Original Article

Skin Lesion Detection And Segmentation Using Deep Transfer Learning Approach

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Abstract

The recent depletion of the ozone layer due to industrial pollution has resulted in an increase in UV radiation, which is a significant environmental risk factor for invasive skin cancer and other keratinocyte tumors. Over the last few decades, cancerous deaths have increased alarmingly throughout the world. For dermatological diagnosis, deep learning has been practised successfully. This study, therefore, presents a deep-learning-based technique for automatically segmenting skin lesions and identifying skin cancers from dermoscopy images. The lesion is segmented from the adjoining areas of the skin by using the U-Net which limits the use of deep neural networks. This problem is resolved through the techniques of data augmentation and transfer learning. In our studies, we added a variety of augmentation effects to the training images to improve the data samples, and we utilised U-Net with dropout to solve the overfitting issue. On two separate datasets, the model was analysed. On the ISIC 2018 dataset, it had a mean Jaccard Index of 0.80 and an average dice score of 0.87. Using a transfer learning strategy, the trained model was evaluated against the PH dataset and got a mean dice score of 0.93 and an average Jaccard index of 0.87. A DCNN-SVM model was used to classify malignant melanoma, and to evaluate how well transfer learning is being used in the field of dermatological diagnosis, we compared cutting-edge deep architectures as feature extractors. On the PH2 dataset, our top model had an average accuracy of 93%.

Keywords: Deep learning, Segmentation, Skin cancer, Augmentation, transfer learning, Melanoma classification, Dermoscopy image.

1. INTRODUCTION

One of the most prevalent malignancies, skin cancer comprises about half of all cancer diagnoses globally [1]. Skin cancer affects more than five million individuals annually in the US alone. Melanocytes, a group of pigment-containing cells, give rise to melanoma which is a malignant skin cancer. The rate of incidence and fatality of melanoma in recent years has considerably increased. In the United States, there were about 10,000 new melanoma-related fatalities and about 87,000 new cases of melanoma recorded in 2017. A study predicts that in the US, the lifetime risk of getting malignant melanoma will rise to more than 1. But Melanoma can be treated if it will be diagnosed at an initial stage. Seborrheic keratosis, which is categorised as benign, is mistakenly used to describe melanoma. So, by supporting dermatologists, automated melanoma identification could increase diagnostic precision. [6] Pham et al. employed support vector machines, random forests, neural networks, data augmentation, and Inception-v4 for feature extraction to categorize skin lesions [1]. The authors of [2] introduced a deep learning system for categorizing melanoma utilizing a variety of pre-processing techniques, like morphological procedures and harmonic inpainting for eliminating hair from skin images. A comprehensive convolutional-deconvolutional framework is provided in [6] and uses vgg16 to classify lesions using transfer learning. This architecture achieves a Jaccard index of 0.507 on the ISIC 2017 dataset. For segmenting skin lesions, the authors of [7] introduced U-Net with residual connections. The article presents a transfer learning-based automated deep learning system for segmenting skin lesions and categorising various forms of cancer. The lack of sufficient data to train deep models in medical imaging is a drawback. To expand the training set, we added several extensions to the original training photos. For segmentation and classification problems, respectively, the ISIC 2018 and PH datasets were used to evaluate our model. The essay's remaining sections are organised as follows: In Section 2, the suggested methodology is covered. A thorough analysis of the findings is provided in the following part and lastly, a conclusion is drawn.

2 Methodology

The main goals of the approaches used in the present paper are lesion classification and lesion segmentation. Deep learning provides novel approaches for solving problems in different domains with very good accuracy. To train DCNNs for lesion segmentation, nevertheless, is challenging due to the lack of datasets for annotated dermoscopic images. U-Net with Data augmentation and dropout which is shown in Fig.1 is used for the segmentation task [23-24].

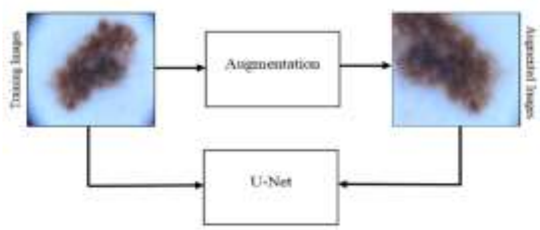

Figure 1: U-Net trainning with augmention Data

We offer a support vector machine (SVM)-based deep convolutional feature extractor approach for melanoma identification. Fig. 2 presents the overall categorization model [25].

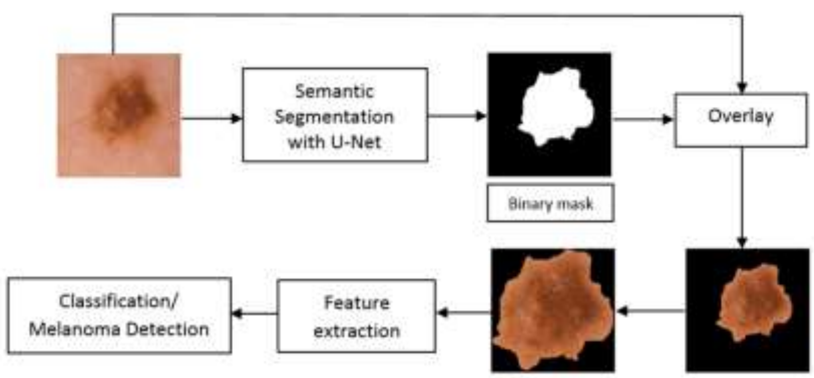

Figure 2: Proposed architecture for Melanoma detection

2.1 Dermoscopic Image Augmentation

Augmentation should be used with extreme caution since medical pictures are very sensitive to noise since too much augmentation can produce too many outliers, which can skew the distribution of the training data. In [1, 8], the authors improved the results by applying several data augmentation techniques to skin lesion images. In our proposed methodology, we utilized multiple types of image augmentation techniques to training data: random zoom, random flip, random brightness, random rotation, random contrast, Gaussian distortion, random colour, histogram equalization, and random elastic distortion [9]. The skin lesion images were obtained from various sources. As a result, the data augmentation is carried out in an approach that allows us to increase the variety of our training dataset without decreasing the accuracy of the training photos. For the test dataset, 390 of 2594 lesion pictures were initially kept. Through data augmentation, 2500 more lesion pictures were produced. Lastly, 3815 of the 5094 lesion mages were utilized to train the model and 889 photos for validation. Model variance is decreased by augmentation, while model generalization error is enhanced. Fig. 3 illustrates the augmented samples [26,27].

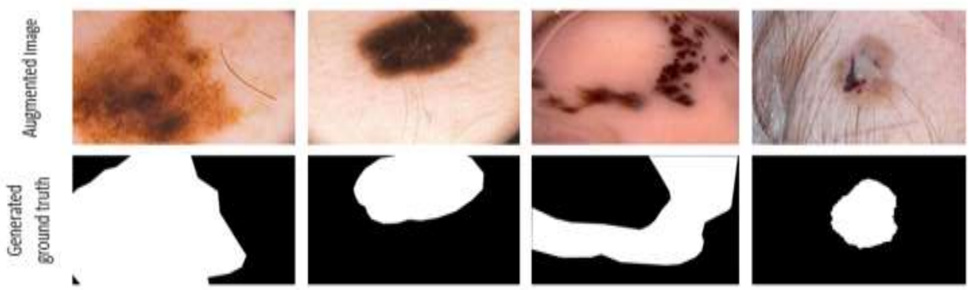

Figure 3: Augmented sample Images

2.2 Lesion Segmentation with U-Net

An effective fully convoluted network called U-Net has been suggested for biomedical image segmentation [10]. In this study, we developed a fully convolutional neural network framework that was inspired by U-Net and that can be continually trained to differentiate skin cancer lesions from Dermoscopic pictures. We employed batch normalisation and spatial dropout on our network, which demonstrated better efficiency. The network comprises recurring layers of two 33 convolutions with the same number of feature mappings. The activation function is ReLU, and the downsampling method is 22-max pooling. In the second half of the network, feature concatenation, two 33-convolutions, and a 22-up convolution are used to upsample the feature maps. A sigmoid activation and an 11 convolution are employed in the final layer. Fig. 4 and Table 1 both display the proposed model's elaborate network design. Gradient scaling and batch normalisation are used to decrease the network's internal covariance shift and enhance backpropagation performance. Along with data augmentation, spatial dropout is employed as a regularisation technique. Figure 6 illustrates the model's improved generalisation with dropout and augmentation [28]. 3815 photos were used to train the model over 100 epochs with a learning rate of 0.001. A 32-byte stack size was utilised with the Adam optimizer. The Dice coefficient loss approach was applied to train this network [29].

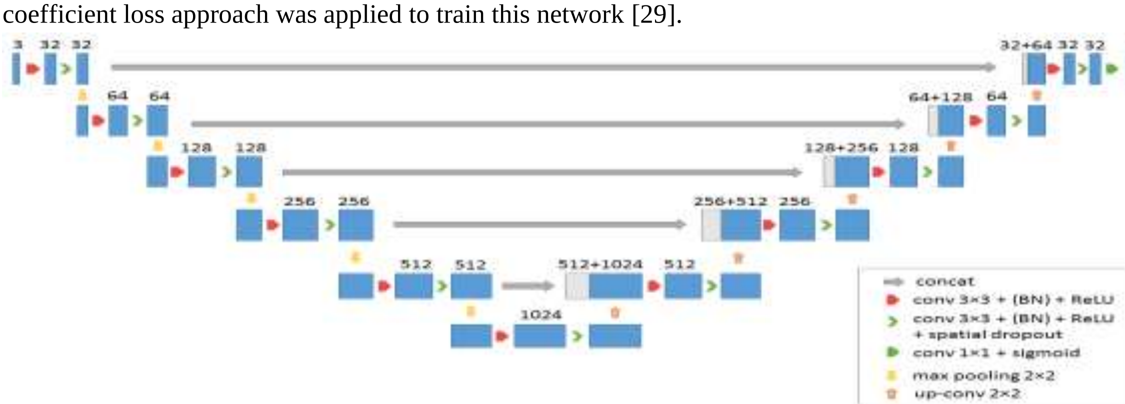

Figure 4: Proposed architecture for lesion Image Segmentation

2.3 Feature extraction with DCNN

Deep CNNs have shown remarkable success in solving many computer vision problems across multiple domains. The characteristics are retrieved by employing multiple convolutional and pooling layers layered together. The extracted features are given as input to a classifier. Mallat developed the mathematical study of Deep CNN as a feature extractor using scattering neural networks, when signals are given to convolutional layers that calculate semi-discrete wavelet transformations without pooling operations. This makes the network translation invariant and can be used as a feature extractor. It has been further pointed out that feature invariance depends on pooling operations and the depth of the network. The translational invariance property is determined by the network depth, whereas vertical translational invariance requires pooling [13,14]. Deep CNN feature a lot of parameters, therefore the network needs a lot of training data to be properly trained. Using a representation language from one domain in another is called as transfer learning, and it is a deep learning approach. On the representation map, a trained deep CNN may be used as a feature extractor with other machine learning models to tackle a particular problem. To extract features in this study, pre-trained Deep CNN that were trained on a large ImageNetdataset are used [15-16]. A deep CNN called DenseNet uses a lot of feature reuse. DenseNet provides numerous benefits over conventional models, such as dampening the vanishing gradient issue, resilient function Propagation, decreased feature sharing and parameters [17]. The Feature Extractor with DenseNet block architecture is depicted in Figure 5 [30].

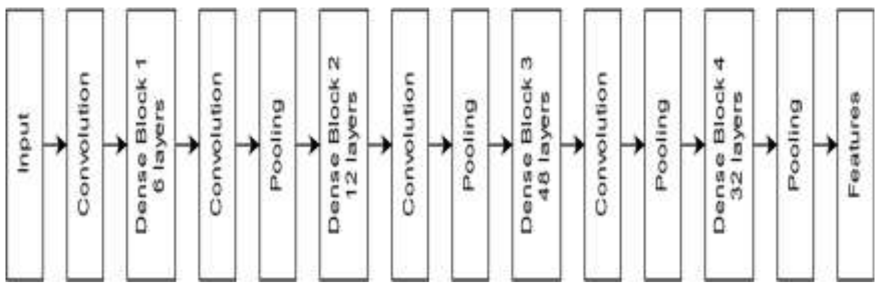

Fig.5. DenseNet Feature extraction

3 Result Analysis

The PH dataset and ISIC 2018 were used to test the model and evaluate the efficacy of our suggested segmentation procedure. 2500 extra training samples for the ISIC-2018 dataset were produced using the data augmentation technique. 390 of the 2594 training images were kept to test the model. Finally, 889 images out of 5094 were used for validating the model [18-20].

The model was then retrained on the PH data set [21]. The proposed model obtained the best outcomes on the PH dataset because transfer learning was used. During training, the model's two variations—U-Net with and without dropout—were assessed. In Fig. 7, U-Net with dropout and data augmentation had good generalisation capability and outperformed the initial segmentation model. The binary masks that the model predicted are compared in Figure 8. U-Net with augmentation and dropout prevent the model from overfitting and produced better results, as seen in Fig. 6 because augmentation and dropout functioned as a regularisation technique [31].

Table 2. SEGMENTATION RESULTS

Dataset	**Dice-coefficient score**	**Jaccardindex**
ISIC2018	0.87	0.80
PH^2	0.93	0.87

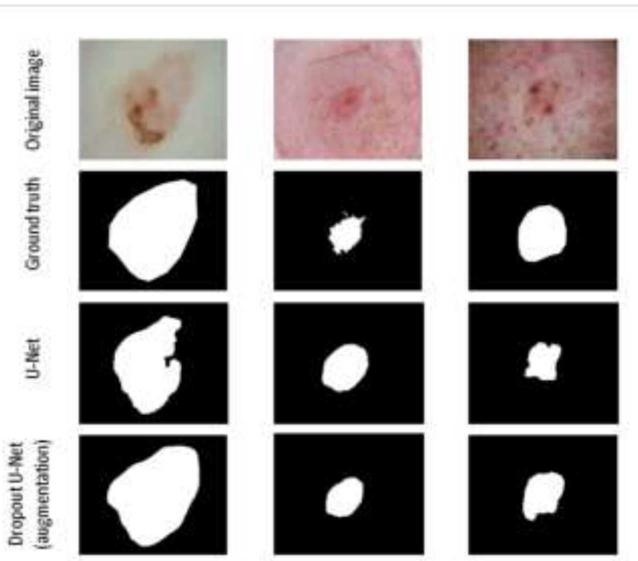

Fig.6. Predicted binary masks using U-Net and Dropout U-Net (augmentation)

Table 3. Classification results

"Feature-extractor	Total no.of features	Classifier	Accuracy with 10-fold cross-validation)
VGG-16	25088	SVM	0.89
		RandomForest	0.86
		DecisionTree	0.82
		Gradient boosting	0.91
		AdaBoost	0.89
VGG-19	25088	SVM	0.90
		RandomForest	0.86
		DecisionTree	0.76
		Gradient boosting	0.86
		AdaBoost	0.91
InceptionResNetV2	38400	SVM	0.90
		RandomForest	0.82
		DecisionTree	0.82
		Gradient boosting	0.88
		AdaBoost	0.88

ResNet50	2048		SVM			0.91	
			RandomForest			0.85	
			DecisionTree			0.85	
			Gradient boosting			0.88	
			AdaBoost			0.90	
Xception	100352		SVM			0.89	
			RandomForest			0.86	
			DecisionTree			0.79	
			Gradient boosting			0.82	
			AdaBoost			0.86	
InceptionV3	51200		SVM			0.89	
			RandomForest			0.81	
			DecisionTree			0.78	
			Gradient boosting			0.83	
			AdaBoost			0.86	
DenseNet201	94080		SVM			0.93	
			RandomForest			0.84	
			DecisionTree			0.83	
			Gradient boosting			0.84	
			AdaBoost			0.91”	

The segmentation performance parameters are summarized in Table 2, and a histogram analysis of the model's effectiveness is shown in Figure 8. We initially compared the most advanced deep CNN as feature extractors for classification, which may be employed with little additional training due to the little amount of training data. After extracting the features, we used various classifiers to categorize the lesion types, and we evaluated them by comparing our findings to the best practices currently available [32].

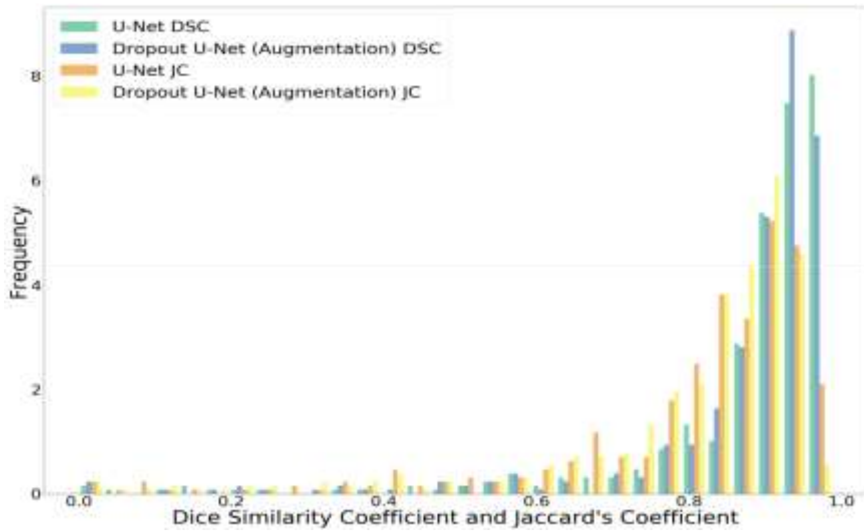

Fig.8. Histogram analysis of Dice Coefficient Score and Jaccard's Coefficient

In our experiment, DenseNet showed the best results on transfer learning as a feature extractor. DenseNet as a feature extractor and SVM as a classifier obtained the highest mean accuracy of 93% on the PH dataset. 200 dermoscopic pictures were utilised to examine the efficiency of the classification model for the diagnosis of melanoma (MEL). To extract the specific lesion area of interest from pictures, the input images and the binary masks generated by U-Net were combined. The generated image is then utilised to extract features. The features are utilized as input for a classifier. Due to the uneven distribution of this dataset, the class weight was enforced to train the SVM. For the validation of our model, 10-fold cross-validation is used. A comparative analysis was carried out with multiple possible feature extractor-classifier pairs. The obtained results are summarised in Table 3.

4 Conclusion

The paper demonstrated an automated deep-learning-based system for segmenting skin lesions and melanoma identification. There are various drawbacks to methods for tackling these problems that use parameterized algorithms that are challenging to fine-tune and deep neural networks that need a large training data. Due to the usage of additional augmented training images, U-Net with Spatial Dropout worked well. Transfer learning is useful in situations where there aren't enough data samples. Modern computer vision models that have been trained on natural pictures were employed as feature extractors to identify skin lesions from dermoscopy images, and they perform better. The model can also be used in a domain with limited data sample sizes due to its better generalisation capacity in automatic classification and segmentation. Future research could look into further augmentation methods to enhance the efficiency of the model. This model can be tested using various lesion images that were taken from people of various racial and ethnic backgrounds.

References

1. Pham, T.-C., Luong, C.-M., Visani, M., Hoang, V.-D.: Deep CNN and Data Augmentation for Skin Lesion Classification. In: Lecture Notes in Computer Science. pp.573–582 (2018).doi:10.1007/978-3-319-75420-8_54
2. Salido, J.A.A., De La Salle University, Philippines, Ruiz, C., Jr.: Using Deep Learning for Melanoma Detection in Dermoscopy Images. International Journal of Machine Learning and Computing. 8, 61–68(2018). doi:10.18178/ijmlc.2018.8.1.664
3. Kohli, J.S., Tolomio, E., Frigerio, S., Maurichi, A., Rodolfo, M., Bennett, D.C.: Common DelayedSenescenceofMelanocytesfromMultiplePrimary MelanomaPatients. J.Invest. Dermatol.137,766–768(2017).doi:10.1016/j.jid.2016.10.026
4. Ahmed, H.M., Al-azawi, R.J., Abdulhameed, A.A.: Evaluation Methodology between Globalization and Localization Features Approaches for Skin Cancer Lesions Classification. J. Phys.Conf.Ser.1003,012029(2018).doi:10.1088/1742-6596/1003/1/012029
5. 5. Glazer, A.M., Winkelmann, R.R., Farberg, A.S., Rigel, D.S.: Analysis of Trends in US Melanoma Incidence and Mortality.

JAMA Dermatol. (2016). doi:10.1001/jamadermatol.2016.4512
6. Thao, L.T., Quang, N.H.: Automatic skin lesion analysis towards melanoma detection. In: 2017 21st Asia PacificSymposiumonIntelligent andEvolutionarySystems(IES)(2017). doi:10.1109/IESYS.2017.8233570
7. Venkatesh, G.M., Naresh, Y.G., Little, S., O'Connor, N.E.: A Deep Residual Architecture for Skin Lesion Segmentation. In: Lecture Notes in Computer Science. pp.277–284 (2018).doi:10.1007/978-3-030-01201-4_30
8. Frid-Adar, M., Diamant, I., Klang, E., Amitai, M., Goldberger, J., Greenspan, H.:GAN- based synthetic medical image augmentation for increased CNN performance in liver lesion classification. Neurocomputing. 321, 321–331 (2018). doi:10.1016/j.neucom.2018.09.013
9. DBloice, M., Bloice, M.D., Stocker, C., Holzinger, A.: Augmentor: An Image Augmentation Library for Machine Learning. The Journal of Open Source Software. 2,432(2017). doi:10.21105/joss.00432
10. Ronneberger, O., Fischer, P., Brox, T.: U-Net: ConvolutionalNetworksforBiomedical
11. Image Segmentation. In: LectureNotesinComputerScience.pp.234–241(2015).doi:10.1007/978-3-319-24574-4_28
12. F. Chollet, Keras, https://github.com/fchollet/keras,2015.
13. Weiss, K., Khoshgoftaar, T.M., Wang, D.: A survey of transfer learning. Journal of BigData. 3, (2016). doi:10.1186/s40537-016-0043-6
14. Wiatowski, T., Bolcskei, H.: A Mathematical Theory of Deep Convolutional Neural Networks for Feature Extraction. IEEE Trans.Inf. Theory. 64, 1845–1866(2018). doi:10.1109/TIT.2017.2776228
15. Mallat, S.: Group Invariant Scattering. Commun. Pure Appl. Math. 65,1331–1398(2012). doi:10.1002/cpa.21413
16. Garcia-Gasulla, D., Parés, F., Vilalta, A., Moreno, J., Ayguadé, E., Labarta, J., Cortés, U., Suzumura, T.: On the Behavior of Convolutional Nets for Feature Extraction. J. Artif. Intell. Res.61,563–592(2018).doi:10.1613/jair.5756
17. Esteva, A., Kuprel, B., Novoa, R.A., Ko, J., Swetter, S.M., Blau, H.M., Thrun, S.: Corrigendum: Dermatologist-level classification of skin cancer with deep neural networks. Na- ture.546,686(2017).doi:10.1038/nature21056
18. Huang, G., Liu, Z., vander Maaten, L., Weinberger, K.Q.: Densely Connected Convolutional Networks. In: 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2017). doi:10.1109/CVPR.2017.243
19. ISIC2018:SkinLesionAnalysisTowardsMelanomaDetection.
20. Codella, N.C., Gutman, D., Celebi, M.E.e.a.: 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). arXivpreprintarXiv:1710.05006 (2017).doi:10.1109/ISBI.2018.8363547
21. Li, X., Chen, H., Qi, X., Dou, Q., Fu, C.-W., Heng, P.-A.: H-DenseUNet: Hybrid Densely Connected Unet for Liver and Tumor Segmentation from CT Volumes. IEEETrans. Med. Imaging.(2018).doi:10.1109/TMI.2018.2845918
22. Mendonca, T., Ferreira, P.M., Marques, J.S., Marcal, A.R.S., Rozeira, J.: PH2-adermoscopic image database for research and benchmarking. Conf.Proc.IEEEEng.Med.Biol. Soc.2013,5437–5440(2013).doi:10.1109/EMBC.2013.6610779
23. Irfan, Daniyal, et al. "Prediction of Quality Food Sale in Mart Using the AI-Based TOR Method." Journal of Food Quality 2022 (2022).
24. Paricherla, Mutyalaiah, et al. "Towards Development of Machine Learning Framework for Enhancing Security in Internet of Things." Security and Communication Networks 2022 (2022).
25. Narayan, Vipul, and A. K. Daniel. "CHHP: coverage optimization and hole healing protocol using sleep and wake-up concept for wireless sensor network." International Journal of System Assurance Engineering and Management 13.Suppl 1 (2022): 546-556.
26. Choudhary, Shubham, et al. "Fuzzy approach-based stable energy-efficient AODV routing protocol in mobile ad hoc networks." Software Defined Networking for Ad Hoc Networks. Cham: Springer International Publishing, 2022. 125-139.
27. Narayan, Vipul, and A. K. Daniel. "Energy Efficient Protocol for Lifetime Prediction of Wireless Sensor Network using Multivariate Polynomial Regression Model." Journal of Scientific & Industrial Research 81.12 (2022): 1297-1309.
28. Narayan, Vipul, and A. K. Daniel. "IOT based sensor monitoring system for smart complex and shopping malls." International conference on mobile networks and management. Cham: Springer International Publishing, 2021.
29. Narayan, Vipul, and A. K. Daniel. "A novel approach for cluster head selection using trust function in WSN." Scalable Computing: Practice and Experience 22.1 (2021): 1-13.
30. Narayan, Vipul, and A. K. Daniel. "Novel protocol for detection and optimization of overlapping coverage in wireless sensor networks." Int. J. Eng. Adv. Technol 8 (2019).
31. Narayan, Vipul, and A. K. Daniel. "Design consideration and issues in wireless sensor network deployment." (2020): 101-109.
32. Narayan, Vipul, A. K. Daniel, and Ashok Kumar Rai. "Energy efficient two tier cluster based protocol for wireless sensor network." 2020 international conference on electrical and electronics engineering (ICE3). IEEE, 2020.