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FER Based Student Satisfaction Assessment While Online Learning

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Abstract— Abstract— Human Computer Interaction is a most keenly followed and sought after research topic from the past few decades by the research community. Facial expressions play crucial role in understanding the Human satisfaction over a service received by a machine that can see and identify the satisfaction level in reply as a feedback. In this paper we have proposed a consolidated system by using an augmented approach. This approach performs optimized selection of facial features from facial expression database created by Principle Component Analysis. The system is trained with the feedback to classify the emotions into basic six levels by using Emotional Back Propagation Neural Network. The exciting or happy emotions are treated as satisfaction of User and all other classes are treated as dissatisfaction over the service. The service chosen in this system is on-line learning and facial expression images processed through this proposed system yielded fruitful results close to the reality, in Human Computer Interaction.

Index Terms— Emotional Back Propagation Neural Network, PCA, Facial Expression, Human Computer Interaction, User Satisfaction, Online learning, Soft Computing, On-line Learning

I. INTRODUCTION

Facial Expressions play pivotal role in extracting the deep internal meaning of communication amongst humans especially when complicated information is to be exchanged that needs a good feed back to further proceed. These Expressions are a result of Emotions which are a stimuli generated according to the rationale of communication that turn out as a series of patterns in facial musculature. For a developing child's brain it becomes vital to recognize facial expressions in a quick and accurate manner. In order to know the exact emotion, the particular frame of once mind should act accordingly with the knowledge that it acquired from the past about various reactions and then segregate them in categories such as normal, sad, disgust, fear, happy and anger kind of basic emotions to assess the behavior of others.

On the other hand the online learning has been confronted by concerns about quality from the established educational community and society at large. Often, in dealing with these issues, the observations of e-learning students while on-line learning have became vital elements in taking the decisions about the faculties abilities and students' subject understanding and satisfaction to continue further. As the contemporary students of an on-line education rely mainly upon the deliverability of lectures and they act as agents of mouth and social media publicity for the course. So, it becomes thrust force for this work as it is fundamental in every programme educational objectives.

Emerging Technologies are escalating the boundary less nature of teaching learning and research and development over the stereotyped inside class room dissemination of knowledge. Students and teachers interact through modalities of almost every variety, greatly expanding avenues of communication. Norberg, Dziuban and Moskal's model as in [1] is an inter mixed learning model. It changes the trainer's responsibility in teaching-learning pattern based on audience synchronous and asynchronous learning preferences. The guaranteed and accurate assessment techniques for educational programs are in a steep raise for the season which should conquer the challenges thrown by the orthodox patterns of education. The issues about what moderates students' academic expectations and satisfaction, are still having significant research space left as they deal with cognitive issues of human brain.

Many innovative learning techniques prove that the online students are more inclined towards their ambivalence rather than the traditional environment. Students prefer active, rather than passive learning environments, and, because they participate in a highly interactive world, they expect the same in their classes as illustrated in McManus [2] et.al in their work. Today's learners are in thirst of myriads of resources for innovation and collaboration which e-learning environments can accommodate via a wide variety of teaching-learning strategies which are hackneyed. Researchers should not be surprised that identifying the defi1ning elements for satisfaction has become much more dynamic and complex. In this study, we attempt to clarify the latent factors of student satisfaction in lieu of overall course evaluation for students who respond positively to online experiences on end-of-course evaluation protocols. KUO, Yu-Chun et al [3] describe the evaluation problems faced in individual's attitude about an object. DJ Ozer, et.al.[4] summarize the issue about the way how the personality and prediction of its consequences plays a role in human-to-human interactions.

In the work of DJ Ozer, we found that possible ways of estimating the student satisfaction while online learning. The paper discussed the inherent models of image analysis. The Factors explained in that scored with contrasting student's emotions like satisfaction, ambivalence or dissatisfaction during their experiences while learning on-line. Finally, there are three findings surfaced in the study, which are treated as satisfaction components viz., engaged learning, agency, and assessment. The factor score comparisons indicate that students in the general satisfaction categories characterize important differences in engaged learning and agency, but not assessment. These results lead the authors to hypothesize that predetermined, but unspecified expectations (i.e., psychological contracts) for online courses by both students and faculty members are important advance organizers for clarifying student satisfaction.

Human face detection is a significant research issue, which is dealt by many researchers in a comprehensive manner in [5-9]. In this paper we have proposed a consolidated system by using an augmented approach. This approach performs optimized selection of facial features from facial expression database created by Principle Component Analysis. The system is trained with the feedback to classify the emotions into basic six levels by using Emotional Back Propagation Neural Network. The exciting or happy emotions are treated as satisfaction of User and all other classes are treated as dissatisfaction over the service. The service chosen in this system is on-line learning and facial expression images processed through this proposed system yielded fruitful results close to the reality, in Human Computer Interaction.

II. REVIEW OF THE SYSTEM

In the past 20 years there has been much research on recognizing emotion through facial expressions. This research was pioneered by Paul Ekman [10] who started his work from the psychology perspective. In the early 1990s the engineering community started to use these results to construct automatic methods of recognizing emotions from facial expressions in images or video based on various techniques of tracking.

An important problem in the emotion recognition field is the lack of agreed upon benchmark database and methods for compare different methods' performance. The Cohn-Kanade database is a step in this direction.

Since the early 1970s, Paul Ekman and his colleagues have performed extensive studies of human facial expressions and the incorporation of affective computing over the same issue along with Richard Picard et.al [11]. They found evidence to support universality in facial expressions. These "universal facial expressions" are those representing happiness, sadness, anger, fear, surprise, and disgust. They studied facial expressions in different cultures, including preliterate cultures, and found much commonality in the expression and recognition of emotions on the face. However, they observed differences in expressions as well and proposed a model in which the facial expressions are governed by "display rules" in different social contexts. For example, Japanese subjects and American subjects showed similar facial expressions while viewing the same stimulus film.

However, in the presence of authorities, the Japanese viewers were more reluctant to show their real expressions. On the other hand, babies seem to exhibit a wide range of facial expressions without being taught, thus suggesting that these expressions are innate.

Ekman and Friesen [12] developed the Facial Action Coding System (FACS) to code facial expressions where movements on the face are described by a set of action units (AUs). Each AU has some related muscular basis. This system of coding facial expressions is done manually by following a set of prescribed rules. The inputs are still images of facial expressions, often at the peak of the expression. This process is very time-consuming. Ekman's work inspired many researchers to analyze facial expressions by means of image and video processing. By tracking facial features and measuring the amount of facial movement, they attempt to categorize different facial expressions.

Recent work on facial expression analysis and recognition has used these "basic expressions" or a subset of them. Hai & Huwang [13] provide an in depth review of many of the research done in automatic facial expression recognition in recent years.

Multiple approaches define and assess student satisfaction. Rubin, Fernandes & Avgerinou[14] extended research on the Community of Inquiry (Garrison, Anderson & Archer, 2000) which defines social, cognitive, and teaching presence as being essential to the student learning experience and, thus, student satisfaction. They determined that learning management system (LMS) features greatly impact perceptions of community according to the inquiry framework. In a related study, Mahmood, Mahmood and Malik (2012) argued that teaching presence plays the most critical role in how students evaluate online learning.

The interaction construct plays an important role in both face-to-face and online learning modalities (Kuo, Walker, Belland & Schroder, 2013). In fact, many studies have found that both quantity and quality of student interactions are highly correlated with student satisfaction in almost any learning environment. However, investigators have noted that demographic and cultural considerations also impact the design of appropriate interaction techniques in online learning.

Ke and Kwak et.al.in [15] identified five elements of student satisfaction: learner relevance, active learning, authentic learning, learner autonomy, and technology competence. Kuo et al. [16] determined that learner-instructor interaction and learner-content interaction combined with technology efficacy are valid indicators of students' positive perceptions. However, the Ke & Kwak, using a criterion approach, argued that a positive course rating requires effective learner-instructor interaction.

III. METHODOLOGY

Emotion is common word used for what a person is feeling at a given moment. Joy, sadness, anger, fear, disgust, and surprise are often considered the six most basic emotions, and other well-known human emotions (e.g., pride, shame, regret, elation, etc.) are often treated as elaborations or specializations of these six to complex social situations.

All the primary goals of AI researchers are convoluted in to the elaboration of human emotions study. The vantage points from which they are aiming are developing agents and robots that interact with a human in a graceful manner, developing systems that take analog emotions to aid their own reasoning and to create agents or robots that model human emotional interactions and learning. In human-computer or human-human interaction systems, emotion recognition systems could provide users with improved services by being adaptive to their emotions. In virtual worlds, emotion recognition could help simulate more realistic avatar interaction.

The proposed architecture in this work contains the following stages: preprocessing of input images, feature extraction, training, classification, and database. Preprocessing of input images includes, face detection and cropping. Feature extraction is the process of deriving unique features from the data and can be accomplished by specific algorithms like Feature averaging, principal component analysis etc. Training of neural network will be done by giving the extracted features as input to the neural network with specified network parameters. Classification will be done by the neural network according to the specified targets in the network.

Figure 1 shows the framework of a general FER research and development system. It contains six main steps: face pre-processing (face detection, tracking, and normalization), feature extraction, feature selection, emotion classification, emotion representation, and performance evaluation. The input data can be static images or video sequences. The classified facial expressions are then represented in different methods and the performance is evaluated using different measurements as found earlier in our own work Ramachandran et.al.[17-18]. The system architecture of the system is depicted in the following Fig.1.

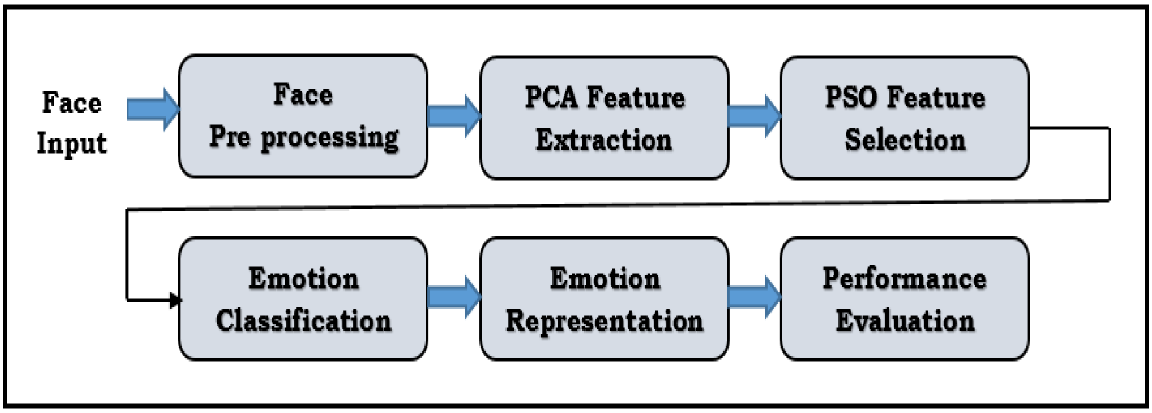

Fig. 1 System Architecture

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling. PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA), as revealed in our previous work [19-20]. The system is initialized with a population of random solutions and searches for optima by updating generations. However, Cross over and Mutation are operators of evaluation in GA, which are not required in PSO In PSO, the viable and vital answers that we get at the end are named as Particles, fly through the problem space by following the current optimum particles. The detailed information will be given in following sections. PSO is relatively simpler to GA as the adjustment parameters were less. For this reason many critical applications prefer to adapt PSO against GA, which include areas like Optimization, ANN Training, Fuzzy System control etc.

PSO is used it to solve the optimization problems. In PSO, each single solution is a "bird" in the search space. We call it "particle". All of particles have fitness values which are evaluated by the fitness function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles.

This work proposes a new solution to the facial expression recognition problem, describing a facial recognition system that can be used in application of Human computer interface. Pre-processing of input images includes, face detection and cropping. Without feature extraction nothing can be done further in to the investigation of images. So Algorithms like Pattern Averaging, Principal Component Analysis etc are employed for identifying conspicuous properties in each image. The specified network parameters play a pivotal role in the training of artificial neural network by taking the extracted images as input.

Based on the pre-specified targets in the network classification is performed. Pre-processing is the next stage after entering the data into the facial expression recognition system. The important data that is needed for most facial expression recognition methods is face position. As a standard practice of pre-processing the images are dimensionally reduced to 280 X 180 from 256 x 256 pixel values. For the edge detection Sobel method is picked up and applied.

The face images used for this experiment are taken from Cohn Kanade database. The time stamp & camera model were also imprinted upon the images. A Separate image is prepared for better performance in extracting the features by detecting and cropping the image These features are given as input to the neural network and will be trained to gain knowledge.

In the process of testing, the test input image will be pre-processed using Pattern Averaging and the trained using EmBPNN, then classified through the neural network classifier with the knowledge database gained from training. The architectural combination of augmented techniques is shown in the Figure 2.

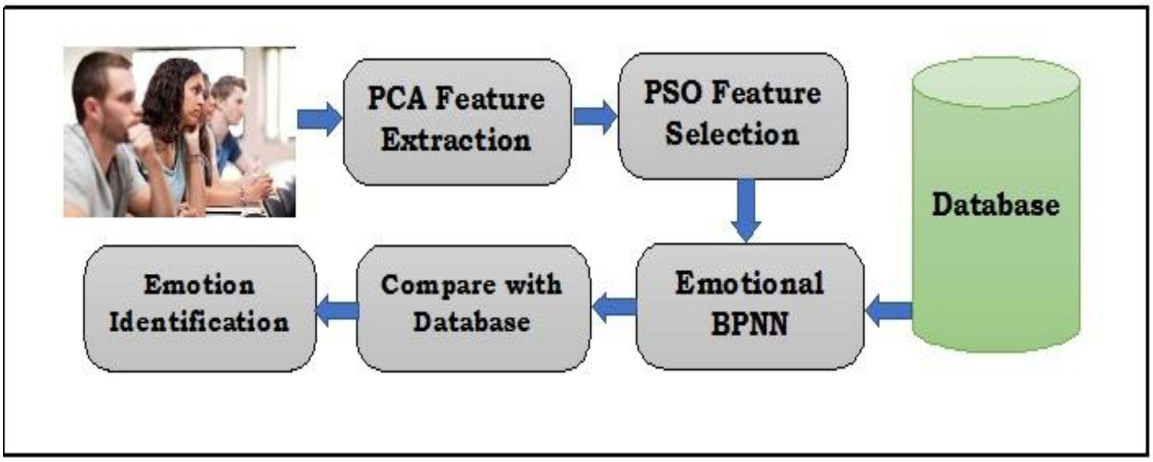

Fig 2 Architecture of EBPNN classification with PCA features optimized by PSO

The confusion matrix is created for each of the test. The test is performed on five subjects.

	Surprise	Fear	Happy	Sad	Anger	Disgust
Surprise	64	12	5	7	8	4
Fear	5	70	6	9	4	6
Happy	4	5	70	10	3	8
Sad	12	5	6	62	10	5
Anger	8	6	5	5	72	4
Disgust	7	2	8	7	3	73

Fig. 3 PSO+PCA+BPNN Confusion Matrix

The confusion matrix shows the percentage of correct classifications and misclassifications also. Diagonal elements show the correct classification results. All other elements are the misclassifications. Since the emotional parameters were introduced, the training time for the single iteration may be little more but the overall training time is reduced in achieving the minimization of error.

IV. RESULTS AND DISCUSSIONS

The recognition performance increases as the number of training samples increases. The lower the number of training samples the lesser the recognition rate. It is found that the combination of PCA with Emotional BPN Network is yielding the winning results even when the training samples are tuned low. A performance graph plotted among orthodox combination algorithms to proposed algorithm-pack against a number of training images. The facial expressions are taken periodically for a varying time slot and all are classified and accumulated to find the happy and exciting emotions to assess the student satisfaction over subject dealt with in the on-line.

Table 1 Comparison of results on Various Methods

Method	Surprise	Fear	Happy	Sad	Anger	Disgust
DCT+FFNN	10	1	80	3	2	4
PCA+FFNN	8	2	82	3	3	2
DCT+BPNN	6	1	84	4	2	3
PCA+BPNN	4	2	86	4	2	2
FAVG+FFNN	2	2	88	4	3	2
FAVG+BPNN	3	2	90	2	2	1
GA+FFNN	3	1	92	2	1	2
GA+BPNN	2	1	94	1	1	1
PSO+FFNN	1	0	96	1	1	1
PSO+BPNN	0	0	98	1	0	1

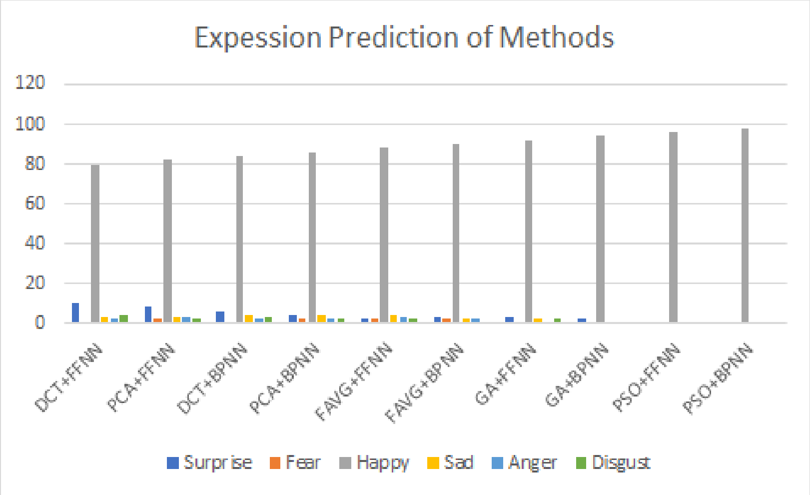

Fig. 4 Plot against various results

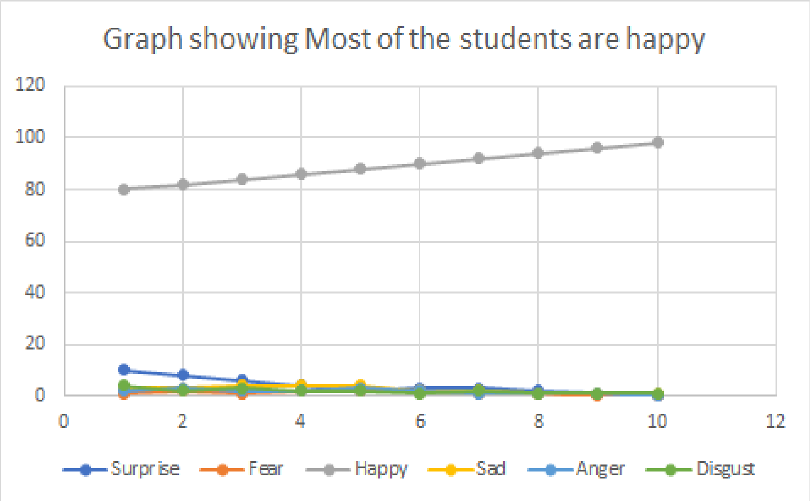

Fig. 5 Plot showing the final assessment

The implementation of neural network consists of training and testing. Cohn Kanade Databases are employed for the training and testing of facial expression from its database. The database comprises 200 subjects each having 2000 images. An exact number of 600 images were used in this work which is obtained from a session of 30 minutes attended by 10 students for a typical topic delivery on-line. The face snapshots were taken every half a minute and used in training & testing process. Sample images from the Cohn Kanade database are shown in Fig.5.

The performance of the system is measured by varying the number of images of each expression in training and testing. Table 1 shows the performance of the proposed method in comparison with other prominent methods.

The recognition performance increases as the number of training samples increases. The lower the number of training samples the lesser the recognition rate. It is found that the DCT with Emotional BPNN stood as best network even when the training samples are undersized.

For each test the strategic confusion matrix developed to assess the percentage of correct and miss classifications. All other elements are the misclassifications. The tests conducted and results of various facial emotional classification methods against a same stretch of on-line learning are shown in Fig4 & 5. Experimental results demonstrate that the proposed architecture improves the ability to assess the student satisfaction while online learning by taking their periodic facial expressions throughout the course. Based on the results we can conclude that the proposed emotional back propagation neural network with PCA is best in artificial neural network training time minimization and overall system performance also. With the introduction of emotional parameters, the time for single iteration training gets hiked significantly but while tuning for the error minimization the overall training time is reduced.

The performance of the system depends on the training time of the neural network which intern directly affected by the selection of values for the parameters like learning coefficient and momentum factor. The number of hidden neurons is also affecting the performance of the neural network. Experiments were carried out by varying the learning coefficient and the hidden neurons number and by varying the sigmoid function types.

The optimal value for learning rate is 0.02, which produces the best performance for facial expression recognition. The number of hidden neurons is same as the number of input neurons. Sigmoid action function is used in both hidden layer and output layer for activating the neurons. In the classification part of the emotional back propagation neural network, the time very less when compared to other neural networks.

V. CONCLUSION & FUTURE WORK

Experimental results elicit that the planned architecture improves the performance of the facial expression recognition of students while on-line learning. Based on the results it can be concluded that the proposed emotional back propagation neural network with Principal Component Analysis is best in extracting the on-line learning student satisfaction based on the performance it achieved through the this experiment. The methodology adopted in this paper minimizes the ANN training time and maximizes the performance of overall system. To achieve the error minimization we introduced the emotional parameters. The time for training a single iteration, the epoch, may be a little lengthy, but grand time for training the entire network is dramatically condensed.

The research can be extended into universal recognition of facial expressions in other service domains also. The work done is under constrained environment can be extended to open environment as a challenge and can be applied over the other Human Computer Interaction Systems, where the socially interactive robots are used.

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REFERENCES

[1] Anders Norberg, Charles D. Dziuban, Patsy D. Moskal, (2011) "A time- based blended learning model", On the Horizon, Vol. 19 Iss: 3, pp.207 - 216

[2] McManus, D. The two paradigms of education and the peer review of teaching, *(2001). NAGT Journal of Geosciences Education*, v 49 n 6., pp. *423-434.*

[3] KUO, Yu-Chun et al. "A predictive study of student satisfaction in online education programs", The International Review of Research in Open and Distributed Learning, v. 14, n. 1, p. 16-39, jan. 2013.

[4] DJ Ozer, V Benet Martinez, "Personality and the prediction of consequential outcomes", - Annu. Rev. Psychol., 2006 - annualreviews.org

[5] M. Jones and P. Viola, "Fast Multi-View Face Detection," Mitsubishi Electric Research Lab TR-20003-96, 2003..

[6] H. Chang, A. Haizhou, L. Yuan, and L. Shihong, "Vector Boosting for Rotation Invariant Multi-View Face Detection," in Computer Vision, 2005.ICCV 2005. Tenth IEEE International Conference on, 2005, pp. 446-453 Vol. 1.

[7] S. Z. Li and Z. Zhenqiu, "Floatboost Learning and Statistical Face Detection," Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 26, pp. 1112-1123, 2004..

[8] V. V. Alexander Vezhnevets, "'Modest Adaboost' - Teaching Adaboost to Generalize Better," Graphicon-2005, Novosibirsk Akademgorodok, Russia, 2005.

[9] M. Rydfalk, "Candide: A Parameterized Face," Dept. of Electrical Engineering, Link opings universitet, Sweden, Report No. lith-isy-i-866, 1987.

[10] Paul Ekman, " American Psychologist. 47 (4): 470–471. April 1992. doi:10.1037/0003-066x.47.4.470

[11] R. W. Picard, "Affective Computing," The MIT Press, Cambridge, MA, 1997.

[12] Paul Ekman & Wallace V.Freisen, "Unmasking the Face", Malor Books, ISBN 1-885536-36-7,Cambridge

[13] T. Hai and T. S. Huang, "Explanation-Based Facial Motion Tracking Using a Piecewise Bezier Volume Deformation Model," in Computer Vision and Pattern Recognition, 1999. IEEE Computer Society Conference on., 1999, pp. 611-617

[14] Rubin, B., Fernandes, R., & Avgerinou, M. D. (2013). The effects of technology on the community of inquiry and satisfaction with online courses. The Internet and Higher Education, 17, 48-57. doi: 10.1016/j.iheduc.2012.09.006

[15] Ke, F., & Kwak, D. (2013). Constructs of student-centered online learning on learning satisfaction of a diverse online student body: A structural equation modeling approach. Journal of Educational Computing Research, 48(1), 97-122. doi: 10.2190/EC.48.1.e

[16] Kuo, Y. C., Walker, A. E., Belland, B. R., & Schroder, K. E. (2013). A predictive study of student satisfaction in online education programs. The International Review of Research in Open and Distance Learning, 14(1), 16-39.

[17] V. Ramachandran B. Sivaiah and Dr. E. Srinivasa Reddy, "Facial Expression Classification System with Emotional Back Propagation Neural Network", International Journal of Scientific & Engineering Research, Volume 4, Issue 10, October-2013, ISSN 2229-5518, pp. 383-390.

[18] V.Ramachandran, B.Sivaiah and Dr.E.S.Reddy," An Enhanced Facial Expression Classification System Using Emotional Back Propagation Artificial Neural Network with DCT Approach", International Journal of Computer Science Engineering and Information Technology Research(IJCSEIT) ISSN (Print):2249-6831; ISSN (Online): 2249-7943, Volume 5, Issue 4, Aug-2015, pp. 83-94

[19] V.Ramachandran, B.Sivaiah and Dr.E.S.Reddy, "A novel Facial Expression Classification System using Emotional Back Propagation Artificial Neural Network and Genetic Algorithm ",International Journal of Applied Engineering Research (IJAER), Volume 10, Issue 17, Nov-2015, pp. 38583-38588

[20] V.Ramachandran & Dr.E.S.Reddy, "Facial Expression Classification with Enhanced Feature Extraction Using Particle Swarm Optimization and Emotional Back Propagation Neural Network ", International Journal of Applied Engineering Research ISSN 0973-4562 Volume 11, Number 10 (2016), pp. 6911-6915

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