

Original Article

# An Affective Computing Model for Online Tutoring using Facial Expressions

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Received: 01 June 2023

Revised: 07 July 2023

Accepted: 02 August 2023

Published: 31 August 2023

**Abstract** - Online tutoring is becoming increasingly popular as a way to get extra help outside of the classroom. It can help students close knowledge gaps in core topics and improve their grades by giving them a convenient, personalized and safe resource they can use when they need extra academic help. Online learning is not new, but throughout the pandemic, the shift from conventional to online educational institutions forced changes to rules, techniques, apps, and infrastructures to accommodate the new learning culture. Examining the possibilities of online learning has become more critical due to COVID-19. With advanced technology, it is possible to bring effective online tutoring modules. Assessing the coordination of students engaging in the process is a difficult task. Using facial expressions, one can grasp their mode in the interaction. Thus affective computing plays a vital role in designing online tutoring. In this paper, a deep learning model for examining students' mode is experimented with and evaluated against popular practice models. The experimental results provide better performance as compared to other models of interest.

**Keywords** - Affective computing, Convolutional Neural Network (CNN), Deep learning, Facial expressions, Online tutoring.

## 1. Introduction

Online tutoring makes it easy for students to get involved in their communities by giving them various ways to connect, such as by computer, email, phone or video conferencing. Online tutoring can help students in multiple studies from different fields, just like face-to-face learning assistance programmes. Online tutoring programmes can help students with many things they must do to do well in their classes. For example, they can help students develop ideas, organize information, format research papers, and study for tests. To do well in these areas, teachers and students must have online experiences that are the same as face-to-face tutoring.

Online tutoring is a versatile tool that can be used to assist students using any of these educational distribution strategies. According to the Rostrum written material named "Successful Online Tutoring," it is said that "the goal of online tutoring is to create a virtual tutoring environment for students that emulates a face-to-face experience which can help a student achieve success in a given class", as described by Smith, 2012 [1]. Because of this, online tutoring was

created to meet the needs of all community college students. These services are particularly beneficial for the large number of commuter students who attend community colleges as well as students who have difficulties or disabilities and are unable to attend on-campus academic tutoring support physically. As a result, online tutoring programmes cater to the requirements of all community college pupils and offer real chances for students to access support services away from the campus.

According to an interesting poll conducted by Bramble, most users regarded online tutoring as either more or equally successful than in-person instruction. The poll, which represents 2,000 consumers across 38 countries, provides a wealth of information about all facets of the tutoring business [2].

Students generally thought that online tutoring was successful, which was the survey's first significant finding from Bramble. 84% of students said remote tutoring was as beneficial as in-person instruction. Furthermore, 72% of instructors and 73% of parents felt that pupils who learn



online get better scores. Online instructors frequently use one of the following formats as in [3]:

### **1.1. Asynchronous Tutoring**

Offline coursework is a prerequisite for asynchronous tutoring. The student completes the tasks after receiving them through email from the tutor and then uploads them online. Although most asynchronous solutions allow students to contact teachers for additional assistance or clarification, that assistance does not require that both sides be online at the exact moment.

### **1.2. Synchronous Tutoring**

In synchronous tutoring, both instructor and pupil communicate in real-time. It needs software enabling direct text, audio, or video communication between the parties.

Khanh Nguyen et al. summarized the significance of online tutoring in their article. They elaborated on the teaching aids and significant challenges in obtaining effective remote tutoring. It was pointed out that JoinNet is an interactive whiteboard with many features, including drawing, a chatbox, etc., and has compatible functionalities emphasized by every tutor [4].

Likewise, Chan Lin et al. [5], David Hart et al. [6] and Junhao Zeng et al. [7] carried out a deep survey among students to reveal the effectiveness of online tutoring. The study's findings show that learners in higher education respond favourably to their use of online tutoring services. The preliminary techniques utilized for knowledge tracing are captured [8-10].

This research aims to bring an effective computing model for online tutoring using facial expressions while improving the system's performance using the intelligent models offered by deep learning.

## **2. Related Work**

The noteworthy efforts by various researchers in this domain are summarized below. Sun Duo et al. [11] attempted to bring an e-learning platform that assists teachers in delivering the context based on the student's emotions instantly. It enabled a man-to-man communication model mimicking the classroom pedagogy in the real world.

Chih-Hung Wu et al. [12] investigated the significant role of affective computing in the education paradigm. Affective computing was applied to evaluate the learner's emotional state and train or motivate them to accommodate better learning styles with hope. The study also addressed the practical limitations of implementing the same.

Paweł Tarnowski et al. [13] developed an emotion recognition system based on facial expressions. The work

captured seven basic emotions like neutral, joy, sadness, surprise, anger, fear and disgust among six informed consents within the age group between 26 and 50. For classification, the system used a K-NN classifier and multilayer perceptron neural network for implementation[14].

Cheng-Hung Wang et al. [15] designed an emotional-based tutoring system to satisfy the learner by teaching the content following their emotional state on a higher note. The work concluded that the application of affective computing in the education system surely elevates the performance of the learner and their respective learning effects.

Jose Maria Garcia-Garcia et al. [16] delivered application software to study the emotional state of students, assess it and facilitate the same as an input to propose effective content delivery. The software was evaluated with control groups and proved that affective computing yielded better learning performances than non-emotional ones. Smith and Windeatt [17] attempted to classify facial actions using the multi-class classifier. Liliana et al. [18] employed the convolutional neural network algorithm to detect emotions using facial features automatically[19]. The experiment was proposed on Cohn Kanade (CK+) dataset and successfully revealed eight emotions with an accuracy rate of 92.75%.

Elaheh Yadegaridehkordia et al. [20] presented a systematic review of affective computing and its part in redefining learning practices in real. The system vastly summarized the measurement channels, models for capturing emotions and modern technologies that contribute excellent solutions towards academic industries regarding software applications.

Varun Bajaj et al. [21] designed a human emotion detection system based on electroencephalogram (EEG) signals. The work investigated effective classification techniques to predict emotions accurately and proposed a Multiclass Least Squares Support Vector Machine (MC-LS-SVM) method. Further, Mexican hat and Morlet wavelet transforms were incorporated with radial basis functions for feature selection in EEG signals. The experimental results confirmed that implementing the MC-LS-SVM algorithm provides 84.79% accuracy in predicting the four major classes of happy, fearful, sad and neutral emotions.

Ujjwal Sharma et al. [22] contributed a significant affective database composing stimuli of Indian expressions. Their model used four volunteers, two male and two female candidates, with a mean age of 25. The pictures were captured from five angles and validated using a t-test and Analysis of Variance (ANOVA). Poorna et al. [23] designed human emotion system by developing an effective database about the student community of Amrita University. The system used a discrete wavelet transform for feature

extraction and K-Nearest Neighbour (K-NN) to classify images under the Ekman model with seven basic emotions: anger, happiness, disgust, sadness, fear, surprise and neutral. The K-NN classifier achieved an accuracy percentage of 99.75%. Mishra et al. [24] contributed an effective Radboud Faces Database (RaFD) database with Indian samples with Dutch participants. The database was evaluated with two-way ANOVA. Anvar Sadath et al. [25] conducted a deep survey on expressed emotions adhered to the Indian context.

The primary motive of the study was to identify the contribution towards expressed emotions in India and its significant role in better addressing psychiatric disorders and other illnesses.

According to the past efforts from the detailed survey conducted on “Affective Computing using Facial Expressions”, several limitations exist, and the effort to be proposed in the current work are tabulated below.

**Table 1. Limitations encountered in past efforts**

Limitation/ Gap Area	Proposed Method for Resolving
Evaluated with a minimal set of young volunteers or used the universal database in a reputed repository	Planned to exercise on large community irrespective of gender and age
Challenges related to reliability, usability and so on	Incorporating modern technologies like artificial intelligence, data analytics and computing will address promising performance

### 3. Materials and Methods

The proposed system will execute with the following major phases in its design, elaborated below.

#### 3.1. Affective Database Development and Validation

The human emotions are to be captured using the camera at a particular distance. The various angles are to be assessed in capturing the image. The large sets of volunteers are selected and provided with the necessary procedure knowledge irrespective of age and gender. The volunteers’ emotions are captured in two modes conscious, engaging willingly in the process and unconscious mode by watching movies/scenes. The primary aim of the proposed system is to address as many emotions as possible, not limited to 5, 7, or 10. The captured images are to be validated with techniques like ANOVA. Finally, the validated images are stored in the repository and used as the training data set in classification methods.

#### 3.2. Data Pre-processing

The respective phase will be carried out to enhance the images for further processing. The necessary actions to be implemented in this phase are as follows:

- Gray scale conversion[26]
- Histogram filtering
- Cropping and resizing

#### 3.3. Feature Extraction

The Discrete Wavelet Transform Techniques (DWT) are exercised to reduce the image’s dimensionality, select appropriate features and extract the same effectively. The block diagram of DWT is illustrated in Figure 1. For image processing, discrete wavelet transforms can be utilised in

general. A higher-resolution image uses up a lot of disc space. DWT is used to shrink an image’s size without sacrificing quality, increasing resolution.

DWT is coordinated with kernel Principal Component Analysis (PCA) to improve the effectiveness of the process[27]. PCA decreases the dimension by identifying a small number of principal components (orthogonal linear combinations) of the initial variables with the highest variance. Most of the volatility in the data is accounted for by the first principal component. The leftover variance, which is left over from the first principal component, is captured by the second principal component, which parallels the initial principal component. The number of the principal components matches the number of original variables.

In KPCA, the input data are mapped using a function called the kernel to a feature space with a high degree of dimension, enabling the nonlinear correlations between the data elements to be better captured by linear techniques like PCA. The modified data is then computed for its principal components, which can be applied to classification, clustering, and data visualisation tasks. The algorithmic steps are captured in Table 2.

#### 3.4. Classification Model

Here, deep learning methods are used to lower the categorization error rate. The efficacy of deep learning algorithms like Convolutional Neural Networks (ConvNets / CNN) in mapping historic and serial data within a short execution period has recently attracted attention[28]. Figure 2 shows the steps used in the suggested CNN model for predicting human emotions from input images.

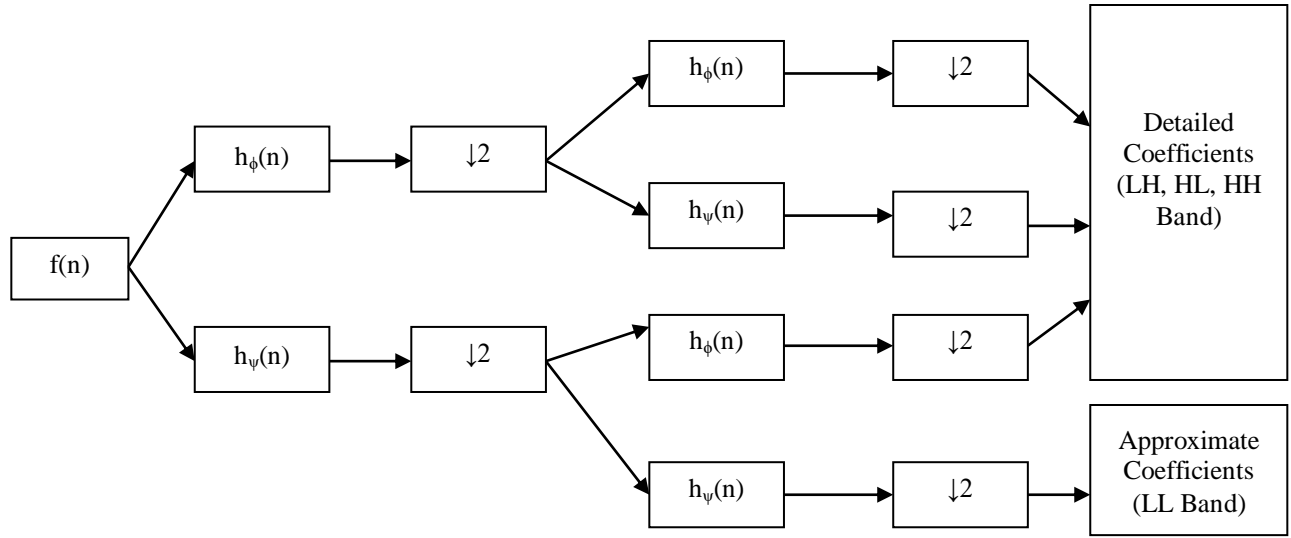


Fig. 1 Block diagram of DWT

Table 2. Algorithmic steps in feature extraction

- 1: Input the image
- 2: Apply DWT and obtain the coefficients
- 3: Propose PCA over LL band coefficient
  - 3.1: For input images ranging,  $S=x_1, \dots, x_m \in \mathbb{R}^n$  and  $d$  as no. of principal components
  - 3.2: Calculate  $K$ , the normalized kernel matrix using equation 1 as below.
 
$$[K]_{i,j} = \frac{1}{m} K(x_i, x_j) \quad (1)$$
  - 3.3: Obtain the top Eigen vectors ( $U$ ) and Eigen values ( $\lambda$ ) using equations (2) and (3), respectively.
 
$$U = \text{TopEigenVectors}(K, d) \quad (2)$$

$$\lambda = \text{TopEigenValues}(K, d) \quad (3)$$
  - 3.4: Nesting through loops, compute the matrix of coordinates  $\pi$  using equation (4) as given below.
 
$$[\pi]_{k,i} = \frac{1}{\sqrt{\lambda_k}} \sum_{t=1}^m K(x_i, x_j) U_{t,k} \quad (4)$$
- 4: Derive Euclidean distance and compute the minimum
- 5: Print the optimal solution

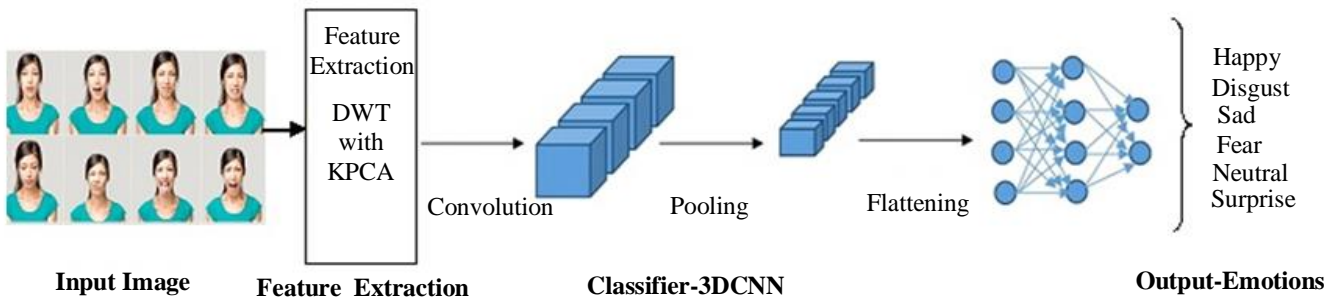


Fig. 2 Deep CNN framework for emotion recognition using facial features

The CNN model of neural networks enables us to derive more accurate representations of the image material. In contrast to traditional image recognition, which requires you to define the image characteristics directly, CNN starts with the unprocessed pixel information from the image, learns the model, and then automatically extracts the features for improved categorization.

Artificial neurons are arranged in numerous layers to form convolutional neural networks. Artificial neurons are mathematical functions that compute the weighted sum of several inputs and output an activation value, roughly imitating their biological counterparts.

Each ConvNet layer creates several activation functions that are then passed over to the following layer when an image is entered. Typically, the first layer extracts fundamental features like edges that run horizontally or diagonally. The following layer receives this output and detects more intricate features like corners or multiple edges. The network may recognize increasingly more complex elements, including objects, faces, etc., as one continues to explore it. The suggested model utilized 3DCNN layers in order to classify the mode accurately.

## 4. Results and Discussion

This section discusses the specifics of the dataset used to test emotion detection, the implementation environment for the proposed deep learning model, and the performance metrics used to judge the proposed model.

### 4.1. Dataset Descriptions

The dataset "fer-2013", publicly available on Kaggle, was used in the proposed study. There are 48\*48 pixel greyscale photos of faces with labels for each emotion. Three columns make up this dataset: emotion, pixels, and usage. The pixels column contains pixels in the form of a string separated by spaces, and usage indicates if the data was created for training or testing purposes. The emotion column contains integer-encoded emotions (0=Angry, 1=Disgust, 2=Fear, 3=Happy, 4=Sad, 5=Surprise, 6=Neutral).

### 4.2. Execution Platform

The Keras package in TensorFlow is utilized for the execution of the suggested model. With Keras, the deep learning network can be executed more quickly and simply. The programming language used to execute the model is Python. In estimating the model, among the data trials, 80 percentage of it was used as training, and the remaining 20 per cent was employed to test the model. In implementing 3DCNN, the basics of CNN are well observed from [29].

### 4.3. Evaluation Metrics

Metrics for evaluation are numerical measurements used to rate the efficiency and performance of a predictive or

machine-learning model. These measurements aid in comparing various models or algorithms and offer information on how well the model works. The model's effectiveness for emotion detection is evaluated by the following measures of interest, projected in Table 3 below.

**Table 3. Metrics for evaluation**

Metrics	Formula
True Positive Rate / Recall	$\frac{TP}{TP + FN}$
False Positive Rate	$\frac{FP}{FP + TN}$
Precision	$\frac{TP}{TP + FP}$
Accuracy	$\frac{TP + FP}{TP + FP + TN + FN}$
F-Score	$\frac{2 * Precision * Recall}{Precision + Recall}$

A table called a confusion matrix is used to describe how well a classification system performs. The output of a classification algorithm is visualized and summarized in a confusion matrix. Each of the columns within the matrix reflects the instances in the anticipated class or vice versa.

In contrast, each row in the matrix indicates the occurrences in the observed class. The confusion matrix of the proposed model is presented in Figure 3. The facial emotion predicted by the proposed 3DCNN over the "fer-2013" is provided below in Figure 4. The model gives its accuracy as 98.9% in determining emotions like happy, fearful, sad, surprised, angry and neutral.

### 4.4. Evaluation Results

The suggested model is tested in comparison to the extensive efforts made in facial expression emotion identification using Artificial Neural Networks (ANN), K-Nearest Neighbour (K-NN) and Support Vector Machines (SVM). Table 4 summarizes the performance metrics attained using different machine learning algorithms.

The most remarkable illustration of the many methods used to predict mood for online tutoring is shown in Figure 5. The proposed model is intended to produce superior outcomes to other approaches used for comparison analysis. As a harmonic mean of precision and recall, the F-Score represents the total test accuracy and projects the classifier's or model's robustness and precision. A higher F-Score guarantees greater accuracy. The proposed model's F-Score value of 88.7% is more significant than other evaluation methodologies.

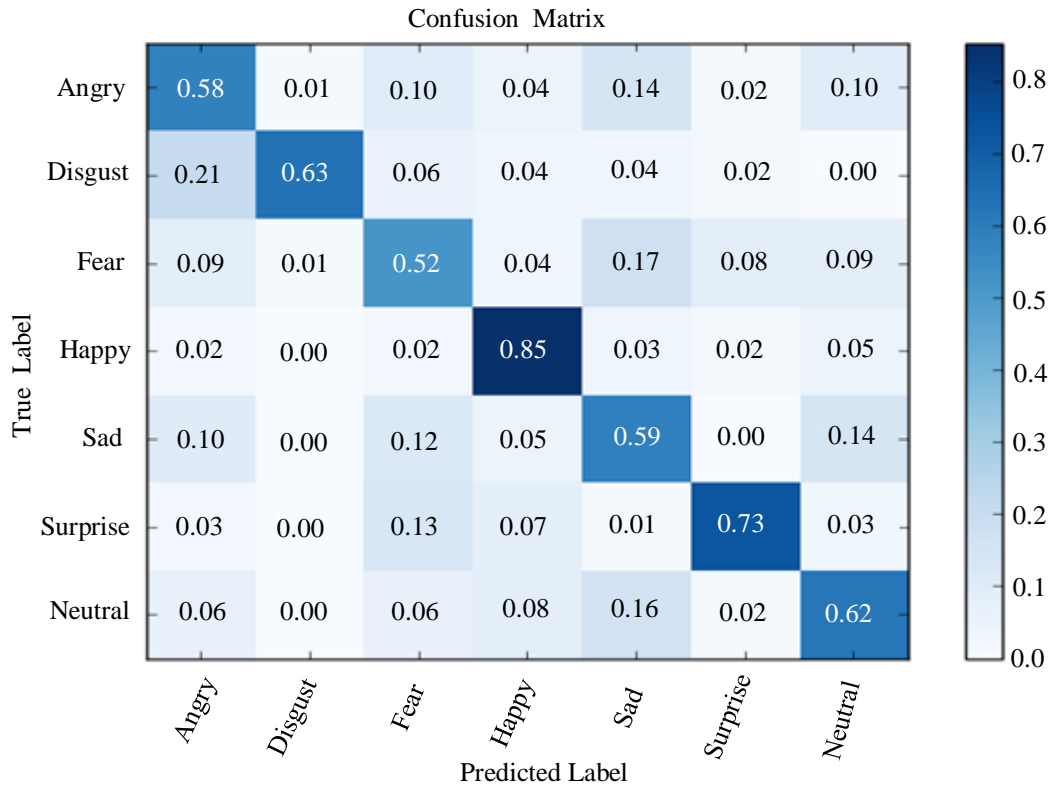


Fig. 3 Confusion matrix of the proposed deep model



Fig. 4 Facial emotions detected by the proposed model

Table 4. Performance analysis of the proposed model

Evaluation Models	Accuracy	Precision	Recall	F-Score
SVM	96.7	86.3	81.4	82.7
K-NN	93.5	89.4	85.6	85.9
ANN	93.7	81.9	82.4	81.8
CNN	95.6	88.9	87.5	83.1
3DCNN	98.9	89.8	80.3	88.7

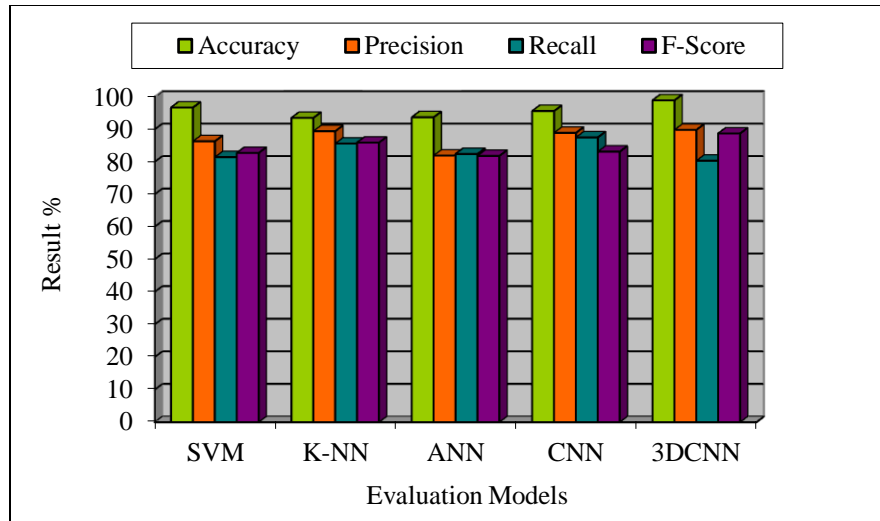


Fig. 5 Assessment map of proposed deep model

## 5. Conclusion

In this work, the importance and high demand for online tutoring is well introduced. The novel classifier for the emotion recognition model with facial expression is experimented. The same is evaluated against the popular machine and deep learning models like ANN, KNN, CNN and SVM. The experimental findings showed that the proposed 3DCNN enabled an encouraging accuracy of 98.9%. The novelty of the online tutoring model lies in addressing the real-time challenges in implementing the collaborative, practical module like readiness, acceptance

and usability ratio. The existing system attempted to produce one-to-one communication. In the future, it is planned to offer a one-to-one model to students and a one-to-many model for the teacher. Moreover, the way to build a voluminous dataset for emotion recognition from facial expressions is prescribed and is in production.

## Acknowledgments

Author 3 provided the ideation and supervision. Author 1 & Author 2 drafted the article along with the implementation support from Author 1 & 4.

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