Yugoslav Journal of Operations Research
(20##), Number #, #-#
DOI: https://doi.org/10.2298/YJOR240515007V

Research Article

PREDICTION OF STUDENT ENGAGEMENT USING DEEP LEARNING-BASED STUDENT FACE EXPRESSION DETECTION METHOD (DL-SFEDM)

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Received: May 2024 / Accepted: September 2024

Abstract: Nowadays, Academics and teachers have paid a lot of attention to computational thinking (CT) because of the wonderful opportunities it presents for developing students' problem-solving abilities, which are in high demand in a technologically advanced world. However, research has shown that educators lack a solid grasp of CT and often misunderstand its idea, which might impede their implementation

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of these initiatives. This problem is even worse because very little research has explored ways to engage students with their learning. In this paper, a Deep Learning-Based Student Face Expression Detection Method (DL-SFEDM) is a method for finding out how engaged students are with online lecture videos that don't depend on data generated by educational management systems. To conduct the classroom engagement analysis, the whole class is treated as a single group and their corresponding group engagement score is calculated. Emotions play a crucial part in learning. Computer vision (CV)-based approaches evaluate online and offline lecture recordings and extract students' emotions. This expressive emotion analysis looks at how Students feel in four distinct states: positive, negative, neutral, and negative. The experimental results show that the proposed DL-SFEDM enhances the teaching technique, motivates better student learning and increases student computational thinking.

Keywords: Computational thinking, deep learning, student, face expression, student emotion.

MSC: 92B20, 68U10, 97D10.

1. INTRODUCTION

In today's dynamic educational landscape, CT has become an essential set of skills. Its significance has grown recently and remains crucial for improving students' problem-solving skills [1]. 68Txx, 68T27, 03Cxx, 03C45, 68Uxx, 68U10, 97Dxx, 97D10

The integration of CT in curricula has gained more attention and it will support many educators in receiving the benefits of CT in preparing students for a technologically oriented world [2]. Despite several benefits, educators may not completely comprehend how to integrate into their lessons. It may also restrict the impacts on the students [3]. To determine the face reactions of students in learning with CV and DL, students FED method analyses the Face Expressions (FE) [4].

When students performing some tasks, the face of the students can be captured with the help of cameras [5]. Expressions like happiness, sadness, confusion and engagement can be evaluated by the captured images [6]. Then, students' emotional states and their level of attention during their learning can be evaluated by teachers with the help of technology [7].

Based on the FE of the students, teachers can adapt their lessons [8]. Based on the need of individual students, extra materials and adapting the level of instructions can be offered by teachers [9]. By considering the FE of the students, teaching methods and course content efficacy can be assessed by this [10].

This is done by establishing a connection between academic achievement indicators and facial emotions [11]. This data-based feedback system helps teachers improve their practices and enhance student learning outcomes [12]. However, concerns about personal data security about these technologies require immediate attention [13]. To ensure the privacy of children/students and the secrecy of data collection and analysis, strict ethical principles must be adhered to, and relevant laws must be respected in all ICT usage in schools or tertiary institutions. Furthermore, to foster trust and acceptance within educational contexts, the purpose(s) behind using facial expression recognition systems must be explicitly shared with students [14].

This problem becomes even more acute due to insufficient research into strategies that activate students' cognitive engagement in educational activities. The paper addresses this gap by proposing another DL-SFEDM method [15]. Regarding online lecture videos, student engagement could be measured without relying on any education administration system datasets, and its use is prohibited under such circumstances. This is a key part of our method since emotions affect learning dynamics. This method uses computer vision techniques to discern students' emotional states from their recorded facial expressions in online and offline teaching materials. This activity asks students to assess their level of engagement with the content by placing themselves in one of four categories: very positive, highly negative, positive neutral, or negative neutral. Existing issues include the subjectivity, inefficiency, and impracticality of using time-consuming and labour-intensive conventional techniques of tracking student engagement, such as questionnaires or physical observation in real-time. Educators find it difficult to adapt their teaching practices on the fly to engage students better since these approaches do not give rapid feedback. Accurately measuring student attention and involvement is already difficult in traditional classrooms; the proliferation of online and hybrid learning settings makes problems difficult. Assessments of student attention may be variable or incorrect if current automated methods have trouble correctly reading facial expressions owing to variances in lighting, camera angles, and individuals.

The goal of these experimental studies is to demonstrate that DL-SFEDM is effective in enhancing pedagogical practices and boosting student motivation. This will enable deeper computational reasoning in learning. The ultimate aim of the paper is to help improve educational technology and provide a more engaging and fruitful classroom setting.

Contributions of the paper:

- The paper introduces DL-SFEDM, a novel method for measuring student engagement in online lectures without EMSs. Consequently, a method for actively involving students is offered, and the challenge of teachers' understanding of CT is tackled.
- By analyzing facial expressions, DL-SFEDM may categorize emotions into different states, offering nuanced insights into the levels of engagement. Research has shown its efficacy in enhancing pedagogical practices and igniting students' interest in learning.
- By providing teachers with a high-tech resource that has the potential to improve pedagogy and foster an engaging classroom environment conducive to students' growth in computer literacy, this paper substantially contributes to the field of educational technology.

In this paper, section 2 shows the related works, section 3 explains the proposed method, section 4 denotes the result and discussion, and section 5 shows the paper's conclusion.

2. RELATED WORKS

Modern distractions and teacher-limited one-on-one time with students enhance the current major problem of student disengagement in modern educational settings. Intelligent solutions for real-time monitoring are important in large offline classrooms since standard methods of evaluating student engagement do not deliver enough results. Facial expression recognition has recently become a promising strategy for accurately measuring students' emotional states and engagement levels in class. Presented here is a novel pipeline for computer vision and deep learning applications. The goal of the pipeline is to derive students' facial expressions from their facial data. This enhances efficiency and privacy by enabling real-time processing without external server uploads. The presented solutions promise to enhance students' experiential learning opportunities and transform classroom dynamics.

CNN-based facial expression recognition (CNN-FER)

Modern distractions and lack of student-teacher contact have made student disengagement a major issue. Large offline classrooms make it hard for instructors to monitor student involvement and maintain the correct degree of interaction [16]. Traditional methods of student engagement tracking require self-reporting or physical equipment, which are limited to offline classroom usage. Student academic affective states (e.g., moods and emotions) analysis might create intelligent classrooms that automatically monitor and assess students' involvement and conduct in real-time. A few computer vision-based methods have been developed in recent literature; however, they only function in e-learning and have real-time processing and scalability issues for big offline classrooms. This paper provides a real-time method for measuring student group involvement by evaluating facial expressions and detecting academic affective states, including 'boredom,' 'confused,' 'focus,' 'frustrated,' 'yawning,' and 'sleepy,' which are relevant in the learning context Face identification, CNN-based facial expression recognition and frame-wise group engagement estimate are pre- and post-processing processes.

Robust optimization method (ROM)

The novel pipeline is proposed based on video facial processing, primarily face detection, tracking, and clustering, which are used to obtain student face sequences. Subsequently, a single efficient neural network extracts emotional information from every frame. An advanced robust optimization method pre-trains this network on face identification and fine-tunes it for facial emotion detection on static AffectNet pictures [17]. Facial characteristics may predict students' involvement levels (from disengaged to highly engaged), individual emotions (happy, sad, etc.), and group-level affect (positive, neutral, or negative) quickly. ROM allows real-time video processing on each student's mobile device without uploading facial video to the distant server or teacher's PC. Saving small clips of student emotions and involvement shows how to summarise a lesson. Experimental results from EmotiW (Emotion Recognition in the Wild) competitions indicated that the suggested network outperforms single models.

Support Vector Regressions method (SVRM)

Massive open online course dropout rates are high because of extrinsic obstacles such as users not having enough time or not wanting to finish the course, and instructors may influence several variables to interest students. To achieve this, they must understand student engagement during video lectures. This paper uses webcams to capture students' facial expressions while watching instructional videos to assess Learner Engagement [18]. Using the Support Vector Regressions method, CNNs were trained to recognize facial action units, which were translated into valence (emotional state) and arousal (attentiveness). Valence and arousal were blended in an innovative way to increase Learner Engagement. To boost model performance, CNNs were combined with geometric feature-based approaches in a novel way. The Learner Engagement detector could recognize facial expressions corresponding to student Engagement levels. Since instructors may get feedback on student Engagement, these findings show potential. More investigation is needed to confirm these findings and solve these limitations.

Deep learning method (DLM)

Engagement is a significant measure of learning experience and a critical factor in intelligent educational interfaces. Any such interface has to detect engagement levels to react accordingly, but there is little data to learn from and fresh data is costly and hard to get. The paper provides a deep learning method to enhance engagement detection from photos that overcomes data sparsity by pre-training on basic facial expression data before training on engagement data [19]. Deep learning trains a facial expression recognition model to represent faces well in the first two phases. The deep learning-based engagement model is initialized using the model's weights in the subsequent stage. The model is trained on more engaged and disengaged samples from our new engagement recognition dataset. The engagement model outperforms effective deep learning architectures that the analysts apply for the primary time to engagement recognition, histogram of directed gradients, and support vector machines.

Adaptive Weighted Local Gray Code Patterns (AW-LGCP)

In educational information technology, online learning engagement detection is a major issue. Efficient learning scenario identification may assist instructors in discovering struggling learners in real-time. Face data (using the AW-LGCP method for facial expression identification) and student mouse interaction data were gathered to enhance learning engagement detection [20]. The innovative learning engagement detection method uses student behaviour data from cameras and mice in the online learning environment. The cameras simultaneously collected data on students' faces and mouse movements. It created two classifier training and testing datasets during picture data labelling. It tested two datasets using multiple methodologies and found that the classifier trained by the former dataset performed better and had a higher recognition rate.

Rama Bhadra Rao Maddu and S. Murugappan [21] suggested the hybrid classification model for Online learners' engagement detection via facial emotion recognition in an online learning context. Following the Face detection procedure begins with the pre-processing stage. Features such as ResNet, Shape Local Binary Texture (SLBT), and Improved Active Appearance Model (AAM) are extracted during the feature extraction phase, which follows the pre-processing stage. The hybrid classification model, which uses an improved deep belief network (IDBN) and a convolutional neural network (CNN) among its components, then applies emotion detection to the attributes obtained. Involvement or engagement on the part of the learner is determined by the emotions detected and their performance via the increased entropy-based procedure. Existing approaches such as DBN, SVM, CNN, LSTM-CNN, LSTM, and RF are tested against the proposed hybrid IDBN+CNN model using different metrics on two datasets. An accuracy of 0.95 was achieved by the hybrid model on the CK+ dataset, with a learning percentage of 80%. Furthermore, regarding FER-2013 datasets, the hybrid model is 60% more sensitive.

Ajitha Sukumaran et al. [22] proposed Deep Learning Techniques for Multi-modal Engagement Recognition from Image Traits. First, a model for facial recognition was put into place. Training a deep learning convolutional neural network on the FER 2013 datasets was the next step in developing the face emotion recognition model. The weights allocated to the identified emotions were based on the academic affective states. Then, the blinking rate of the eyes, state (closed or open), and direction of gaze were determined with the help of Dlib's face detector and pattern prediction algorithm. A proposed engagement recognition system integrates all these modalities derived from image attributes. Passing each session's exam confirmed the suggested system's experimental findings. Utilizing this technique allows for the processing of the student's emotional state in real time via video. Upon completion of the session, the instructor may get comprehensive analytics of engagement statistics in a spreadsheet, allowing for the ease of appropriate follow-up measures.

Bhawesh Rajpal et al. [23] recommended a modified technique for recognizing facial expressions. An algorithm for face expression recognition is studied in this research. Image Processing (IP), Facial FE (Feature Extraction), FE detection are the 3 stages in the technique. By employing Haar cascade classifier, the face area is detected in the initial pre-processing step. Then, the CNN-trained framework receives this face area, then the face area is then related to the features of the model. Through the comparisons, the images are labelled and results are obtained. Finally, this technique will support in accurately detecting FE and it was revealed by the outcomes of the experiments.

The Machine Learning (ML) -based age and gender classification from facial features and Object Detection (OD) is presented by Mehmet Karahan et al. [24]. Based on the facial features, age and gender classification can be done by employing the CNN (Convolution Neural Network). By comparing their median average accuracy and inference time, the performances is evaluated and it is done via testing many ML techniques for OD. The accuracy of the age and gender classification algorithm can be attained by the graphed outcomes by employing Adience dataset. This will validate the accuracy of this technique. The OD technique efficiency can be revealed by the outcomes in employing COCO dataset.

According to the testing findings, machine learning algorithms can recognize issues.

Ramin Safa et al. [25] introduced predicting mental health using social media. This study lays the groundwork for future research using machine learning to identify mental states. Using UGC, the author outlines the standard disorder prediction and identification methods. Methods for gathering data, extracting features, and making predictions form the backbone of this study's structure. In addition, the author looks at several recent studies that have investigated various aspects of candidate profiles and the methodologies used to analyze them. After that, the author explores current and future developments in experimental auto-detection frameworks for detecting users with diseases, and we argue different parts of their evolution. Supplementing screening processes, identifying at-risk individuals via large-scale social media monitoring, and ease of future disorder treatment may be achieved using the provided approaches.

Nuha Mohammed Alruwais et al. [26] investigated deep learning to analyze student activity monitoring in E-learning classes. Innovative algorithms based on deep learning are presented in this research to monitor a student's emotional state in real-time, including anger, disdain, joy, sadness, fear, and surprise. Researchers also examined how well a CNN model with deep learning and 99% accuracy could identify students and track their activities in virtual classrooms. The method outperformed the competition thanks to its batch normalization, dropout regularization, and several convolutional layers. Important attributes were captured, and overfitting was reduced. Findings suggest that deep learning approaches may improve e-learning engagement and performance by spotting these factors earlier and more consistently. Teachers and professors may help students succeed in school and extracurricular activities by using these strategies to understand their behaviours better and provide personalized, customized assistance.

Fatemeh Mirsaeedi et al. [27] suggested the Multi-Criteria Decision-Making Methods for Data Mining Algorithms on Educational Data. The components that influence students' academic performance were discovered, and a database was created based on them using prior research in educational data mining and the views of professionals in the area. After parameter optimization and implementation, the algorithms were evaluated using TOPSIS and VIKOR techniques. Performance scores were generated using a paired t-test based on accuracy, f-measure, and ROC indexes. The TOPSIS Support Vector Machine algorithm achieved a value of 0.999115 in the two-class mode, whereas the VIKOR algorithm achieved a zero value. The TOPSIS and VIKOR Logistic Regression algorithms outperform the competition in the multi-class mode, with respective values of 0.9986044 and 0.0009798. Choosing the most performant algorithm for educational data mining is made easier with the help of the suggested strategy. It's possible to include the algorithm's ability to provide precise findings in counselling sessions to avoid kids' academic failure.

Shahed Mohammadi et al. [28] proposed the Machine Learning-based Speech Recognition System. The objective of this study is to identify the two Persian words that have been chosen in each audio recording. To achieve this goal, we trained and tested the model on two separate standard and native datasets. Audio waveform pictures were created from both datasets. The model could use the object detection method to get unique bounding boxes for each test audio, which were further processed by a convolutional neural network (CNN) classifier and assigned labels. Lastly, a cutoff is established to ensure that output is limited to boxes with high precision. Using object detection to test the model yielded a 50% success rate, whereas the CNN classifier achieved a 93% success rate.

Ali Sarwarkhah et al. [29] identify the factors affecting the satisfaction and dissatisfaction of students from the university. Telephone interviews with students who graduated in the final two years of the program provided the necessary data for this research. Data were evaluated descriptively after the interviews. Regarding the education component, the interview findings reveal that academics are very discontented with their teaching methods. Meanwhile, for the administration, several students were unhappy with the dining hall, the lack of intellectual courses, and the group manager's lack of engagement with them while they worked on their theses. Students are unhappy with the administrative side because of the careless actions and improper conduct of the teaching, administrative, and financial personnel.

Agyan Panda and Azadeh Shemshad [30] presented the automated Class Student Counting Through Image Processing. The traditional method of keeping track of students' attendance was for teachers to call out names or pass out attendance sheets physically. Proxy attendance is necessary for these time-consuming and error-prone operations. The time it takes for instructors to enter data into a database to create reports manually makes digital record assimilation a drawback. Additionally, make sure that both the digital and manual records are consistent. For some time, automated systems have used standard biometrics like iris and fingerprint recognition. Modern technology is required to operate these inherently intrusive devices. Our suggested solution streamlines the process of keeping track of attendance and gets rid of duplicate data in human records.

Samaneh Hoseinpoorian Chabok [31] introduced the Designing Management Methods in Elementary Schools by Creating Enthusiasm to Promote Learning in Students. In addition to a literature review, the current research delves into studies in psychology, happiness, and students' physical and psychological requirements. It emphasizes the significance of creating a revitalized school environment using content analysis, field studies, and library resources. This study aimed to create educational spaces by employing main management methodologies and suitable school design components. It was motivated by the inefficiency of current spaces and the improper management functions in creating a happy learning environment for children. When the author considers human connection's mental and psychological aspects, we find that educational settings are the most important supplier for society's qualitative power. Hence, making schools more enjoyable places to be is the smallest effort that can be made to provide children with physical and mental hygiene. By fostering an environment of positivity and joy in the classroom, we can recognize that each student is going through a process of holistic development that encompasses their physical, mental, emotional, ethical, and moral growth. If even one of these things is lost or broken, the learner will not be able to reach their full potential.

The problem of students' lack of interest in learning is discussed in this analysis, along with new ways to tackle it. Facial expression recognition technology allows continuous tracking of students' emotional states and engagement levels. The successful extraction of emotional information from student faces is achieved by applying rigorous optimization methodologies and deep learning technology, allowing for an accurate appraisal of student engagement. The proposed pipeline safeguards users' privacy and optimizes efficiency by processing data locally and eliminating the need for external uploads. New methods that combine information from cameras and mouse movements have shown to be useful in online learning environments when it comes to improving the identification of engagement. These tactics might completely transform classroom dynamics, make teachers more effective, and improve students' educational experiences. Some obstacles stand in the way of accurate facial expression identification and engagement prediction. These include illumination variations, occlusions (such as when students conceal their faces), and the possibility of small yet detectable variances in facial emotions. Generalizing models to varied student groups may be difficult due to individual variances in emotional expression. To overcome these limitations, this study enhances the model's generalizability using data augmentation methods (such as changing lighting conditions) and robust pre-processing processes (such as face alignment). Combining facial expressions with other engagement markers improves prediction accuracy in complicated situations, and using ensemble techniques or multi-modal approaches (which combine transfer learning with pre-trained models) helps reduce the requirement for huge labelled datasets.

3. PROPOSED METHOD

In the current technology-driven environment, CT's potential for empowering learners with problem-solving skills is a matter of urgency for its inclusion in teaching. This is despite most teachers lacking the necessary knowledge of CT, which significantly hinders the effective use of CT. Furthermore, a research gap on how students can effectively engage themselves hasn't been filled yet. The study presents DL-SFEDM as an innovative deep learning-based method for tracking students' facial expressions, filling this gap. The focus is on studying participation levels distinct from traditional educational information systems by examining how students respond during online classes.

The initial step in this method is Data Collection (DC). Students FE images are collected in various educational settings are included in this step. To ensure consistent data, pre-processing steps like Face detection, alignment, and normalization procedures. To train the framework, Deep Neural Network (DNN) extracts face features. The emotional states can be classified by employing softmax layer.In the evaluation stage, the performance of the model can be evaluated by the metrics like accuracy in learning outcome prediction, students engagement. In live classrooms, student engagement can be monitored by this technique. By FE analysis, student engagement can be predicted by DL-SFEDM.

Several steps are linked in this method. During online lectures, the initial data can be constantly received from video streams of students face by this method. Pre-processing techniques are then applied to input information, such as face detection, alignment, normalization and enhancement of data for the purpose of enhancing the data quality and data consistency. Every student face feature can be detectable in the prepared images with the support of DL techniques. The vital FE of students are involved in the features and it will serve as a basis for predicting engagements.

To analyze the extracted facial features, DL model was established and refined in the next stage. The complex relationships among student appearances and their levels of participation in classroom activities are demonstrated in this model.

The trained main model is then tested on test data to check its accuracy and generalization ability. Figure 1 helps fine-tune it to increase its predictive power.

Predictions can be made by this framework after training and testing. By creating real-time estimates or by analyzing new data streams in the course context, the involvement level of students can be continually assessed by the teachers. For lecturers or involvement level predictions, tools for analytics and visualizations are offered by the DL-SFEDM pipeline. The attention level and rate of students engagement in class are demonstrated by the outcomes. For the purpose of accurately assessing the attention level of all students during online lectures, the FE detection can be attained by DL-SFEDM and it employs CV-DL methods.

$$A(b) = \frac{1}{\sqrt{\alpha}} \int_{-\infty}^{\infty} \frac{\nabla^{-u^2} eu}{u - jk} = j \int_{0}^{\infty} f^{-rs-u/4} ef \quad (1)$$

The measure of student involvement is represented as $A(b)$ in equation 1. A scaling factor that affects the result's interpretation is represented by $\sqrt{\alpha}$. Potentially indicating the analysis of gestures or feelings, the integral terms incorporating \\$\frac{\nabla^{-u^2} eu}{u - jk}$ might be related to operations carried out on provided information j or signals $f^{-rs-u/4}$. Furthermore, ef represent a constant that impacts the system's behaviour.

$$\int_{-\infty}^{\infty} f^{-y^2} ek = \left[\int_{-\infty}^{\infty} f^{-y^2} du \int_{-\infty}^{\infty} f^{-z^2} ez \right]^{1/2} \quad (2)$$

The activity represented by the integral in Equation (2) is probably relevant to the suggested technique, which may be analyzing emotional signals or expressions on the face. The computation of engagement levels might be represented by $f^{-y^2}ek$. It is possible that the equations or factors linked to $f^{-y^2}du$ influences how the incoming data is interpreted. Furthermore, $f^{-z^2}ez$ could stand for constants or properties that impact how the system operates.

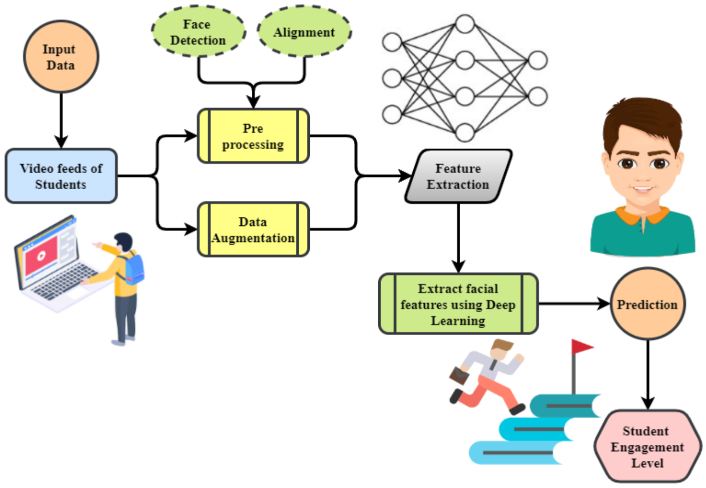

Figure 1: Workflow for the DL-SFEDM method

Figure 2 shows the complex extraction of features procedure essential to the DL-SFEDM Method. The initial phase is to collect picture data using lecture recordings with students' faces. Everything that comes after these raw photos is built upon them. Individuals in the photographs are located and identified accurately for further evaluation using state-of-the-art computer vision algorithms. Afterwards, face characteristics are normalized using approaches that guarantee consistency and make it easier to analyze different photos accurately. The first step in analyzing the expressions and signals of emotion is to locate and extract the most important facial features and characteristics.

Vital data was contained in FE and it is essential for performing engagement analysis. To detect patterns that represent various involvement levels, feature matching techniques compare and connect facial features over several images. One technique for FE is DNN. From facial images, both the low-level features (like edges and textures) and high-level features like facial features can be automatically captured and hierarchically extracted. By utilizing these features, key FE corresponds to several emotional states are then detected.

Classifying expressions by positive, negative, positive neutral, and negative neutral classifications with the FE and it was attained by DL techniques. To predict student participation with FE and classification, key FE that correspond to different emotional states.

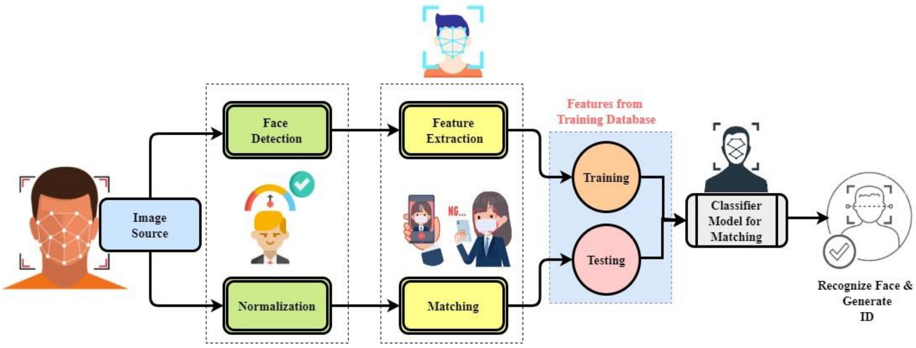

Figure 2: Process of feature extraction

The extracted facial features are used to build a classifier model through DL techniques so that it can comprehend the intricate relationships among the various levels of engagement and FE. In order to train the model to accurately predict levels of engagement from the feature inputs, it optimizes its parameters. Through extensive training, generalizability and accuracy of the trained classification model are assessed with distinct validation data. Testing ensures that the framework is reliable in accurately predicting the degree of involvement on unknown data and validates its effectiveness in real-world scenarios.

The trained subject gets good at identifying faces in photos and developing distinctive characteristics for each person if testing is successful. This feature makes monitoring students' participation levels easier over time, allowing for personalized instruction and comments to improve students' learning. Figure 2 gives a high-level overview of the DL-SFEDM's feature extraction process, which includes face detection, normalization, training, testing, classification model construction, and detection of faces for online course commitment evaluations.

$$\left[\int_0^{Er}\int_0^{w} f^{-s^2} d \mp es\, e\delta\right]^{1/2} = \left[\gamma \int_0^{\infty} f^{-r} pj\right]^{1/2} = \sqrt{\varepsilon} \tag{3}$$

Equation (3) is relevant to studying online lecturers' emotional indicators or facial expressions. It is probable that $es\, e\delta$ represent traits or parameters retrieved from face pictures or signals, which impact the evaluation of involvement levels. Possible functions might capture subtleties in facial expressions, which could be represented by $f^{-s^2}d$. The constants $f^{-r}pj$ may serve as criteria for classifying or evaluating student involvement, which would add to the knowledge of the variables that influence engagement levels$\sqrt{\varepsilon}$.

$$\frac{1}{4\nabla}\int_0^{4\nabla}\frac{e\delta}{b+c\cos\theta} = \frac{1}{\sqrt{d^2-e^2}} + \sqrt{d^2+e^2} \tag{4}$$

The characteristics retrieved from face pictures or signals, such $\frac{e\delta}{b+c\cos\theta}$ in Equation (4), impact the evaluation of involvement levels. The expression θ could stand for an angle parameter that has something to do with the placement or orientation of face features. Furthermore, the usage of δ and ∇ may denote an impact on the comprehension of the entered data, which might capture small changed$d^2 + e^2$ in facial expressions.

$$(f_1 z + c_1)(b_2 y + c_2) = b_1 b_2 y^2 + (b_1 c + b_2 c_1)x + c_1 c_2 \tag{5}$$

The coefficients that impact the analysis of emotions or levels of participation are probably represented by $(f_1 z + c_1)(b_2 y + c_2)$ in Equation (5). The values with $b_1 b_2 y^2$ and $(b_1 c + b_2 c_1)x$ may capture subtle emotional changes by representing face characteristics or geographical coordinates. Furthermore, the $c_1 c_2$ may affect how student involvement levels are categorized or evaluated.

The data are taken from the facial expression Kaggle dataset [32]. Examining student participation in online lectures is the goal of (DL-SFEDM), which is detailed in this structure. The first input is Internet classroom recordings that record students' faces and reactions throughout the class. These recordings are the main data source for interaction analysis. The proposed DL-SFEDM approach analyzes recorded or live class videos for student facial expressions using an advanced deep neural network (DNN) model. The approach advances to studying the classroom stage once facial expressions have been observed. In this case, it can gauge the students' degree of participation by looking at their aggregated facial expressions. Maybe can discover a lot about the class's reaction to the presentation in general from this paper.

The Emotions Retrieval step makes the analysis easier, and it uses algorithms that utilize computer vision to deduce emotional signals from students' expressions. This part of the process allows students to identify their feelings, ranging from happy to sad. The approach calculates lecture participation ratings using the retrieved emotions. Teachers can use these calculated ratings as a quantitative indicator of student involvement to assess the efficacy of their lessons and the material covered.

Experimental evaluation is the last step in validating the performance and efficacy of the framework. The framework's accuracy in measuring student engagement levels is evaluated through extensive experimentation and analysis, yielding useful information for future improvements. The DL-SFEDM's experiment assessment, engagement analysis, gesture identification, and emotion extraction are all part of its thorough architecture, as shown in Figure 3.

$$\beta(a) = \int_0^{\nabla} u^{a-1} f^{-t} eu = \frac{f^{-z\Delta}}{a} \prod_{l=1}^{\exists} \left(1 + \frac{a}{s}\right)^{-1} f^{a/e} \tag{6}$$

The expression in Equation (6) is probably a suggested approach to determining involvement levels, as is the fact that $\beta(a)$are variables related to facial expressions. The functions that capture subtleties $u^{a-1} f^{-t} eu$ in facial expressions or emotional signals $\frac{f^{-z\Delta}}{a}$, and impact the interpretation of the information being provided $\left(1 + \frac{a}{s}\right)^{-1}$. In addition, the symbols \$f^{a/e}$ could stand for attributes crucial for evaluating students' engagement when attending online classes.

$$\Delta \cdot \Delta\beta = \frac{\epsilon^2 \omega}{\theta z^2} + \frac{\beth^2 \aleph}{\beta e^2} + \frac{\pi^2 \gamma}{\sigma z^2} = \frac{1}{r^2 \sin\theta} \left[\frac{1}{\sin\theta} \frac{\mu^2 \rho}{\sigma w^2}\right] \tag{7}$$

The link in Equation (7) is probably crucial to the suggested strategy $\Delta \cdot \Delta\beta$. The variable Δ might be a parameter that affects the interpretation of the level of engagement. The $\frac{\epsilon^2 \omega}{\theta z^2} + \frac{\beth^2 \aleph}{\beta e^2} + \frac{\pi^2 \gamma}{\sigma z^2}$ denote different parameters or coefficients that impact the meaning of the input data, which could capture subtleties in facial movements or Mood indicators.

In addition, the evaluation or categorization procedure can be denoted by $\frac{1}{r^2 \sin\theta}\left[\frac{1}{\sin\theta}\frac{\mu^2\rho}{\sigma w^2}\right]$.

$$g(a) = \sum_{p=0}^{\infty} \frac{g^{(b)}(z)}{m!}(a-c)^m \times \lim_{p\to\infty}\left(1+\frac{1}{c}\right)^m \tag{8}$$

The values $(a-c)^m$ are likely to impact the $g(a)$ in Equation (8), which represents a function or outcome relevant to engagement evaluation. It is probable that the $\frac{g^{(b)}(z)}{m!}$ stand for different coefficients that impact the analysis of the input data, perhaps catching subtleties in feelings or facial expressions. Furthermore, the method of evaluation may be guided by the convergence features shown by the limit process $\lim_{p\to\infty}\left(1+\frac{1}{c}\right)^m$.

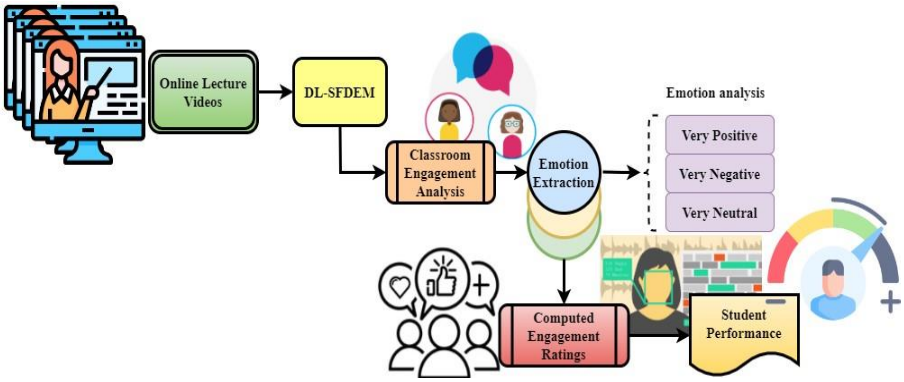

Figure 3: Framework for DL-SFEDM

The design of the Face emotion Recognition System is shown in Figure 4. It includes offline and online options and a combination mode that uses deep learning classification to improve the precision of recognizing emotions. The procedure begins when emotional pictures are entered offline. Face detection is a pre-processing technique to localize facial areas in these pictures. Ensuring the discovered faces are consistent throughout all the photos and normalized afterwards. After the normalization process is complete, the features and landmarks of the face that are most important for the expression analysis may be extracted using methods for feature extraction. Then, to make the feature matrix more comprehensible, a decrease in dimensionality techniques is used to compress the retrieved properties. For expression recognition, a classifier is given the reduced feature matrix.

On the other hand, the online mode processes test photographs in real time, much as the offline mode does. Before feature extraction, test photos are processed using facial recognition and normalization. To make matchmaking efficient, the characteristics extracted are matched to the offline mode's stored basic components (PCs). Fast analysis of facial movements in live or recorded recordings is made possible by using the resultant feature matrix for emotion recognition.

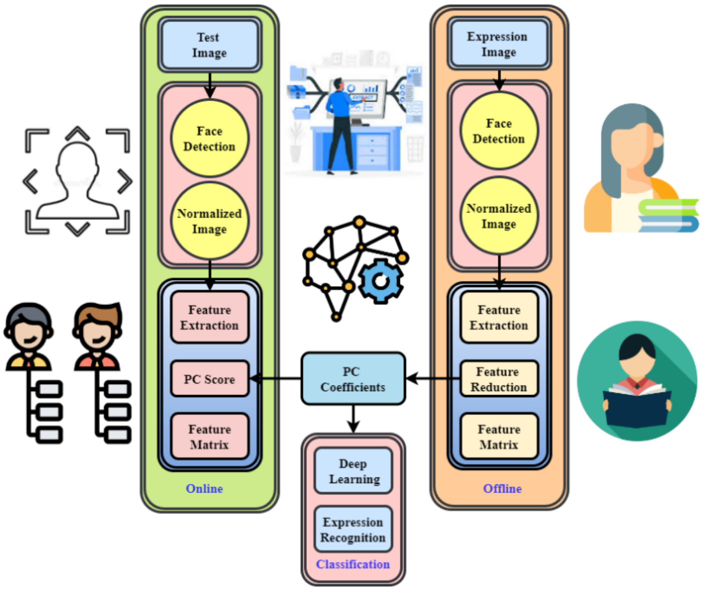

Figure 4: System for recognizing facial expressions

Deep learning classification algorithms merge in the combination mode to improve speech recognition accuracy further. To enhance recognition ability, neural network algorithms are trained on a large dataset of face expressions, where complex patterns and subtleties are acquired. To improve upon previous findings in expression recognition, the combined mode uses deep learning techniques in addition to more conventional extraction of feature methods. Summarising, Figure 4 shows the whole expression identification process, which includes offline, online, and mixed modes. It shows how classic extraction of features methods are integrated with modern machine learning approaches to analyze expressions accurately and efficiently.

$$tan + y \cot n\theta = (\sin\theta + j\cos\theta)^n = f^{vd\forall} \tag{9}$$

Relationships involving analyzing student participation appear to be depicted in Equation (9). The variables $tan + y \cot n\theta$ affect the evaluation of engagement levels since probably characteristics or parameters derived from face expressions or signals. Possible functions or coefficients influencing the comprehension of input data, such as those utilizing $\sin\theta + j\cos\theta$, might capture subtleties in movements of the face or indications of emotion. In online lectures, $f^{vd\forall}$ can stand for traits taken away or analyzed related to student dedication.

$$\iiint_E (\aleph \cdot \mathrm{A}) eU = \oiint_T \mathrm{E} \cdot eF + \frac{\varphi z}{\rho y} \pm \frac{-k \pm \sqrt{g^2 - 4bn}}{3c} \tag{10}$$

When modelling or analyzing student involvement during online lectures, Equation (10) probably depicts the suggested strategy. The variables probably represent it $(\aleph \cdot \mathrm{A})eU$. Expressions in facial expressions or emotional signals can be captured by the terms using $\mathrm{E} \cdot eF$, which might represent functions or coefficients that impact the interpretation of input data. In addition, the integral operators $\frac{\varphi z}{\rho y}$ and $\frac{-k\pm\sqrt{g^2-4bn}}{3c}$ may be used to indicate the volume and surface integrals.

$$M\left(\{Q_j\},\{U_k\}\right) = \frac{1}{M_{class}}\sum_j^k M_{class}(\partial_k,\partial_k^*) + f^p - \sum_k^p \propto_j^* \tag{11}$$

According to the given strategy, a metric M an analysis of student learning outcome seems to be described by equation (11) for evaluating the results of student learning. For their ability to impact the evaluation of learning outcomes, the factors Q_j and U_k probably stand for sets of characteristics or parameters retrieved from student data. Terms such as $\frac{1}{M_{class}}$ and $M_{class}(\partial_k,\partial_k^*)$ could refer to particular metrics, classifiers, or coefficients that impact how student performance data is interpreted. The number of classes or groups being studied $f^p - \sum_k^p \propto_j^*$ affects how the learning outcomes are summed up and calculated.

$$\{(g1,q1)\},(g2,q2),\ldots,(gp,qr),g = \left(g1,\ldots,g_p,g1,\ldots,g_p\right)^U \tag{12}$$

It is quite probable that Equation (12) is a formula for evaluating student engagement in the suggested approach. Pairs of variables indicating student behaviour or involvement during online lectures are denoted by the strings $g1, q1$. Potentially reflecting aggregated or processed data regarding student involvement, the vector g is comprised of the characteristics $\left(g1,\ldots,g_p,g1,\ldots,g_p\right)^U$.

The student's facial expressions are the most telling indicators of their emotional state, which is crucial for reading people's minds and responding appropriately. This has become a major driver of academic interest, inspiring many theories, studies, and practical investigations. Research on individual FER has found several uses in diverse areas, such as recognizing patterns, automation, information security, social media platforms like Facebook and Instagram, and mental health assessments. Take benefit of the best intuitive response to physical technology and digital platforms with FER emotions. This will help understand and explain any platform, concept, or item from the audience's perspective. An analysis of wheel emotions found that while some feelings are universally known, others are more nuanced and difficult to pin down. These feelings are joy, sadness, surprise, dread, wrath, contempt, and neutrality. Research showed that FER has been fine-tuned into four distinct layers, as shown in Figure 5. These layers are as follows: (1) face recognition, (2) data processing, (3) extraction of attributes, and (4) sentiment categorization utilizing predictions (Figure 5).

$$|(g1q2 - q1g2) + (g2q4 - q2g4) + \cdots + (g_mq1 - q_mg1)/2| \tag{13}$$

Within the suggested technique, Equation (13) probably indicates a useful calculation for analyzing student computational thinking. The variables $g1q2$ probably denote the problem-solving tasks that students are given. The absolute value operator probably calculates the differences among the products of pairs of g and q terms.

$$j(m) = u_0 + \sum_{t=1}^{\infty}\left(j_n \cot\frac{rps}{z} + r_t \tan\frac{lsg}{z}\right) \tag{14}$$

Equation (14) stands for expression when evaluating students' performance analysis using the suggested strategy. The variable $j(m)$ probably represents a metric or measure of student performance, which might be affected by several circumstances. Coefficients u_0 that impact the computation of educational metrics might be represented by $j_n \cot\frac{rps}{z}$. The variables $r_t \tan\frac{lsg}{z}$ could represent characteristics or aspects associated with learning materials or classroom settings, impacting students' performance.

$$\propto \forall\left(\mathrm{Student}(x) \wedge \varphi\sigma\left(\mathrm{Time}(z) \rightarrow \mathrm{Happy}(z,a)\right)\right) \tag{15}$$

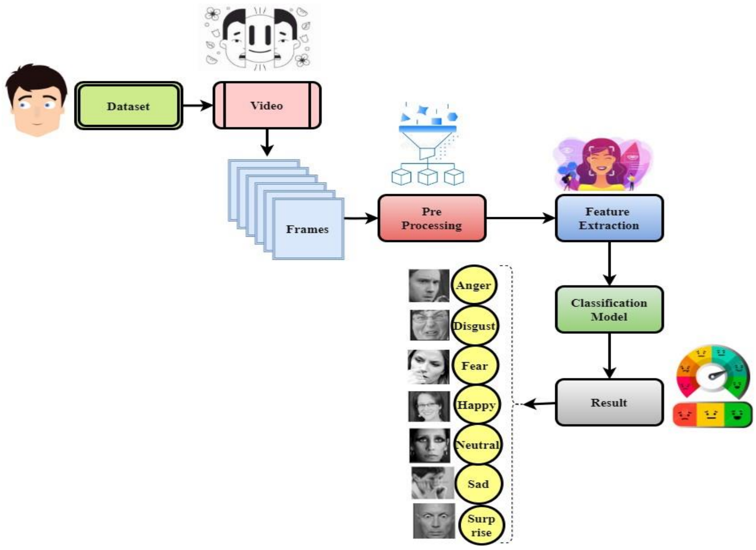

Figure 5: Detection of emotions using video analysis

It is quite probable that Equation (15) is pertinent to the examination of student emotion detection in the suggested technique $\propto$. It is probable that the student $(x) \wedge$ is a predicate that indicates the existence of a student, with x standing for a particular student. The $\mathrm{Time}(z)$ might be a predicate that represents a particular occurrence or period, which could impact how students detect emotions. With z standing for time and a for other characteristics connected to the emotional state, the predicate $\mathrm{Happy}(z,a)$ probably denotes the existence of happy feelings. In an effort to improve the model's adaptability to many environments, this method tried to capture a range of FE from different demographics. By employing data augmentation (DA) techniques to replicate diverse scenarios, such as altered lighting and facial orientations, the model was further enhanced for application in a range of real-world applications.

The DL-SFEDM is one novel methodology to assess the participation of students in online courses. The DL-SFEDM uses computer vision algorithms that determine and interpret the movements of faces to know what students feel. For instance, this technique can generate levels of involvement based on how joyful or sad a person is. When these were tested, it showed great improvement in teaching practices and active student involvement with computational thinking. Finally, they claimed that it was an excellent approach for any teacher who wishes to personalize their teachings.

4. RESULT AND DISCUSSION

The number of students learning in important areas has been analyzed to show factors determining educational results and engagement. Figures 6-10 provide student learning, engagement, computational thinking, performance, and emotion detection issues. A well-rounded study of these traits appears in each figure, which considers the student's progress and well-being from different perspectives based on several measures and approaches used to evaluate the metrics under scrutiny. Thus, practical knowledge from reviewing studies available here may help shape policies towards improving interventions and teaching methods that can encourage learning while enhancing academic achievements among students. The performance of the DL-SFEDM model has been examined based on metrics such as learning outcome, student engagement, student computational thinking, student performance, and emotion detection ratios compared with existing models CNN-FER [16] and ROM [17] methods.

Dataset description: A face expression identification dataset contains thousands of photographs and videos demonstrating various emotions on human faces shot across different circumstances. Developers and researchers involved in face expression identification algorithms or other computer vision applications might find this dataset a treasure trove for themselves. An application built using this technology can train machine learning models, which will give accurate results about facial expressions made by any individual so far [21]. Consequently, researchers can use its existing algorithm more effectively, test new ways to recognize emotions or improve the systems for detecting facial expressions. With diverse facial expressions, lighting settings, and backgrounds within the dataset, more inclusive research is possible because of the full range of data points provided. Images of faces, each 48 by 48 pixels in grayscale, are labelled as angry, disgusted, scared, happy, sad, surprised, or neutral in the Face Expression Recognition dataset on Kaggle. With 28,709 photos for training and 7,178 images for testing, a total of 35,887 images make up the dataset. While the dataset does not disclose the diversity of its participants or the specifics of its data-gathering procedure, it does claim to provide a balanced representation of different emotions for face expression recognition tasks.

4.1. Learning Outcome Ratio

Academic performance, retention rates, and mastery of core ideas are a few metrics that may be used to evaluate the results of students' learning, as shown in Figure 6 and Equation 11. Individual and group levels of understanding may be better understood using formative and summative assessments. In addition, qualitative metrics such as student engagement and feedback provide valuable insights. By analyzing these elements, educators may pinpoint their strengths and areas for improvement, adjust their teaching methods and implement targeted interventions to enhance student learning outcomes. Institutions of higher learning may ensure that students have the knowledge and abilities necessary for academic and professional success by regularly assessing and adjusting their programmes. Compared to the existing method, student learning outcomes gradually increased by 97.54% in the proposed method.

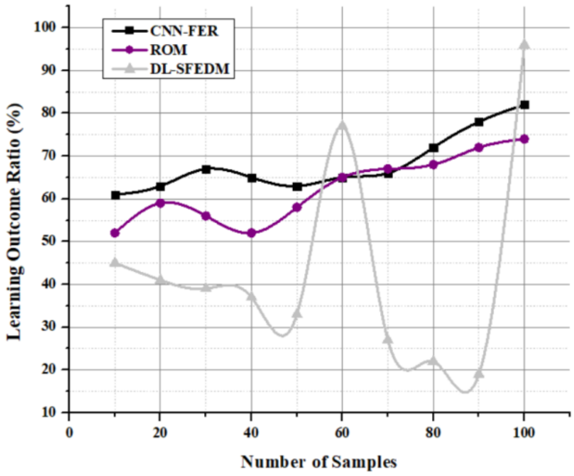

Figure 6: Analysis Of Student Learning Outcome

4.2. Student Engagement Ratio

Figure 7 and equation 12 describe how actively students are engaged in the learning process, which may only be ascertained by investigating student engagement. There are many ways to measure this element of the learning process, such as how many students actively participate, how attentive they are, and how engaged they are with the course contents. Observing verbal and nonverbal cues, such as body language and facial expressions, may provide useful insights into students' interest and motivation levels. By analyzing these factors, teachers might discover strategies that create a more interesting classroom. Consequently, students will be more engaged, learn more, and remember more about present in class. In this proposed method, the analysis of student engagement achieved 95.92%.

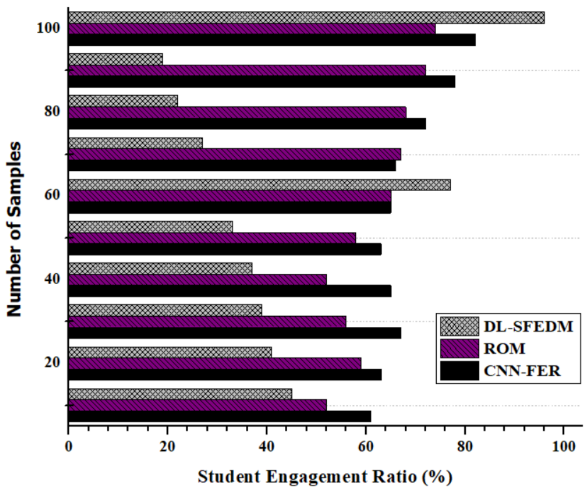

Figure 7: Analysis of student engagement

4.3. Analysis of Student Computational Thinking

One way to assess students' computational thinking is to see how well they can solve problems using algorithms and computational approaches described in Figure 8 and Equation 13. Their capacity to identify trends and patterns in the data, construct algorithms to automate processes and break down large tasks into smaller ones will all play a role in their evaluation. As part of the analysis, everyone can assess students' abilities to develop creative solutions to problems and debug and troubleshoot code. By seeing how students tackle computational activities, collaborate with their peers, and apply computational concepts to other fields, everyone may get valuable insights into their computational thinking ability. Effective analysis helps educators construct curricula and activities to facilitate the development of computational thinking. The student computational thinking analysis ratio has increased by 98.28% in the current method.

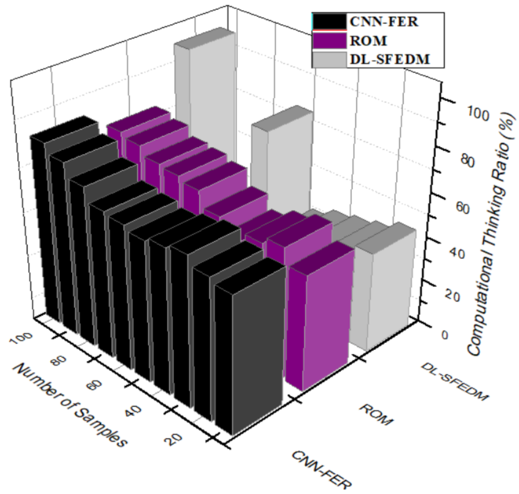

Figure 8: Analysis Of Student Computational Thinking

4.4. Analysis of Student Performance

Figure 9 and Equation 14 evaluate students; all elements that affect grades must be considered. Grades, test scores, and completion rates must be assessed for all accessible courses. Classroom elements, including attendance, involvement and engagement, may also reveal students' progress. To alter instructional tactics to match students' various learning requirements, formative and summative evaluations may reveal each student's strengths and weaknesses. Monitoring data over time can identify trends and patterns to help us tailor treatments for struggling students and identify high achievers. Self-evaluation and qualitative feedback may assist teachers in assessing students' progress, identifying areas for improvement, and enhancing learning outcomes. Compared to the existing method, the student performance is obtained by 99.15% in the proposed method.

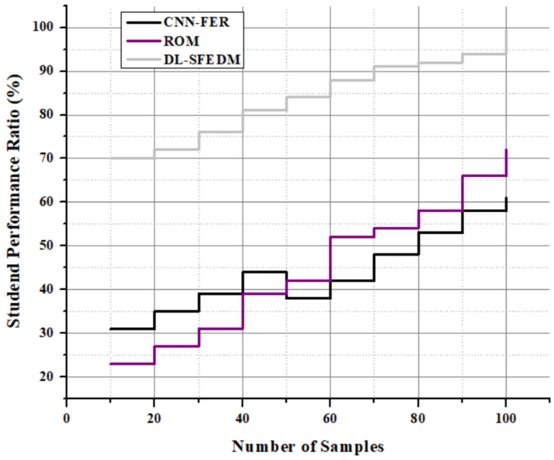

Figure 9: Analysis of student performance

4.5. Analysis of Student Emotion Detection

Emotion detection analysis uses technology to interpret students' body language, facial expressions, and vocal intonation to gauge their emotional states, as described in Figure 10 and Equation 15. This data provides a window into how students feel, how invested they are, and how healthy they are while studying. By analyzing these emotional cues, educators can enhance their teaching methods, provide timely support, and foster a positive learning environment. In addition, emotional patterns may be tracked over time using longitudinal analysis. This allows for preemptive interventions to address potential concerns and improve students' socio-emotional development alongside their academic growth. The student emotional detection analysis shows the ratio of this proposed method is 97.4%, which varies from the existing method. These analyses aid educators by shedding light on student development and welfare, facilitating a rich learning environment conducive to academic success.

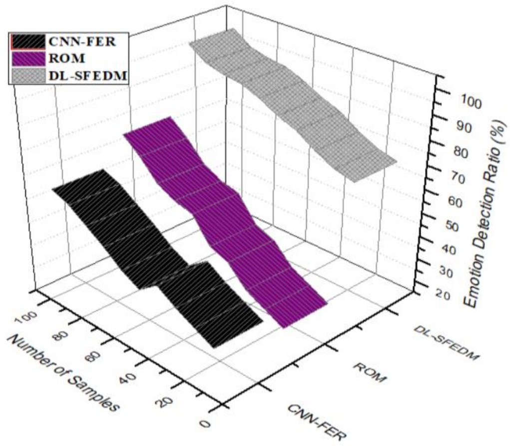

Figure 10: Analysis of student emotion detection

There are ethical considerations to consider when using facial expression recognition technology in schools, especially when protecting students' personal information. If not adequately protected, these technologies can acquire sensitive personal information and might lead to their abuse. Strict data anonymization procedures were included in the research design to address these issues; specifically, face data was handled without relating it to personal identifiers. Furthermore, safeguards were put in place to prevent unauthorized individuals from accessing or storing the data. To further guarantee that the rights and privacy of the students were maintained during the research, consent was also collected from participants. Educators may monitor and analyze student involvement in real time based on facial expressions using the DL-SFEDM approach. Teachers may create a more adaptable and encouraging environment in the classroom by studying their students' emotional states and using that information to personalize their lessons. To enhance learning outcomes and classroom dynamics as a whole, this strategy may aid in the early detection of disengagement or confusion.

5. CONCLUSION

CT offers great potential to improve student problem-solving abilities in a tech-driven environment. However, instructors misinterpret CT, which inhibits its deployment. Student involvement is essential to education and has garnered limited literature attention. The paper presents the DL-SFEDM, which does not use educational institution data to measure online lecture engagement. The DL-SFEDM improves computational thinking by improving teaching and learning. This is done by assessing students' emotions. This unique strategy emphasizes instructional skills and student participation to maximize digital education. The experimental outcomes demonstrate that the suggested DL-SFEDM model increases the emotional detection analysis ratio by 97.4%, student performance by 99.15%, student computational thinking analysis ratio by 98.28%, student engagement ratio by 95.92%, student learning outcomes by 97.54%

Future studies may examine if DL-SFEDM in real classrooms can provide instructors with rapid feedback on student engagement. Improved emotion detection algorithms might help identify these youngsters' emotions and provide more sophisticated insights. Examining how DL-SFEDM findings affect personalized instructional interventions and long-term pedagogical effectiveness would also be useful. For wider deployment, DL-SFEDM must be researched for viability and scalability in diverse educational environments, and privacy and ethical problems must be addressed. These research approaches might increase instructional technology and student learning.

Funding: This research received no external funding.

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