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COGNITIVE PERCEPTION FOR SCHOLASTIC PURPOSES USING INNOVATIVE TEACHING STRATEGIES

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Abstract. The influence of emotion on attention is particularly strong, changing its selectivity in particular and motivating behavior and action. The degree to which a student participates in class determines their level of conceptual knowledge. Various teaching techniques have been developed over time to improve not only the attention of a student but also their engagement of a student. The level of engagement of a student can help us decide the amount of understanding a student can attain throughout the session. Though these techniques have been developed over time, the basic tests to determine the authenticity of these activities have been done mainly by the use of assessment-based methods. According to research in the field of neuroscience, a person's emotions can assist us to determine a student's level of participation. We also have the affective circumplex model to show us the correlation between emotions and the level of engagement of a person. Taking this into account, we developed an attentivity model with the help of an emotion recognition model (made with the help of VGG-16 architecture in CNN) and the eye tracking system to analyze the amount of engagement being displayed by the student in the class. This model applied to the students on the various teaching models helps us in deciding the effectiveness of various teaching methodologies for the primitive methods of teaching.

Key words: Emotion Recognition, Convolutional Neural Network, Eye tracking system, Attententivity, teaching methodologies**.**

AMS subject classifications. 68T05

1. Introduction. Human cognitive functions like perception, attention, learning, memory, reasoning, and problem-solving are significantly impacted by emotion [1]. There exist various methods to increase the amount of engagement of a student in a class. These strategies primarily recognize students' gaining knowledge of capacities for higher expertise and engagement. The present situation requires students to attend their lectures in the online mode but the experiment done can still be relevant for classroom teaching online or offline with a few differences due to the change of environment. Learning is the process of acquiring knowledge, behaviours, skills, standards, or preferences, and learning research has been intimately connected to the growth of psychology as a field of study [2]. Because it demonstrates students' involvement in the in-depth processing of course material and exposes the amount of time spent on the task, the degree of students' (dis)engagement in learning activities can be regarded as an important measure of both cognitive activation and classroom management [3][4].The quantity of information a student can learn depends on how involved they are in the class. There exists a fine line between engagement and attention, while attention is merely to focus, Understanding of the idea is what is meant by participation. The effective circumplex model, developed in the field of neurology, can be used to determine a student's level of engagement. The model indicates different emotional states, such as active positive, activated negative, deactivated positive, and deactivated negative. The best way to understand negative and positive emotions is to use the examples of sadness and happiness. Sadness is a negative emotion, and happiness is a positive emotion. Emotions are complicated phenomena that involve numerous connected subsystems that determine the activated section. Now as we have encountered these, further going into concept the positive activated emotions and the negative activated emotions can lead to better engagement performance in a person, such emotions can be happy, surprise, angry, etc, and vice versa as we can see in Figure 1.1. Taking this model into account we are capable of making a model that can help us in understanding the engagement of

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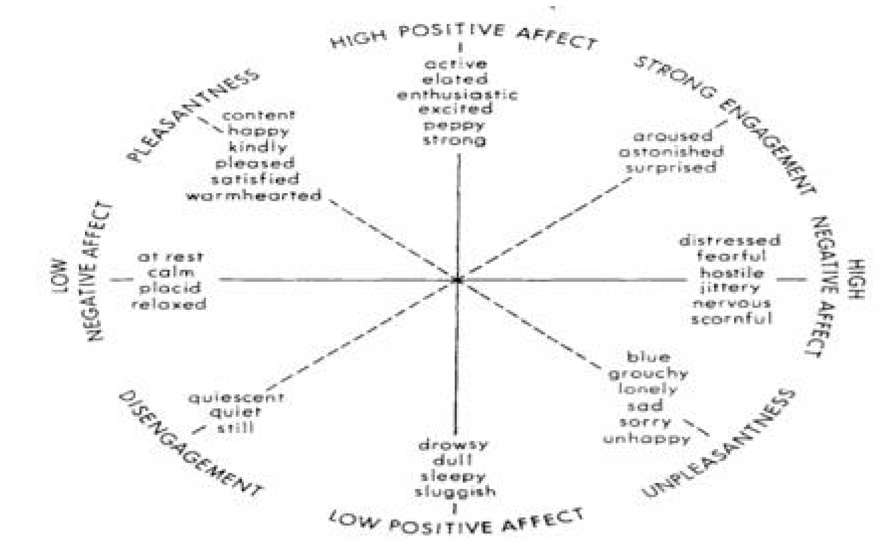

Fig. 1.1: Effect's two-dimensional organisational structure. from article "Toward a Consensual Structure of Mood" A. Watson and Tellegen. Psychological Bulletin, vol. 98, no. 221, 1985. American Psychological Association copyright, 1985

a student through various innovative teaching strategies, these strategies have been used to better understand the effects of these strategies on the students understanding in a classroom along with the amount of focus that the teacher needs to exert while taking a class forms the crux of the paper. This is made possible with the help of the attentivity model which uses two models to capture the attention and engagement of a student. The model uses eye-tracking technology and emotion detection to collect data from different students during the lecture.

The usage of the transfer learning approach with modified CNN and the eye tracking system allows the current paper's model to stand out from those utilized in other works., the experiments before have set to use the approach of using head pose which may still not produce accurate results and using eye tracker calculates the gaze, hence providing a better estimation of attention.

2. Related Work. The importance of the teacher-student relationship for teaching and learning is mentioned in a work by Ashley S. Potvin titled Students speaking to you: teachers respond to student surveys to improve classroom atmosphere. According to the information gathered from the students' experiences, teachers' conversations can be divided into two categories: routines for their classroom setting and pedagogical practice. The survey's findings impact instructors' actions by motivating them to evaluate their classrooms formally. Data collection and data analysis are used to classify the teacher's talk. This analysis of data helps teachers to improve their relationship with students and to create a caring classroom environment [5].

A paper by Zeinab Abulhul titled Teaching Strategies for Enhancing Student's Learning mentions Learning is enhanced only when students actively do something to learn rather than passively listening to the teacher [6]. Teachers have to be compelled to return up with effective teaching methods associated implement innovative solutions to satisfy each student's individual wants within the class. a number of the strategies that lecturers may use in their teaching methods for encouraging students to participate actively in learning method are giving a short lecture as an introduction to the category topic, conducting group action activities, cluster reports that facilitate students summarize the class meeting, on-line resources, and review lesson key points.

Another study called the Transfer learning approach tries to conserve time and resources by avoiding the requirement to train several machine learning models from scratch to complete related tasks. An increase in online learning has been observed as a result of the COVID-19 pandemic, according to a study by Vedant Bahel and Karan K. V[7]. This efficiency gain can be attributed to the use of natural language processing or image categorization, two machine learning techniques that require large amounts of resources. Smart online learning systems must start by measuring student engagement. Analyzing student behavior is necessary to gauge pupils' levels of participation. This can be achieved by taking a screenshot of the pupils' video feed and sending the faces that are spotted.

They suggested seven potential web-based visualizations in this study that could help them scale the complexity of the depth data they had gathered to track changes in head posture and emotion[8]. While a lecture is taking place, a smart application for teachers is being created to comprehend students' emotions and gauge their degrees of involvement. Computer vision-based approaches are used to evaluate both online and offline lecture films to extract the emotions of the students, as emotions are crucial to the learning process. Using a pre-trained Convolutional Neural Network, the six types of basic emotions—angry, disgusted, fearful, happy, sad, surprised, and neutral—are extracted[9]. Natural user interaction in e-learning is the most ongoing task for researchers. E-learning will be more effective when following the activities of traditional classroom teaching. This work investigated existing methods and presented a survey on head movements and emotion recognition[10].This study examines several face detection, feature extraction, and expression classification methods and techniques and comes to the conclusion that various algorithms and feature extraction approaches may effectively recognise facial expressions. The eye-ball tracking technique is also described in detail because it is crucial for nonverbal communication [11].

This study offers a methodology for automatically recognising facial expressions and focuses on the connection between facial expressions and learning outcomes with an eye toward the unique characteristics of online teaching mode [12]. The automated computer instructor known as AutoTutor converses with students in everyday language while simulating a human tutor. We discovered dominant frequent item sets that predict the following set of replies using a priori data mining techniques[13]. This study investigates the relationship between interactions and epistemic emotions in large-scale MOOC (massive online open courses) data. By assembling the large amount of data generated, this study combined deep learning and social network analysis (SNA) to identify patterns of epistemic emotions concerning interactions on a MOOC platform. [14].

In this study, they demonstrated that the combination of parameters such as MFCC, Root mean square, Spectral contrast, Tonnetz, Zero-crossing rate, Mel spectrogram frequency, and Chroma is effective in properly identifying emotion from the audio frequencies. RAVDESS and TESS, two open-source audio emotion datasets, were used to train the model [15].

The present focus of this study is on using frequency analysis to predict four emotions: angry, sad, neutral, and pleased. To do this, they first extract seven attributes, namely from a single audio file, and 195 sub-features. The qualities includeMFCC, Root Mean Square, Tonnetz, Spectral ContrastZero-crossing rate, frequency of the Mel spectrogram, and Combining chroma helps identify emotion from the audio frequency range precisely [16].

3. Methodology. As mentioned in the content above we will know the engagement of the student in the classroom, but to do so we need to have a model which can aid us in achieving the goal. We use the attentivity model which is an integration of the emotion recognition model made with the help of a Convolutional Neural Network (CNN) with the architecture of VGG-16 (although with a few modifications to make the model compatible with the input size of the dataset) along with the eye tracking system which was made with the help of image processing in the real-time.

The emotion recognition model uses a dataset of around 37K images with each image being of the size 48x48 as we can see in Figure 3.1, these images are in the black and white mode, and the name of the dataset is the FER dataset. The model made takes the RELU activation function to process the input data along with the batch normalization technique to make the model run for a lower amount of time in each epoch, the absence of batch normalization can make each epoch of the model run for at least 90 minutes each. The model is later flattened with the use of the same activation function and then later the output layer in the model has been taken as the SoftMax function which helps us in making a fully connecting layer. The model uses the Maxpooling function to pool the best feature onto the next layer as seen in Figure 3.2.

Though the model is can be perfectly made with the help of a current number of images in the dataset, it achieved an accuracy of 88% with the use of the CNN model using the VGG-16 architecture as seen in the layers in Table 3.1 and Figure 3.3 below, the need to add more images to the dataset was understood due to two schools of thought, one being the improvement of the model by increasing the number of inputs for better

Fig. 3.1: Images from FER dataset showing expressions of anger, fear, happiness and sadness

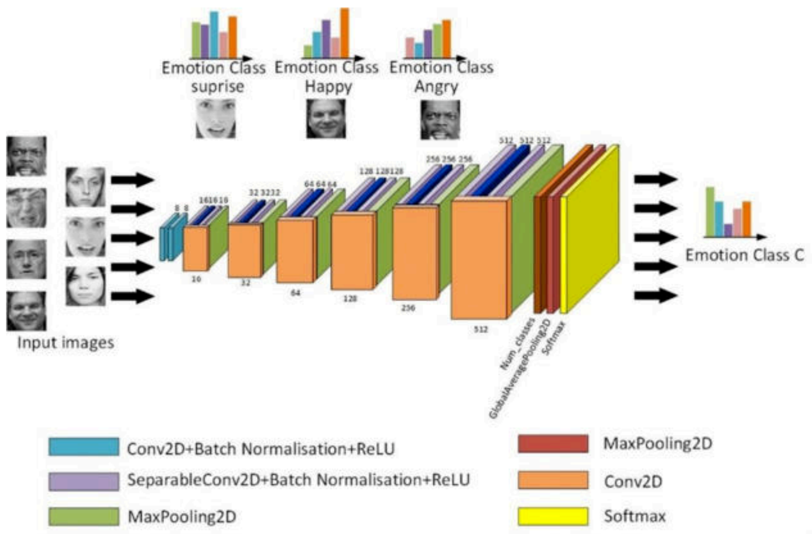

Fig. 3.2: CNN Model for Emotion Recognition

predictability and other being the inclusion of more local emotions as per saying the emotions of self and the local people with the help of transfer learning process.

3.1. Mathematical representation of the CNN model. The initial 4 convolution layers with ELU activation function is as follows

$$hl_{nj}^{1} = conv_{n+1,j}^{1} = Act\left(u_{2n,j}^{1}\right)$$

$$Act = \begin{cases} x, \ x \geq 0 \\ \alpha\left(e^{x} - 1\right), \ \mathrm{x} \ll 0 \end{cases} \tag{3.1}$$

After the 4 convolution layers, there are two flatten layers and they are mathematically represented as given in eqn. (3.2) to (3.4)

$$h_{Z}^{1} = \left\{a_1 h_1^1, a_2 h_2^1, a_3 h_3^1, a_4 h_4^1\right\} \tag{3.2}$$

$$out_{f1}^{1} = Flatten\left(F_n \ Act\left(h_z\right)\right) \tag{3.3}$$

Table 3.1: Layers in CNN

	Layer 1	**Layer 2**	**Layer 3**	**Layer 4**	**Layer 5**	**Layer 6**	**Layer 7**
Type	Convolution	Convolution	Convolution	Convolution	Flatten	Flatten	Dense
Activation	Elu	Elu	Elu	Elu	Elu	Elu	Softmax
Input layer	48X48 X32	24X24X64	12X12X128	6X6X256	256	512	512
Output layer	24X24X64	12X12X128	6X6X256	256	512	512	7
Batch norm	Yes	Yes	Yes	Yes	Yes	Yes	-
padding	Same	Same	Same	Same	-	-	-
Dropout	0.2	0.2	0.2	0.2	0.25	0.25	-
Kernel Site	2	2	2	2	2	2	-
Maxpool size	2X2	2X2	2X2	2X2	-	-	-

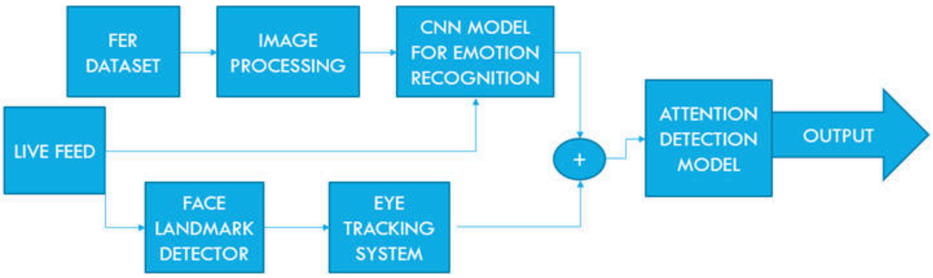

Fig. 3.3: Proposed model for attention estimation system

$$out_{f2}^{1} = Flatten\left(F_{n+1}\ Act\left(out_{f1}^{1}\right)\right) \tag{3.4}$$

Finally, the dense layer is calculated as given in eqn. (3.5)

$$out_{F}^{1} = Dense\left(Den_c, Act_{soft\max}\left(out_{f2}^{1}\right)\right) \tag{3.5}$$

The above mathematical represents the layers in the CNN model from eqn. (3.1) to (3.5). It shows the types of layers, number of layers and the activation functions used for achieving the desired output to calculate the attentiveness in students. Eqn. (3.6) is to calculate the percentage obtained the normal distribution

$$Z = (X - \mu)/\sigma \tag{3.6}$$

where X is data, μ = Mean of the data and σ = Standard Deviation.

The model was later able to achieve an accuracy of around 96%. This is paired with the eye tracking system, which uses image processing by taking a photo in real-time from the video being taken and extracting the eyes in particular from the given image with the help of harr_cascade_classifier [17]. Now, taking this cropped part we try to distinguish the white part of the eye from the colored part and approximately calculate the centroid of the eye after extracting the pupil of the eye by taking the average of the x – coordinates and the y- coordinates of the eye. The ratio of the eye position and the relative center position of the pupil is calculated and the vertical and horizontal ratio of the eye is calculated which is bound to be between the values 0 and 1. Now, these values state the extreme position of the eye. This method works better than calculating the head pose of a particular individual, which helps in accurately calculating the attention of the person as the person

Fig. 3.4: Result from main runner function integrating both the emotion recognition model and eye tracking model

can be keeping the perfect head pose and still not be concentrating which can be perfectly identified with the help of an eye-tracking system.

The proposed model as in Figure 3.3 shows the integration of the models formed by combining the emotion recognition model and the eye tracking model to get the attention detection model, which takes input as a live feed which is then converted to data accordingly by both the models and the calculation of attentiveness is performed in the final stage.

Taking both of these models, we make a report with the help of the effective circumplex model as mentioned above to state the various emotional engagement of the student. This experiment is carried out for the various teaching strategies and the report generated through these models will help us in identifying the various advantages and disadvantages of various teaching strategies as seen in Figure 3.4.

The following experiment being done is done based on the computational model built with the help of CNN whereas the earlier models used the normal methods of taking the emotions based on what can be seen or taking one from the student. But as discussed the experiment here is focused on the computational model. The CNN model made uses the relu activation function the usage of relu helps to prevent the exponential growth in the computation required to operate the neural network. If the CNN scales in size, the computational cost of adding extra ReLUs increases linearly. The experiment conducted uses around 57,600 images in the data in total from all the methods conducted. The experiment is made possible with the help of an attention estimation system, which uses emotion recognition made with the help of CNN to track the emotions and the eye tracking system to know the attentivity of the student. Every student was observed taking the emotions of the students into account and their emotions and attentivity throughout the experiment were noted. The students were mainly checked upon the three methods: role play, predict-observe-explain, and lastly a normal ppt lecture. As mentioned, the experiment focused on the emotion and attention of the student and also the lecturer in the session. The sessions were designed in a way to differentiate between the normal teaching method and the innovative teaching methods to prove the involvement of students in the lectures of innovative teaching methods. The experiment also helps us to draw out the amount of attention that the teacher had to use in various teaching methods. The involvement of engagement emotions as per the circumplex model describes the correlation between the emotions and the engagement of the student. The model takes the images of the videos of classes and stores them in a folder which later are used to calculate the attentivity the frame rate has been set to 2s to get as much varied data as possible and also the model works faster with a lesser frame rate.

3.2. Algorithm for the proposed model. The steps for the calculation of attentiveness of students in a classroom using CNN model is as follows:

Step1. Collect live feed from a classroom with many students. Feed is collected for various teaching strategies to identify the advantages and disadvantages of them.

Step2. The live feed is sent to the two models - Emotion recognition model and eye tracking system.

Step3. The feed is sent through the efficient deep learning CNN model for emotion recognition. The model

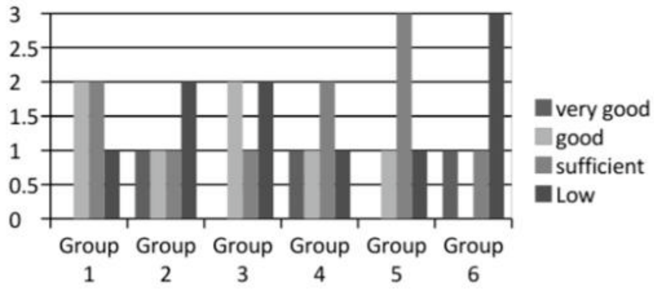

Fig. 4.1: Students' performance analysis by comparing against the role play technique of study

has 4 convolution layers, 2 flatten layers and 1 dense layer through which the images pass. The ELU and SoftMax activation functions are used.

Step4. The results from both the models are generated and used to create the attention detection model.

Step5. The result of attention detection model calculates the attentiveness of students. If the results are not satisfied again the data will be checked from the step 1 till the optimal solution is obtained.

3.3. Dataset used. To train the CNN model for emotion recognition, the FER data set was used. The data consists of 48 x 48 pixel grayscale images of faces. The faces are placed such that the face is centred and occupies almost the same amount of space in each image. This data set has around 37000 such images and are labelled as angry, disgust, happy, sad, neutral, surprised and fear. Hence, there are 7 classes in total.

4. Experimental Results. The first model to be experimented upon is the role-play model. The model consisted of around 19,200 images obtained through the video lectures. Role-play is a technique that allows students to explore realistic situations by interacting with other people in a managed way to develop experience and trial different strategies in a supported environment.

There have been various experiments done on this technique. The implementation of role play in the education of pre-service is where they try to understand the way a student is behaving to role play and without role play. They divided the students into 6 groups to determine its effects as seen in Figure 4.1.

The result of the student's reaction to role-playing confirmed that gaining knowledge of models: made it college students less difficult in knowledge gaining knowledge through role play than gaining knowledge via way of means themselves (100%); being capable of a domesticate mindset and educating the student's responsibility (90%); turned into clean to put into effect in college-level (90%); cultivated the mindset and educated student's awareness (100%); being capable of domesticating the mind-set and to educate the student's independence (75%); educated the scholars as a potential teacher (100%).

Individual results of the experiment conducted show the change in students' engagement to differ by a great margin of 81% when the experiment has been done from our end. This acts as a clear indication of the superiority of a teaching method applied in the enhancement of students understating of concepts. The use of concepts not only allowed us to identify the role of the teacher in making learning more prudent but also the use of groups to allow students to explore the topic to point out the mistakes in it their 'own way. The way of the experiment is sure different yet both of the experiments determine that role play is a better way of teaching strategy. As seen in Figure 4.2, the percentage change in positive emotions of the students is greater in this section as amounting to about 45.4% of the total suggesting more involvement of the student in a class the next model, we have used is for predict observation explain.

In Predict-Observe –Explain (POE) strategy students are required to predict the outcome of an event or experiment. The experiment is then performed and observations made by students are probed. The use of the POE experiment was also previously conducted to conduct a study to compare it with the effect of the Predict-Observe-Explain (POE) strategy on students' conceptual mastery and critical thinking in learning oscillations and waves by Dandy Furqani1*, Selly, to compare Fernie, Nanang Winarno1 who used the method using the

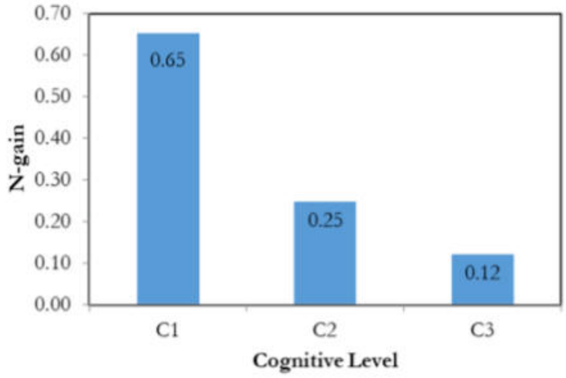

Fig. 4.2: Various cognitive levels in the stages of Predict Observe Explain (POE)

wave and vibration concepts to understand the student's understanding of the concept. [18].

The POE method shows an improvement in the conceptual mastery of university students, indicated by the normalized N-gain score of 0.29 about vital question ability. The POE method seems to be suitable for improving the ability to ask vital questions [19]. Using the POE method, the final result confirmed that university students use the increase in vital questioning from level 1,30 (challenged thinker) to 2,07 (beginner thinker). POE is suitable for implementing the know-how of the students. The results being compared shows the effectiveness of the technique while the experiment from the perspective of the other researcher may not show a better result when compared to our experiment, it can also mean the involvement of other factors which could affect the understanding of a student in this method, yet there is no denying the fact of its effectiveness to be better than another method of teaching. As shown in Figure 4.2 the cognitive levels according to the various methods in predict (c3), observe (c2), and explain (c1).

The results obtained with the help of the 3 methodologies take attention and engagement as the core details to identify the attention of a particular student during the entire session, as mentioned in the experiment section a snap of every 2 sec is recorded in the system and an aggregate is generated by the combination of attention and engagement, now taking a ratio of 3:7 we can calculate the normal distribution of the given sample as given in table 4.1.

The results are obtained after experimenting with the model on the students and the data obtained from them is taken as the percentage calculated as proportions obtained after the normal distribution of data to a group of 8 recorded as from p1…p8 is done for all the 3 categories as shown below in table 4.2.

When predictions and observations are inconsistent with each other the students' explanations are explored and as the experimental results suggested the change in positive emotions of the students is around 43.8% lastly the normal teaching method using the ppt had attention estimating a 10.7% of the total. Now we can conclude that innovative teaching methods have shown more positive results than normal teaching methods as seen in Figure 4.3.

Though the innovative teaching method sure makes a difference there is yet to observe the attention of a lecturer during the process and doing so we have obtained the following results. The role plays though producing promising results also invoke a lecturer to pay more attention towards the whole session which was calculated to be around 2.5% of the total. The ppt follows the lead with 25.4% of the total engagement, not producing results on par with role-playing or predict-observe-explain. Lastly, the predict-observe-explain uses the least engagement by the lecturer and yet produces more results as seen in Figure 4.4.

These two results help us to understand the difference between innovative teaching strategies and also normal methods and also their correlation with the amount of attentiveness paid by the student and also the lecturer in these sessions.

Table 4.1: Sample data obtained from the emotion recognition and eye tracking.

S.NO	Horizontal Ratio Average	Vertical Ratio Average	Attentiveness	Engagement
1	-1	-1	Not Attentive	0
2	-1	-1	Not Attentive	0
3	0.60622645	0.734680954 Attentive	Attentive	0.710312457
4	0.59317995	0.736744499 Attentive	Attentive	0.707882594
5	0.57516877	0.736418482 Attentive	Attentive	0.706953285
6	0.57913352	0.757323251 Attentive	Attentive	0.706096863
7	0.58773354	0.748190621 Attentive	Attentive	0.705938095
8	0.58765688	0.737449167 Attentive	Attentive	0.705532512

Table 4.2: Percentage of normally distributed engagement of students across different methods of teaching.

S.NO	Normal Activity (ppts etc)	Role Play Activity	PEO Activity
P1	10.53168	44.6858	43.1109
P2	11.22503	47.6277	45.9492
P3	12.53242	53.1749	51.3009
P4	5.314356	22.5488	21.7541
P5	16.14461	68.5014	66.0873
P6	9.917002	42.0778	40.5948
P7	9.139172	38.7774	37.4108
P8	10.79573	45.8062	44.1919

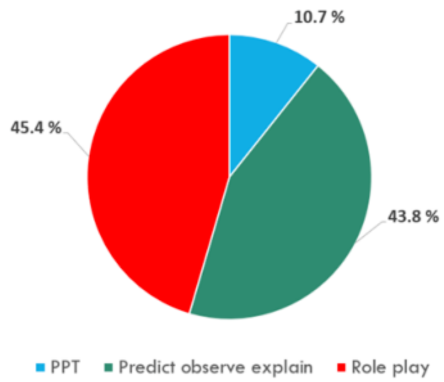

Fig. 4.3: Percentage of positive emotion change in various teaching strategies for students

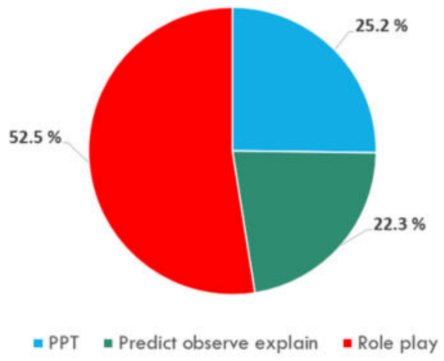

Fig. 4.4: Percentage of positive emotion change in various teaching strategies for lecturers

Though the role play seems to act better in gaining attention, yet has to also be provided with much attention by the lecturer, whereas the involvement of the lecturer is least in the predict observe explain was still able to draw out nearly as much attentiveness as the role-play and the normal ppt method has been proved to be least efficient of all methods.

5. Conclusion. The model successfully was able to prove the superiority of innovative teaching strategies in increasing the engagement of a student in a class. The model can be made better with the inclusion of various other types of inputs such as audio, video, etc which would allow the model to work in diverse situations, and also the model can be made more appropriate. The use of emotion detection can also be done for texts where a sentence can be analyzed to be displaying a certain kind of emotion possibly using methods like using a significant number of words must be entered into clustering techniques like K-Means, Cosine Similarity, Latent Discelet Allocation, and others[20]. The innovative teaching strategies like role play and predict observe explain proved to be more engaging in a class and thus produced better results whereas on other hand the conventional teaching strategy shows less promising results. Though this stands true, there is also another angle for the things to be seen, where we analyze the engagement of the teacher, which would help us understand the amount of involvement and focus that the teacher needs to exert in the whole session. Even though where we were able to see practically less difference in the role play and ppt though we can see the difference in the amount of output being given by both of them when compared side to side. Thus taking everything into account, we can finally conclude without any doubt that the innovative teaching strategies far exceed engaging a student in class rather than conventional teaching methods.

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