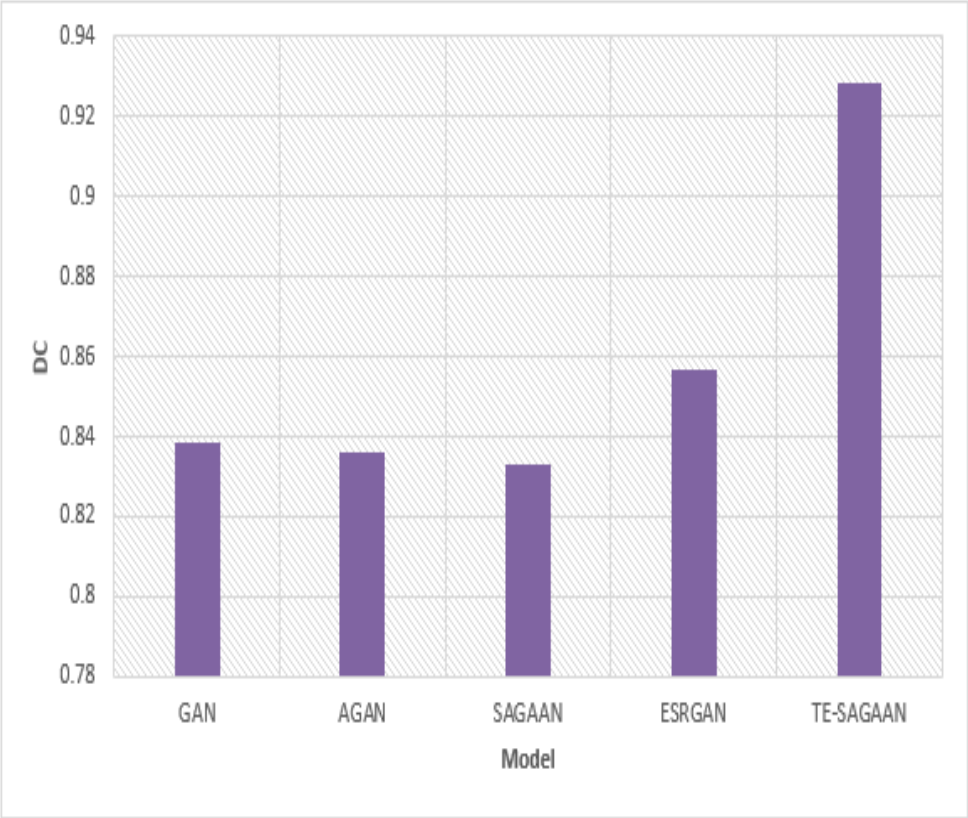


Figure 6: DC

Figure 6 presents the results of the DC analysis that compares the recently proposed TE-SAAGAN to the GAN, AGAN, SAGAAN, and ESRGAN that are already in existence. The results of the simulations performed on a variety of subtypes of melanoma show that the strategy that was proposed represents an advancement over the state of the art in terms of the DC rate. The results demonstrate that the proposed model does not take into consideration the rate of false negatives to the same extent that the methods that are currently being used.
Figure 7 presents the findings of the dice-coefficient analysis performed on the proposed TE-SAAGAN in comparison to the GAN, AGAN, SAGAAN, and ESRGAN that are already in existence.
According to the findings, the TE-SAAGAN model performs better than the other existing methods when it comes to calculating the necessary dice coefficient for various kinds of skin cancer.

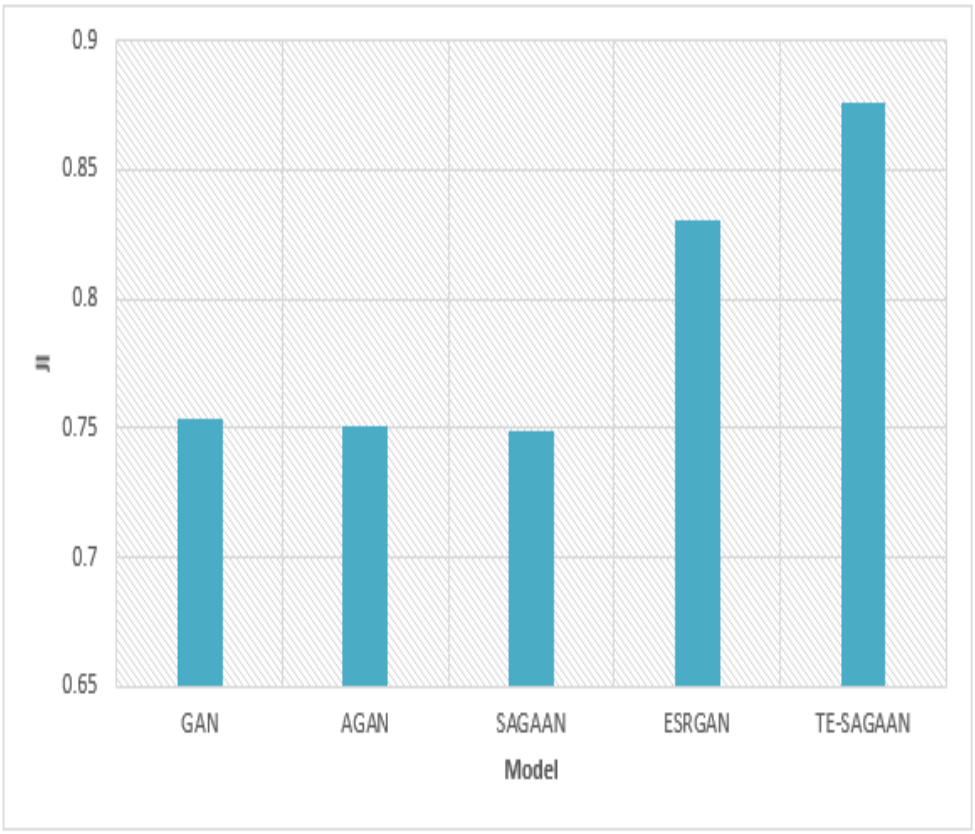


Figure 7: Jaccard Index

The implementation of the residual generative adversarial adaptation network (RGAA-Net) for the classification of melanoma in clinical practice would require further validation and testing. However, if the results of the study indicate high accuracy and robustness of the RGAA-Net in classifying melanoma images, it could have several potential applications in clinical practice, including:

• Improving diagnostic accuracy: Melanoma classification is a complex and challenging task, and the accuracy of diagnosis is critical for patient outcomes. By incorporating the RGAA-Net as a diagnostic tool, it may help clinicians accurately and efficiently classify melanoma images, leading to earlier detection and improved outcomes.

• Enhancing clinical decision-making: The RGAA-Net can provide a valuable tool for clinicians in making more informed clinical decisions. By providing accurate and reliable predictions, clinicians can better determine the most appropriate course of treatment for their patients.

• Facilitating telemedicine and remote consultations: Telemedicine has become increasingly popular, particularly during the COVID-19 pandemic. The RGAA-Net can be used to classify melanoma images in real-time, facilitating remote consultations between healthcare providers and patients. This could improve access to specialized care for patients in remote or underserved areas. Overall, the implementation of the RGAA-Net for the classification of melanoma in clinical practice has the potential to improve diagnostic accuracy, enhance clinical decision-making, and facilitate telemedicine and remote consultations. However, further research and validation are needed before it can be fully integrated into clinical practice.

5 CONCLUSION

In this study, we generate novel melanoma subtypes by using the TE-SAAGAN imaging technique, which is an improvement over conventional GANs since it -overcomes their limitations. In addition, the TE-SAAGAN is used as a binary classification module for six different sets of melanoma images so that the ability of the GAN models to make accurate predictions can be evaluated. When compared to the existing GAN protocols, the proposed method detection accuracy for the test images is significantly higher, and the production of the training images does not involve any mode problems. Through a series of experiments using a variety of datasets, it has been hypothesised that addressing imbalances in the data can lead to improved classification findings. However, even after categorization, the training data still needs to be fine-tuned quite a bit to ensure that everything is perfectly balanced. The presence of cancer in a lesion image is investigated in most of the research aimed at

detecting skin cancer. The research that has been done to date is, however, unable to answer the question posed by a patient regarding whether a specific skin cancer symptom expresses itself anywhere on their body. Studies conducted up to this point have solely focused on tackling the unique difficulty of signal image classification. This procedure will become more streamlined and effective as autonomous full-body imaging becomes more prevalent in mainstream medical practise.

Declaration:
Participation Consent and Ethical Approval: This procedure is carried out without the involvement of people. Rights of Humans and Animals: Animal and human rights are not being violated in any way.

Competing Interests:
There is no potential for a conflict of interest with this project.

References

[1] Ahmad, B., S. Jun, V. Palade, Q. You, L. Mao, and M. Zhongjie. 2021. "Improving skin cancer classification using heavy-tailed Student t-distribution in generative adversarial networks (TED-GAN)". Diagnostics. 11(11): 2147. DOI: 10.3390/diagnostics11112147

[2] Ahmed, N., X. Tan, and L. Ma. 2022. "A new method proposed to Melanoma-skin cancer lesion detection and segmentation based on hybrid convolutional neural network". Multimedia Tools and Applications. 1-24. DOI:10.1007/s11042-022-13618-0

[3] Codella, N. C., D. Gutman, M. E. Celebi, B. Helba, M. A. Marchetti, S. W. Dusza, and A. Halpern. 2018. "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. 168-172. DOI: 10.1109/ISBI.2018.8363547

[4] Joson, N., and M. S. Nair. 2022. "On the Performance of CNN and GAN models for Melanoma Classification". In 2022 2nd International Conference on Artificial Intelligence and Signal Processing (AISP). 1-6. DOI: 10.1109/AISP53593.2022.9760626

[5] Kumar, A. S., L. T. Jule, K. Ramaswamy, S. Sountharrajan, and A. H. Gandomi. 2021. "Analysis of false data detection rate in generative adversarial networks using recurrent neural network." In Generative Adversarial Networks for Image-to-Image Translation. 289-312. https://doi.org/10.1016/j.jjimei.2020.100004

[6] Maiti, A., B. Chatterjee, and K. C. Santosh. 2021. "Skin cancer classification through quantized color features and generative adversarial network". International Journal of Ambient Computing and Intelligence (IJACI). 12(3): 75-97. DOI:10.1016/j.matpr.2020.07.366

[7] Rawat, V., D. P. Singh, N. Singh, P. Kumar, and T. Goyal. 2022. "A Comparative Study of various Skin Cancer using Deep Learning Techniques." In 2022 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES).505-511. DOI:10.1109/CISES54857.2022.9844409

[8] Saeed, J., and S. Zeebaree. 2021. "Skin lesion classification based on deep convolutional neural networks architectures." Journal of Applied Science and Technology Trends. 2(1): 41-51. DOI:10.38094/jastt20189

[9] Teodoro, A. A., D. H. Silva, R. L Rosa, M. Saadi, L.Wuttisittikulkij, R. A. Mumtaz, and D. Z. Rodriguez. 2022. "A skin cancer classification approach using GAN and RoI-based attention mechanism". Journal of Signal Processing Systems. 1-14. DOI:10.1007/s11265-022-01757-4

[10] Zhou, Y., C. Koyuncu, C.Lu, R. Grobholz, I. Katz, A. Madabhushi, and A. Janowczyk. 2023. "Multi-site cross-organ calibrated deep learning (MuSClD): Automated diagnosis of non-melanoma skin cancer". Medical Image Analysis. 84: 102702. https://doi.org/10.1016/j.media.2022.102702

[11] Poloju, n.,& rajaram, a. (2022). Data mining techniques for patients healthcare analysis during covid-19 pandemic conditions. Journal of environmental protection and ecology, 23(5), 2105-2112.

[12] Kalaivani, K., Kshirsagarr, P. R., Sirisha Devi, J., Bandela, S. R., Colak, I., Nageswara Rao, J., & Rajaram, A. (2023). Prediction of biomedical signals using deep learning techniques. Journal of Intelligent & Fuzzy Systems, (Preprint), 1-14.

[13] Indira, D. N. V. S. L. S., Ganiya, R. K., Ashok Babu, P., Xavier, A., Kavisankar, L., Hemalatha, S., ... & Yeshitla, A. (2022). Improved artificial neural network with state order dataset estimation for brain cancer cell diagnosis. BioMed Research International, 2022.

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