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Online Signature Authentication using Pre-trained Optimization Techniques

M. Ranga Swamy[1],Vijayalakshmi P.[2,*],V. Rajendran[3]

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Abstract: - Authorization is essential in order to handle the document assurances and security. Nowadays it constitutes one of the top responsibilities in case of securing information and effectiveness in every domain. The development of technological advances has made interacting with machinery more effortless. As a result, the demand for authentication grows quickly for a variety of legitimate causes. Therefore, biometric-based identification has dramatically accelerated. It is a sort of improvement beyond various other approaches. The author presented Conv Neural Networks for mining features moreover supervised machine learning techniques for the verification of handwritten signatures. Raw images of signatures are used to train CNN models for extracting features along with data augmentation. CNN Architectures especially pre-trained models as VGG16, Inception-v3, ResNet50, and Xception are used for identifying signature either original or forgery. Using Euclidean distance, cosine similarity, and supervised learning algorithms such as Logistic Regression, Random Forest, SVM, and its derivatives, the extracted characteristics are categorized into two classes: authentic or fake. Data for testing is gathered from the ICDAR 2011 Signature Dataset and structured in pairs. The metadata consists of 69 subjects' signatures.

Keywords: *Conv Neural Network (CNN) model, VGG16, Xception, ResNet50, Optimizers.*

1 Introduction

The procedure of effortlessly and instantaneously confirming signings in order to identify the validity to check whether they are genuine is known as "signature verification and forgery detection." Basically, there are two kinds of signature verification namely Static/ Offline and Dynamic/Onlline. Dynamic or On-line verification occurs as an individual signs an agreement using an electronic ipad or analogous gadgets, as opposed to stable or off-line authentication, which happens once a signing verified has been done. Following this, the signature of the individual in question is compared against earlier examples of the individual's sign that were used to create the record comprise signature data. While electronic signature that has been saved in an information format might be utilized as authentication of signatures, writing a signature on a document requires the machine to capture specimens in order to conduct an inquiry. Perhaps the most widely used individual traits for confirming personality, regardless of if it be for finance or company, is a signature that has been handwritten.

1.1 Problem Statement

From the beginning of the year 1990s, scientists have focused on studying the identification of offsite signatures that are handwritten. Subsequently, numerous approaches have been developed, created by Jose Lopes et al. [1] for solving these issues. An outline with significant advancements is shown in Figure 1.

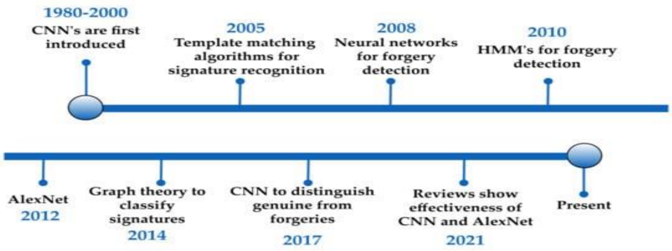

Fig 1. Overall signature detection survey during the year 1980-present

Moreover, the authors of Hsin et al. [2] used CNN approach for verifying offline signature and identified forgery signature which appropriate in various business circumstances as bank check payment sign verification procedure based on human assessment. This author developed the framework of Convolutional Neural Network depicted as Figure 2.

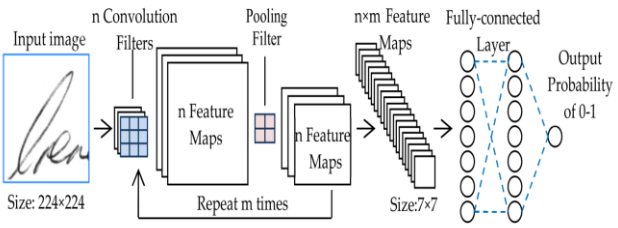

Fig 2. Framework of Convolutional Neural Network by [2]

[1] *Research Scholar, Department of ECE,Vels Institute of Science, Technology and Advanced Studies,Chennai, Tamil Nadu, India*
[2] *Associate Professor, Department of ECE,Vels Institute of Science, Technology and Advanced Studies,Chennai, Tamil Nadu, India*
[3] *Professor and Director, Department of ECE,Vels Institute of Science, Technology and Advanced Studies,Chennai, Tamil Nadu, India*
** Corresponding Author Email: viji.se@velsuniv.ac.in*

The layers known as convolutional Girshick [3] use numerous convolution filtering methods (or convolution kernels) to separate the more advanced data out of lower-level data, including identifying boundaries, angles, connecting scores, and numerous other characteristics of the images being used. Here, the author employs pooling layer in order Schener et al. [4] to lower the characteristic map dimensions, which results in quicker convergence rates for connections because using numerous filters for convolution will significantly increase the overall dimension of the characteristic image and must be accompanied by tiresome computations He et al. [5]. Layers of FCC then receives all multifaceted characteristic mappings as feed in the form of an a single-dimensional vector of features to produce predicted classes for subsequent categorization assignment, the fully-connected layer, which is essentially an ordinary perceptron with multiple layers (MLP), was employed in previous work Zehua Zhang et al. [6]. Moreover, Inception v1 and Inception v3 model along with CNN was utilized by Jahandada et al. [7] to verify offline signature. In this research work, we propose VGG-16, Inception V3, ResNet 50, and Xception model in our experiments, since these models are well designed which exposed its immense capability in VGG16 for identifying online based forgery signature. Moreover, optimization algorithm includes SGD, RMS Prop, Adagrad and Adam to obtain optimal solution in detecting and verifying the signature is forgery or not.

The main intention of this research work are mentioned as follows

- To establish signature authentication approach with the help of most up-to-date advancement in deep based approach especially CNN model.
- The novel signature dataset which is sufficient to train the neural network based approach for signature based authentication.
- The aforementioned system accepts the combination of identical fingerprints in PNG appearance and returns a Boolean expression either 1 or 0.

2. Research Background

Several investigations had done regarding signature verification online and offline using various techniques. This survey explains the signature verification using deep networks Alajrami et al. applied CNN approach for detecting offline signature attained tested accuracy as 99.7% Fayyaz et al [8] used Gaussian distribution for finger vein detection by extracting features based on auto-encoders. Fayyaz [9] showed the outcomes as reduction in error rate also enhancement in accuracy range in online signature verification. Ghosh [10] compared the evaluation of signature verification using CNN along with Recurrent Neural Network approach. During the year 2016, kim et al. [11] found that verifying signature using CNN much more better, in 2018 signature verification has done using Hidden Markov Model [12]. Signature verification via handwritten/offline done by Soelistio et al. , using deep learning [13] and Poddar et al. [14]. Menotti et al. [15] applied CNN for signature spoofing verification, ANN by Adewole [16], CNN by Zhang et al. [17]. Various signatures are analyzed by sadkhan et al. [18] biometric recognition by sherin et al [19], ISRSAC determined by yang et al. [20], Deep Air Segmentation by Malik et al. [21], Fully Connected layers appropriate in detection of very signature by FCNN.

3. Proposed Method

The scribbled signatory is a cognitive fingerprint because depends on behavioral rather than specific physiological aspects of the person's signatures. The examination and approval of an autograph might require quite a while the signature of someone changes with duration, leading mistakes to occasionally be increased. Increased incorrect rejection percentages result from mismatched signatures for signers whose weren't doing so consistently.

The framework for our proposed model is depicted in figure 3 in which how the signatures are verified using deep based optimization techniques.

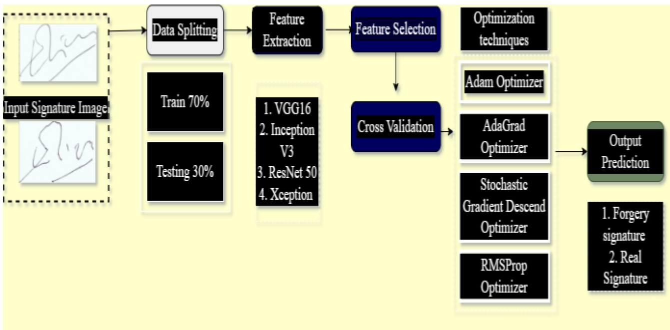

Fig 3. Proposed architecture for signature authentication

3.1 Dataset

To build an understanding database of all individuals, signatures that have been written are gathered, and some distinctive elements are retrieved. To assess the effectiveness of the confirmation of signature system and to compare the results of other approaches used to the same database, a standard database of each person's signature is required. Figures 4(a) and 4(b) illustrate examples of indivisible genuine and fake signatures, respectively. In this research work, the author utilized around 600 signature images gathered from 69 subjects along with 420 real and 180 forged signatures per individual person. These signature image dataset collected from ICDAR 2011 which described in RGB format.

Left image represents the input raw image which is an original signature signed by an individual whereas the right image corresponds to forgery signature image which is signed by unauthorized users. Look at the comparison of both images Figure 4 (a) and Figure 4(b) by that we can easily identified fake/forgery signature. Such kind of forgery signature illegally supported in stealing several domains such as withdrawal of cash from bank, registration of land and field based documents etc.

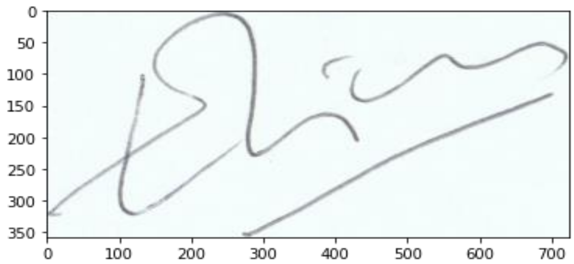

Fig 4 (a) Raw Input Image

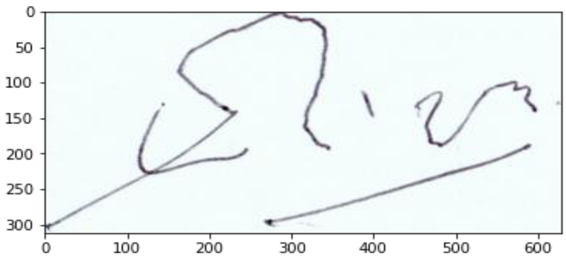

Fig 5 (b) Forgery signature image

3.2 Feature Extraction

The crucial phase in the digital signature authentication procedure is feature extraction which is typically divided into two categories: manually created characteristic extraction as well as pattern systems for learning Hafemann et al. [22]. People create the tools used in handmade extraction of features strategies according to their own perceptions. The handmade extraction and classification of features approaches employed for verifying signatures are being examined in an assortment of review publications Diaz et al. [23] . In order to determine the fingerprints' bending characteristics, Deng et al. [24] employed a wavelet-based feature extractor. Local binary patterns (LBP) and uniform local binary patterns (ULBP) were chosen by Pal et al. [25] as their technique for texture-based feature extraction.

However, feature learning techniques may obtain characteristics devoid of manipulation by humans. In comparison to manually created characteristics, this particular type of approach also known as CNN along with other deep learning approaches has demonstrated outstanding efficacy across a wide range of applications related to computer vision. In order to learn features for author categorization from signatures picture pixels, and Khalajzadeh et al. presented an extensive CNN approach. A CNN-based technique which can additionally acquire reliable characteristics using variable-size signatures was proposed by Hafemann et al [22].

Basically, Conv Neural Network (CNN) is most significant architectures applicable for functioning behind image based input data. In this research work, overall 16 models were trained to compare the accuracy in signature authentication dataset to identify forgery images. Among 16 models, four pre-trained models have been used for features extraction namely:

- VGG16 model
- Inception-v3
- ResNet-50
- Xception

Moreover, Optimizers used to compile the models are mentioned as

- Stochastic gradient descent (SGD)
- Root Mean Square Propagation (RMSprop
- Adaptive Gradient Algorithm (Adagrad)
- Active Design and Analysis Modelling (Adam)

3.3 Parameters selection

Here the author describes the parameters for all models such as VGG16, Inception V3, ResNet-50, Xception architecture as 138M, 24M, 23M and 23M along with the features namely 512, 2048, 2048 and 2048 depicts in figure 5.

Architecture	VGG16	Inception-v3	ResNet-50	Xception
Parameters	138M	24M	23M	23M
Features	512	2048	2048	2048

Fig 5. Parameters & Features used for detecting signature

3.4 Accuracy score in 3-folds

	Optimizers			
	SGD	RMSprop	Adagrad	Adam
VGG16	0.8648	**0.9645**	0.8821	**0.9584**
Inception-v3	0.8042	**0.9827**	**0.9567**	**0.9922**
ResNet50	**0.9515**	**0.9991**	**0.9991**	**0.9974**
Xception	0.7730	**0.9835**	0.8215	**0.9939**

Training Accuracy (3-Fold)

	Optimizers			
	SGD	RMSprop	Adagrad	Adam
VGG16	**0.7091**	**0.9717**	0.5111	**0.9556**
Inception-v3	0.5818	0.4202	**0.6020**	**0.6323**
ResNet50	0.4182	0.5879	0.5818	0.4182
Xception	0.5697	0.5818	0.5657	0.5899

Validation Accuracy (3-Fold)

	Optimizers			
	SGD	RMSprop	Adagrad	Adam
VGG16	**0.4497**	**0.0918**	0.3716	**0.1069**
Inception-v3	0.4485	**0.0448**	0.2218	**0.0176**
ResNet50	0.1561	**0.0050**	**0.0324**	**0.0084**
Xception	0.5424	**0.0642**	0.4889	**0.0221**

Training loss (3-Fold)

	Optimizers			
	SGD	RMSprop	Adagrad	Adam
VGG16	**0.5971**	**0.0793**	**0.9206**	**0.1127**
Inception-v3	**0.7371**	8.5688	**0.7872**	2.3959
ResNet50	1.2646	**0.6738**	1.4782	**0.7494**
Xception	**0.7339**	7.0186	**0.7754**	3.2455

Validation loss (3-Fold)

Fig 6. 3-Fold Cross validation using Deep learning

Here, 3-fold Cross validation is utilized directly to perform model selection using deep learning based pre-trained models moreover optimizers such as SGD, RMSProp, Adagrad, and Adam are used for obtaining optimal solution in signature authentication shown in figure 6.

As seen from figure 7, 3-fold cross validation has done for evaluating the model performance based on metrics such as validation accuracy and loss in which VGG16 + RMSProp optimizers has training accuracy as 96.4%, whereas validation accuracy as 97.17% also VGG16 + Adam optimizer set the training accuracy as 95.8% but validation accuracy reached as 95.56%. Similarly, we are comparing training and validation loss among various models in which ResNet 50 + RMSProp minimum loss during training as 0.005 whereas losses during validation of signature images as 0.67. Here the minimum loss during validating the signature image dataset in which VGG16+ RMSProp model reaches 0.07 by this evaluation of models had analyzed.

Based on this evaluation, VGG-16 model along with RMSrop optimizer attained maximum accuracy around 97% with least loss as 0.07 in verifying signature images and classifying the same either real or forgery.

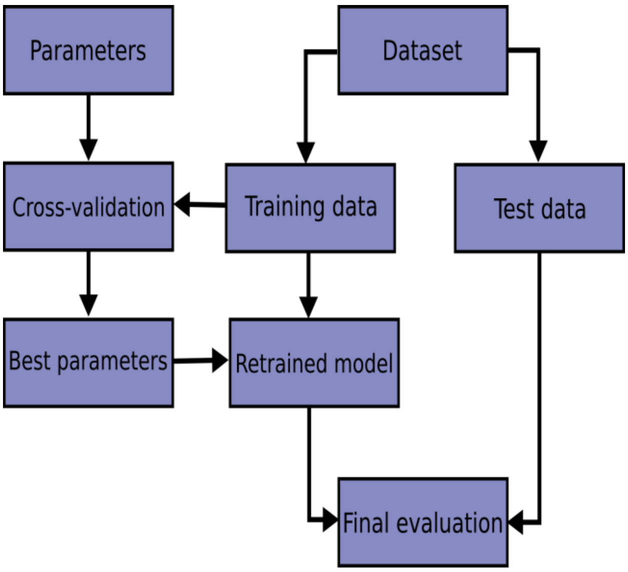

Fig 7. Signature verification based on feature selection via cross-validation

Our deep learning model employed for training is provided to cross validate function's estimator parameter. The actual value has taken as parameter X. The target variable is passed as the parameter y. By that, metrics such as validation accuracy and loss are evaluated which are entered into the parameter score. Finally, the author needs to launch a set of measures as accuracy, loss that intends appropriate to validate our model.

3.5 Feature Selection

In this phase, selection of features or dimensionality reduction has done on given signature image dataset. This selection of features helps to enhance accuracy score as well as improve the performance of high dimensional signature image dataset. The initial insight taken from preceding statistics The VGG16 layout surpassed any additional designs plus characteristics extracted from algorithms for classification having a minimum of 95% precision for training along with 60% evaluation performance. Four different designs were selected to put our categorizing methods to the challenge.

a. VGG-16 model

VGG-16 model has 16 layers deep convolutional Neural Network which is pre-trained model where signature based images is trained from ImageNet database. This pre-trained network categorizes the images into pixels and fed into various layers of neural network to predict the outcome as single output layer. The network has an image input size of 224 by 224.

Here the optimization techniques such as Adam, RMSProp, Adagrad and SGD are used for obtaining optimal solution in verifying the signature and identified that whether verified signature is forgery or real.

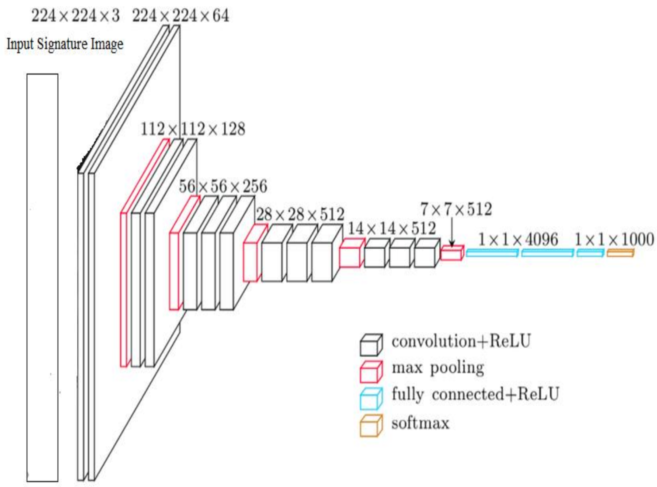

Fig 8. Architecture of VGG-16 layers

Architecture of VGG-16 layers illustrated in figure 8 Moreover the layers in VGG-16 model are described as follows:

Input layer: Signature image of size 224x224 is fed into VGGNet model. By removing a 224×224 square from the center of each image submitted for the ImageNet concurrence, the model's developers were able to maintain a constant image size as an input.

Convolutional Layer: The smallest 3×3 reactive surface is used by the convolutional filters of the VGG algorithm.

Also 1×1 convolution filter is also used by VGG to linearly convert the input signature image data.

Activation layer: This layer contains function as Rectified Linear Unit (ReLU) which reduces learning time of the network. Moreover, this function is linear which presents corresponding outcome for positive input image also provides the outcome as zero for negative kind of inputs images.

Hidden Stage: Rectified Linear Unit employed to maintain AlexNet Simultaneous Data Standardization across the whole VGG network's concealed phases. The final strategy extends workouts and consumes more mental capacity, but does not result in total efficiency.

Pool Stage: This layer reduces the dimensionality as well as quantity of features in feature maps built by every stage of convolutional. Pooling methods is critical given the sudden rise for the total amount of viable filtering through 64-128, 256 also lastly 512 in last three stages.

FCC layers: Entirely, VGGNet composed of three interlinked tiers. The first and second phases contains 4096 routes, whereas third phase contains 1000 channels, one for every kind. Finally, the output layer produces the outcome as whether the input raw signature image is authenticated as forgery sign or signed by authorized person.

b. Inception V3 model

A complexity-separated convolution layer is used in Inception as an addition to the Xception architecture in place of the conventional convolution layers. A neural network called the Inception model is used to classify objects in signature images. Google Net is an alternative name for Inception. During training phase, ImageNet dataset is used. The resolution of the images for Inception must be 299×299×3. Inception convolutional neural networks can produce more efficient computing and deep connections by reducing dimensionality with a stacked 1×1 convolution layer. The components were created to deal with problems like generalization and computing complexity Rajeena et al. [26].

c. ResNet 50 model

ResNet features multiple parts and sub-module configurations compared to other architectures, setting it apart from other common subsequent communication networks like VGGNet and Alex Net. It could be better to move to the lowest layer and disregard the level changes. This problem is addressed by ResNet's architecture, which also increases the network's success rate by making it easier to recall the system. A 177-layer neural network is ResNet. This model was trained with signature images that were 224 x 224 x 3.

d. Xception model

The Xception network has gradually replaced the Inception network. Extreme inception is referred to as xception. Instead of using conventional fully connected layers, the Xception architecture uses larger values with discrete convolutional sections. Numerous space along with parametric connections in which CNN-extracted features may be completely detached, are accessed by Xception. Convolution in the Xception architecture might be divided into 14 different alternative paths, however the fundamental architecture of Inception has been kept for around 36 more years than Xception. There remains a continuous residue link encircling each level after the first and last levels have been deleted. The input image is transformed to determine the chance of collecting cross-channel correlations across every outcome. Subsequently the depth-wise 11 convolution method is used. The interconnections can be depicted as a 2D + 1D projection instead of three-dimensional projections. A two-dimensional sector correlation sets the stage for emergence, whereas one-dimensional space correlates would do first.

4. Introduced Methodologies and classification

This section provides proposed methodology by importing necessitate modules from Keras API that serves as binding for TensorFlow backend. Here our model was constructed using the backend TensorFlow. Initially, programming of python trained Neural Network using distinctive class namely genuine and forged signatures. This work proposed various deep learning models to train the network by splitting the dataset into train-test ratio as 70:30.

4.1 Network training and validation

Here, the author evaluate the difference among expected value as well as label's true value throughout network training stage using the task called loss function otherwise called cost function in addition, the network are trained to reduce this difference. The anticipated outcome is more closely related to the actual label the lower the loss value. As seen in Equation (1), our output layer is a sigmoid function that manages binary issues and produces an S-shaped curve with values between 0 and 1. Also, cost function have been selected appropriate known as binary cross-entropy (BCE), as illustrated in Equation (2), where y denotes the true signing and is the projected likelihood that the objective is a real identity.

$$Sigmoid\ (x) = \frac{1}{1+e^{-x}} \qquad (1)$$

$$Binary\ Cross\ Entropy = -y\log(\hat{y}) - (1-y)\log(1-\hat{y}) \qquad (2)$$

Afterwards, while eliminating the BSE parameter in Equation (4), we improve our neural networks using the widely used stochastic gradient descent (SGD) strategy [30]. We chose an extremely low amount for e^-4 with the velocity factor as 0.9, which happens to be most frequently utilized in SGD, because an excessive speed of learning could prevent convergence from taking place. 48 photos are in our collection, with two real authors and eight imposters.

5. Experimental Results

In this research, images are binarized and store them properly. Then, the images are splitted in the ratio of 70:30, subsequently file handling and management procedures had done to divide the batches of signature based images. Following the construction of deep learning models, plots of accuracy and loss are created.

To determine whether there is any over fitting or under fitting, additionally deep learning pre-trained models are built for various data splits and plot the training and validation accuracies. In validation part optimal resolution of 97% has achieved in detecting forgery signature and verifying the same as shown in Figure 9. Since the accuracy of training and testing is nearly comparable, there exists quite a bit excess fitting. The evaluation of training and validation loss, training accuracy and validation accuracy for VGG-16, Inception V3, ResNet 50 and Xception along with four optimizers namely Adam, Adagrad, RMSProp and SGD for forgery signature authentication is depicted in Figure 9.

Fig 9. Validation Accuracy vs loss using opimization approaches

6. Conclusion

This research work summarizes verification of online signature by using ICDAR 2011 Signature Dataset. Several existing research work introduced deep learning based Convolutional Neural Network, Multi-Layer Perceptron for verifying digital/ handwritten signature that makes security for land, payment etc. In this research, datasets of various signatures has been collected from open source website, feature extraction has performed to extract relevant features, feature selection also executed by building various models such as VGG-16, ResNet 50, Inception V3 and Exception model for identifying forgery signature. To obtain optimal solution in authentication of signature and classifying the signature into either real or forgery, the author used four deep based optimization methods as RMSProp, Adam optimizer, SGD and AdaGrad in which validation accuracy attained around 97% with minimum loss.

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Author's Biography:

M RangaSwamy Research Scholar, Department of Electronics and Communication Engineering, Vels Institute of Science, Technology and Advanced Studies, Chennai, Tamil Nadu, India.

Dr. Vijayalakshmi.P is presently working as an Associate Professor in the Department of Electronics and Communication Engineering, Vels Institute of Science, Technology & Advanced Studies (VISTAS) Chennai. She completed her B.Tech. in Instrumentation from the Madras Institute of Technology, Anna University Campus, Chennai and M. E. Applied Electronics from Anna University, Chennai, India. She was awarded Ph.D degree in the year 2020 for her outstanding research contribution in the field of Underwater Communication & Machine learning applications from VISTAS, India. She has total of 18 years of rich experience in Teaching and as well as in Industry. Her area of interest includes Underwater Communication Sensor Networks and System design with Machine Learning & Data Science. She has published around 34 papers in both Scopus & other indexed journals and published 4 Books and 4 Book Chapters. She is fellow in IETE with Life time member and has professional membership in IEEE, ISOI, IAENG and IGEN. She also contributed in extension activities and services through NSS as Programme Officer.

Dr. V. Rajendran: Graduated from Maduari Kamaraj University, completed his M. Tech from IISC, Bangalore and received doctorate from Chiba University, Japan in 1993. He has been working in different institutions like Indian Institute of Science (IISc), Bangalore, Indian Institute of Technology (IIT), Madras and National Institute of Ocean Technology (NIOT), Chennai. He is a Professor and Director in the Department of Electronics and Communication Engineering, Vels Institute of Science, Technology and Advanced Studies, Chennai, Tamil Nadu, India. He received MONBUSH of Fellowship Award of Japanese Government and Distinguished Scientist Award from Jaya Engineering College. He has also been Elected Member twice as Vice Chairman-Asia of Executive Board of Data Buoy Cooperation Panel (DBCP) of Inter-Governmental Oceanographic Commission (IOC) / World Meteorological Organization (WMO) of UNSCO, in October 2008 and September 2009.