University of Ibadan
Journal of Science and Logics in ICT Research

A Framework for Facial Expression Recognition Based Feedback Tracking in Online Educational Platforms

[1]Ogundoyin, I. K., Jimoh, K. O., Omotosho, L. O. and Odelade T. B.

Department of Information and Communication Technology
Osun State University, Osogbo, Nigeria.
[1]Ibraheem.ogundoyin@uniosun.edu.ng

Abstract

During times of worldwide pandemic, online teaching platforms are becoming increasingly popular as an alternative to traditional learning environment. However, while many online platforms have been reported in the literature, many of them lack a reliable feedback tracking mechanism through which the emotional state of students or users can be determined for effective teaching and learning. This has necessitated the need to design and simulate an online feedback system. Sample facial images were obtained from FER-2013 Dataset, and pre-processed. Principal Component Analysis (PCA) was used in extracting the facial features in the sample images. A total of 31,885 images with six different emotional classifications which are happy, sad, fear, neutral, angry, disgust were considered. The images were then split into training and test images with train consisting of 75% of the whole dataset while test had 25%. Ensemble of Support Vector Machine, Random Forest and k-nearest neighbour were used in classifying the images. The results of classification serve as inputs to the feedback tracking mechanism of the proposed model, which was formulated as an algorithm. The performance of the proposed ensemble model was compared with its based classifiers using metrics such as Precision, Recall, F1-score, and Accuracy. The simulation results during training showed that ensemble (SVM +RF+KNN) had accuracy 98.92%, RF had accuracy 92.94%, SVM had accuracy 95.57%., and KNN had accuracy 85.42%. Likewise in test dataset, Ensemble (SVM +RF+KNN) had accuracy 93.92%, RF had accuracy 90.94%, SVM had accuracy 91.57%, and KNN had accuracy 83.42%. Other performance metrics such as Precision, F1-Score, and Recall were also measured during simulation. The study designed a system for obtaining feedback based on facial expression of online participants for an improved online educational platform usage and acceptance. The developed online feedback framework could be integrated into the existing online educational platforms for improved usage and acceptance.

.

Keywords: *Model, Performance, Facial Expression, Online Platform, Feedback*

1. Introduction

Online teaching is characterized as learning experiences that take place in synchronous or asynchronous environments using a variety of electronic devices (e.g. computers, laptops, smartphones, etc.) with internet access. Online education has the potential to make the educational process more student-centered, creative, and flexible. When it comes to offering content to students in rural and remote places, online distribution of courses is both cost-effective and convenient [1].

Ogundoyin, I. K., Jimoh, K. O., Omotosho, L. O. and Odelade T. B. (2022). A Framework for Facial Expression Recognition Based Feedback Tracking in Online Educational Platform, *University of Ibadan Journal of Science and Logics in ICT Research (UIJSLICTR),* Vol. 8 No. 1, pp. 1-11

Online education technology has been able to fill the void left by the recent epidemic by making classroom experiences virtual and unrestrained by the four walls of a classroom, allowing students to learn at any time and from any location. E-mail, Usenet, chats, discussion forums, wikis, blogs, collaboration (CSCW) tools, simulation software, testing and assessment software, e-portfolios, vocabulary trainers, and games are all examples of software and network services that can be utilized for Online Teaching [2].

The teacher's activities and the students' responses to the current activity in class are referred to as classroom interaction. Facial expression recognition in the classroom offers the potential to predict the significance of students' emotions. In comparison to traditional assessment techniques, an interactive feedback system for student behavior during lecture delivery may not only improve the learning environment, but it may also save time and resources. [3]. Providing more flexible teaching and learning experiences, opening channels for synchronous and asynchronous communication and interaction, allowing for more collaboration and interaction with peers, providing access to learning resources in various formats, and promoting authentic and situated teaching are some of the reported benefits of online teaching for learners [4].

However, one of the disadvantages of online education platforms is the lack of an interactive feedback mechanism for learning attitudes. Other flaws include a lack of standard user management and authentication, inconsistent user interfaces, and limited tool compatibility. However, while numerous studies have been published on online teaching platforms, they lack a reliable feedback monitoring method for determining the emotional state of students or users, which is necessary for effective teaching and learning. [3, 5, 6, 7, 8].

The study therefore, designed a system for getting feedback based on facial expression of online participants for an improved online educational platform usage. The developed online feedback system could be integrated in the existing online educational platforms for improved usage and acceptance

.

2. Related Works

There have been contributions in literature in area of machine learning and facial expression recognition through which Emotion of individual could be determined. Facial Expression Recognition has a vast area of application, most especially in the area of Online Teaching Platforms.

For instance, Yusra *et al* in [1], developed a feedforward learning model for an instructor's facial expression recognition approach in a classroom. For efficient high-level feature extraction, the face was first recognized from obtained lecture videos and important frames were selected, removing all unnecessary frames. Then, using several convolution neural networks and parameter optimization, deep features were retrieved and supplied to a classifier. State-of-the-art approaches, classical classifiers, and convolutional neural models were compared to the suggested method. The findings of the experiments revealed a considerable improvement in accuracy, F1-score, and recall.

Hanusha and Varalatchoumy in [6] explored convolutional neural network in developing facial expression recognition model for online teaching platforms using facial expressions of students. The low involvement of the listener to the instructor was noted as a major issue in the online learning environment. The educational institutions and instructors were accountable for ensuring the best learning environment for online learners with the highest level of engagement in educational activities. Instructors and educational institutions were able to monitor their classes and listener behavior in real time helped to effectively determine listener interest. It was deduced that there were numerous approaches for detecting online class engagement. Based on the approaches utilized for engagement detection, existing methodologies were divided into five primary categories in the study: mouse click, ECG, body, head movement, eye movement, and facial expression.

Moutan *et al* in [9] created a model using Convolutional Neural Network in order to assess student's state of mind. In terms of emotion classification and state of mind identification, the results revealed 65% and 62 % accuracy, respectively.

Junge et al [3] created a novel face expression recognition-based system for gauging learning engagement. To solve the challenge of web-camera photographs with complicated backdrops, illumination, and resolutions, an attentional mechanism was added to the network for feature extraction. The CNN for categorization was created using a lightweight architecture optimized for real-time applications. Domain adaptation was also utilized to address the problem of missing labeled data. Experiments in the study also showed that the suggested technique can accurately distinguish emotions with limited labeled data.

Ho-Jung and Deokwoo [7] proposed an approach for process-focused assessment

(PFA) utilizing the concept of deep neural networks. A deep neural network model was used to build a method for PFA by learning facial expressions.

Facial expressions are divided into three categories by the model: easy, neutral, and tough. PFA is essential to achieve efficient, convenient, and confident assessment because the demand for online learning is increasing.
The research focused on a series of 2D picture data from students who were answering exam problem. Sasirekha [10] developed a model using XGBoost and Convolutional Neural Networks in order to achieve profiling student attentiveness to different gradients of engagement level.

Facial expressions of various people were collected by Nazir et al [11] using a Panasonic camera (Model DMC- LS5) with a focal length of 5mm.Images of six basic expressions of each individual were taken at a distance of four feet between the camera and the person. After facial features were retrieved, K Nearest Neighbor was employed for classification. Happy was 100% accurate, Anger was 80 % accurate, Sadness was 80 % accurate, Fear was 100 % accurate, disgust was 80 % accurate, and surprise was 100 % accurate. The total accuracy rate was 90%.

Henrique et al. [12] presented Ensembles with Shared Representations (ESRs) based on convolutional networks to show their data processing efficiency and scalability to large-scale datasets of facial expressions, both statistically and qualitatively.

The branching level of the ESR can be changed to reduce redundancy and computational load without sacrificing variety or generalization capacity, which are both critical for ensemble performance. Experiments on large-scale datasets showed that ESRs reduce residual generalization error on the AffectNet and FER+ datasets, achieve human-level performance, and beat state-of-the-art approaches in the wild employing emotion and affect concepts.

Balasaranya et al. proposed a system in [8] that checked the emotion from frame to frame in a video medium to recognize the feelings that a person is having at any one time. A multistage image processing system was utilized to extract feature representations, including face feature extraction using the Gabor filter and dimensionality reduction techniques to lower the matrix representation of an image. Finally, Convolutional Neural Networks were used to classify the data. Face recognition was 90% accurate as a result of this; however, face expression recognition was likewise 90% accurate.

Uğur *et al* [13] Presented several classification methods used to learn instant emotional state with the kNN and SVM algorithms in the paper titled “Use of Facial Emotion Recognition in E-Learning Systems”. The methodology used provided the best accuracy rates of hybrid information system for visual and interactive e-learning systems that combined computer vision and machine learning technology. The result obtained from the study indicated that the proposed model had high accuracy value of 98.24%.

The above reviewed existing literature have contributed immensely to facial expressions and emotion recongnition in online teaching platforms. However, none of the literature computed feedback from emotinal state of the student as expressed in the facial expressions in most of the studies. This study, therefore, proposed a framework through which exxiting online forum or educational platform could return feedback to a teacher from facial expressions of the students for decision taking, improve online usage and acceptance. ,

3. Methodology

This study's approach involves a variety of methods for achieving the paper's purpose.
The methods include data collection and description, model formulation, simulation, and model performance evaluation. Figure 1 is the conceptual view of the proposed feedback system in online education platform. The proposed system has the end user, the network and the tutor side. During teaching session, the facial expressions of the users or the students are captured, this would enable the emotion of the students to be determined, consequently the feedbacks calculated. In order to achieve the aim and objectives of this paper, the facial image data used in the study was obtained

from FER2013 dataset. The feature extraction on the data was performed using principal component analysis. The feedback tracking system proposed in this study has two components: the facial expression recognition and feedback tracking components. The facial expression recognition component was design using ensemble of Random forest, K-nearest neighbor and support vector machine learning techniques. The feedback tracking component was formulated as an algorithm. The result of facial expression recognition serves as an input into the feedback tracking component. The simulation of the proposed model was done in Python programming environment. The performance of the model was evaluated by comparing the proposed ensemble model with the based classifiers Random forest, K-nearest neighbor and support vector machine learning techniques using performance metrics such as precision, recall, F1-score, accuracy and computational time. The system architecture of the proposed ensemble model is shown in Figure 2.

3.1 Dataset Description

There are so many image datasets available online but for the purpose of this study, FERdata from KAGGLE was used. KAGGLE is an online machine learning repository where different types of dataset can be accessed and used for any modelling tasks. The images available in the FERdata dataset were grouped into six categories: angry, sad, happy, neutral, fear and disgust. The total of 31,885 images were collected, and partitioned into two: training set of 25,538 images while the test dataset contained 6,347 images.

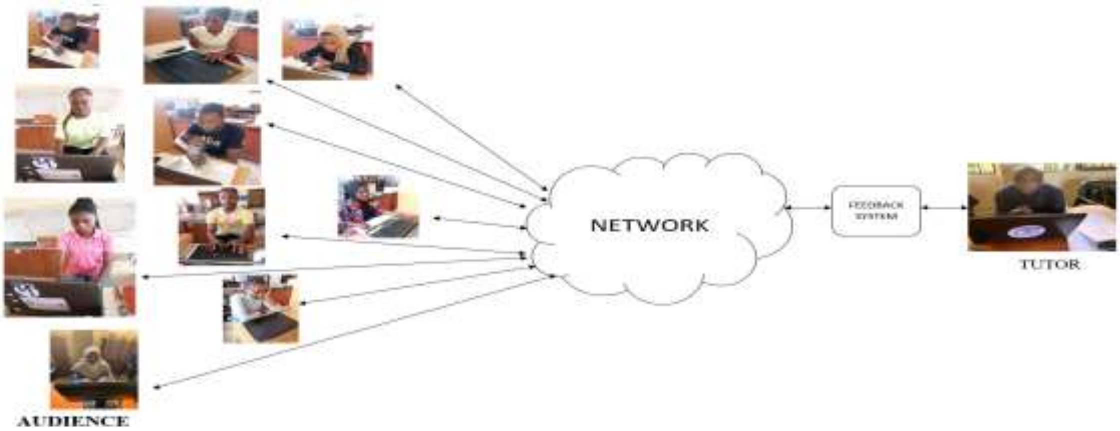


Figure 1: Conceptual view of the system

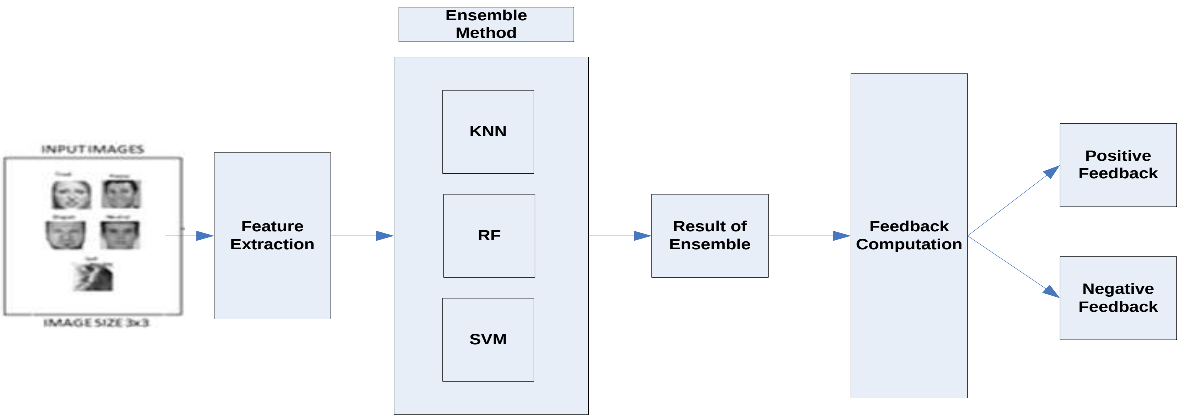


Figure 2: Architecture of the Proposed Ensemble Model

3.2 Model Formulation

Let= $[x, x, x \ldots \ldots x] \ldots \ldots \ldots \ldots . equation\ 1$
Let X be the set of dataset collected from Kaggle (FER)

Let F ( ) represent feature extraction function. X was passed as a parameter into F( ) for purpose of extracting relevant feature or attributes needed for classification of the dataset X. The feature extraction technique used in the study is Principal Component Analysis (PCA). Let

$Y = F(X)$……………. equation 2

be the dataset passed into feature extraction function.

The extracted feature were extracted and stored in Y.

Let C ( ) be classifier function. The proposed classifier in the study is the ensemble of SVM, KNN and RF.

W = C (Y) ………………..equation 3

In equation 3, the relevant features and attributes extracted in equation 2 as stored in Y was passed into the classifier function C (Y), which is the proposed ensemble model.

The result of classification performed in equation 3 was stored in W. Therefore, W, stored the classified facial expression of the images. The facial expression of the images determines the emotional state of the students or participants on the online educational platforms as contained in equation 4.

W = [sad, happy, neutral, fear, disgust] …… equation 4

At any point in time, the emotional state of the students would be determined by the facial expression which is could be any of the element in list W.

Based on facial expression classification in W, the feedback was computed. The detail Feedback computation is shown in Figure 3**.**

3.2.1 Feature Extraction - F ( )

The feature extraction as used in this study was PCA. The PCA is a technique for reducing dimensionality. Principal Component Analysis is a non-parametric method for extracting useful data from huge datasets that is straightforward to use. Principal Component Analysis aids in the discovery of a mapping from original d-dimensional inputs to a new k (k<d) dimensional space with minimal information and data loss. The PCA on the other hand is considered to be a powerful tool for analyzing data of a dataset. Principal component analysis (PCA) is a statistical technique that is useful for compression and extraction of useful information from multivariate data sets. The variance-covariance of a set of variables (multi-variant).

$x_1, x_2, x_3, \ldots, x_p$ ……….equation 5

Through a few linear combinations of these variables to capture the variability of original dataset (Covariance Matrix)$a_1x_1 + a_2x_2 + a_3x_3 \ldots + a_px_p$ ……….equation 6

The variance of each variable is the average squared deviation of its n values around the mean of that variable.
$V_i = \frac{1}{n-1} \sum_{m=1}^{n} (x_{im} - \bar{x}_i)^2$ …..equation 7

The degree to which the variables are linearly correlated is represented by their covariance's.

$$C_{ij} = \frac{1}{n-1} \sum_{m=1}^{n} (X_{im} - \bar{X}_i)(X_{jm} - \bar{X}_j)$$

….. equation 8

Where C_{ij} = Covariance Of variables i and j
$\sum_{m=1}^{n} =$ Sum over All n objects
X_{im} = Value of variable i in object m
$\bar{X}_i$ = Mean of variable i
X_{jm} = Value of variable j in object m
$\bar{X}_j$ = Mean of variable j

3.2.2 Classifier Function - C ( )

The classifier function used in this study is ensemble of KNN, RF, and SVM method. For the purpose of this study, Bagging method was used. Bagging (short for "bootstrap aggregation") entails using many samples of data (training data) instead of simply one. The bagging method works with fixed-size training samples. The Algorithm is as shown below.

Input: Training Set *D*, Base Classifier *L*, integer M (number of bootstrap sample)

For i = 1 to M
{
D_i *= bootstrap sample from D (i.i.d. sample with replacement)*

$C_i = L(D_i)$
}
$C^*(x) argmax_{y \in Y} \sum_{i:Ci(x)=y} 1$ *(the most often predicted label y)*

Output: Compound Classifier C^*

3.2.3 The base Classifiers
The base classifiers making up the ensemble model include:

i. **Random Forests**
A random forest is a machine learning technique for solving classification and regression problems. It employs ensemble learning, which is a strategy for solving complicated problems by combining multiple classifiers. Many decision trees make up a random forest algorithm.

The random forest algorithm's 'forest' is trained using bagging or bootstrap aggregation. Bagging is a machine learning approach that uses an ensemble meta-algorithm to increase accuracy. The random forest training algorithm applies to tree learners the general approach of bootstrap aggregating, or bagging. Given a series of exercises
$X = x_1, \ldots, x_n$………………..equation 9
with responses
$Y = y_1, \ldots, y_n$, ……………..equation 10

bagging repeatedly selects a random sample with replacement of the training set and fits trees to these samples:

For b = 1, ..., B:
1. Sample, with replacement, *n* training examples from X, Y; call these X_b, Y_b
2. Train a classification or regression tree f_b on X_b, Y_b

ii. **Support Vector Machines (SVMs)**

Support Vector Machines (SVM) are a collection of supervised learning methods for classification and regression. They are members of the generalized linear classifier family. In other words, a Support Vector Machine (SVM) is a classification and regression prediction tool that employs machine learning theory to enhance predicted accuracy while avoiding over-fitting to the data.

All data objects in a feature space are divided into two classes by the SVM The data objects must have features $\{X_1 \ldots X_n\}$ and a class label, y_i. Each data object is treated by SVM as a point in feature space that belongs to one of two classes. A data object (defined by its feature vector) either belongs to a class (in which case the class label is y i. = 1) or does not belong to a class (in which case the class label is y i. = -1). Therefore, the definition for the data is:

$$\mathrm{Data} = \{(x_i, y_i) \mid x_i \in \Re^p, y_i \in (-1,+1)\}_{i=1}^{n}$$ …
……………..equation 11

where p is the dimension of the feature vector and n is the number of data points.

iii. **K-nearest neighbors (KNN)**
The supervised learning technique K-nearest neighbors (KNN) is used for both regression and classification. The k-Nearest Neighbors algorithm (or k-NN) is a non-parametric classification and regression approach. The K-Nearest Neighbor classifier is based on distance measurement.

It tries to classify numerical data records by determining the K-Nearest neighbor and measuring the distance between the training and test samples using Euclidian measurements.

3.3 The Feedback Tracking Computation and Design
Based on the classified facial expression, the feedback was computed. The detail Feedback computation is shown as presented in the algorithm below:

// **Algorithm**: Feedback Computation Model
1: Initiate online teaching session .
2: Capture facial expression of participants during the current online session

3: Perform feature extraction on the captured facial images using PCA

4: Classify the preprocessed facial images into angry, sad, happy, neutral, fear and disgust using ensemble method

Let P_E = Positive Expression = [Happy, Neutral]

Let N_E = Negative Expression = [Sad, disgust, fear, angry]

5: Count number of P_E = nP_E ; Count number of N_E = nN_E ; Total number of participants = T_{par}

6: Calculate Positive feedback as:

$P_f = (nP_E / (nP_E + nN_E))*100$,

where, P_f = Positive feedback

$N_f = (nN_E / (nP_E + nN_E))*100$,

where, N_f = Negative feedback

7: Test if $P_f > N_f$

8: {

9: If ($P_f >= 69$ .OR. $P_f <= 74$)

10: {

11: Return "fair Positive feedback"

12: }

13: Elseif ($P_f >= 75$ .OR. $P_f <= 84$)

14: {

15: Return "Good Positive feedback"

16: }

17: Else ($P_f >= 85$ .OR. $P_f <= 100$)

18: {

19: Return "Excellent Positive feedback"

20: }

21: }

22: Else

23: If ($N_f >= 0$ .OR. $N_f <= 49$)

24: {

25: Return "fair Negative feedback"

26: }

27: Elseif ($N_f >= 50$ .OR. $N_f <= 64$)

28: {

29: Return "Bad Negative feedback"

30: }

31: Else ($N_f >= 65$ .OR. $N_f <= 100$)

32: {

33: Return "Extreme Negative feedback"

34: }

35: }

From the above algorithm, line 1 initiated an online teaching session, and facial expressions of participants captured in line 2. Feature extraction, other preprocessing activities and classification of facial expression into six main categories of: angry, sad, happy, neutral, fear and disgust were carried out in the subsequent lines. Happy and neutral were tagged positive expression, while others were tagged negative expression. Line 5 -6 counted the number of positive expression, nP_E , negative expression nN_E and also calculated positive, P_f and negative N_f feedbacks. Lines 7 -34 show different degrees of positive and negative feedbacks for decision making of the tutor.

3.4 Experimental Design

Simulation was setup for the proposed ensemble based model for feedback in online educational platform in Python programming language in the Anaconda environment. The platform runs on a 64-bit Windows 10 operating system with a 4 GB RAM and Intel Core i3 CPU with 2 GHz processor speed. The overall simulation procedure is as presented in Figure 3.

In Figure 3, the simulation commences by initialization of various variables which will be used for the computation of feedback system. The variable include: P_E = Positive Expression, N_E = Negative Expression, C_P = Classified Participants, N_P = Number of Participants, P_F = Positive Feedback, N_F = Negative Feedback .

The next step is the commencement of online session, during which facial expression of the students or the participants in the online educational platform would be captured and Preprocessing of facial expression performed.

After the preprocessing feature extraction was carried through PCA function. The extracted features by PCA were fed as input to the classifier function implemented as ensemble model consisting of SVM, RF, KNN for the classification of facial expression initially captured. This stage of the simulation led to the computation of the feedback by the designed feedback mechanism. To achieve the goal of the model simulation, the collected FERdata from kaggle was used to drive the simulation. The data set had six classes: angry, sad, happy, neutral, fear and disgust. The total of 31,885 datasets were collected, and partitioned into two: training set of 25,538 images while the test dataset contained 6,347 images .The simulation was run for both training and test datasets, results were obtained and analysed.

3.5 Evaluation Parameters

In order to evaluate the performance of the proposed ensemble model for designing feedback in online educational platforms some metrics such as Accuracy, Precision, F1-Score and Recall were used:

i. Accuracy

Accuracy in classification problems is the number of correct predictions made by the model over all kinds predictions made. The formula for Accuracy is

$$\frac{TP+TN}{TP+TN+FP+FN} \text{ ………..equation 12}$$

ii. Precision

Precision is a measure that shows what proportion of actual predictions from the dataset. The formula for this is

$$\frac{TP}{TP+FP} \text{ ……………..equation 13}$$

iii. Recall

Recall is the measure of our model correctly identifying True Positives. The formula for this is

$$\frac{TP}{TP+FN} \text{ ………..equation 14}$$

iv. F1-Score

F1-score is the Harmonic mean of the Precision and Recall. The formula is

$$2 * \frac{Precision * Recall}{Precision + Recall} \text{ ………..equation 15}$$

4. Results and Discussion

4.1 Results

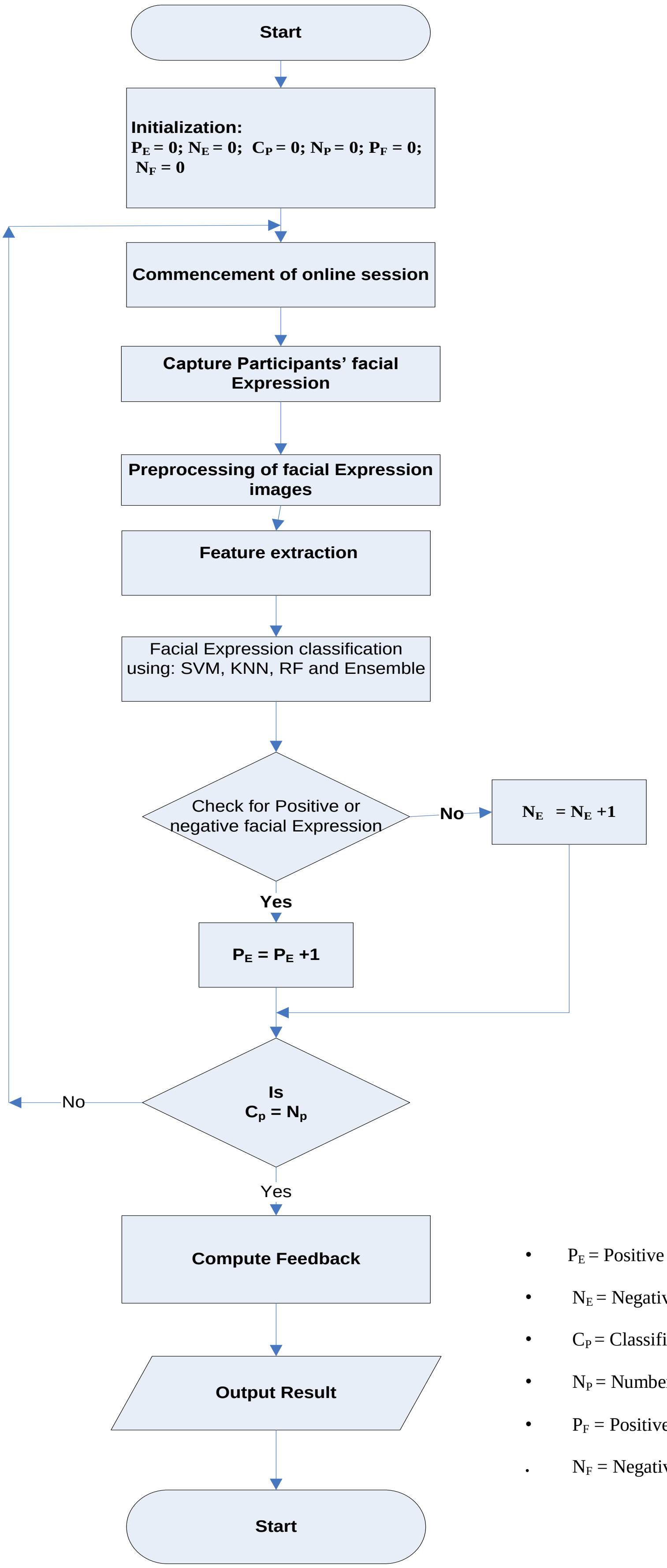
In this section, the performance of the proposed framework for feedback tracking in online platform was measured by evaluating its classification component. This was carried out by comparing the performance of the ensemble classifier with the based classifiers – SVM, RF, and KNN as proposed in the study. This is because the accuracy of the feedback is a function of the reliability of the classification model. The proposed framework was evaluated with training and test datasets. The comparative performance evaluations of the proposed framework for training and test datasets were presented in Table 1 and Table 2.

In Table 1, the performance of the proposed ensemble (SVM, RF,KNN) was compared with various machine learning models using training dataset. Ensemble (SVM, RF,KNN) had Precision of 98.92%, Recall of 97.92%, F1-Score of 96.93% and Accuracy 98.92%. RF had Precision of 92.80%, Recall of 90.80%, F1-Score of 91.60% and Accuracy 92.94%. SVM had Precision of 95.44%, Recall of 93.71%, F1-Score of 94.64% and Accuracy 95.57%. KNN had Precision of 85.77%, Recall of 86.75%, F1-Score of 85.71% and Accuracy 85.42%.

Likewise in Table 2, using test dataset, Ensemble (SVM, RF,KNN) had Precision of 92.92%, Recall of 91.92%, F1-Score of 92.93% and Accuracy 93.92%. RF had Precision of 91.80%, Recall of 90.80%, F1-Score of 88.60% and Accuracy 90.94%. SVM had Precision of 92.44%, Recall of 91.71%, F1-Score of 91.64% and Accuracy 91.57%. KNN had Precision of 82.77%, Recall of 81.75%, F1-Score of 80.71% and Accuracy 83.42%.

4.2 Discussion

The proposed ensemble method produced the most reliable result in terms of the performance metrics used. The lower performance of the ensemble and other methods during test period as compared to training period was because the test dataset were not used for the model training, and so the methods were not conversant with the test dataset. From the results, both at training and test periods, the adoption of the ensemble method to design the proposed framework for generation of feedback on online education platform will be adequate and reliable. The integration of the feedback framework will enhance the usage of the platform and their acceptance.



- P_E = Positive Expression
- N_E = Negative Expression
- C_P = Classified Participants
- N_P = Number of Participants
- P_F = Positive Feedback
- N_F = Negative Feedback

Figure 3: System Flow Chart for Simulation Procedure of the Proposed Feedback Model

Table 1: Comparative Performance Evaluation of the Proposed Framework with other base Classifiers During Training.

Classifiers	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
Ensemble(SVM, RF,KNN)	98.92	97.92	96.93	98.92
RF	92.80	90.8	91.60	92.94
SVM	95.44	93.71	94.64	95.57
KNN	85.77	86.75	85.71	85.42

.Table 2: Comparative Performance Evaluation of the Proposed Framework with other base Classifiers During Test Period

Classifiers	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
Ensemble(SVM, RF,KNN)	92.90	91.92	92.93	93.92
RF	91.80	90.8	88.60	90.94
SVM	92.44	91.71	91.64	91.57
KNN	82.77	81.75	80.71	83.42

5. Conclusion

In this research, a framework for feedback tracking through Facial Expression Recognition was designed and simulated. The framework detected students emotional state through Facial Expression Recognition and send corresponding feedback to the teacher/tutor so as to know the attitude of the student towards a teaching or discussion session.

The FER Dataset was analyzed, preprocessed, extracted facial features and inputted into the models: ensemble (SVM, RF, KNN), SVM, RF and KNN. The result generated was then analyzed and then used to classify sample images into the various classes of emotions i.e., Sad, Happy, Neutral, Fear, Disgust, Angry.

The simulation results of the proposed framework was viable, and showed possibility of designing a mechanism for feedback tracking which could be integrated in online teaching platforms for improved usage and acceptability.

References

[1] Marwa, M. Z., Mona, S. H., and Sarah, A. B. (2021). The experiences, challenges, and acceptance of e-learning as a tool for teaching during the COVID-19 pandemic among university medical staff. PLoS ONE, 16(3), 1-12.

[2] Michael, R. I., and Sam, E. W. (2020). A Survey on Human Face Expression Recognition Techniques. Journal of King Saud University, 1-11.

[3] Junge, S., Haopeng, Y., Jiawei, L., and Zhiyong, C. (2021). Assessing learning

[4] engagement based on facial expression recognition in MOOC’s scenario. Springer, 1-10.

[5] Fatimah, A. A. (2020). Online Teaching Skills and Competencies. TOJET: The Turkish Online Journal of Educational Technology, 9-20.

[6] Yusra, K. B., Afshan, J., Nudrat, N., Muhammad, H. Y., Serestina, V., and Sergio, A. V. (2021). Facial Expression Recognition of Instructor Using Deep Features and Extreme Learning Machine. Hindawi Computational Intelligence and Neuroscience, 1-17.

[7] Hanusha, T., and Varalatchoumy. (2021). Facial Emotion Recognition System using Deep

Learning and Convolutional Neural Networks . nternational Journal of Engineering Research & Technology (IJERT), 803-811.
[8] Ho-Jung, L., and Deokwoo, L. (2020). Study of Process-Focused Assessment Using an Algorithm for Facial Expression Recognition Based on a Deep Neural Network Model. Electronics, 1-14.
[9] Balasaranya, K., Pacha Shobha, R., AbhignaSriya, P., and Rumana, T. S. (2021). Real Time Emotion Recognizer And Classifier For Facial Expressions Based On Machine Learning. Turkish Journal of Computer and Mathematics Education , 1958-1964.
[10] Moutan, M., Saurabh, P., Anand, N., Pijush, K. D., Niloy, D., and Prasenjit, C. (2020). Facial Emotion Detection to Assess Learner's State of Mind in an Online Learning System. ICIIT 2020: Proceedings of the 2020 5th International Conference on Intelligent Information Technology, (pp. 107-115).
[11] Sasirekha, A. (2021). Unobtrusive Assessment Of Student Engagement Levels In Online Classroom Environment Using Emotion Analysis. Georgia: Electronic Theses and Dissertations.
[12] Nazia, P., Nazir, A., M Abdul, Q. B. K., Rizwan, K., Salman, Q. (2016). Facial Expression Recognition Through Machine Learning, International Journal of Scientific and Technology Research, 5(3), 91 -97
[13] Henrique, S., Sven, M., and Stefan, W. (2020). Efficient Facial Feature Learning with Wide Ensemble-Based Convolutional Neural Networks. AAAI, 5800-5809.
[14] Uğur, A., Hüseyin, G., Mehmet, O. D. (2017), Use of Facial Emotion Recognition in E-Learning Systems, Information Technologies and Learning Tools, 60(4), 95-104