

# Improvising Connectivism by the use of Local Binary Pattern and Bayesian Network

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**Abstract**— The use of computer has increased in the field of education in today's scenario. The availability of Massive Open-Source Online Courses(MOOCs) is changing the way where the subjects are taught. Many mechanisms are combined with MOOCs where the user experiences new methodologies that makes the understanding of concepts more simple and easy to live with. This paper focuses on one such mechanism, which supports the ideology of connectivism which states that the computer can be used as a guiding tool in the field of education. The Local Binary Pattern (LBP) based object detection is used which helps to track the face in real time. Along with the angular distortions observed the LBP can be used to track the focus of the students and the teaching program can be made to pause if the student does not focus towards the computer. The ADA-Boost machine-learning algorithm is used to create a Cascade file, which includes the features of the face observed and recorded by LBP. The paper has 6 teaching methodologies in all, which includes teaching methods for the Deaf and Blind students too. For this purpose the Bayesian Networks are used to study and examine the student's mindset and their understanding style to provide accurate teaching. The aim of this paper is to provide a teaching methodology, which can be used for self studies and can bring some revolution in the education field.

**Keywords**— *Local Binary Pattern, Bayesian Network, Ensemble Learning, Object Detection, Connectivism, MOOCs.*

## I. INTRODUCTION

In this paper an approach is introduced to support better learning techniques for student. Currently, students for learning different things mostly use YouTube tutorials and pdf files. Students can learn or acquire required knowledge from these sources but every student has different grasping power. In this paper an approach is used where student's current activity is tracked and taught accordingly.

In this project, LBP algorithm is used for real time object detection instead of HAAR. LBP is 20% faster than Haar. It helps to track student's current status or activity. Bayes net algorithm is used instead of MLP algorithm for mood detection of student or user. MLP algorithm takes 10 more seconds than Bayes.

Here, by combining the LBP and bayes-net algorithms efficient way of learning is introduced through electronic media. In this project, Openstack is used for deployment purpose. It also reduces power consumption, memory consumption and solves compatibility issue.

## II. METHODOLOGY

This paper contains 4-stage mechanism, which includes Technique selection, Face detection, Face track and Ideology.

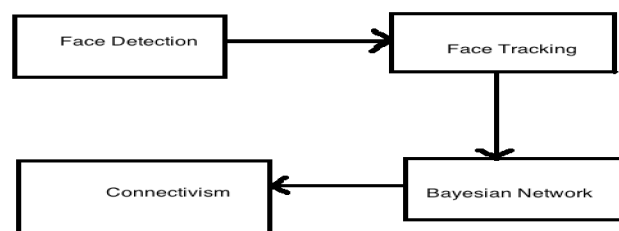


Fig. 1. Methodology

### 1.) TECHNIQUE SELECTION:

- a. Bayesian Network

### 2.) FACE DETECTION:

- a. LBP Features
- b. Integral Image

- c. ADA Boost
- d. Cascading

### 3.) FACE TRACK:

- a. Mean Shift
- b. CAM-Shift
- c. Histogram Back-Projection

### 4.) IDEOLOGY:

- a. Conectivism

## III. FACE DETECTION:

### A. LBP:

For various computer vision applications like texture classification and segmentation,

Image retrieval and surface inspection LBP features are used. The face image is divided into many parts from which LBP features are extracted and combined into aggrandize featured vector which is used as face for description of texture. The operator assigns a label to every pixel of image. This work is done by thresholding the 3x3 neighborhood of every with value of center pixel by considering the result as binary value.

Then the histogram of the labels must be considered as a texture descriptor.

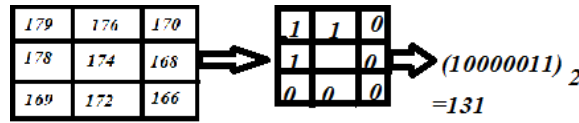


Fig. 2. Histogram

Spot, Flat, Line end, Edge, Corner these are the different texture primitives. LBP operator uses different neighbor sizes. In  $LBP_4$  operator, 4 neighbors are used while in  $LBP_{16,2}$  operator, 16 neighbors are used along with radius 2.

#### *LBP based facial representation:*

LBP operator effectively detects each face image, which can be considered as composition of micro patterns. A LBP based face representation for face detection is introduced by Ahonen at al. Face images are divided into 'm' small non-overlapping regions  $R_0, R_1, \dots, R_m$  to consider the shape information of faces which is shown in following figure. From each sub-regions, LBP histograms are extracted which are then concatenated into single.

The spatially enhanced feature histogram is defined by following formula:

Where  $i = 0, \dots, L-1, j = 0, \dots, M-1$ .

The local texture and global shape of face images are described by extracted feature histogram.

### B. ADA-BOOST:

ADA-BOOST is a machine-learning algorithm used for detection purpose in computer vision. It can track the best features. To improve performance, ADA-BOOST algorithm can be combined with other algorithms. It combines weak classifiers and creates strong classifier. Performance of weak classifier is poor but it is better than random guessing. But when strong classifier is formed, it can detect faces or any objects.

Following formulae demonstrate the concept of strong classifier and weak classifier.

$$F(x) = a_1f(x) + a_2f(x) + a_3f(x) + a_4f(x) \quad (1)$$

$a$  = assigned weight.

$fN(x)$  = weak classifiers (tracked features).

$F(x)$  = compiling features to generate strong classifiers.

Consider the following figure:

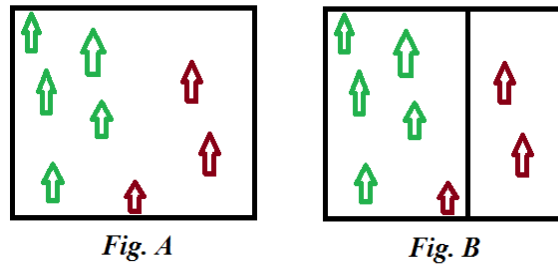


Fig. 3. weights of positive and negative images

The green arrows shown in the above figure are positive images or the objects, which are required whereas maroon arrows are the negative images. In figure A, positive and negative images are mixed while in figure B, a black line is drawn to separate positive and negative images.

Here, there is a false detection in figure B. It can be rearranged by increasing weight of falsely detected image.

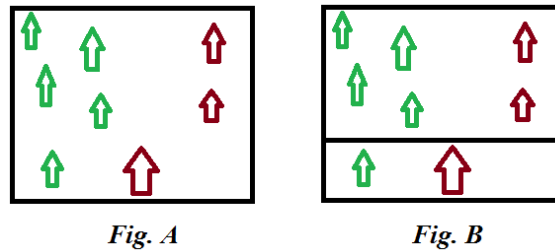


Fig. 4. weights of positive and negative images

Now, consider figure A, weight is increased of falsely detected image. Now again, based on their weight, rearrange and classify images as shown in figure B. Here again, there are two falsely detected images shown in figure B. Now again repeat those same procedures where higher weighted images are separated from lower weighted images. By this separation, positive images and negative images can be easily identified.

#### ADA-BOOST ALGORITHM:

For  $n$  rounds we consider:

- 1.) Weighted error is calculated and best value is chosen.
- 2.) Weight of the example has to be changed.
  - a.) Correct examples = weight is lower than other examples.
  - b.) Incorrect examples = weight is higher than other examples.

#### C. INTEGRAL IMAGE:

There is a limitation with the approach of combining weak classifiers to form strong classifier. In this approach, algorithm scans the same image again and again with the different size of window. This leads to increase in time consumption and energy consumption.

Consider there are 'p' number of positive images and 'n' number of negative images and  $n > p$ . The algorithm must scan the faces effectively with high speed and high efficiency and should immediately discard the negative images or non-faces and focuses on positive images. Hence for this purpose, cascading the classifier method is used. In cascading the classifier method, strong classifiers are combined. In this method, features are scanned in step-by-step manner. Every stage checks whether given image contains face or not. If the result is positive means given image contains image then it means that classifier is satisfied and this result is passed to next stage classifier and if result is negative, then image window will be discarded.

Following are the three main steps in designing a classifier:-

- 1.) Summation of total number of stages
- 2.) Summation of total number of features
- 3.) Threshold value for each single strong classifier

Formula:

$a$  = co-ordinates of the rectangle of the edge which is required.

$L$  = co-ordinates of the edge which is located to the left of that edge.

2	3	4		2	5	9
1	6	5	→	3	12	31
2	3	1		5	17	27
A				B		

Fig. 5. Theoretical Example for calculation of the mentioned formula.

Here in matrix A, those are is the normal image co-ordinates and  
In matrix B, those are the co-ordinates which are generated using integral image.

**Practical Example:**

P	Q	
	1	2
R	S	
	3	4

Fig. 6. Integral Image representation in terms of rectangle

Now, area of the block ‘S’ can be calculated by using following formula:  
 $Area(S) = ((1+4) - (2+3))$ . Area of ‘P’ or any block can also be calculated in terms of other blocks. It is given by:-  
 $Area(S) = P + (P+Q+R+S) - ((P+Q)+(P+R))$

*D. CASCADING CLASSIFIERS:*

There is the limitation with the approach of combining weak classifiers to form strong classifier. In this approach, algorithm scans the same image again and again with the different size of window. This leads to increase in time consumption and energy consumption.

Consider there are ‘p’ number of positive images and ‘n’ number of negative images and  $n > p$ . The algorithm must scan the faces effectively with high speed and high efficiency and should immediately discard the negative images or non-faces and focuses on positive images. Hence for this purpose, cascading the classifier method is used. In cascading the classifier method, strong classifiers are combined. In this method, features are scanned in step-by-step manner. Every stage checks whether given image contains face or not. If the result is positive means given image contains image then it means that classifier is satisfied and this result is passed to next stage classifier and if result is negative, then image window will be discarded.

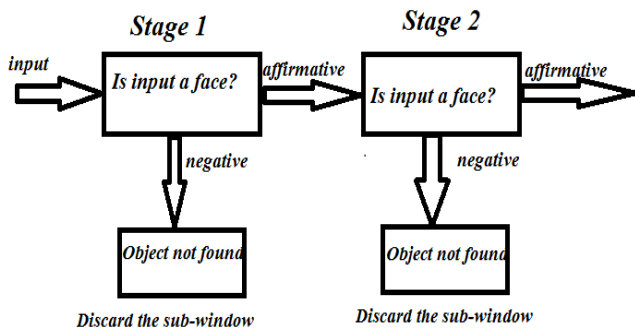


Fig. 7. Cascading Classifiers

- Following are the three main steps in designing a classifier:-
- 1.) Summation of total number of stages
  - 2.) Summation of total number of features
  - 3.) Threshold value for each single strong classifier

#### IV. CONNECTIVISM:

Connectivism is a learning theory for a digital world. It explains complex learning in a continuously changing social digital world. **Human-to-Human interaction is age old and efficient way to impact on education.** Connectivism is an ideology, which can be efficiently used to increase human computer interaction and to get its benefits over human-to-human interaction. The knowledge, which is present in non-human computer appliances, is defined by connectivism

##### Connectivism principles:

- 1.) Various range of options for delivering knowledge.
- 2.) Learning is a process, which connects various information sources.
- 3.) More focus on acquiring new knowledge rather than focusing on present knowledge.
- 4.) Knowledge can be acquired from non-human appliances.
- 5.) Proper maintenance of connectivism leads to efficient learning.
- 6.) Maintaining proper connection is required for efficient learning
- 7.) Maintaining connections between ideas, concepts and fields is core skill.
- 8.) Accuracy and up-to-date knowledge is currency in connectivism.
- 9.) Decision-making is named a learning process.

#### V. IMPLEMENTATION

The Bayesian Networks has a dual purpose mechanism where an appropriate teaching mechanism is chosen for students and also the dataset of the Bayesian Network is increased if the student find the teaching method acceptable. Hence it improves the usability and accuracy of the project.

- 1.) Check the student's condition if he/she is deaf, blind or normal.
- 2.) Impart teaching k1 if the student is deaf.
- 3.) Teaching k2 is imparted if the student is blind.
- 4.) For the students who are neither blind nor deaf, 11 psychological questions are asked based on a pool of 500 random qs to find their mood and confidence level based on which the one of the remaining 4 methods can be applied.
- 5.) The answers provided by the students are given to the Bayesian network and the Teaching methodology is predicted accordingly. The teaching set  $K_i = \{K1, K2, K3, K4, K5, K6\}$
- 6.) After the lessons are taught, a feedback is taken from the student. If the feedback is positive then the database updates itself with the current students' data, if not the student is provided the freedom to choose the teaching methodology.
- 7.) Step 1 to 7 is repeated for every student.

List Of Attributes  $X = \{\text{Self-Learning Level, English understanding level, Imagination skills, Conceptual knowledge, Presentation on paper, Concentration, Marks, Attendance}\}$

NOTE: 4 types of levels are shown namely:

Very High(>90%), High(75%-90%), Medium(40-75%), Very Low(<40%).

##### TEACHING METHODS:

K1= Teaching with voice.

K2= Scan concentration for display.

K3=Teaching with basic flowcharts.

K4= Pause and Play Videos.

K5= Basic reading by using pdfs.

K6= Question answer formats.

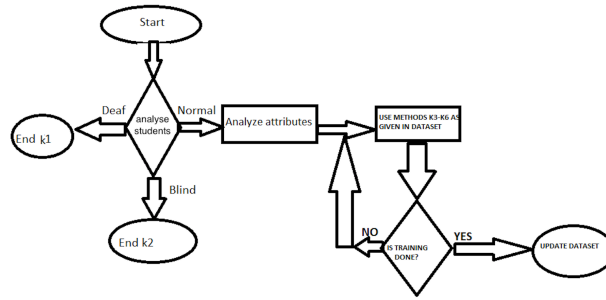


Fig. 8. Implementation to check student condition

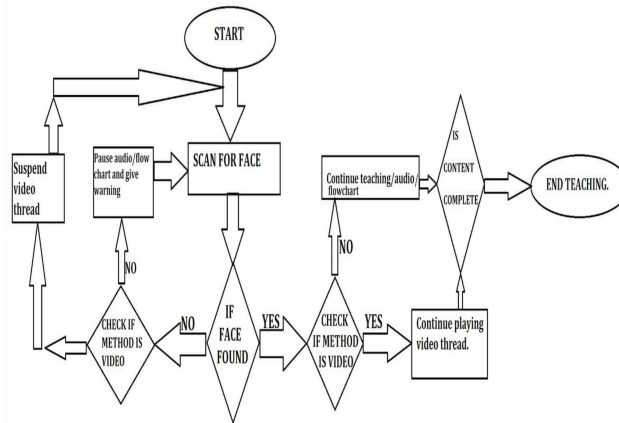


Fig. 9. Implementation to check student condition

## VI. BAYESIAN NETWORK:

A Bayesian Network is a probabilistic Directed Acyclic Graphical model. Bayesian networks are composed of Directed Acyclic Graphs where the nodes are related with each other. The nodes have random values associated with each other where as the connectors provides a representation of relationship between them. There are total of 11 values present in the dataset. Naming them according to the columns their relationship is drawn below which also denotes the build configuration. The following shows the Bayesian graph and the probabilistic model is shown below.

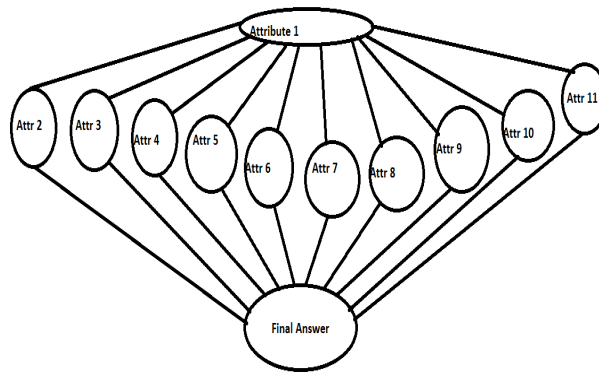


Fig. 10. Bayesian Model For attributes

Model : -  $P(1) \cdot P(1/2) \cdot P(1/3) \cdot P(1/4) \cdot P(1/5) \cdot P(1/6) \cdot P(1/7) \cdot P(1/8) \cdot P(1/9) \cdot P(1/10) \cdot P(1/11) \cdot P(ans|2-11)$ .

## VII. RESULTS

No.	Attribute 1 Numeric	Attr2 Numeric	Attr3 Nominal	Attr4 Nominal	Attr5 Nominal	Attr6 Nominal	Attr7 Nominal	Attr8 Nominal	Attr9 Nominal	Attr10 Nominal	Attr11 Nominal	Answer Nominal
1	63.0	200.0	H	VH	M	M	M	M	M	M	M	B
2	73.0	184.0	H	VN	H	VH	H	H	VH	H	H	B
3	83.0	187.0	VH	VHH	H	H	H	H	VH	VH	VH	A
4	88.0	190.0	H	VH	M	VH	H	M	VH	VH	VH	C
5	60.0	180.0	M	H	M	M	M	M	M	M	M	C
6	90.0	181.0	H	VH	VH	M	VH	VH	M	VH	VH	C
7	97.0	200.0	VH	VH	VH	VH	VH	VH	VH	VH	VH	A
8	90.0	200.0	VH	M	VH	H	VH	VH	VH	VH	VH	A
9	46.0	200.0	VH	L	H	L	L	L	VH	L	L	E
10	71.0	150.0	M	VH	M	H	H	M	H	H	H	C
11	99.0	175.0	VH	VH	VH	H	VH	VH	VH	VH	VH	E
12	100.0	182.0	VH	VH	VH	VH	VH	VH	VH	VH	VH	A
13	75.0	193.0	H	M	H	M	H	M	H	H	H	B
14	55.0	188.0	M	L	H	M	M	L	M	L	L	E
15	76.0	177.0	H	H	H	M	H	H	M	H	H	C
16	42.0	147.0	L	M	L	L	L	L	M	L	L	E
17	97.0	200.0	VH	VH	VH	H	VH	VH	VH	VH	VH	A
18	75.0	185.0	H	VH	H	H	H	H	H	H	H	C
19	82.0	185.0	VH	VH	H	H	H	H	VH	VH	VH	B
20	71.0	190.0	H	VH	H	H	H	H	VH	H	H	A
21	83.0	180.0	VH	VH	VH	VH	H	H	VH	VH	VH	A
22	70.0	200.0	VH	H	VH	VH	H	H	VH	H	H	B
23	88.0	200.0	VH	H	V	H	VH	H	VH	VH	VH	A
24	77.0	200.0	VH	H	VH	H	H	H	VH	H	H	C

Fig.11. Dataset Representation

Abbreviations: VH- Very High, H- High, M- Medium, L- Low, Attr – Attributes.

Answer Selection: A=k1, B=k3, C=k4, D=k5, E=k6.

The screenshot shows the Weka software interface for the Bayesian Classifier. The 'Classifier' dropdown is set to 'BayesNet -D -Q weka.classifiers.bayes.net.search.local.K2 -- -P 1 -S BAYES -E weka.classifiers.bayes.n'. Under 'Test options', 'Cross-validation' is selected with 'Folds' set to 10. The 'Result list' on the left shows two entries: '08:28:03 - bayes.BayesNet' and '08:28:28 - bayes.BayesNet', with the latter selected. The 'Classifier output' pane on the right displays the following information:

```

mass(2): class
pedi(2): class
age(2): class
class(2):
LogScore Bayes: -4030.960854130862
LogScore BDeu: -4053.744069918824
LogScore MDL: -4054.1531320488457
LogScore ENTROPY: -3991.037129583943
LogScore AIC: -4010.037129583943

Time taken to build model: 0.06 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances      571           74.349 %
Incorrectly Classified Instances    197           25.651 %
Kappa statistic                    0.429
Mean absolute error                 0.2987
Root mean squared error             0.4208
Relative absolute error             65.7116 %
Root relative squared error         88.28 %
Total Number of Instances          768

=== Detailed Accuracy By Class ===

```

	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC
	0.816	0.392	0.795	0.816	0.806	0.
	0.608	0.184	0.639	0.608	0.623	0.
Weighted Avg.	0.743	0.319	0.741	0.743	0.742	0.

Fig. 12. Bayesian Probability and results.

The use of Bayesian Network is done where the accuracy of the results is 74.3%. This reading can be increased when software works in real time to achieve more accuracy by students' feedback.

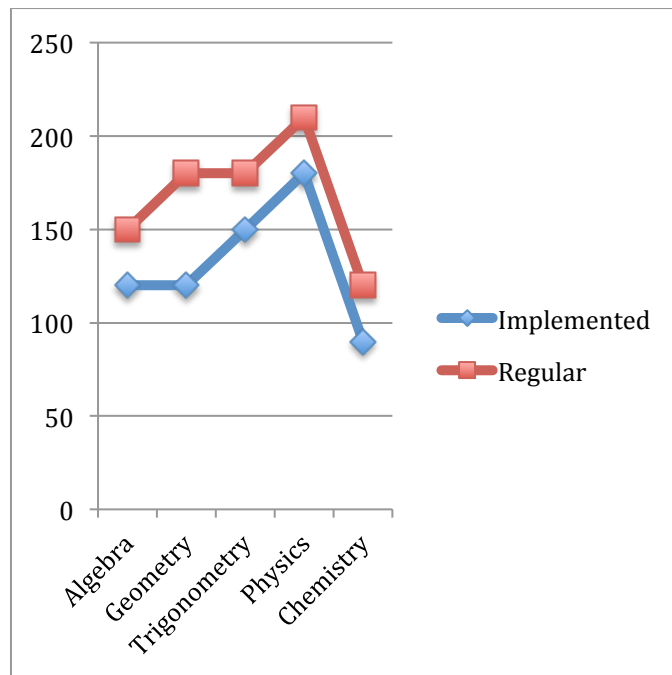


Fig. 13. Learning Time

The above figure shows the comparison between the regular method and implemented method. The comparison is based on learning time of the students. The blue line show the learning time used by the implemented method and the red line shows their regular method for learning

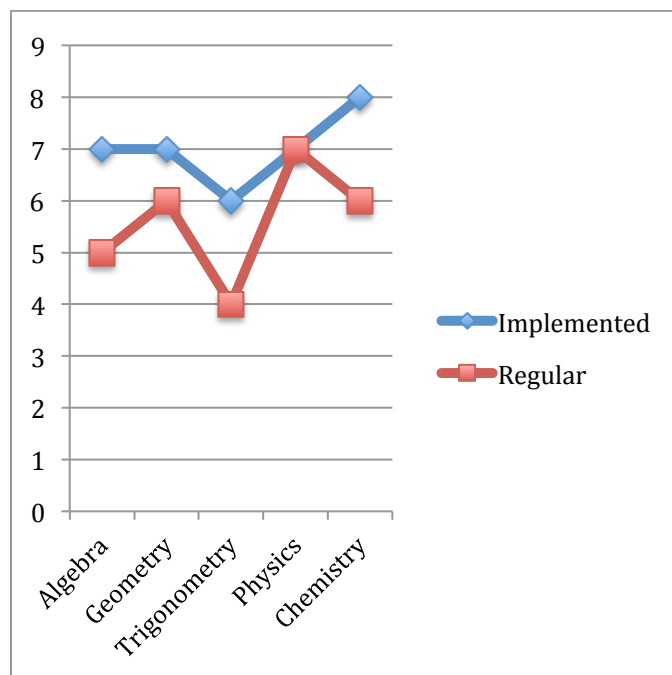


Fig. 14. Number of questions answered

Here the above figure denotes the number of questions answered by the students

## VIII. DISCUSSION

The above result was calculated on class 9 students (100 students having 75%-80% aggregate) where the students' attributes were taken from their mathematics score and attendance. A series of 150 questions was chosen from Internet, which was used to observe the students and find their mental level. Based on their level of understanding the best teaching method from the 6 were chosen and implemented on them. The feedback obtained from the students helped to create the dataset from which the project



could be implemented on real time. Moreover it was observed that the previous model, which used the Haar, based detection system and Multi-Layer Perceptron was comparatively slower and less accurate than this model used. The students were divided in groups where they were distributed on the basis of the score they obtained in class tests. These students were further divided into 2 groups of 50 students each. Group 1 were told to study in their regular format of self study and the remaining 1 group were the software in which they had to choose the teaching technique from K3 to K6. This group also included the blind and deaf students and K1 method and K2 method were assigned automatically to them. The next day tests were conducted which included 10 objective based questions randomly chosen by the teacher on the spot. Student who used this software were found to have a better result than the students who studied using their old self study method. The project has a voice assistance system to make the student focus towards the computer if they tend to waver. The LBP algorithm in combination does this with Sphinx4 Text to speech conversion engine.

#### IX. CONCLUSION:

Here the Bayesian Networks are used to analyze the data obtained from the students based on the attributes mentioned in the discussion. Based on these data 6 teaching methods K1 to K6 are implemented which includes Vocal teaching, Scanning concentration for display, Teaching with flowcharts, Pause and play of the videos, Pdfs and Question answer format where the above methods use the Local Binary Pattern to detect the face for the purpose of concentration. Here after the students complete the training given by the computers, their feedbacks are taken. Based on this feedback, if the teaching is successful the data is added to the list otherwise the student is given a chance to choose his own method, which eventually leads to data generation. More use of this system will improve the dataset leading to higher accuracy, which helps in choosing a better system for the students. It was well observed that the students learning time increased by 1.3-1.5 times from the graph tables. For specialized teaching for the students the use of Eigen Face algorithms can be used which can recognize the students' face while teaching. Above all this combination of algorithm is faster than the previous version which used Haar based detection method and Multi Layer Perceptron(MLP). Since MLP is comparatively slower than Bayesian Network and Local Binary Pattern is comparatively faster than the Haar based detection technique by 20%, the speed of this ideology has significantly improved.

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