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Intelligent Multimodal Online Learning System with Face Recognition and Feedback Analysis

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Abstract

The exploration of multimodal learning enhances our understanding of the educational process. However, it faces challenges, particularly regarding the significance of facial recognition, which is closely linked to its extensive potential in various multimedia applications. To address these challenges, a novel strategy known as the Horned Lizard Segformer Prediction System (HLSPS) has been developed. Initially, a dataset containing student online feedback was collected and utilized for training purposes. Facial recognition is first employed to analyze students' emotions. Subsequently, the feedback is analyzed and presented to educators to assess the effectiveness of learning activities. Finally, performance indicators such as precision, accuracy, recall, F-measure, and error rate are used to evaluate the robustness of HLSPS. The method has been validated against a range of existing models, demonstrating a significant improvement in performance.

Keywords: Online Learning, Emotion Recognition, Intelligent Training System, Feedback Generation.

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1. Introduction

The application of multimodal learning analytics (MMLA) technology in this context offers compelling alternative solutions through the integration of diverse educational methodologies [1]. In recent years, researchers have leveraged MMLA and social network analysis (SNA) to examine the behaviors of individuals collaborating in group settings to address specific problems [2]. The rise of distance education has introduced new challenges in overseeing teaching and learning processes. Engaging students who participate with black screens and without cameras during class significantly complicates the task of fostering social interactions between educators and students, as well as effectively assessing their learning progress [3]. These challenges underscore the necessity for educators to be equipped with innovative technological resources to enhance feedback mechanisms [4].

In the established field of multimodal communication, advancements in data collection and sensing technologies have facilitated the comprehensive gathering of data related to various aspects of human activity [5]. Generally, the emphasis on quality in distance learning tends to be lower than that found in traditional classroom environments [6]. Continuous monitoring and management of quality are often neglected within the overall educational delivery system [7]. Despite the widespread popularity of distance learning across nations, organizations frequently dismiss world-class projects in favor of in-person interactions. It is critical for employers and the public to recognize the value of distance learning courses [8]. The program undergoes stringent quality control measures to ensure its relevance and effectiveness [9]. Distance students are afforded appropriate treatment and support, which is particularly advantageous when they are enrolled in the same course, as it simulates an industry-equivalent experience comparable to face-to-face recruitment [10].

Feedback is a complex and comprehensive process, characterized as a loop wherein performance-related information is exchanged among individuals, such as between the student and instructor [11]. A key element of any feedback loop is that the information relates to performance and influences subsequent actions. These concepts are widely acknowledged as essential to the educational process, as they enable students to achieve their learning objectives and develop the critical skills necessary for independent learning [12]. Currently, instruction on complex texts typically involves educators presenting a text and posing supplementary questions to facilitate student comprehension [13]. Students with lower proficiency levels require additional support in language, instructional scaffolding, and the use of technological resources to enhance their understanding of multimodal texts [14]. This study serves a dual purpose: (i) to evaluate the effectiveness of a structured learning approach that provides students with language and pedagogical support, and (ii) to assess a prototype multimodal analysis software designed to furnish students with technical resources for annotation and analysis [15]. The process begins with establishing the foundation of the study through the clarification of fundamental concepts related to multimodal literacy and associated costs [16].

Additionally, a systematic approach to multimodal texts is introduced, utilizing software to facilitate analysis [17]. Various methodologies for understanding learning and communication have emerged, particularly emphasizing the multifaceted methods of assessment feedback. Diversity is recognized as a key element in the contemporary advancement of semiotic approaches to education, which advocate for a holistic perspective on different modes of communication and their integration [18]. Learners are encouraged to enhance their autonomy in the feedback process, engage in discussions with instructors, and strive to improve their skills. This approach not only benefits them in their current academic endeavors but also fosters a broader transition from "mechanical" to "responsive" feedback, cultivating effective lifelong learning habits [19].

The diverse forms of learner engagement are instrumental in identifying interventions and making adjustments to the online engagement platform [20]. Assessing engagement levels across various categories enables learners to evaluate the efficacy of the engagement system [21]. Numerous scholars have acknowledged the effectiveness of the online learning engagement system and its impact, as it improves learning outcomes while reducing costs and eliminating the need for extensive travel [22]. Developing customized educational resources for online interaction can significantly enhance its success rate [23]. This approach to learning engagement is expected to gradually integrate into traditional educational settings, contributing to the establishment of a more efficient and streamlined educational system in India [24].

The primary contributions of this study are outlined as follows:

- Initially, a dataset containing online feedback from students was collected and utilized for training purposes.
- Facial recognition technology was employed to analyze students' emotions.

- The feedback was subsequently analyzed and provided to teachers to assess the effectiveness of learning activities.
- Finally, primary metrics such as recall, precision, accuracy, error rate, and F-score were evaluated and compared with alternative models.

The document is organized into multiple sections. Section 2 provides a summary of the literature review; Section 3 details the system design; Section 4 addresses the resolution of the specified problem; Section 5 discusses the outcomes of the validated individual solutions; and Section 6 offers concluding thoughts.

2. Related Works

The relationship between humans and machines is currently evolving and plays a crucial role in extracting and comprehending emotions. Nevertheless, a difficult aspect of online learning is the limited number of participants and the lack of support offered by e-learning platforms. To solve this problem, [25] introduced a promising solution, the Heuristic Multimodal Real-Time Method for Emotion Identification. This method is employed to ensure the punctual delivery of suitable online feedback by analyzing learners' vocal sounds and facial expressions, thereby enhancing their learning experience. Nevertheless, there is a downside to this. Various individuals may interpret the same voice differently based on their unique perspectives.

Assessing student engagement is critical to addressing the barriers students face in online education. [26] have implemented a cutting-edge approach named Deep CNN in order to tackle this issue. The utilization of these techniques enables educators to gauge the level of student engagement during online learning by predicting it through the EI value. This valuable information assists teachers in assessing the effectiveness of student engagement. Nevertheless, it possesses disadvantages stemming from its inability to acquire comprehensive global context information as a result of inherent structural constraints. [27] presented a novel approach known as K-Nearest Neighbors (KNN) in their study. This technique is employed to design an educational system that can tailor teaching materials based on the emotional condition of students. This approach aims to inspire students throughout lectures. The suggested system offers educational engagement to students experiencing negative emotions and delivers additional learning resources to learners in positive emotional conditions. Nevertheless, KNN is accompanied by certain limitations and obstacles, including high computational expenses, sluggish processing and memory, and storage concerns when dealing with extensive datasets.

MMLA has opened up substantial prospects for progress in the realms of education, student instruction, and the learning journey. The recent rapid advancements in artificial intelligence technologies have significantly impacted the landscape of related fields. This has led to a transformation in the way information technologies are utilized [28] have created an AIaaS (Artificial Intelligence as a Service) solution to address this issue. Assessments should also be highlighted as a tool to assist students in recognizing their strengths and weaknesses, as well as establishing goals. Despite the presence of security risks associated with hacking, as well as the absence of human-like creativity and empathy, it is important to acknowledge the potential drawbacks.

Online education has emerged as a crucial method of learning; however, instructors need to ensure that students remain engaged and focused [29] devised a ground-breaking approach to tackle this issue by formulating a unique technique for evaluating the level of engagement of online learners in a MOOC setting. This technique is employed to document the temporal fluctuations in the emotional states of the learners. Nevertheless, there are certain disadvantages associated with offering personalized curricula and individualized teacher support. It can be challenging to monitor student progress and involvement effectively.

3. System Model with Problem Statement

An essential requirement in today's education sector is the thorough and unbiased evaluation of educational quality from an intellectual and multidimensional perspective. However, this problem is exacerbated in the online learning environment, where educators face difficulties in monitoring student participation and sustaining appropriate levels of interaction. Numerous methods are available, yet students and teachers encounter challenges in receiving immediate feedback while engaging in e-learning.

A traditional systematic forecasting method produces a low level of accuracy, which is less than optimal. Moreover, the facial recognition technique proved to be quite challenging. Furthermore, the approach fails to offer any clarification regarding its evaluation of feedback. The method's lack of accuracy resulted in its failure to detect accurately. Fig. 1 illustrates the system model with problems.

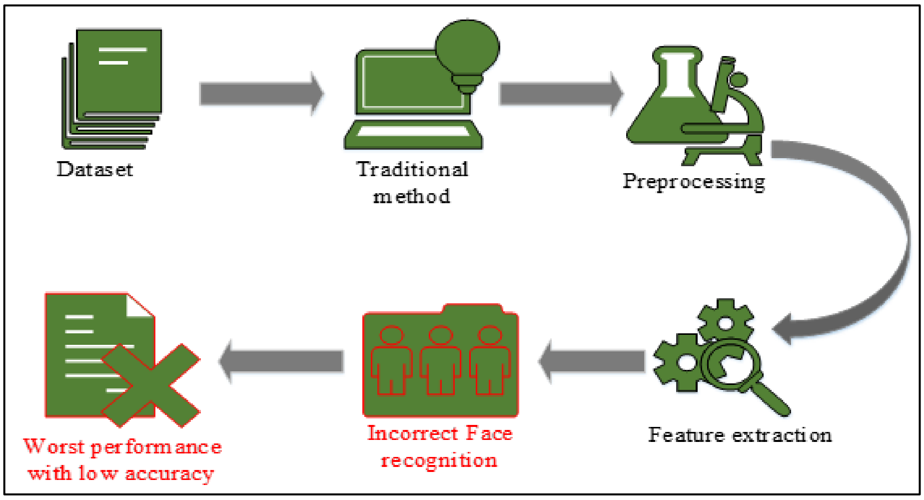


Figure 1. System Model with Problem

4. Proposed Methodology

This study introduces an innovative approach called the Horned Lizard Segformer Prediction System (HLSPS) for facial recognition prediction and feedback generation. Additionally, the designed framework involves executing various procedures, including preprocessing, feature extraction, face recognition, prediction, and feedback generation. The facial recognition system within the established framework forecasts the emotions of students. The framework offers improved feedback generation by engaging with both students and teachers.

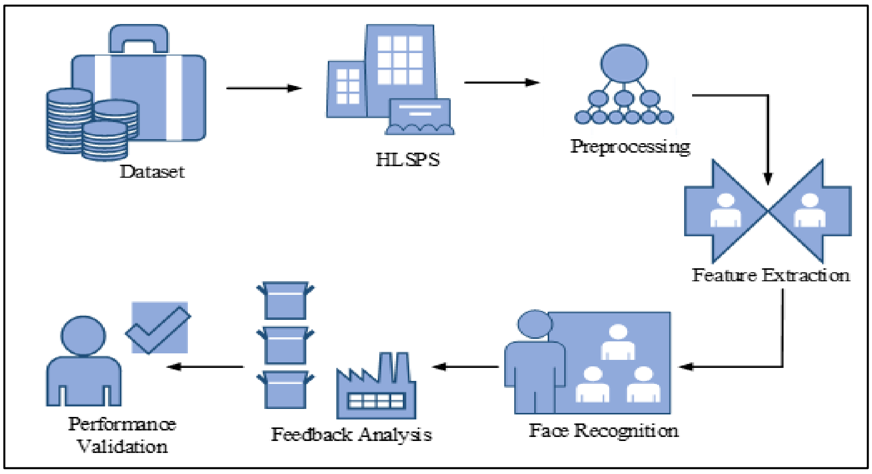


Figure 2. Proposed Methodology

The process of the proposed method is outlined in Figure 2. The preprocessing stage successfully eliminated the noise features, followed by the execution of the feature analysis.

The algorithm has been simplified, leading to a higher level of accuracy. Following this, the effectiveness of the established model is confirmed through various metrics such as F-score, accuracy, recall, and precision.

4.1 Process of the Proposed HLSPS

The HLSPS method plays a crucial role in ensuring precise face recognition forecasting. In this context, the data initialization procedure must be carried out. The preprocessing phase commenced subsequently to eliminate the undesirable noise characteristic. The feature extraction process involved extracting the suitable features from the dataset. In the end, the forecasting phase is able to pinpoint characteristics that enable exact forecasts about whether a feedback loop exists. The output guarantees the consistency of forecasting in order to achieve precise forecasting outcomes.

4.1.1 Data Initialization

In the beginning, the LAPA dataset was collected, and the HLSPS operation was started. The process of initialization may be explained in Eqn. (1)

$$S[D_m] = (I_{n1}, I_{n2}, I_{n3}, ...I_{nk}) \tag{1}$$

Here, S denotes the initialization variable, D_m represents the collected dataset, I_{nk} denotes the data, k denotes the total count of data. The data gathered to test the proposed framework contains certain noisy characteristics. The feature analysis and prediction process may become more complex as a result of this. To simplify matters, a preprocessing step was carried out. Within this preprocessing function, all undesired noise features in the data were eliminated. The data preprocessing step reduces the size of the dataset in comparison to the initial dataset, leading to enhanced performance of the HLSPS model.

4.1.2 Preprocessing

After initializing and training the dataset, the next step involves preprocessing. The main goal of preprocessing is to exclude any potentially noisy characteristics from the dataset. Eqn. (2) represents the preprocessing function.

$$P[D_m] = a[D_m - F_n] \tag{2}$$

Where, P denotes the preprocessing variable, a denotes the noise tracking variable, F_n represents the present noise feature from the dataset. Consequently, the preprocessing function eliminated the unnecessary noise features from the trained database.

4.1.3 Feature Extraction

Once the preprocessing phase has been completed, the feature extraction procedure can commence. Furthermore, the filtered data, which has been processed to remove noise, is subsequently introduced into the feature analysis stage in order to extract valuable characteristics for prediction. The extracted characteristics aid in identifying the general appearance of the building and enhancing the precision of the suggested design. It is described in Eqn. (3).

$$FE = F(D_m) + x(D_m - R_f) \tag{3}$$

Where, FE denotes the feature extraction variable, x represents the feature tracking variable,

R_f denotes the relevant feature; therefore, relevant characteristics were tracked and extracted from the database. Moreover, the processed data, after undergoing noise elimination, is then fed into the feature analysis phase to extract significant attributes for predictive purposes.

4.1.4 Face Recognition

Following the feature extraction process, the chosen features are inputted into the face detection function. In the process, it recognizes facial emotions. Facial emotion tracking requires recognizing an image that follows a regular pattern. The procedure for facial recognition is explained in Eqn. (4).

$$FR = \sum_{i=1}^{i} \left(\frac{n}{i} \right) * (T-1) + 2a^2 \tag{4}$$

Here, FR represents the face recognition variable, i denotes the internal mental state, n represents the samples, a^2 denotes the emotions and T denotes the tracking variable. It can identify facial emotions, anticipate them, and determine the specific emotion being expressed.

4.1.5 Feedback Analysis

Once the face recognition process is complete, the feedback analysis process can begin. During this phase of feedback analysis, it is possible to assess students's progress in their learning. Their facial expressions can recognize students' interest in learning. Subsequently, the teacher receives feedback to determine the effectiveness of the learning activities. The feedback analysis process can be described in Eqn. (5).

$$if \begin{cases} p = 0 & effective \\ p = 1 & ineffective \end{cases} \tag{5}$$

In this context, the value $p = 0$ represents effective learning feedback, while the value $p = 1$ represents ineffective learning feedback. The feedback data encompasses facial expressions and the performance of e-learning activities. Following the analysis of the e-learning activities, the feedback is forwarded to the teacher.

Algorithm 1: HLSPS

Start

```
{
    Data initialization
    {
        int S, D_m, I_nk
        //initialize the values
        S[D_m] ← (I_n1, I_n2, I_n3,......I_nk)
        //the data was initialized
    }
    Preprocessing()
    {
        int p, D_m, F_n
        //Initializing the preprocessing variables
        preprocessimg ← a[F_n]
        // noise features are removed
    }
    Feature Extraction()
    {
        int FE, x, R_f
        //initialize the feature extraction variable
        featureextraction ← F(D_m) + x(D_m − R_f)
        //the unwanted data are removed
    }
    Face recognition()
```

```
{
    int FR, n, i, T, 2a^2
    //initializing the face recognition variables
    FR ← Σ_{i=1}^{i} (n/i) * (T − 1) + 2a^2
    //The face recognitions are identified
}
Feedback analysis()
{

    if (p = 0)
    {
    Effective
    }
    if (p = 1)
    {
    Ineffective
    }
}

}
```

$$FR \leftarrow \sum_{i=1}^{i}\left(\frac{n}{i}\right) * (T-1) + 2a^2$$

Stop

The step-by-step algorithm fully describes the procedures and techniques outlined in the proposed framework. By following these steps, the Python code is executed, and the outcomes are verified. All parameters of the mathematical functions are compiled into pseudocode format by the algorithm. Figure 3 shows the HLSPS flowchart.

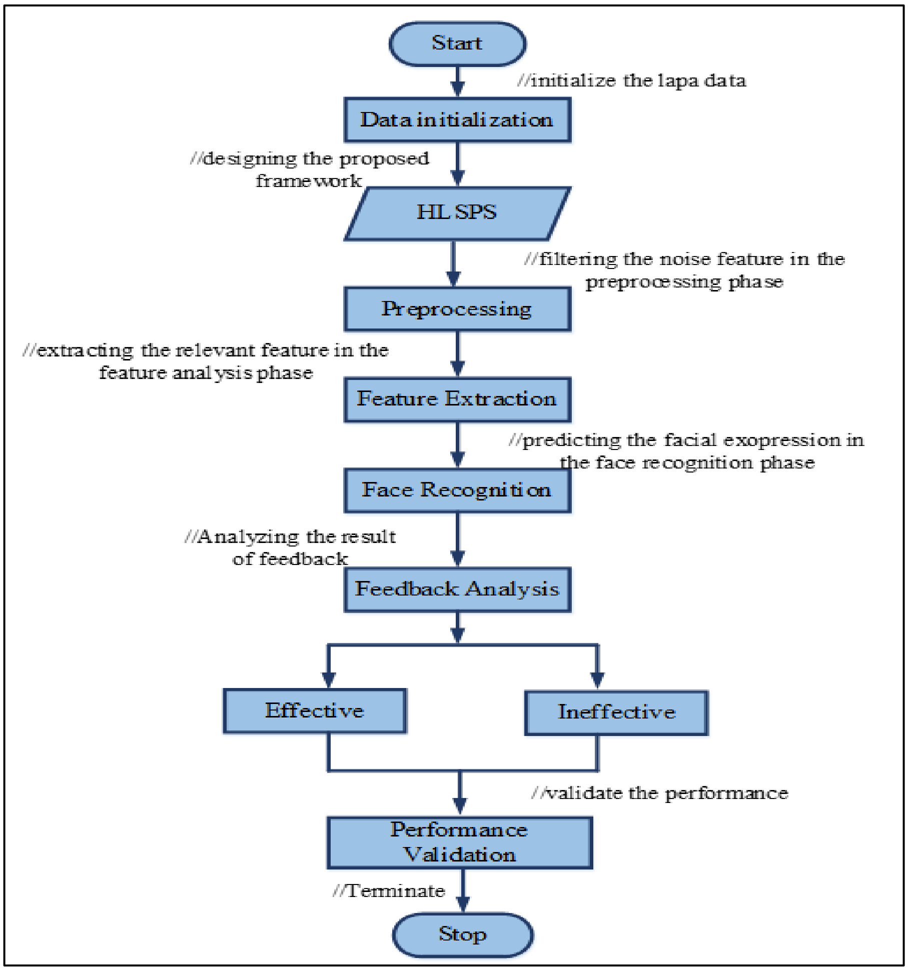


Figure 3. Flowchart of HLSPS

5. Results And Discussion

The novel Python environment has been utilized to design and implement HLSPS. The computer was initially used to collect and train the LAPA dataset. A thorough case study has verified the effectiveness of the unique model. Furthermore, a thorough evaluation is conducted to determine how well the model generated model performs on the dataset. Table 1 demonstrates the operational variables.

Table 1. Implementation Parameter

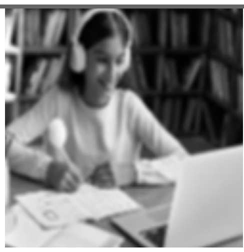
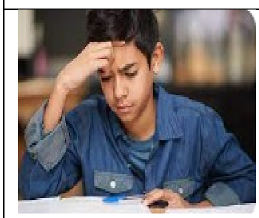
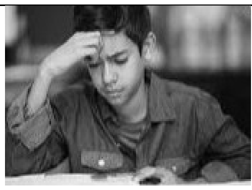
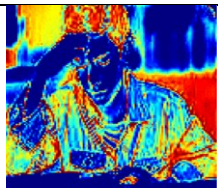
Parameter	Specification
Operating System	Windows 10
Version	3.8

Platform	Python
Optimization	Horned Lizard
Dataset	Lapa dataset

5.1 Case Study

To guarantee the validity of the proposed method, its efficacy was empirically verified. The performance evaluation of the designed model is conducted by analyzing the novel HLSPS. Additionally, the datasets are employed to evaluate the effectiveness of the formulated models. Moreover, this method offers an intricate account of the effectiveness of the suggested framework. The study utilizes a comprehensive dataset called Landmark Guided Face Parsing (Lapa) to analyze facial features. The Lapa dataset includes more than 22,000 face photos with a variety of occlusions, positions, and expression modifications. A 106-point landmark and an 11-category pixel-level label map are also included with every picture in the collection. It offers clear benefits in terms of annotation quality and performance when compared to other face-parsing datasets available. As far as we know, this is the most extensive public dataset for face segmentation at the moment.

Table 2. Process HLSPS

Input Image	**Pre-processing**	**Feature Extraction**	**Face Expression**	**Feedback Analysis**
			Pleasure	Effective
			Confusion	Ineffective

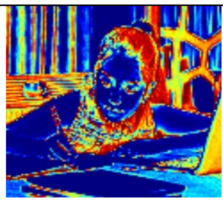
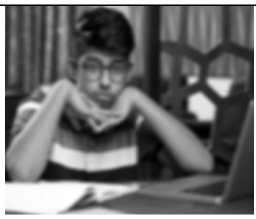
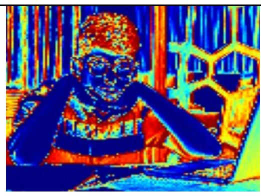
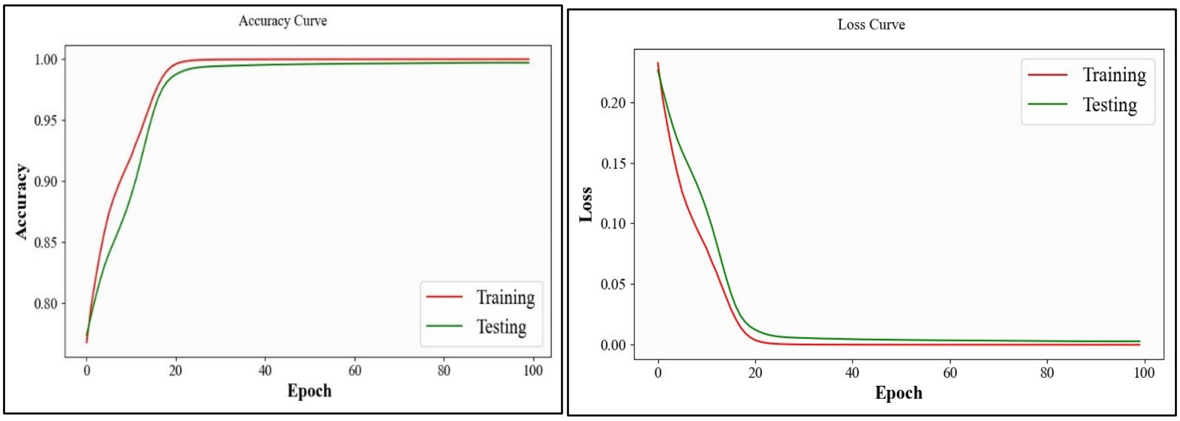
			Concertation	Effective
			Boredom	Ineffective

Table 3. Dataset Details

Emotion	Total Samples	Training Samples (80%)	Testing Samples (20%)
Pleasure	8,989	7,164	1,825
Concentration	6,198	4,982	1,216
Confusion	6,077	4,938	1,139
Boredom	549	438	111
Total	17,520	14,016	3,504

The image data input is subjected to data decomposition analysis in order to remove noise features and improve important properties. Tracking methods were employed to analyze and monitor the development of facial expressions across image features. Then, the facial expressions were segmented and divided using HLSPS methods. Upon recognizing the facial expression, the instructor obtains the ultimate evaluation regarding the educational session. Table 2 illustrates the process of HLSPS.

The HLSPS suggested in epoch Figure 4 is undergoing validation for accuracy. The train and test extraction scores confirmed the face recognition system's predictive accuracy. The loss value is employed to calculate the rate of inaccuracy of the suggested mechanism. These metrics are evaluated throughout simultaneous phases of training and test validation.



A B)

Figure 4. A) Accuracy B) Loss

5.2 Comparative Analysis

The proposed method's performance score was validated by evaluating key performance metrics, including precision, accuracy, recall, error rate, F-measure, etc., which were utilized for validation purposes. For analyzing performance improvement, the recently associated model was used. The existing models, such as Educational Mental Health Detection (EMHD) [30], Multimodality Decision Fusion Classifier (MMDFC) [31], K-Nearest Neighbors (KNN) [32], Long Convolutional Short-Term Memory (LCSTM) [33], and Fake News Detection (FND) [34], are compared.

5.2.1 Accuracy

Evaluating the effectiveness of the approach was crucial in determining its ability to produce accurate forecasts. The accuracy was computed by calculating the ratio of accurate predictions to all forecasts produced. Accuracy measurements can be calculated using the formula given in Eqn. (6).

$$Accuracy = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \tag{6}$$

Here, the symbol T_p denotes the confirmed positive, T_n represents the confirmed negative, F_n signifies the unconfirmed negative, F_p and stands for the unconfirmed positive.

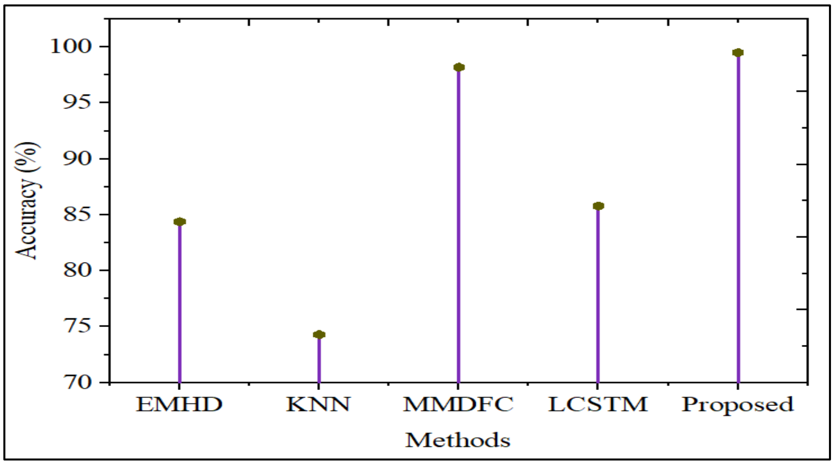


Figure 5. Comparison of Accuracy

The implemented model's accuracy in handling the dataset is compared to other established techniques, showcasing its superior performance. The results of the accuracy validation are depicted in Figure 5. The HLSPS attained 99.5% accuracy, whereas EMHD, KNN, MMDFC, and LCSTM reached 84.4%, 74.3%, 98.2%, and 85.8%, respectively.

5.2.2 Precision

The positive classes that have been identified are the ones that were accurately predicted. This metric evaluates the classification's overall accuracy by taking into consideration cases of inaccurate categorization. It is determined using the provided Eqn (7).

$$precision = \frac{T_p}{T_p + F_p} \tag{7}$$

The assessment of the HLSPS precision is utilized to gauge the efficiency of the system. Typically, greater precision signifies a greater degree of utility.

The model's effectiveness in managing the dataset is evaluated by comparing it to other well-established techniques, demonstrating its exceptional performance. The precision validation outcomes are illustrated in Figure 6. The HLSPS framework attained 97.8% precision, while KNN and FND reached 70.8% and 93.4%, respectively.

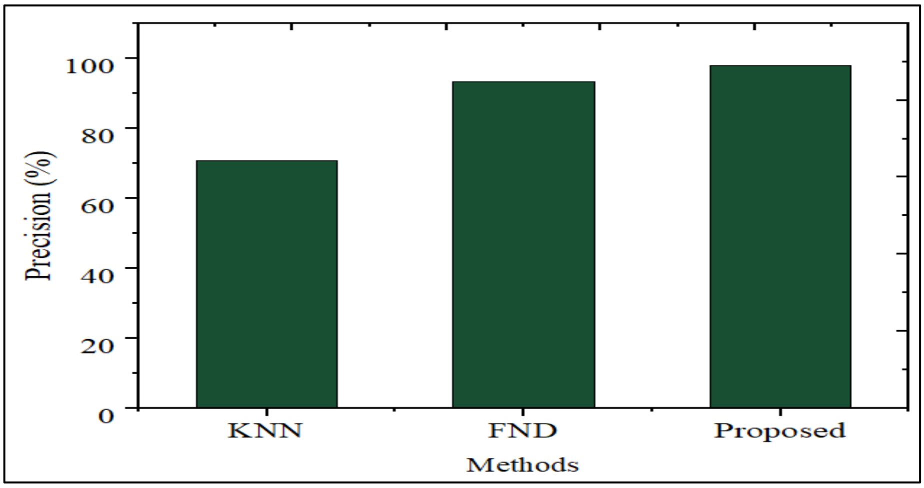


Figure 6. Comparison of Precision

5.2.3 Recall

The sensitivity score for data prediction is calculated by analyzing the recall metric of a system. As it is indicated in Eqn (8). The equation demonstrates how the system's recall metric is calculated.

$$\mathrm{Re}call = \frac{T_p}{T_p + F_n} \tag{8}$$

Improving the recall score is crucial for achieving a highly effective system.

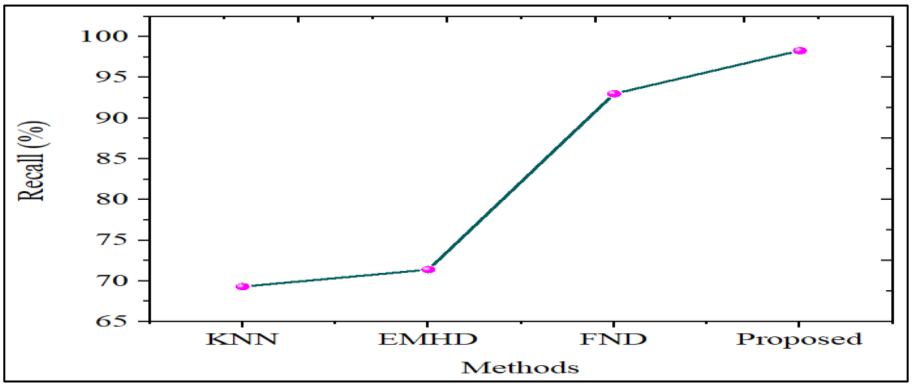


Figure 7. Comparison of Recall

The recall value of the designed scheme reached 98.3%, whereas EMHD, KNN, and FND achieved recall values of 71.4%, 69.3%, and 93%, respectively. Figure 7 presents an intricate analysis of the data. The effectiveness of HLSPS was evaluated through its impressive recall rate.

5.2.4 F-Measure

The effectiveness of measurements is demonstrated by the harmonic mean of recall and precision, which aids in balancing the precision and recall rates. The F-score is the optimal metric to use when dealing with imbalanced classes, and it can be computed using Equation (9).

$$F - Measure = 2 \times \frac{precision \times recall}{precision + recall} \tag{9}$$

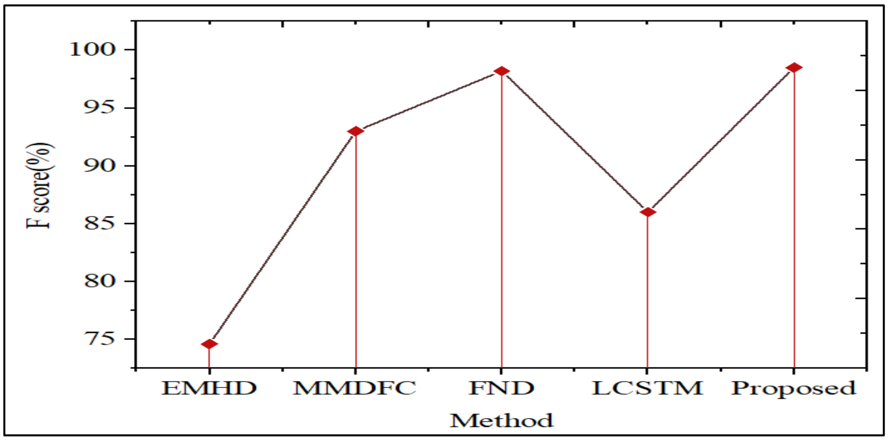


Figure 8. Comparison of F-Measure

The validation results for the F-measure can be seen in Figure 8. The HLSPS framework attained 98.5% F-measure, while other approaches like EMHD, FND, MMDFC, and LCSTM reached 74.6%, 93%, 98.2%, and 86%, respectively.

5.2.5 Error Rate

The error rate metrics are utilized to assess the misclassification rate of the designed model. It is derived by dividing the total number of missing predictions by the total number of datasets. This metric is referred to as Eqn. (10) and serves to identify errors and facilitate their correction.

$$Errorrate = \frac{F_p + F_n}{Totaldata} \tag{10}$$

The implemented model's exceptional performance was shown by comparing its error rate to other well-known techniques.

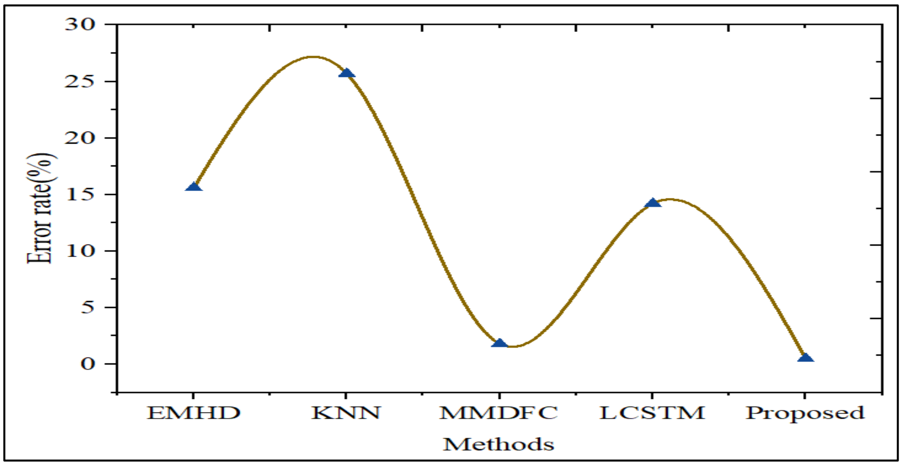


Figure 9. Comparison of Error Rate

The contrast in error rates can be observed in Figure 9. The proposed HLSPS model achieved a 0.5% error rate, while other approaches, such as EMHD, KNN, MMDFC, and LCSTM, obtained 15.6%, 25.7%, 1.8%, and 14.2% error rates, respectively.

5.3 Discussion

The main goal of creating the HLSPS model was to provide insight into the processes of face detection and feedback analysis. The study's concluding section validated the improvement in performance by conducting comparative analyses. Furthermore, the model's stability score is calculated and contrasted with other models currently in use to confirm its efficiency. Table 4 illustrates the performance of the HLSPS.

Table 4. Performance of HLSPS

Metrics	Percentage (%)
F-Measure	98.5
Accuracy	99.5
Recall	98.3
Precision	97.8
Error Rate	0.5

The outstanding outcomes of the applied model are shown by contrasting its performance with other approaches. The HLSPS model attained 99.5% accuracy, 97.8% precision, 98.5% F-measure and 98.3%—recall score.

6. Conclusion

The current document outlines the development of the HLSPS system, which is designed for face recognition and feedback generation. Furthermore, it evaluates and compares the projected outcomes of the proposed model with those of existing methods. The analysis indicates that the generated model exhibits a higher stability score compared to current models. Subsequently, the effectiveness of the proposed model will be assessed using various evaluation criteria. The HLSPS model achieved an accuracy of 99.5%, a precision of 97.8%, an F-measure of 98.5%, and a recall of 98.3%. The model demonstrated exceptional precision, recording a mere 0.5% error rate on the acquired dataset. Future initiatives will focus on creating icons in a distinctive style, as well as developing a face widget to collect facial data from learners while ensuring the protection of their personal information.

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