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Artificial Intelligence Based Branch Retinal Vein Occlusion Detection

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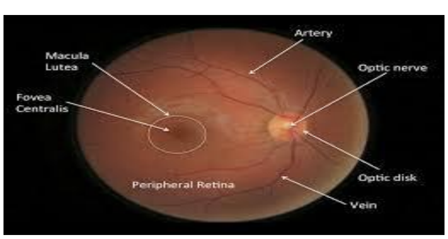
Abstract**—** The second most common visually disabling disease after Diabetic Retinopathy is Retinal Vein Occlusion (RVO). There are three types of Retinal Vein Occlusions: Central Retinal Vein Occlusion (CRVO), Branch Retinal Vein Occlusion (BRVO) and Hemi-retinal Vein Occlusion (HRVO). Here, CRVO is the blockage of the center vein, BRVO is the blockage of smaller veins i.e. branches of the vein and HRVO is the blockage of sub-veins of the main vein. Branch Retinal Vein Occlusion (BRVO) is three times more prevalent than Central Retinal Vein Occlusion (CRVO). Vision loss or blurry vision, floaters are some of the common features of BRVO. The treatment of BRVO aims at avoiding further damage to the patient's vision but it cannot heal or help regain the vision. Due to this reason, the detection of BRVO requires proper attention. Also, fundus machines for detection of BRVO are not available in remote areas. The symptoms of this disease cannot be easily detected due to very small variations in the early stages and also due to the absence of an ophthalmologist. To serve this purpose an Artificial Intelligence is developed with the aim of providing the first level of diagnosis of BRVO. For this, different preprocessing techniques and layers are used to build four Convolutional Neural Network models.

Keywords**—**occlusion, Artificial Intelligence, Convolutional Neural Network.

I. INTRODUCTION

A. About Retina

Human Retina is the light-sensitive tissue covering the interior surface of the eye. The cornea and the lens focus light rays on the retina. Then, the retina transforms the light received into the electrical impulses and sends them to the brain via the optic nerve. These impulses are thereby interpreted by the brain as images. The retina is approximately 0.5 mm thick and lines the back of the eye. The optic nerve contains the ganglion cell axons running to the brain and, additionally, incoming blood vessels that open into the retina to vascularize the retinal layers and neurons. The macula or macula lutea is an oval-shaped pigmented area near the center of the retina.



Source:https://ocularmanifestofsystemicdisease.weebly.com/anatomy.html
Fig 1 Retina image from Vision Express Photography

The optic disc represents the beginning of the optic nerve and is the point where the axons of retinal ganglion cells come together. The optic disc is also the entry point for the major blood vessels that supply the retina. The horizontal meridian lies nearby the optic disc and macula, the vertical meridian passes through the center of the eye and is perpendicular to the horizontal meridian.

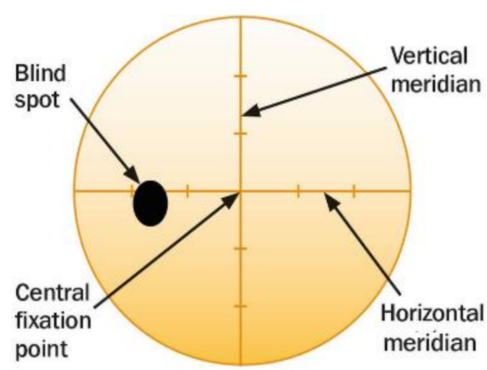


Fig 2 Normal Eye labeled image.

B. About Branch Retinal Vein Occlusion

Branch Retinal Vein Occlusion(BRVO) was first described by the German ophthalmologist Theodor von Leber in 1877. Since then, researchers have revealed that BRVO can have multiple underlying causes, including age, hypertension, diabetic retinopathy, or hypercoagulability.[1] Branch retinal vein occlusion can be subdivided into major BRVO (retinal vein occlusion) and macular BRVO (macular vein occlusion).

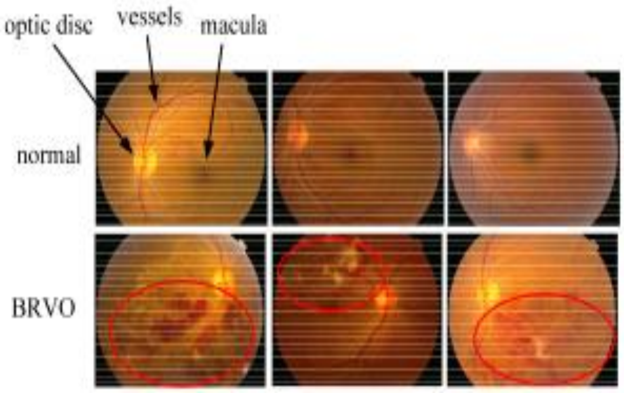


Fig 3 Occluded eye images

Regardless of the underlying cause, BRVO refers to the obstruction of a branch of the retinal vein at an arteriovenous crossing. This compression of the vein is thought to cause turbulent blood flow that leads to thrombus formation.[1] The quadrant of the retina most commonly affected is the superotemporal quadrant in 63% to 66% of eyes affected with BRVO.

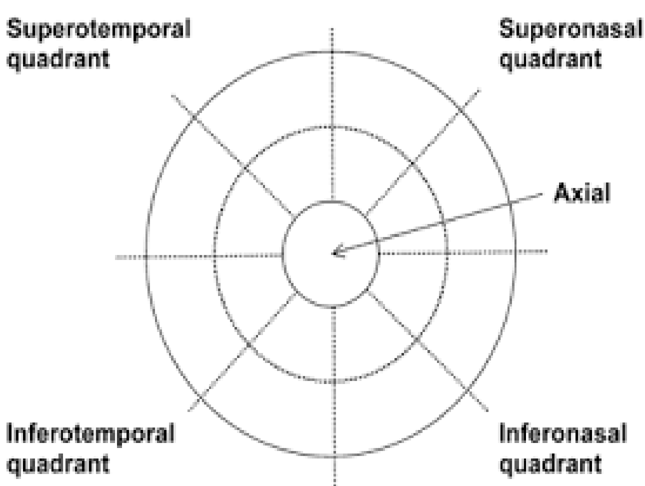


Fig 4 Eye image with quadrant info

C. Features of BRVO

BRVO affects branches of the central retinal vein. Hayreh divided BRVO into two groups: major BRVO and macular BRVO. Major BRVO involves occlusion of 1 of the 4 major retinal vein branches, and it involves all retinal regions drained by this branch. Macular BRVO arises from occlusion of the macular branch of the retinal vein[2].

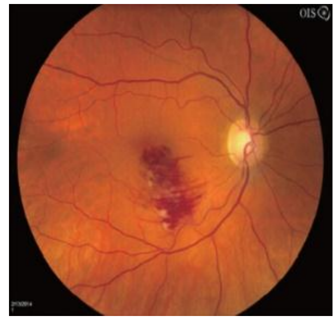


Fig 5 Color fundus image of macular BRVO

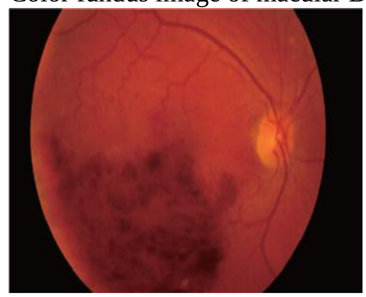
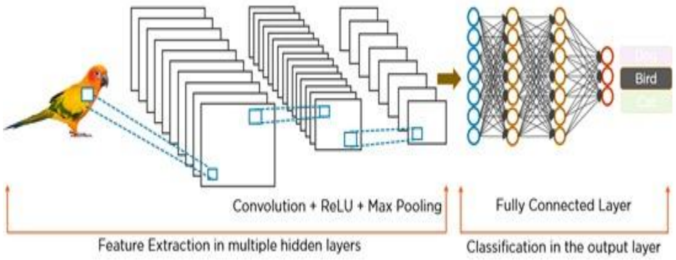


Fig 6 Color fundus image of major BRVO

BRVO can be diagnosed in the nasal or temporal quadrants, or in the superior or inferior retinal quadrants. Nasally-located BRVOs are usually diagnosed incidentally because they are far away from the macula and they do not affect visual acuity. They may manifest as a vitreous hemorrhage from retinal neovascularization or as secondary neovascular glaucoma that results from neovascularization on the iris surface. Temporally located BRVOs usually affect the macula lutea, and they manifest as a decrease in visual acuity. Mainly superotemporally-located BRVOs tend to spread across the macula lutea because of the effect of gravity on the intra-retinal fluid. Some temporal BRVOs may be asymptomatic, similar to nasal BRVOs if they are located a large distance away in the peripheral retina.

A main characteristic of BRVO is venous dilatation peripherally from the site of occlusion. Occlusion usually occurs on the arterio-venous crossing. Both vessels have a common adventitia and the retinal artery compresses the retinal vein. An additional characteristic of BRVO is retinal hemorrhage. In severe cases, sub- or pre-retinal hemorrhages may be seen. Retinal edema is also present in affected areas, and if retinal ischemia is present, cotton-wool spots can be detected. Hard exudates can also be detected in the transition to the ischemic and non-ischemic retina.

D. The need for designing a Convolutional Neural Network



Source:https://www.quora.com/What-is-an-intuitive-explanation-of-Convolutional-Neural-Networks

Fig 7 Basic Convolutional Neural Network

Convolutional Neural Networks (CNN) is a powerful tool for image recognition. It has achieved many successes in various fields, e.g., large-scale image classification [3], 3D object recognition [4], and face recognition [5], etc. One main advantage of CNN is that it can automatically learn abstract and effective features from raw image pixels. Also, there is no need for manually designing the feature extraction algorithms for each specific recognition task. CNN is therefore adapted to detect BRVO. In this paper, we will utilize CNN to automatically learn features for BRVO recognition.

The rest of this paper is organized as follows.
Section II describes related work.
Section III describes the system.
Section IV reports the results.
Section V concludes this paper with final remarks.

II. RELATED WORK

There are two tests that eye care professionals use to detect and identify the extent of Branch retinal vein occlusion:

1. Fluorescein angiography (FA): In this technique, Sodium fluorescein is injected into a vein in the arm. This is done so that a special camera can record circulation in retina and choroid in the back of the eye.
2. Optical coherence tomography (OCT): The Inner layer hyper-reflectivity in the areas of retinal hemorrhage is shown by OCT. Hence it is considered as a useful tool.[6]

The images received from both of these machines are RGB images. They form the dataset for the Neural Network.

Four different Artificial Intelligence systems are developed using convolutional neural networks. Different preprocessing techniques and CNN layers are adopted in each of these four systems.

III. METHODOLOGY

A. Preprocessing of input

PREPROCESSING TYPE 1:

In this type, the entire image of the retina is directly fed to the Neural Network. A high amount of data augmentation is done. This is used in models: Model 1 and Model 2

PREPROCESSING TYPE 2:

The preprocessing of the input is decided according to the features of BRVO discussed earlier. As the BRVO rarely crosses the horizontal meridian, i.e the hemorrhages are present either in the upper section or in the lower section of the eye across this meridian, the input image is cut along the horizontal meridian. For this, the optic disc is detected and then the image is cut along the tangent to this disc. So, now the final parts of the retina are Upper section and the lower section as shown in Fig 8. This is used in models: Model 3 and Model 4.

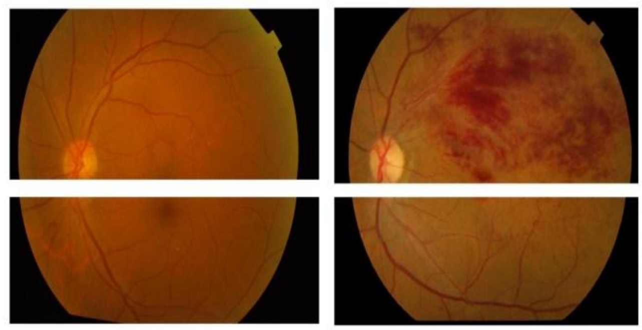


Fig 8 Normal and occluded eye images divided into two parts

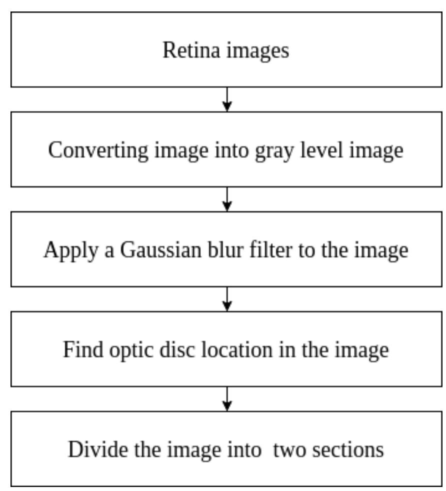
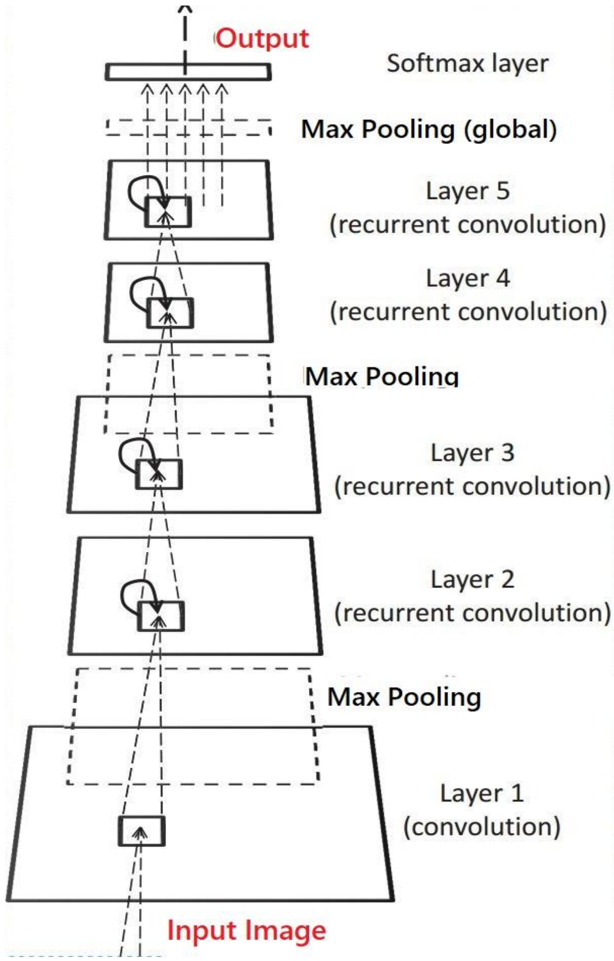


Fig 9 Flowchart for PREPROCESSING TYPE 2

B. Convolutional Neural Network

A Convolutional Neural Network (CNN) is made up of one or more convolutional layers followed by one or more fully connected layers. These layers mainly include the input layer, an output layer, and hidden layers. The hidden layers can be multiple convolutional layers, pooling layers, and fully connected layers.



Source:https://wiki.tum.de/display/lfdv/Recurrent+Neural+Networks+-+Combination+of+RNN+and+CNN

Fig 10 A classical convolutional neural network model

A classical convolutional neural network model is shown in Fig 10. The model consists of hierarchical convolution layers and pooling layers. For image recognition, image is given as an input to the CNN. Then, operations like multilayered convolution, pooling, etc. are performed on this input image. At the final layer is a full connection layer which is connected to the previous convolution layer. The result of this fully connected layer is the CNN output. The number of output nodes is equal to the number of image classes. For example, there are two image classes in this paper, i.e., normal and BRVO. Then the CNN has two output nodes.

For the models: Model 1 and Model 2, only one neural network is used per model. The prediction of the model directly determines whether the eye is occluded or not, no decision blocks are required in this case.

For the models: Model 3 and Model 4, instead of training a single neural network for the entire image, two different neural networks are designed and each of one of them is then trained for a specific section of retina ref Fig 11. Now, during testing, the image is divided into two parts and each part is fed to a separate trained CNN and predictions are noted. The logic of the decision block is developed according to the features of BRVO, that hemorrhage should be present in either of the two halves and it does not cross the horizontal meridian.

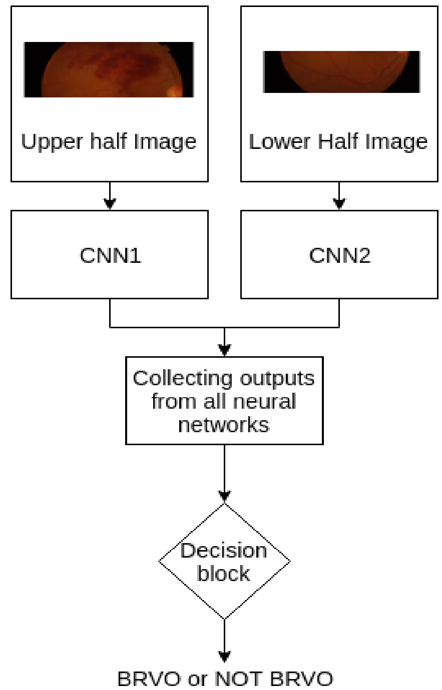


Fig 11 System Flowchart

This approach is introduced in order to achieve proper training of network and accuracy of the final results. Also, due to this approach, it becomes easier to detect whether the hemorrhages are present in a linear fashion, only in one of the two hemispheres and not in both. This approach makes it easier to check whether the hemorrhages cross the horizontal meridian. Thus, false alarms are avoided.

C. CNN Layers Information

Models: Model 1 and Model 3 uses Layers Type 1
Models: Model 2 and Model 4 uses Layers Type 2

LAYERS TYPE 1: LAYERS TYPE 2:

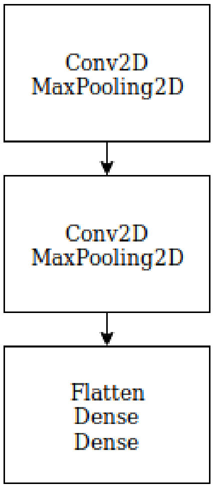


Fig 12 Model Layers TYPE 1

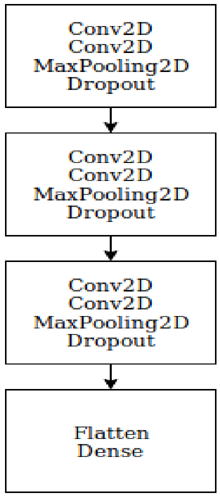


Fig 13 Model Layers TYPE 2

D. Model Information

Table I Model Information

Model Name	Type of Image Input (Preprocessing)	Type of Layers used
Model 1	Full Image (Preprocessing Type 1)	Layers Type 1
Model 2	Full Image (Preprocessing Type 1)	Layers Type 2
Model 3	Half Image (Preprocessing Type 2)	Layers Type 1
Model 4	Half Image (Preprocessing Type 2)	Layers Type 2

IV. Results and Discussion

A. Dataset and Configuration

The dataset contains 215 BRVO fundus images and 215 NOT BRVO fundus images. All the images are resized to 64*64. Now for models: Models 1 and Model 2, full images are used. So, after performing data augmentation the resulting dataset is divided into the training set and test set. For models: Model 3 and Model 4, the images are divided into two parts along the horizontal meridian. New labels are given to each new image. The image is labeled BRVO only if that section of the eye is occluded else it is labeled NOT_BRVO. After this, data augmentation is done in order to increase the size of the dataset. Then the dataset is divided into testing and training set. Hence, two different datasets are prepared for the four models.

B. Neural Network Results

Table II Model 1 prediction

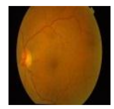
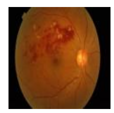
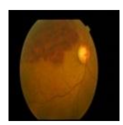
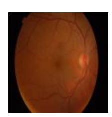
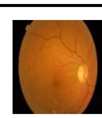
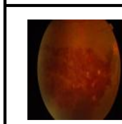
Image	Prediction
	The Prediction is: Not_brvo
	The Prediction is: Not_brvo
	The Prediction is: Not_brvo
	The Prediction is: brvo
	The Prediction is: brvo
	The Prediction is: brvo

Table III Model 2 prediction

Image	Prediction
	The Prediction is: Not_brvo
	The Prediction is: Not_brvo
	The Prediction is: Not_brvo
	The Prediction is: brvo

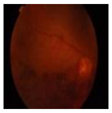
	The Prediction is: brvo
	The Prediction is: brvo

Table IV Model 3 prediction

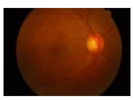
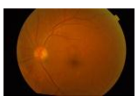
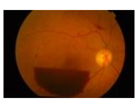
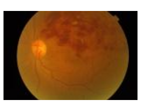
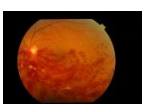
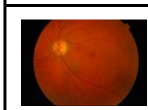
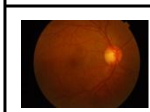
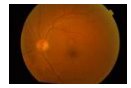
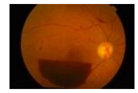
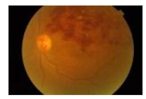
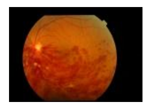
Image	Upper half Image prediction	Lower half Image prediction	Final Decision
	Not BRVO	Not BRVO	Not BRVO
	Not BRVO	Not BRVO	Not BRVO
	Not BRVO	Not BRVO	Not BRVO
	Not BRVO	BRVO	BRVO
	BRVO	Not BRVO	BRVO
	Not BRVO	BRVO	BRVO

Table V Model 4 prediction

Image	Upper half Image prediction	Lower half Image prediction	Final Decision
	Not BRVO	Not BRVO	Not BRVO
	Not BRVO	Not BRVO	Not BRVO
	Not BRVO	Not BRVO	Not BRVO
	Not BRVO	BRVO	BRVO
	BRVO	Not BRVO	BRVO
	Not BRVO	BRVO	BRVO

C. Comparison of all models

Each model was tested for 30 images (15 of NON-BRVO and 15 of BRVO).

Table VI Accuracy Table for all models

Model Name	No. of correct predictions	Accuracy
Model 1	21/30	70%
Model 2	18/30	60%
Model 3	24/30	80%
Model 4	23/30	75%

V. Conclusion and Future Scope

The main aim of this paper is to propose an Artificial Intelligence system for detection of Branch Retinal Vein Occlusion. This is done by building four artificial intelligence models using convolutional neural networks. In models: Model 1 and Model 2, PREPROCESSING TYPE 1 is used. This means full RGB image of the retina is fed to the CNN. In the other two models: Model 3 and Model 4, PREPROCESSING TYPE 2 is used. This means the image is divided into two parts and each part is fed to a separate CNN. The records from Table VI show that accuracy increases when PREPROCESSING TYPE 2 is used for a CNN with LAYERS TYPE 1. Model 3 gives the best results amongst all the four models. Here, each CNN is trained for a specific section of the retina. These sections: Upper and Lower Sections are decided according to an important features of BRVO. This feature is the location of hemorrhages in one only of the two hemispheres. Hence, it gives the most accurate results because, in this model, two different CNNs are used.

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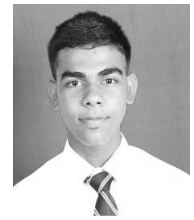
Authors Profile



Mr. Jecko Anto Kattampally was born in Thrissur, Kerala, India in 1997. He is in the final year of B.E. in Electronics and Telecommunication Engineering from the Fr. Conceicao Rodrigues Institute of Technology, Navi Mumbai, Maharashtra, India.

Mr Koshy C Oommen was born in Thiruvananthapuram, Kerala, India in 1997. He is in the final year of B.E. in Electronics and Telecommunication Engineering from the Fr. Conceicao Rodrigues Institute of Technology, Navi Mumbai, Maharashtra, India.

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Dr. Pranali Choudhari was born in Bhusawal, Maharashtra, India in 1978. She has received the B.E. degree in Electronics and Telecommunication engineering from MKSSS Cummins College of Engg., Pune, India in 2002. She has received MTech degree in Communication and Signal Processing from I.I.T. Bombay, Mumbai, India in 2009. She has also received a Ph.D. degree in Electronics from V.J.T.I., Mumbai.

She is currently an Asst. Professor in Fr. C. Rodrigues Institute of Technology, Vashi from 2010 till date. Earlier she has been a Senior Lecturer from 2009 till 2010 and a Lecturer from 2002 till 2008 Fr. C. Rodrigues Institute of Technology, Vashi. She has been a Reviewer of the paper submitted to International Journal for Numerical Methods in Biomedical Engineering, Wiley Journals and International Conference on Nascent Technologies in the Engineering Fields (ICNTE_2017), Fr. C Rodrigues Institute of Technology, Vashi, Navi Mumbai on January 27-28,2017.

