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Enhancing single image dehazing with self-supervised convolutional neural network and dark channel prior integration

Unnikrishnan Hari[1], Alla Bukshu Bajulunisha[2], Pramod Pandey[3], Joseph Arul Michiline Rexie[4], Velusamy Sujatha[5], Thankappan Saju Raj[6], Athiyoor Kannan Velmurugan[7]

[1]Department of Electronics Communication Engineering, Saveetha Engineering College, Chennai, India
[2]Department of Computer Science and Engineering, Chennai Institute of Technology, Chennai, India
[3]Faculty of Engineering, Symbiosis Institute of Technology, Nagpur Campus, Symbiosis International (Deemed University), Pune, India
[4]Department of Computer Science and Engineering, Karunya Institute of Technology and Sciences, Coimbatore, India
[5]Department of Electronics and Communication Engineering, Shree Sathyam College of Engineering and Technology, Salem, India
[6]Department of Computer Science and Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, India
[7]Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vijayawada, India

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ABSTRACT

The removal of noise from images holds great significance as clear and denoised images are vital for various applications. Recent research efforts have been concentrated on the dehazing of single images. While conventional methods and deep learning approaches have been employed for daytime images, learning-based techniques have shown impressive dehazing results, albeit often with increased complexity. This has led to the persistence of prior-based methods, despite their slightly lower performance. To address this issue, we propose a novel deep learning-based dehazing method utilizing a self-supervised convolutional neural network (CNN). This approach incorporates both the input hazy image and the dark channel prior. By leveraging an encoder, the combined information of the dark channel prior and haze image is encoded into a condensed latent representation. Subsequently, a decoder is employed to reconstruct the clean image using these latent features. Our experimental results demonstrate that our proposed algorithm significantly enhances image quality, as indicated by improved peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) values. We perform both quantitative and qualitative comparisons with recently published techniques, showcasing the efficacy of our approach.

Corresponding Author:

Pramod Pandey
Faculty of Engineering, Symbiosis Institute of Technology, Nagpur Campus, Symbiosis International (Deemed University)
Pune, Maharashtra, India
Email: pramod.pandey@sitnagpur.siu.edu.in

1. INTRODUCTION

The advancement of prominent computer vision technology has led to the widespread adoption of image processing systems across various domains. These domains include video surveillance, intelligent transportation, aerial surveillance, remote sensing, medical diagnosis, and more. Scenario like outdoor video surveillance and intelligent transportation, image acquisition process is affected by some uncontrollable factors like bad weather, fog ,dense clouds and rain. Images capture under poor visible conditions results in degraded quality and becomes difficult to get useful information by human visual system (HVS) and outdoor computer vision system (CVS) based applications.To enhance poor visibility of the degraded images there exists many techniques-image denoising, image inpainting, deblurring, deraining, dehazing, and low-light enhancement. In this paper we focus on dehazing of hazy images using deep learning baseself supervised technique which avoids use of paired datasets which need clean image and its haze version for supervised learning.

Airborne suspended particles like dust, smoke, pollution, and fog are responsible for reducing the transparency of the ambient air. When light interacts with these suspended particles, it scatters and interferes with the direct light reflected from object surfaces. This occurrence is known as the haze effect. Haze has detrimental effects on images, causing a decrease in contrast and color vibrancy. It also poses challenges for both human visual perception and computer vision systems in terms of object recognition and subsequent processing. Hazy images are characterized by diminished brightness, low contrast, a restricted grayscale spectrum, and color distortion. These factors make parameter estimation particularly difficult for images suffering from haze-induced quality degradation.

The use of conditional normalizing flow and attention-based coupling layers discussed by Li *et al.* [1] can introduce significant computational overhead. This can lead to longer training and inference times, requiring more computational resources, which may not be feasible for real-time applications. While SwinIR [2] reduces the number of parameters compared to some state-of-the-art methods, the use of Swin transformer layers and residual connections can still result in high computational complexity. Nighttime dehazing methods [3] need to carefully handle these color variations to avoid unnatural color shifts and artifacts in the enhanced images.The availability of high-quality, labeled nighttime hazy image datasets for training and evaluation can be limited. Although RepLKNet [4] aims to improve efficiency, large kernels (31×31) inherently involve higher computational costs compared to smaller kernels (3×3). This increased computation can lead to higher demands on processing power and memory. Khan *et al.* [5] proposed vision transformer (ViT) based model can be less interpretable than traditional convolutional neural networks (CNNs). Collecting, annotating, and processing large-scale datasets can be resource-intensive and may not always be feasible.

Non-local color line attenuation prior is discussed in [6] and modified dark channel prior (DCP) using fusion methods is presented in [7]. Studies [8], [9] have investigated the dehazing of both daytime and nighttime images and suggested a novel approach that combines dehazing with the enhancement of poorly illuminated images. On fusing the hazy input image with non-local retinex and dark channel prior methods, thereby adjusting the transmission estimation with a locally generated ambient light component that maximizes reflectance. Attention mechanisms have been directly applied to dehazing processes, as demonstrated by the feature fusion attention network (FFA-Net) proposed by Qin *et al.* [10]. Dong *et al.* [11] introduced a GAN network with a fusion-discriminator (FD) that excels in dehazing, producing images with enhanced contrast. The U-Net architecture [12], renowned for its efficacy as an encoder-decoder network, has been effectively utilized in image restoration and dehazing tasks.

Recent haze removal approaches, including atmospheric optical depth network (AOD-Net) [13], transformer model [14]–[16]. Dehaze network (DehazeNet) [17], multi-scale convolutional neural network (MSCNN), and progressive prediction dehazing network (PPD-Net) have universally adopted CNNs as their cornerstone, resulting in significant performance enhancements. Despite the notable progress made by these CNN-based strategies, DehazeNet [18], densely connected pyramid dehazing network (DCP-DN) [19], [20] conveys that there remains an opportunity for further refinement and improvement in their applications. Enhancement of low-light (LoL) images based on unsupervised CNN using attention mechanism is discussed. Along with hazy image bright channel prior also applied [21]. The retinex methods [22]–[24] attempts to address this by predicting an illumination map as a precursor to image restoration. Algorithms such dark channel prior uses the mathematical degradation model to describe a hazy image is atmospheric scattering model. Algorithms such dark channel prior [25] uses the mathematical degradation model to describe a hazy image is atmospheric scattering model. However, this approach faces mathematical complexities, especially in cases of extremely low light with accompanying noise.

In this study, we propose a solution for haze removal using self-supervised convolutional neural network with encoder-decoder pipelined auto-encoder like architecture. The self-supervised net model normally performs better than supervised models in real time outdoor environment conditions since supervised models require a pair of clean image and hazy image for processing. So our proposed method rely on the original hazy image and its DCP and not on clean haze free image pair dataset which can be practically difficult and unrealizable for real time scenario. The subsequent sections of this paper are structured as follows: Section 2 provides an overview of recent advancements in learning-based methods for dehazing hazy images. Section 3 outlines our proposed learning model, followed by a presentation of experimental results and ensuing discussions. The paper concludes in section 4 with final remarks and potential avenues for future enhancements.

2. PROPOSED METHOD
2.1. Problem statement
A new deep learning model built upon the concept of the atmospheric scattering model using dark channel prior [26] has been introduced for the purpose of removing haze in images. In recent research, deep learning techniques have primarily focused on learning and incorporating aspects such as color, contrast, and brightness to achieve more expressive and improved results. These models typically rely on training with pairs of synthetic or corrupted images alongside clean image counterparts. In reality it is possible to extract the DCP from the hazy image to generate an initial illumination map as pseudo ground-truth. But it is practically difficult to get both clear hazy free and hazy images in outdoor environment at time of image capturing for same situation in real time scenario. So supervised methods are focussing with synthesised paired datasets and need large numbers and not suitable for real time applications. Hence study of the self-supervised network models become great significance for deep learning and network training is a process of solving optimization.

Our contributions include: i) The proposed method self-supervised, method has good generalization ability, even if the pretrained network is not well enough in new environment. It performs retraining without paired haze free images data set; ii) We propose a self-supervised dehazing network, which can complete the training with even one single hazy image without paired dataset for supervised network models; and iii) We propose a new loss function optimization by difference between transmission map obtained from hazy images and its dehazed output image. The transmission map is obtained from inversion of DCP which are applied along with hazy input images.

2.2. Architecture description
To achieve satisfactory results, as mentioned above supervised learning methods often require paired datasets and more complex neural networks that generate a large number of model parameters during the training phase [27]. To address the challenges mentioned above, we present a novel self-supervised approach designed for single image dehazing. For low light enhancement using unsupervised learning method using bright channel prioris presented. In our proposed method for single image dehazing, vital part is self-supervised loss function and its implementation. Figure 1 explains schematic of proposed self-supervised encoder-decoder network model.

The proposed deep network comprises an encoder and decoder, organized in a CNN pipeline. This network is designed with the encoder, decoder, and a fully connected layer. The encoder is fed two inputs: a hazy image and the essential DCP from the hazy image to generate an initial illumination map as pseudo ground-truth [28]. Initially, proposed method processes haze free clean images. Encoder learns to extract set of feature representations of the image. The output from the encoder is transformed to one flattened vector then passed through a fully connected layer (FC) to get the mean and the standard deviation of the encoder distribution. Also reduces the dimensions of the parameters. The FC layer output follows the normal distribution and pass it through the decoder network with two deconvolutional and upsampling layers to reconstruct the image. Decoder receives the set of feature representations and generates an enhanced image.

In the encoder the first convolution layer, performs feature extraction. This is accomplished by applying multiple filters with a kernel size of [3×3] to capture various features such as edges or corners. After feature extraction, feature enhancement is performed to establish a mapping between dark and normal light images. Max pooling and batch normalization are employed for this purpose. Non-linear mapping, facilitated by the rectified linear unit (ReLU) non-linear activation function, maps these extracted features to a high-dimensional space where they can be more distinctly separated and classified into reflectance and illumination components. The high-dimensional feature maps generated in the previous layer are then reconstructed into smaller-dimensional vectors [29]. A smaller-dimensional convolutional layer is responsible for projecting the reflectance and illumination components from this feature space.The overall architecture follows a simple encoder-decoder pipeline structure. The encoder block employs a CNN structure with seven convolutional layers, with each layer being complemented by a corresponding activation function. These layers are organized into two stages, with the first stage comprising four sub-layers equipped with pooling and batch normalization. Following the encoder, there is a decoder consisting of seven deconvolutional layers, each complemented by an activation function and normalization. This encoder-decoder pipeline behaves akin to an Autoencoder, effectively functioning as a self-supervised network. Table 1 explains a description of architecture of proposed technique.

The encoder's various layers specialize in learning fundamental image features, encompassing aspects like edges, colors, brightness, and higher-level texture characteristics. To efficiently manage parameters and prevent unnecessary resource consumption while connecting different feature maps, a channel-wise fully-connected layer is utilized. Following this layer, there are five up-convolutional layers along with learned filters, each incorporating a ReLU activation function.

Deconvolution is the technique used to map low-dimensional features back into a high-dimensional space, essentially the inverse of the convolution operation. The encoder network reduces the spatial dimensions of the input image while increasing the channel dimension, whereas the decoder network performs the reverse operation by reducing the channel dimension and expanding the spatial dimension.Training involves the simultaneous training of both the encoder and decoder as a unified model. This training process entails minimizing the disparity between the original data and the reconstructed output through the application of a loss function.During feature extraction by the encoder, a specialized training strategy combines the feature extraction network with the decomposition module network. In the loss function of the encoder-decoder network, the L2 error between the low-light image and the predicted image from the decomposed module is employed, effectively enhancing the underexposed low-light image. Additionally, gradient descent is utilized to minimize the reflectance loss using L1 error, thereby updating the model parameters. In each batch of every iteration, regularization coefficients are updated through loss minimization [30].

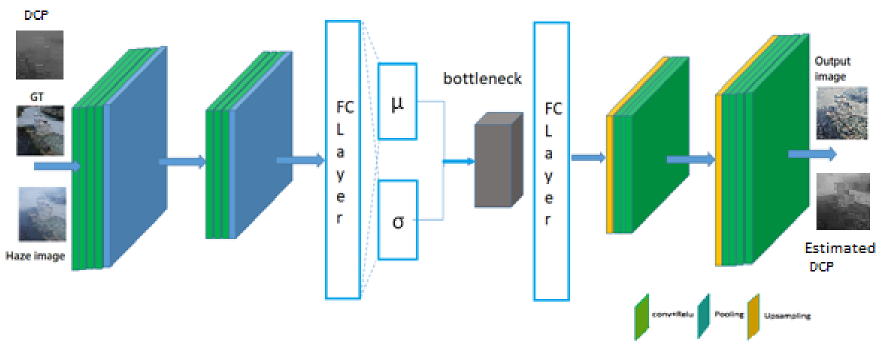

Figure 1. Schematic of proposed self-supervised encoder- decoder network model

Table 1. Description of architecture of proposed technique

Layers	Kernel	Operation	Output channels	Stride
Input R, G, B	---	---	3	-
Conv1_1	3×3	Conv+ReLU	32	1
Conv1_2	3×3	Conv+ReLU, pooling	32	2↓
Conv1_3	3×3	Conv+ReLU	64	1
Conv1_4	3×3	Conv+ReLU, pooling	64	2↓
Conv2_1	3×3	Conv+ReLU	128	1
Conv2_2	3×3	Conv+ReLU, pooling	128	2↓
Conv2_3	3×3	Conv+ReLU	256	1
DeConv1_1	3×3	deConv+ReLU, Upsampling	128	2↑
DeConv1_2	3×3	deConv+ReLU	128	1
DeConv1_3	3×3	deConv+ReLU	128	1
DeConv2_1	3×3	deConv+ReLU, Upsampling	64	2↑
DeConv2_2	3×3	deConv+ReLU	64	1
DeConv2_3	3×3	deConv+ReLU	32	2↑
DeConv2_4	3×3	deConv+ReLU	32	1
Conv	1×1	Conv+ReLU	3	-

2.3. Loss function optimization

The architecture of the self-supervised networks influences loss function analysis to enhance their performance. The decoder component plays a crucial role by conducting back-propagation through loss function optimization. This involves weight adjustments aimed at minimizing the disparity between the predicted output and any available ground truth. To ensure a holistic evaluation of the haze-free image generated and to provide improved guidance during training, an amalgamated loss function is employed. This composite loss function incorporates both reconstruction loss and perceptual loss.

$$loss_{recon} = \lambda_1 \sum_i \|G(I_i) - Q_i\|_1^1 + \lambda_2 \|\tau - \hat{\tau}\|_2^2 \tag{1}$$

where I_i denotes hazy input and Q_i represents for the successive i^{th} pixel of pseudo ground truth image. The function $G(\bullet)$ is the encoder-decoder net, and $L_1(\bullet)$ signifies least absolute error. Reconstruction loss quantifies the deviation in pixel values between the dehazed image and the ground truth as well as DCP as pseudo ground-truth. The reconstruction loss quantifies the transmission map (τ) estimated from DCP of the hazy image and the transmission map ($\widehat{\tau}$) that estimated from DCP of the dehazed image. However, it often lacks alignment with human visual perception. To address this limitation, the concept of perceptual loss is introduced. Perceptual loss is (2):

$$loss_{percp} = \lambda_3 \sum_i \|(G(I_i)) - (Q_i)\|_2^2 \tag{2}$$

The total loss function is calculated by (3),

$$loss_{Total} = loss_{rec} + loss_{percp}$$
$$loss_{Total} = \lambda_1 \sum_i \|G(I_i) - Q_i\|_1^1 + \lambda_2 \|\tau - \hat{\tau}\|_2^2 + \lambda_3 \sum_i \| G(I_i) - Q_i\|_2^2 \tag{3}$$

where the $G(\bullet)$ notation represents an encoder-decoder structure, Q denotes the pseudo ground truth image, and $L2(\bullet)$ signifies the least square error computation. In this context, $G(\bullet)$ indicates a pre-trained encoder-decoder network. The values of $\lambda 1, \lambda 2$, and $\lambda 3$ are $0.1, 0.5$, and 0.01, respectively. The optimization process involves minimizing this loss using the stochastic gradient descent method along with the backpropagation learning rule.

Similar to an autoencoder, proposed self-supervised encoder-decoder network is trained. It has the capability to extract various image attributes like edges, colors, brightness, textures, and even deeper, less perceptible semantic features. This approach mimics the nuances of human visual perception and is a widely adopted technique using the CNN encoder-decoder architecture. The proposed encoder-decoder CNN model, employing loss function optimization, yields improved dehazed results from hazy images without excessively fitting to the input data [31].

3. RESULT AND DISCUSSION

A simulation tool was employed, utilizing the TensorFlow framework within the Anaconda platform, with the Jupyter notebook integrated development environment (IDE). In this experiment, 10% of the image data was allocated for testing purposes, while the remaining 90% was utilized for training. The model underwent training for a range of epochs, spanning from 50 epochs to 150 epochs. During this training process, the Adam stochastic optimization algorithm was employed with a learning or update rate set at 0.0001. A computer system comprised with i5-1250PE CPU of intel, 16 GB of RAM, and a 500 GB SSD is being used for network training and for testing. Table 2 shows the parameter details used in the implementation.

Table 2. Parameter details

Parameters	Value
Name of the dataset	O-Haze; I-Haze; SET 5/14/91
Standard haze images	1000
No of images–O-Haze	90
I-Haze dataset	90
LIME&SET 5/14/91	100
Training	500
Testing	50

Figure 2 shows the dehazing of O-Haze dataset hazy images. Figure 2(a) shows the four different hazy input images of the O-Haze dataset. Then Figure 2(b) shows the dehazed output generated by the proposed method. As mentioned above we use ground truth (GT) initially for few images and then replaced by the DCP of the images as pseudo-GT. The atmospheric light is computed from the DCP with the patch with maximum value and the transmission map is estimated with inverse of DCP. The same process performed for the DCP at the output of the decoder. Then the loss function is optimized with the transmission maps (τ) estimated from applied DCP and transmission maps ($\widehat{\tau}$) evolved from SSED Net generated DCP along with the dehazed output image.

Table 3 demonstrates a comparison of peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) with existing methods. Comparison of the output obtained by the proposed self-supervised encoder-decoder net method against the ground truth and existing recent methods are shown in Figure 3. Figure 3(a) shows input hazy image, Figure 3(b) explains a DCP [1], Figure 3(c) explains a CAP [3], and Figure 3(d) shows Ancuti *et al.* [7], Figure 3(e) explains AOD-Net [17], Figure 3(f) describes proposed method, and Figure 3(g) demonstrates GT. Table 3 given below presents a summary of the evaluation metrics, including PSNR and SSIM, using the O-Haze dataset. It provides quantitative results for the proposed method in comparison against both traditional and deep learning (DL) based existing methods.

(a)

(b)

Figure 2. Dehazing of O-Haze dataset hazy images (a) input hazy image and (b) dehazed output of proposed method

Table 3. Comparison of PSNR and SSIM with existing methods

Methods	PSNR (in dB)	SSIM
DCP [1]	16.09	0.7391
Fattal [6]	16.23	0.6818
Ancuti [7]	17.26	0.7536
Ren [19]	19.07	0.7650
DehazeNet [18]	16.12	0.6357
AOD-Net [17]	15.03	0.5385
DCP-DN [21]	15.16	0.6626
Proposed SSED Net method	20.26	0.6752

(a) (b) (c) (d) (e) (f) (g)

Figure 3. Comparison of output with existing methods and ground truth (a) input hazy image, (b) DCP, (c) CAP, (d) Ancuti *et al.* [7], (e) AOD Net, (f) proposed method, and (g) GT

Table 3 presents a summary of the evaluation metrics, including PSNR and SSIM, using the O-Haze dataset. It provides quantitative results for the proposed method in comparison against both traditional and DL based existing methods. Comparison of the output obtained by the proposed self-supervised encoder-decoder net method against the ground truth and existing recent methods are shown in the Figure 3. The average values of the dataset images were computed and then compared with other established methods, both traditional and deep learning-based methods. Since our proposed approach is self-supervised, unlike supervised learning models proposed method can adapt to new situations but trained with less number of paired datasets. So, the proposed SSED Net method obtained lesser value for SSIM index though produced largest PSNR value. In terms of PSNR, the proposed method outperforms existing methods by 22%, 21%, and 26% when compared to DCP [1], DehazeNet [18], and the AOD-Net [17], and DCP-DN [21] methods, respectively. Regarding SSIM, the proposed method exhibits superiority with improvements of 8%, 21%, and 3% compared to DehazeNet [18], AOD-Net [17], and DCP-DN [21] methods only, respectively; but lesser

SSIM than references [11] and [19]. The model was trained over a period of 50 epochs to 150 epochs. Adam stochastic optimization with a learning/update rate of 0.0001 is used to train the network. The network is trained and tested with the Tensor-flow framework using anaconda platform with Jupiter IDE. PSNR and SSIM increase gradually with increase in number of epochs. But after 120 epochs due to overfitting the performance reduces. In future work we will train with more number of dataset images and enhance the performance metrics by increasing the quantum of input hazy images and respective DCP for both training as well as testing process. Hence the proposed SSED Net would improve the value of both metrics PSNR and SSIM on increasing the number of training images but still it would be minimum when compared with supervised models which need in thousands of volumes with paired datasets.

4. CONCLUSION

The proposed self-supervised encoder-decoder network (SSED Net) is based dark channel prior method. The scene radiance recovery is performed by encoder–decoder pipelined CNN like an Auto encoder architecture Results determined using the quantitative metrics shows that the network can produce a better contrast images and can be improved for real-time performance with little training time and without paired clean image like in supervised deep learning methods. For PSNR index evaluation, the proposed method outperforms existing methods by 22%, 21%, and 26% when compared to DCP, DehazeNet, and the AOD-Net, and DCP-DN methods, respectively. Regarding SSIM, the proposed method exhibits superiority with improvements of 8%, 21%, and 3% compared to DehazeNet, AOD-Net, and DCP-DN methods, respectively. Because our approach is self-supervised, it can adapt to new situations but trained with less number of paired datasets lesser value for SSIM index is obtained though produced largest PSNR value. In future work we will train with more number of training datasets and extend this for performing both dehazing and low light enhancement together with face detection using NIR camera for real time applications.

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BIOGRAPHIES OF AUTHORS

Unnikrishnan Hari is working selection grade assistant professor in Department of Electronics and Communication Engineering, at Saveetha Engineering College, Chennai. He has more than twenty-five years of teaching experience. He received his bachelor's degree in electronics engineering from Madras institute of Technology, Anna University, Chennai, in year 1993. He completed a master's degree in power electronics and drives from the College of Engineering, Anna University, Chennai. He completed Ph.D. at SRM Institute of Science and Technology, Tamil Nadu, India. He has published many research papers in national and international conferences and indexed journals. His research interests include signal processing, image processing, machine learning and wireless communications. He is a member of Institution of Engineers (IE), India. He can be contacted at email: hariu@saveetha.ac.in or uharih86@gmail.com.

Alla Bukshu Bajulunisha received a Ph.D. in information technology from Anna University Chennai. Since June 2024, she has been employed as an associate professor in the Department of Computer science Engineering at Chennai Institute of Technology. She had previously been an associate professor at M.A.M College of Engineering and Technology and Roever Engineering College. Her areas of expertise include Mobile ad hoc networks, distributed systems, cloud computing, and wireless communication. At Jayaram College of Engineering and Technology, she earned her postgraduate degree in computer science engineering in 2007. She worked in engineering colleges for 17+ years, holding a variety of positions, giving her teaching experience. She has published more than 10 research papers in various reputed journals like SCI, Scopus and UGC. She has taught many engineering subjects like object-oriented system, data structures, design and analysis of algorithms, distributed systems, grid computing, mobile computing and wireless networks. She got cash award for securing 100% result in various subjects in her career. She attended 6 international conference and around 25 FDP and seminar at various well established engineering colleges and universities. She also delivered guest lecturer and seminar for engineering students. She is now interested in developing deep learning algorithms for energy efficient multicast routing in mobile ad hoc network. She can be contacted at email: nbajulu.cse2011@gmail.com.

Pramod Pandey was born in India in 1975. He received his M.Tech. and Ph.D. degree from Indian Institute of Technology Kanpur India in 2004 and 2012 respectively. He has worked as scientist at Korea Atomic Energy Research Institute Daejeon South Korea, Marie Curies Post-Doctoral Fellow at DCU Dublin Ireland, Research Establishment officer at IIT Kanpur, and has R&D Industrial experience in design and development of ophthalmic instruments. Presently he is working as an assistant professor at Symbiosis Institute of Technology Nagpur. Apart from this Dr. Pandey has worked in several other projects funded from Science Foundation Ireland and European Union Commission. Dr. Pandey is trained Laser Safety officer, from Pro-Lite Technology Ltd, Innovation Centre, Cranfield University United Kingdome. He is a member of IEEE and has about 13 international journal publications in reputed journals and attended about 25 international and national conferences. His research interest includes laser plasma applications in industries and medical fields and many more related fields. He can be contact at email: pramod.pandey@sitnagpur.siu.edu.in.

Joseph Arul Michiline Rexie earned her doctoral degree from Karunya Institute of Technology and Sciences, Coimbatore. Her research focuses on developing efficient approaches for pattern matching in bioinformatics data and machine learning algorithms for pattern predictions. Her area of interest is data science, analysis of algorithms, data structures, and theory of computation. She can be contacted at email: rexie@karunya.edu.

Velusamy Sujatha received her doctoral degree and post-graduation from Anna University, Chennai, and her undergraduate degree from Madras University. Her research focuses on designing charge pump phase-locked loops, with a keen interest in analog VLSI. She began her career as a lecturer in 1993 and has served as an academician in various reputed institutions, holding several positions and guiding numerous UG and PG projects. Currently, she is a professor in the Department of Electronics and Communication Engineering (ECE) at Shree Sathyam College of Engineering and Technology, Sankari, Tamil Nadu. She can be contacted at email: info@shreesathyam.edu.in.

Thankappan Saju Raj received the B.E. degree in computer science and engineering from Dr. Babasaheb Ambedkar Marathwada University, India and ME degree in computer science and engineering, from Madurai Kamraj University, India. He has completed his PhD degree from Anna University, India. He has more than twenty-six years of teaching experience. He is currently working in the Department of Computer Science and Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Avadi, Chennai, Tamil Nadu 600062. His areas of interest are reliability in grid computing, cloud computing, automata theory, machine learning, wireless sensor network, parallel and distributed computing. He can be contacted at email: drsajurajt@veltech.edu.in.

Athiyoor Kannan Velmurugan is currently as a professor in the School of Computing at Koneru Lakshmaiah Education Foundation (Deemed to be University), Vijayawada, Andhra Pradesh, India. He graduated in computer science and engineering at Arunai Engineering College, Affiliated to University of Madras Chennai, Tamil Nadu, India. He did his Master of Technology in computer science and engineering at Dr MGR Educational and Research Institute (Deemed University) Chennai, Tamil Nadu, India. He obtained his Ph.D. in the research area of wireless sensor networks in computer science and engineering at St. Peter's Institute of Higher Education and Research (Deemed University) Chennai, Tamil Nadu, India. He published a number of research articles in preferred journals, chapters in books and conferences. His areas of interests include wireless sensor networks, internet of things, artificial intelligence, and machine learning. He can be contacted at email: akvel47@gmail.com.