

# Predicting learner preferences from emotions using Deep Learning Techniques

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## Abstract

Recommender System is the stage to overcome the information overload resulting from the rapid growth of information on the web. E-learning Recommender systems estimate user preferences based on learning interests of the learner observed through learning behaviors. In a Recommendation system, Deep Learning can contribute for better understanding of the user preferences through its multiple processing layers to learn representation of data such as images, sound, and text. Emotion plays an important role in identifying the user preferences. Recommender System considering emotion for finding the user preferences can be more appropriate. In Deep Learning, the facial expression methods can be used to identify the emotions such as interest, satisfaction, boredom, confusion, etc. of the learner. In the proposed method, learning content prepared using David Merrill's First Principles of Instruction (FPI) approach having the Problem at the center, Activation, Demonstration, Application and Integration are the four phases. Learning Content have been categorized in to text, audio and video. To predict the preferences of the learner, the concentration level of the learner is identified with the help of emotions exhibited during the actual learning engagement from the total learning time. Therefore, the Recommender Systems can propose to offer the preferred learning content to suit the learner needs.

Keywords: E-learning, Deep Learning, Facial Expression, Emotion Recognition, Learner Preferences.

## Introduction

E-Learning gives emphasis to pervasive and personalized learning technologies. Pervasive learning refers to learning that is available anywhere anytime. E-Learning better engage learners in the learning process. The truly engaged learners are intellectually and emotionally involved in their learning tasks from the engaged learning perspectives. Recommender Systems can provide more appropriate learning content to the learner based on their learning preferences. Learning Content must be prepared with the help of Instructional Strategy. David Merrill's FPI approach is the one proven Instructional Strategy suitable for E-learning for preparing the learning content. To engage the learner in engaged learning perspectives, the learner preference must be predicted; by using Deep learning techniques will be more appropriate.

Deep learning allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction. Deep convolutional

nets have brought about breakthroughs in processing images, video, speech and audio, whereas recurrent nets have shined light on sequential data such as text and speech (LeCun et al., 2015).

## **Literature Review**

### ***E-learning System***

E-learning is used for learner to gain Knowledge by accessing materials. It is one of the way in which a learner can have access to a topic in different form of materials like text, audio, video, etc (D.Deenadayalan et al., 2017). To improve the e-learning capability, the learner's learning curve must be evaluated as to improve the involvement of the student by improving the content being taught (Abdulkareem et al., 2016).

### ***Learning Content***

Learning content could use an FPI approach which contains four phases of instruction that are Activation, Demonstration, Application and Integration. The first principle relates to problem-centered instruction that ideally suits e-learning environment. Four more principles are stated for each of the four phases for effective instruction. Learning is promoted when learners are engaged in solving real-world problems. Problem is engaging in some form of simulation of a device or situation. Problem-centered instruction is contrasted with topic-centered instruction where components of the task are taught in isolation before introducing the real world task to the students. Activation recalls the prior knowledge or experience and create learning situation for the new problem. Demonstration shows a model of the skill required for the new problem. Application applies the skills obtained to the new problem. Integration provides the capabilities and to show the acquired skill to another new situation (Merrill, M. D., 2007).

Learner needs multimedia learning contents in the form of video, audio, images, text, etc. as a learning material in E-learning (B.K.Poornima et al., 2017). Learners can quickly locate their interested content in a colossal volume of video data; the extraction of content descriptive features is required. However, it is well recognized that low-level features as measures of color, texture and shape (S. Antani, R. Kasturi, & R. Jain, 2002) are not enough for uniquely discriminating across different video content.

### ***Emotion Recognition***

Emotion recognition study can be broadly categorized into three steps that are Face detection, Facial feature extraction and Emotion classification. These three categories are concerned with the central background pertaining to the issue of facial emotion recognition (Abdulkareem Al-Alwani, 2016). One of the important methods to detect emotion, the better way is to understand the emotion symptoms through facial expression. It is easy to observe the learners and their reaction on a particular topic which is being taught by the instructors during an instructor led course (Krithika.L.B et al., 2016).

The techniques of facial expression recognition, emotion recognition of speech and motion recognition are used to construct affective computing module. Learners' expressions are gathered and recognized however the basic technology of facial expression recognition. Then, the emotion state is judged and understood. Teaching strategies and learning behaviors are familiar to learners' emotion state (Jingjing Chen et al., 2008).

Emotional features over facial expressions provide a natural feedback of the learner on the content being delivered. For this purpose, authors carried out a study to investigate the possibility to understand learner's interest by using their facial expressions as a feedback to

evaluate interestingness of the content being delivered during e-learning (Abdulkareem Al-Alwani, 2016). The facial expressions can provide acute information on learner's emotions and thus can point out the involvement during e-learning (S. Wang et al., 2010, C. M. de Melo et al., 2015, A. Chakraborty et al., 2009).

Engagement level of a learner in e-learning is dependent upon learner's focus and learner's interest level. Facial expressions over short spans of time cannot ascertain these two attributes, and a long time frame analysis leads to classification of facial expressions, which can be then used to classify emotional states. For example, frustration and confusion was studied in image data using temporal and order based patterns (Aghababayan, 2014).

### ***Deep Learning Techniques***

Deep learning is a sub research field of machine learning. It learns multiple levels of representations and abstractions from data, which can solve both supervised and unsupervised learning tasks (Li Deng et al., 2014).

Shuai Zhang et al., 2017 surveyed the deep learning concepts are as follows:

- Multilayer Perceptron (MLP) is a feedforward neural network with multiple (one or more) hidden layers between input layer and output layer. Here, the perceptron can employ arbitrary activation function and does not necessarily represent strictly binary classifier.
- Autoencoder (AE) is an unsupervised model attempting to reconstruct its input data in the output. In general, the bottleneck layer (the middle-most layer) is used as a salient feature representation of the input data. There are many variants of autoencoders such as denoising autoencoder, marginalized denoising autoencoder, sparse autoencoder, contractive autoencoder and variational autoencoder (VAE) (Minmin Chen et al., 2012, Ian Goodfellow et al., 2016).
- Convolutional Neural Network (CNN) (Ian Goodfellow et al., 2016) is a special kind of feedforward neural network with convolution layers and pooling operations. It is capable of capturing the global and local features and significantly enhancing the efficiency and accuracy. It performs well in processing data with grid-like topology.
- Recurrent Neural Network (RNN) (Ian Goodfellow et al., 2016) is suitable for modelling sequential data. Unlike feedforward neural network, there are loops and memories in RNN to remember former computations. Variants such as Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU) network are often deployed in practice to overcome the vanishing gradient problem.
- Deep Semantic Similarity Model (DSSM), or more specifically, Deep Structured Semantic Model (Po-Sen Huang et al., 2013), is a deep neural network for learning semantic representations of entities in a common continuous semantic space and measuring their semantic similarities.
- Restricted Boltzmann Machine (RBM) is a two layer neural network consisting of a visible layer and a hidden layer. It can be easily stacked to a deep net. Restricted here means that there are no intra-layer communications in visible layer or hidden layer.

### **Proposed Approach**

The proposed approach is as represented in Figure 1. Learners Facial Expressions Data are captured. This instrument capture four type of emotions that are engagement, Satisfaction, confusion, boredom. In particular, the work focus on engagement emotion for analyzing the learners learning preferences. Learners are to be categorized using David Merrill’s FPI. The four phases are considered as the learning methods for the learners. Learner should be classified as various levels namely Beginner, Low level learner, Middle level learner and High level learner.

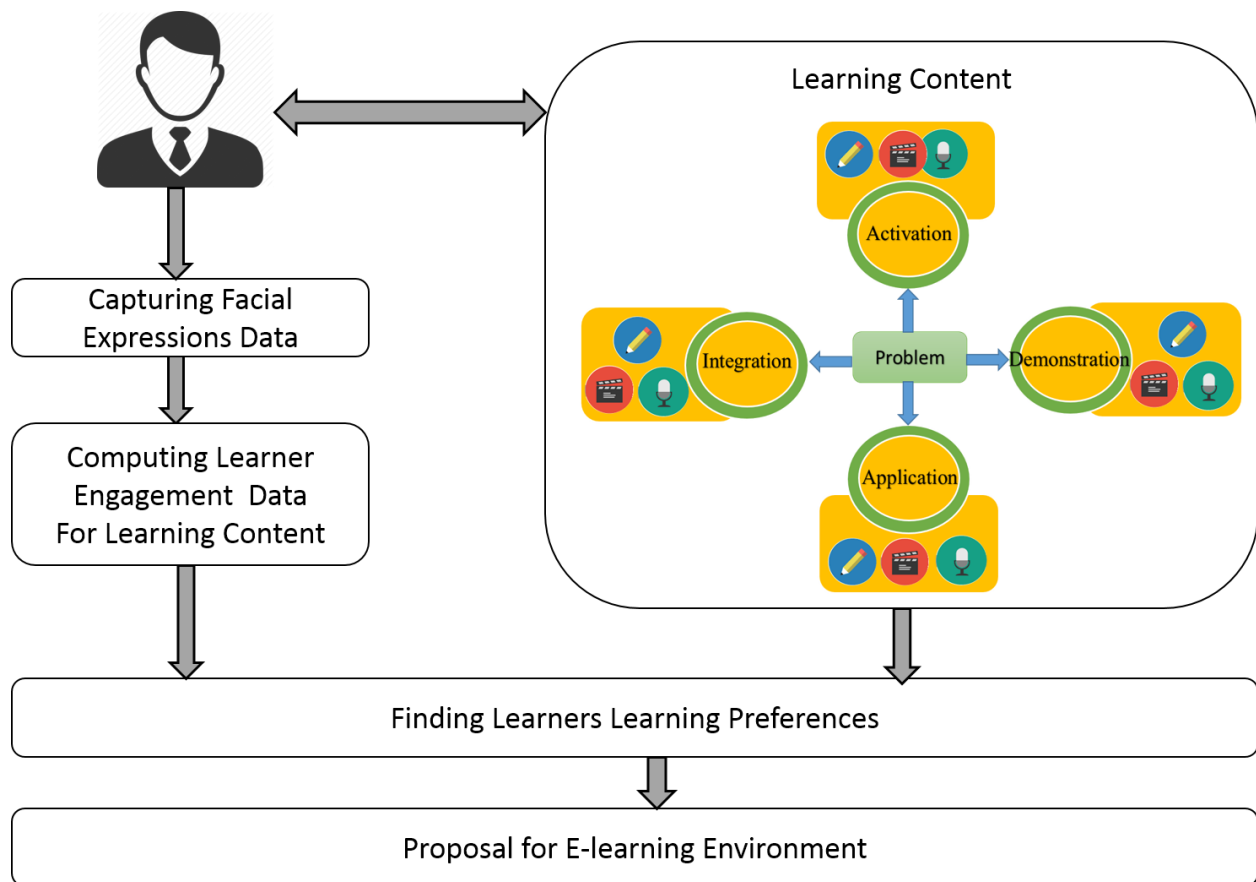
Learning style identified by David Merrill’s FPI approach is as follows:

1. *Activation*: Learners have limited prior experience; learning is facilitated when the instruction provided relevant experience that can be used as a foundation for the new knowledge.

2. *Demonstration*: Learning is facilitated when the instruction also shows descriptions of the information.

3. *Application*: It provides opportunity for the learner to apply the new knowledge to new specific situations. It involves solving whole problems or doing whole tasks and is more than merely answering questions about one step, one action or one event in the whole.

4. *Integration*: Instruction provides an opportunity for the learners to create, invent or explore new and personal ways to use their new knowledge and skill.



**Figure 1: Learning Preferences identified from learner Facial Expressions Data**

The learner facial expressions data can be captured for the purpose of classifying learner engagement data. Once the learner engagement data is got then the learning content log data is to be computed. If both engagement and content log data have been with the same time scale, comparing that is to give the learner's learning preferences. That is finally left as a proposal in the E-learning environment for recommending the learning content to the Learner.

### **Scope and Objectives of the Proposed Approach**

Indeed, human emotions cannot be predicted for longtime. However, a short period of time like seconds and minutes can be predicted based on past and present context of mind and thoughts. In that way, to provide a list of recommendation for assisting the e-learning system to offer the learning environment suitable for an e-learner, this proposed system would serve. Proposed system covers the broad set of objectives such as:

- The present state of cognizance of the learner can be matched to offer the learning content.
- It counterparts the present subjective assessment methods, being predominantly useful in situations when continuous assessment is necessary.
- It allows assessing and quantifying the outcome of numerous factors on learner's Emotions in that Learners need not be provided input on their perceived experience.
- It facilitates advanced monitoring and analysis of Learner and Learning environment improving the entire learning assessment procedure.
- It would confirm the prospective for finding engagement and commitment exhausting learner Facial Expressions and learning content.
- The cognitive characteristics of learner are captured from learner Facial Expressions data is real-time.
- It proposes a recommendation for the e-learners in the background of corresponding e-learning environment.

### **Feasibility of the Proposed Work**

It is seen from the literature that a vast list of experiments have been conducted and succeeded in observing and assessing the human emotions. Hence, the e-learners can be assessed of their kind just before actually entering into learning to predict the needs and requirements with more accuracy and so the best matching content be offered for learning use. As it is possible to employ Deep learning to capture emotions; Learning content to devise learning preferences, the feasibility and viability of this work is well confirmed.

### **Applications of Proposed Work**

In the wide spectrum of applications, the proposed approach is more suitable and required in the context where and all human are involved. Thus, every field of work relating to the study, observation, creation, assembling and production, driving, stimulating, experimenting, experiencing, etc. kind of circumstances, this work would be more appropriate and found useful. The list of applications cannot be listed as an exhaustive one but to mention a few:

- Medicine
- E-learning

- Monitoring
- Entertainment
- Law
- Driving Assistance
- Animal-Behavioral Study
- Simulation Applications
- Banking Applications

## Conclusion

This research work proposed works around predicting the learners learning preferences using Learner facial expression data. Using facial expression data, one can easily identify the learning related emotions that determine engagement of the learner. Learner engaged data are captured from the facial expression of the learner are identified using FPI approach. FPI approach can easily categorize the learner level with the help of the concentration level of the learner. Which learning content is of interest in E-learning can be identified from matching steps. Multimedia content is used to predict the learner's learning preference. Thus this proposed work would be of use o propose a recommendation for the e-learners in the context of that e-learning environment.

## References

1. Abdulkareem Al-Alwani, "Stimulation Of Mental States Using Facial Features To Improve A Student's Performance In E-Learning", Proceedings of Academics World 52nd International Conference, Los Angeles, USA, 21st-22nd November 2016, ISBN: 978-93-86291-30-1
2. Abdulkareem Al-Alwani," Mood Extraction Using Facial Features to Improve Learning Curves of Students in E-Learning Systems", (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 7, No. 11, 2016.
3. Aghababayan, Ani. "E3: Emotions, Engagement and Educational Games." In Educational Data Mining 2014. 2014.
4. Antani S., R. Kasturi, & R. Jain. (2002). A survey on the use of pattern recognition methods for abstraction, indexing and retrieval of images and video, Pattern Recognition Vol. 35. 945-965.
5. B. K. Poornima, D. Deenadayalan and A. Kangaiammal, "Text Preprocessing On Extracted Text from Audio/Video Using R"
6. Chakraborty A. , A. Konar, U. K. Chakraborty and A. Chatterjee, "Emotion Recognition From Facial Expressions and Its Control Using Fuzzy Logic," in IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, vol. 39, no. 4, pp. 726-743, July 2009.doi: 10.1109/TSMCA.2009.2014645.
7. De Melo C. M., J. Gratch and P. J. Carnevale, "Humans versus Computers: Impact of Emotion Expressions on People's Decision Making," in IEEE Transactions on Affective Computing, vol. 6, no. 2, pp. 127-136, April-June 1 2015.doi: 10.1109/TAFFC.2014.2332471.
8. Deenadayalan D., A.Kangaiammal, "EEG Based Learner's learning style and Preference Prediction for E-learning", IEEE 2017.

9. Ian Goodfellow, Yoshua Bengio, and Aaron Courville. 2016. Deep Learning. MIT Press. <http://www.deeplearningbook.org>.
10. Jingjing Chen and Qi Luo, "Research on E-learning System Model based on Affective Computing", 2008.
11. Krithika.L.B, Lakshmi Priya GG, "Student Emotion Recognition System (SERS) for e-learning improvement based on learner concentration metric", International Conference on Computational Modeling and Security (CMS 2016).
12. LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. "Deep learning." *Nature*521.7553 (2015): 436-444.
13. Li Deng, Dong Yu, et al. 2014. Deep learning: methods and applications. *Foundations and Trends® in Signal Processing* 7, 3–4 (2014), 197–387.
14. Merrill, M. D., "First principles of instruction: a synthesis". *Trends and Issues in Instructional Design and Technology*, 2nd Edition, pp.62-71. 2007.
15. Minmin Chen, Zhixiang Xu, Kilian Weinberger, and Fei Sha. 2012. Marginalized denoising autoencoders for domain adaptation. arXiv preprint arXiv:1206.4683 (2012).
16. Po-Sen Huang, Xiaodong He, Jianfeng Gao, Li Deng, Alex Acero, and Larry Heck. 2013. Learning deep structured semantic models for web search using clickthrough data. In *Proceedings of the 22nd ACM international conference on Conference on information & knowledge management*. ACM, 2333–2338.
17. Shuai Zhang, Lina Yao, Aixin Sun, "Deep Learning based Recommender System: A Survey and New Perspectives", *ACM J. Comput. Cult. Herit.*, Vol. 1, No. 1, Article 35. Publication date: July 2017.
18. Wang S. et al., "A Natural Visible and Infrared Facial Expression Database for Expression Recognition and Emotion Inference," in *IEEE Transactions on Multimedia*, vol. 12, no. 7, pp. 682-691, Nov. 2010. doi: 10.1109/TMM.2010.2060716.