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RESEARCH ARTICLE

Deep Learning-Based Interactive Dashboard for Enhancing Online Classroom Experience Through Student Emotion Analysis

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ABSTRACT An interactive analytical dashboard that analyzes students' facial expressions during online lectures is crucial for digital learning platforms. This research addresses the need for educational institutions to analyze individual students' emotions to improve teaching standards. Given the challenge of occluded facial data, we employ a regenerative Generative Adversarial Network (GAN) to reconstruct these occluded regions. Subsequently, the emotions of the students are predicted and analyzed using our proposed interactive dashboard, which incorporates additional inputs such as subject name and teaching faculty. The dashboard visualizes various charts and analytics to support informed decision-making. We validated our deep learning model using the CK+ dataset, achieving notable accuracy in classifying each type of emotion. Our results demonstrate that the model can effectively interpret student emotions, even in the presence of occlusions, thereby providing educators with precise, real-time emotional insights to tailor their teaching methodologies effectively.

INDEX TERMS Analytical dashboard, classroom monitoring, deep learning, emotion analysis, student outcomes.

I. INTRODUCTION

Dashboard is a graphical user interface that displays key performance indicators (KPIs) and other important information in a concise and easily digestible format. Dashboard visualizations typically consist of charts, graphs, tables, and other visual elements that present data in a way that is easy to understand and interpret. They can be deployed in various formats, including web-based applications, mobile apps, and desktop software. Generally, a dashboard is a powerful tool for visualizing complex data sets and enabling better decision-making. Users can customize dashboards to display different image type data, such as heat maps, scatter plots, or time-series data, according to their needs. Dashboards can visualize various image type data, such as medical images, satellite imagery, or photographs, and help identify patterns and trends that may be difficult to see in raw data.

Simulating occlusion data can improve the accuracy of deep learning models for facial reconstruction [1]. This can be achieved by pairing the simulated occluded images with the original student images to create a training dataset. The deep learning models can then learn to reconstruct the complete face from the occluded image by identifying the underlying patterns and features of the facial data [2].

When it comes to image data, dashboards for visualization can be particularly useful for monitoring trends and patterns in image data sets and identifying areas of improvement or potential issues. They allow tracking changes over time, such as changes in student's emotions during class time. Facial recognition algorithms can analyze a student's facial

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emotions and predict their interests and preferences based on their expressions [3]. Machine learning models can be trained on historical data to improve accuracy over time. Different emotions, such as happiness, surprise, or disgust, may be associated with different course preferences. By identifying the key emotions associated with different courses, recommendations can be tailored to a student's interests [4]. It can also be customized to display recommendations based on a student's interests and preferences. These recommendations can help increase engagement and motivation by offering courses relevant to their interests. Facial reconstruction from occluded images is a challenging task in computer vision and image processing. It aims to reconstruct the individual face even when parts of the face are occluded or missing in the input image.

Our approach is to use deep learning techniques such as convolutional neural networks (CNNs) and generative adversarial networks (GANs) to learn the mapping between occluded images and the corresponding complete faces [4]. These models can be trained on large datasets of faces to study the underlying patterns and features of facial images. Once the complete face is reconstructed, facial landmarks and features can be extracted to identify the displayed facial emotions. For instance, facial landmarks, such as the corners of the mouth, eyebrows, and eyes, can be used to detect smiling or frowning. At last, the emotion is recognized from the reconstructed image.

Visualizing facial emotions in a dashboard can be a powerful tool for recommending courses to students based on their interests and preferences. Based on the insights gained from the dashboard, Instructors can identify areas where they can improve operations, performance, or decision-making. It can also help instructors set realistic goals and targets based on the insights provided by the data visualization. These visualizations can help instructors to drive continuous improvement and optimize operations to improve student learning. Once courses have been recommended, instructors can use dashboards to monitor student engagement and performance. These visualizations can help them identify issues early and take corrective action when needed.

II. RELATED RESEARCH

The Literature review mainly focuses on visualizing recommendations and dashboards and also on occlusion generation, reconstruction of the image and recognition of the emotion from the reconstructed image.

In [5] the authors carefully mask rectangular portions of the input image with a specified size and position to produce occluded images. The occluded images are then sent through the network, and the network output is recorded. They can determine the relative significance of different portions of the image for the predictions made by the network by repeating this process for various regions and sizes of masks. More specifically, the authors created occluded images using a sliding window method. They separate the image into a grid of k x k pixel cells that do not overlap. After repeatedly masking each grid cell, they run the obscured image through the network to get a forecast. The predictions made by the network are recorded after the authors carry out this approach for each grid cell. Some researchers [1] suggest the Lucas-Kanade algorithm as an iterative process for estimating the optical flow of unobstructed pixels. These estimates are then propagated to obstructed pixels using an interpolation method. The interpolation method relies on the Delaunay triangulation of the unoccluded pixels, which calculates the motion of the occluded pixels using the motion of the unoccluded pixels around them. The authors use the iterative approach to refine the optical flow estimate till convergence in the partially obstructed region. The result is a reconstructed optical flow map that depicts the mobility of the partially obscured facial region. The facial expression recognition stage uses the reconstructed optical flow map data as a starting point for feature extraction and classification. The suggested method for identifying facial expressions under partial occlusion relies heavily on the reconstruction phase. This method increases the precision of facial expression detection by recreating the optical flow of the partially occluded region to collect the motion data that would otherwise be lost owing to the occlusion [1]. The authors use a combination of texture and form descriptors to extract characteristics from the reconstructed optical flow map. The shape descriptors capture data about the geometric structure of the facial region, whereas the texture descriptors capture data about the motion patterns in the reconstructed optical flow map. The support vector machine (SVM) classifier, trained to identify the various facial expressions based on the retrieved features, is then fed the extracted features.

The Cohn-Kanade (CK+) dataset and the Oulu-CASIA dataset, which both feature face expressions with various degrees of partial occlusion, are publicly available datasets on which the authors test the efficiency of their method for facial emotion recognition. They demonstrate how their approach outperforms several cutting-edge methods for identifying facial expressions in the presence of partial blockage. In [6], the visual analytics solution described by the authors allows for interactive exploration and analysis of cohorts of prostate cancer patients. The technology is created to support the analysis of massive datasets of prostate cancer patients to spot trends and connections between clinical, demographic, and genomic aspects that could influence the course of the disease. The system has a web-based user interface which combines interactive tools and visuals to let users explore and evaluate the data. The visualizations, which show many sorts of data, such as patient demographics, clinical outcomes, and gene expression levels, include scatterplots, bar charts, heatmaps, and network diagrams.

The interactive tools have options for filtering, sorting, grouping, and clustering that let users choose patient subsets based on a range of factors like age, race, tumour stage or gene expression levels. Additionally, users can directly engage with the visualizations by choosing data points or network nodes from a network diagram, or by zooming and panning the display to concentrate on particular interest areas.

The system's capacity to combine diverse data kinds, such as clinical and genetic data, is one of its valuable features. This feature allows it to find correlations and patterns that might not be obvious from studying each data type alone. Users can investigate whether any age-related variations in gene expression may be vital to disease outcomes by seeing, for instance, a scatterplot of patient age vs gene expression levels on the system's display. In [7], the authors outline a system for leveraging a collection of visual dashboards to visualize and analyze healthcare statistics and blood measurements. The KnowYourColors system, which gives real-time visual feedback on blood metrics, including glucose, haemoglobin, and hematocrit levels, as well as other healthcare data like medication adherence and vital sign trends, is intended to assist healthcare workers in keeping track of patient health. The visual dashboards are based on a colour-coding system that offers an intuitive approach to recognizing aberrant values and patterns and are created to be simple to use and interpret, even for non-technical people. Green, for instance, denotes typical values, yellow, borderline values, and red, critical values. Users can choose which metrics to display and how to display them on the dashboards using bar charts, line graphs, or pie charts. They can filter data by several factors, including the time frame, patient demographics, and medical condition. The paper summarizes the findings of a pilot research carried out by a few healthcare professionals who used the KnowYourColors system to continuously monitor patient health. The technique was effective in detecting aberrant values and patterns, and the study discovered that the colour-coding system was simple to comprehend and apply. In [8], the authors discuss a DataScope programme that offers big multidimensional datasets and interactive visual exploration dashboards. The technology makes it easier for users to browse through and evaluate big datasets with many dimensions, such as healthcare information, that may contain patient demographics, medical issues, and treatment outcomes. By using a range of visualizations, including scatterplots, histograms, and heatmaps, the system enables users to examine the data interactively. Large dataset exploration and analysis are made simple for users of DataScope by several essential features. These capabilities include the capacity to select variables to display on the dashboard and filter the data by numerous parameters, including period, patient demographics, and medical condition. The system also provides several data analysis tools that let users find patterns and links in the data, including trend analysis, clustering, and correlation analysis. In [9], the authors developed a framework to assist users in building personalized dashboards for various applications, including marketing, finance, and healthcare.

The system uses deep learning algorithms to examine large datasets and find patterns and relationships in the information. MultiVision creates recommendations for the dashboard layout and visualization styles that best suit the user's needs based on these patterns [10], [11], [12], [13].

One of MultiVision's standout features is its recommendation engine, which makes dashboard layout suggestions based on the user's data and preferences. Users can select from various suggested visualizations and layouts or create their own using the drag-and-drop interface provided by MultiVision.

Different data analysis capabilities, including clustering, trend analysis, and anomaly identification, are also included in MultiVision, allowing users to explore and examine the data in greater detail. Facial emotion analysis using deep learning techniques is widely demonstrated in [14], [15], [16], [17], [18], and [22]. The facial image occlusion makes the emotion recognition task very challenging in the online learning platform. The occluded facial data reconstruction was the primary focus in [19], [20], and [21]. The system can also automatically update the dashboard design and visualizations when new data is uploaded or the user's needs change. Table 1 provides a comparative analysis of various studies on interactive dashboards and emotion recognition techniques, highlighting their methodologies, key contributions, and challenges. This comparison contextualizes the advancements and challenges in the field, supporting the relevance and innovation of our research.

III. METHODOLOGY

This proposed work focuses on creating a dashboard tool for viewing facial emotion recognition and reconstruction outcomes, which can provide a user-friendly and intuitive interface for evaluating the performance of these models, as illustrated in Figure 1. The tool will offer a variety of data and visualizations to assist users in assessing their model's efficiency and pinpoint areas for development. The dashboard tool's visualizations will include heat maps outlining the parts of the face that are crucial for each emotion, bar graphs illustrating how well each emotion identification test was performed, and 3D animations of reconstructed facial expressions. Users can determine whether emotions are correctly recognized, and which facial features are crucial for each emotion using these representations. This research may also help in other settings, such as the workplace and the healthcare industry, where keeping an eye on people's emotional states may be necessary to ensure their safety and wellness. Teachers can swiftly and easily identify any kids who may require further support or intervention, which will eventually improve the students' achievements.

The pandemic has forced classes online, and many students have developed creative methods to miss class. One strategy to avoid being called upon by their teachers is to hide their faces. Although it might appear innocuous at first, this might hurt a student's education and future. To determine whether they are interested in the specific subject being taught by the course instructor, we attempt to regenerate facial expressions in this work. The student is advised to take the particular courses based on the insight into their future.

TABLE 1. Comparative analysis of interactive dashboards and emotion recognition techniques.

Ref.	Methodology	Datasets	Key Contributions	Challenges
[5]	Occlusion generation, sliding window	Custom dataset	Identify critical image regions for predictions by masking and evaluating occluded images using a sliding window approach.	Computationally intensive due to repeated masking and evaluation.
[1]	Lucas-Kanade algorithm, interpolation	CK+, Oulu-CASIA	Utilized iterative optical flow estimation and interpolation based on Delaunay triangulation.	High computational cost, sensitivity to noise in optical flow estimation.
[6]	Visual analytics for cancer data	Prostate cancer cohort	Interactive web-based user interface combining clinical, demographic, and genomic data visualizations for cancer patient analysis.	Integration of diverse data types poses challenges, high complexity.
[7]	Color-coded healthcare dashboards	Pilot healthcare study	Designed a color-coded dashboard system (KnowYourColors) for real-time monitoring of health metrics.	Limited to specific health metrics, challenges in scaling.
[8]	Interactive multidimensional data exploration	Healthcare datasets	Enabled interactive exploration and analysis of large multidimensional datasets using visualizations/	Handling large datasets efficiently, ensuring real-time interaction.
[9]	Personalized dashboard creation	Various applications	Developed MultiVision, a system using deep learning to analyze datasets and provide dashboard layout.	Requires significant computational resources with data usage.
[14]	Deep learning for emotion recognition	CK+, Oulu-CASIA, etc.	Demonstrated the application of GANs for reconstructing occluded facial data.	Data privacy and ethical concerns, high variability in emotion expressions, computational intensity.
[19]	Occluded facial data reconstruction	Various datasets	Using deep learning methods to improve emotion recognition accuracy in online learning platforms.	Reconstructing highly occluded, potential inaccuracies in complex scenarios.

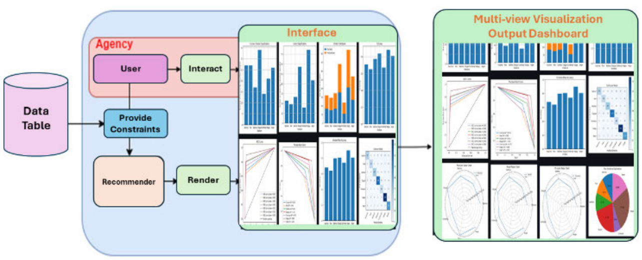


FIGURE 1. Dashboard design.

A lack of interest and respect for the instructor and the educational process can be shown when students hide their faces during class. The student conveys their lack of interest in the subject matter being covered and their unwillingness to participate in class debates or activities by not making eye contact. As a result, they could perform less academically and have a more difficult time grasping the subject. Teachers can verify if all pupils are paying attention in class by rebuilding their faces and facial expressions.

The system will contain three main components: data collection, deep learning models, and the dashboard. The data collection component will collect a dataset of facial images of students in a classroom setting. This dataset will train the deep learning models for facial emotion recognition and image reconstruction. The deep learning models will be built using convolutional neural networks (CNNs) for facial emotion recognition and generative adversarial networks (GANs) for image reconstruction. The CNN will be trained to recognize emotions in the facial images, while the GAN will be trained to reconstruct the facial images based on the recognized emotions. The dashboard will allow for customization, enabling teachers to choose which visualizations they want to display and how they want them to be arranged. These features will allow teachers to tailor the dashboard to their specific needs and preferences.

A dashboard often consists of several significant data visualizations, such as tables, charts, and graphs. Also, the tool will offer several indicators, like precision, recall, and F1 score, to assist users in assessing the effectiveness of their

TABLE 2. CK dataset.

Emotion	Sample Images
Anger	
Contempt	
Disgust	
Fear	
Happy	
Sadness	
Surprise	

models. After that, the dashboard will visualize the results of facial expression recognition and picture reconstruction, enabling teachers to monitor **their pupils' emotions in real** time and identify any signs of anxiety or discomfort. This project can improve students' mental health and wellness by allowing teachers to identify and respond to emotional distress in **real time** and offering them courses based on their interests.

The results from facial emotion identification and image reconstruction will be displayed in the dashboard using a combination of heatmap, scatter plot, image grid, histogram, and activation map techniques. The scatter plot will indicate the distribution of emotions throughout the classroom, and the heatmap will highlight the parts of the face that were most important in identifying a specific emotion. Teachers can view a visual representation of the student's emotional condition thanks to the picture grid displaying the students' reconstructed images. While the activation map will draw attention to the precise aspects of the face used for emotion recognition, the histogram will show the distribution of emotions over time. By enabling teachers to better understand their student's emotional states, the dashboard can enhance not only the mental health and well-being of the students but also the environment of the classroom as a whole. Teachers can address these problems and establish a more supportive learning environment by seeing any early indications of worry or discomfort. This data can result in the pupils performing better academically and getting better results.

Our strategy aims to give the impression that some portions of the image are entirely or partially obscured by other things. In this study, we simulate occlusion to conceal the various facial features, including the eyes, nose, and mouth. We simulate the occlusion in the CK dataset after determining the locations of the regions. Our goal is to create a dashboard that will allow instructors of courses to make more data-driven and informed decisions by giving quick access to significant data and insights about the students and the course in which the student hides a portion of their faces by wearing a mask or glass to avoid them. Dashboards can drill down into particular areas of interest for additional in-depth information, historical data, trend analysis, and other features. Finally, depending on facial expression, students will be recommended similar courses.

In our method, the facial regions are occluded virtually. We use the Haar Cascade classifier to identify facial features like the nose, eyes, and mouth. This classifier can identify objects in images regardless of their size or location in the frame. Following that, we simulate occlusion in the face regions by drawing a rectangle over the detected regions of the mouth, nose, and eyes and filling it with black to represent the occlusion. Two different methods are being used to simulate the occlusion. The occlusion in two regions, including the mouth and eyes, is first being simulated. We simulate the occlusion on the eyes and mouth after deducting the two regions with the aid of the Haar cascade classifier. We are also modelling the occlusion in three regions - the eyes, nose and mouth.

In this work, for inpainting, we are employing Regenerative GAN. ReGAN creates a full image with the missing pieces restored from an image with damaged or missing portions as input. ReGAN accomplishes this by instructing the generator to fill in the missing portions of the image using the data from the intact portions of the image. The discriminator assesses the quality of the completed image to make sure that it looks realistic and is consistent with the intact parts of the image, while the generator takes the incomplete image and creates a completed version. The various types of emotion are then examined using the data.

Figure 2 shows the working of Regenerating GAN in which it reconstructed the facial regions. An occluded image is used as the input by the generator in a GAN to produce a sample of data that is representative of the real data. The generator is trained to minimize the difference between the generated real data to provide data identical to the original data. Generators gain information from the input data and alter it to produce realistic facial features like eyes, noses, and mouths. The Discriminator is a neural network that accepts generated data

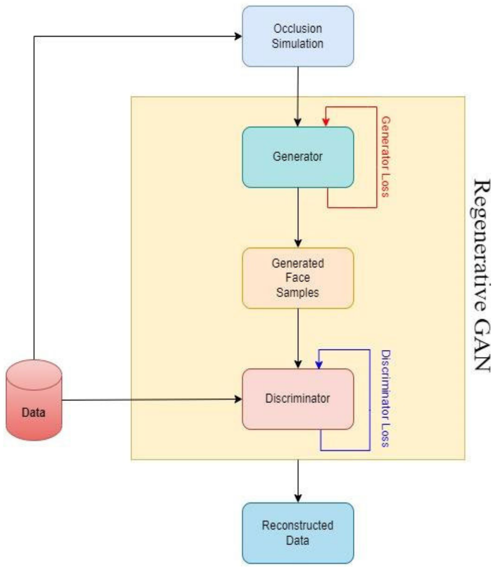


FIGURE 2. Shows the proposed methodology – Initially occlusion is simulated in the CK dataset and trained using the GAN with both occluded data and the original CK dataset and after that the facial emotion is recognized and then the output data is visualized in the dashboard.

samples as input and tries to categorize them as real or fake. It distinguishes between the real data from the training set and the generated artificial data. The output image from GAN is a complete facial image with realistic details, including skin texture, and facial emotions as well as the missing or damaged parts of the input image.

A dataset created to recognize facial expressions is known as the CK (or CK+) dataset. The CK dataset has 981 image sequences of 123 subjects, each one of which shows a person's face exhibiting one of the seven basic emotions: anger, contempt, disgust, fear, happiness, sadness, and surprise. These pictures were taken in a lab under carefully regulated lighting circumstances with a uniform background and head orientation. By performing such experimentation, it is made sure that the dataset is of the highest calibre and that there are no outside influences that might change the expression.

IV. EXPERIMENTS

Loss Function: To enable the generator to produce realistic images of faces and the discriminator to discern between genuine and created images with accuracy, we intend to simultaneously optimize the generator and discriminator networks. So, we are utilizing Binary cross Entropy loss for the discriminator and L1 and L2 Loss for the generator. The discriminator loss and generator loss combined are reduced using the GAN loss.

A. GENERATOR

Our Regenerative GAN trains the generator network using both L1 loss and L2 loss. It measures the typical difference, (pixel-by-pixel), between the generated and the true image.

FIGURE 3. Two regions - Train-val-test results.

Even if there are a few minor deviations, L1 loss in the context of facial reconstruction can assist in guaranteeing that the resulting image is a near match of the true image. L2 loss can ensure that the resulting image is a very good match to the original, but it might not work as well when the data contains outliers.

$$L1 = \frac{1}{bh}\sum_{i=0}^{b-1}\sum_{j=0}^{h-1}|X_i - Y_i| \tag{1}$$

$$L2 = \frac{1}{bh}\sum_{i=0}^{b-1}\sum_{j=0}^{h-1}[X_i - Y_i]^2 \tag{2}$$

where,
b-breadth
h-height
X-GAN output
Y - original CK image

B. DISCRIMINATOR

While the discriminator's job determines if an input image is real or fraudulent, the BCE loss determines the difference between the actual label and the projected output. The discriminator loss and generator loss combined are reduced using the GAN loss. This shows that the generator is trying to give samples that fool the discriminator while the discriminator is trying to classify the samples correctly.

$$BCE\ Loss = \frac{1}{b}\sum_{i=1}^{b}[log(x + log(1 - Z))] \tag{3}$$

where,
Z - regenerated image
X - original image

$$GAN\ Loss = Gen_{Loss} + Disc_{Loss} \tag{4}$$

where,

$$Gen_{Loss} - generator\ loss$$
$$Disc_{Loss} - discriminator\ loss$$

FIGURE 4. Three regions - Train-val-test results.

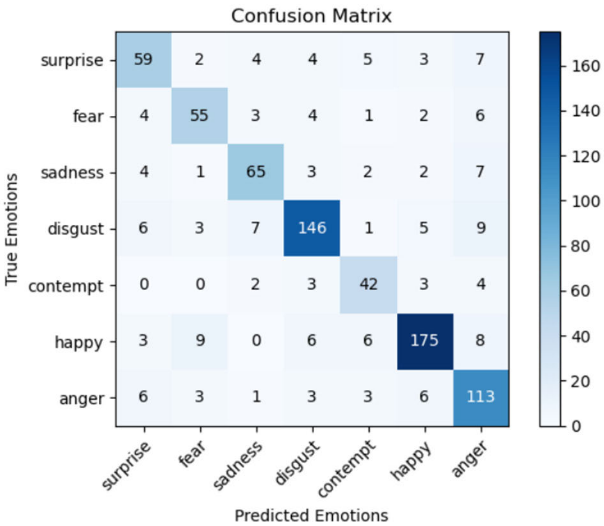


FIGURE 5. Confusion matrix.

Figure 3 shows the outcomes of simulating the occlusion for two regions such as the eyes and mouth and the Train-Test-Validation results. With the Haar cascade classifier, we first identify the various regions, such as the eyes and mouth, and then we determine the position. By drawing a rectangle around the actual positions of the eyes and mouth and filling it with black to represent the occlusion, we may simulate occlusion in the facial regions.

Once the occlusion is simulated, the occluded picture is regenerated with the Regenerated GAN. An occluded image is used as input by the generator in a GAN to produce a sample of data that is representative of the original data. Generators use the information from the input data to create facial characteristics like the eyes and lips. The Discriminator then accepts the produced data samples as input and attempt **s** to categorize them as genuine or counterfeit. It distinguishes between true data from the training set and data created intentionally. Then, the facial information is recreated from this model.

Figure 4 shows the outcomes of simulating the occlusion for three regions (eyes, nose and mouth) and the Train-Test-Validation results. The facial characteristics are likewise

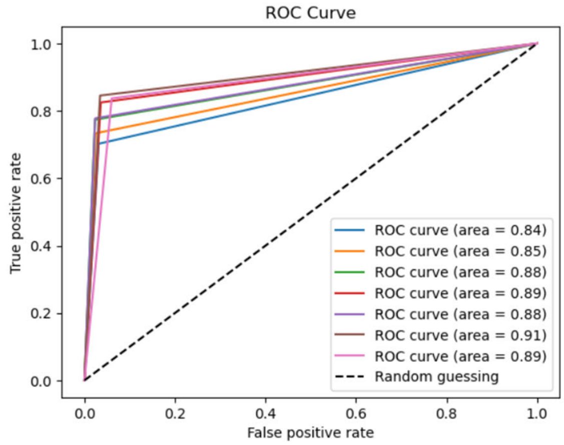


FIGURE 6. ROC curve for assessing a face reconstruction model's effectiveness on the CK dataset.

generated in the same manner, however the occlusion simulations comprised three different locations. In addition, we simulate occlusion in the nose region. As predicted by the CNN classifier, Figure 5 displays the confusion matrix for the seven emotions (anger, contempt, disgust, fear, happiness, sadness, and surprise) in the CK dataset. The matrix provides an overview of each emotion's true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN).

A section of the dashboard might be devoted to showing the output from the facial reconstruction and emotion recognition algorithms. The performance of the models on the CK dataset may be shown in this section's ROC curve graph as illustrated in Figure 6. At various threshold settings, the true positive rate (TPR) and false positive rate (FPR) are plotted on the ROC curve graph. The TPR would indicate the proportion of successfully reconstructed faces in the case of face reconstruction, whereas the FPR would reflect the proportion of wrongly reconstructed faces. To give a sense of the overall performance of the model, the area under the curve (AUC) will also be shown. For assessing the effectiveness of the models and contrasting them with other models, the ROC curve graph might be helpful.

For each emotion or reconstructed face, we have a Precision-Recall curve on this dashboard that illustrates the trade-off between precision and recall for various thresholds. Each curve in Figure 7 shows how well the model did when recognizing a particular emotion or reconstructed face. This assessment is conducted through a series of metrics including accuracy, precision, recall, and F1-score for each emotion category. The dashboard visualizes these metrics in confusion matrices and performance trend graphs, highlighting areas where the model excels and where it falls short. For instance, discrepancies in the confusion matrix can indicate specific emotions that are often misclassified, guiding targeted improvements. Additionally, the dashboard uses heatmaps to display the effectiveness of GAN-based reconstructions, showing before-and-after comparisons of

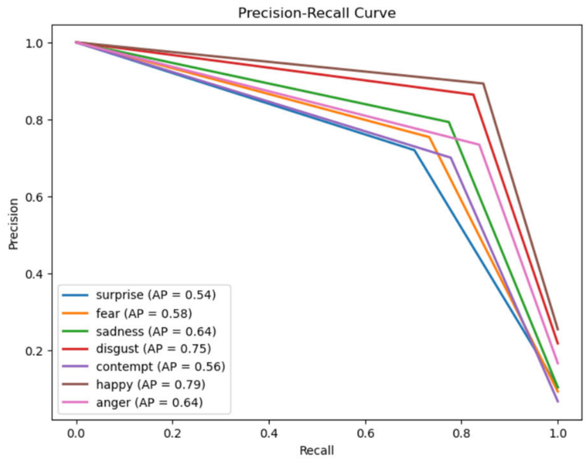


FIGURE 7. The precision-recall curve for each emotion of the reconstructed face illustrates the trade-off between the two for various thresholds.

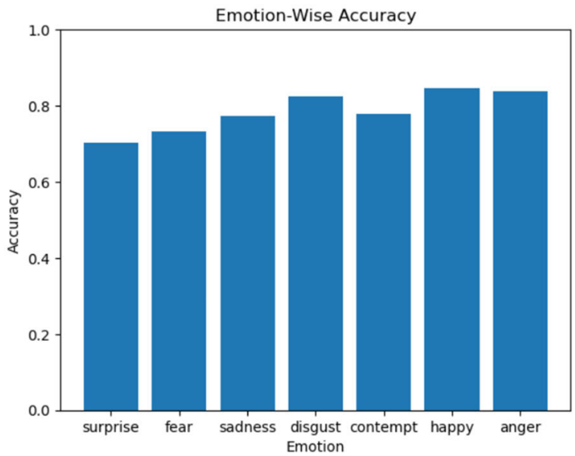


FIGURE 8. Emotion-wise accuracy for evaluating the performance of a face reconstruction model using the CK dataset.

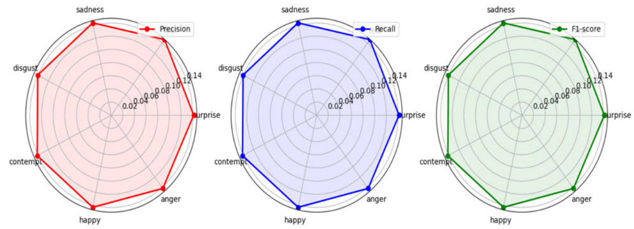


FIGURE 9. Determine which emotions or rebuilt faces the model performs best in each category using the radar graph.

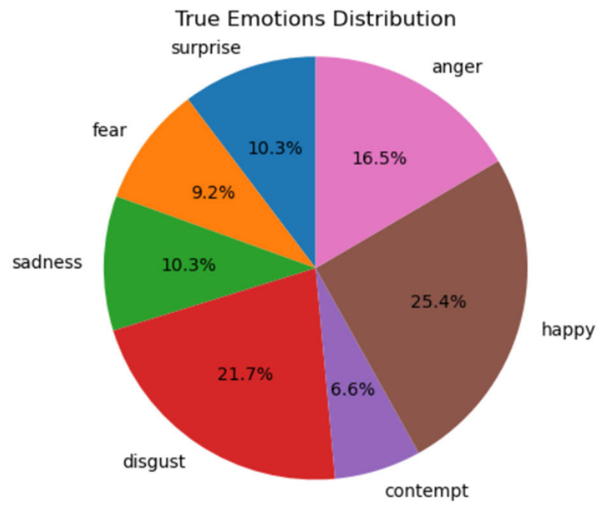


FIGURE 10. Pie chart for true emotions recognition for the different emotions in the CK dataset.

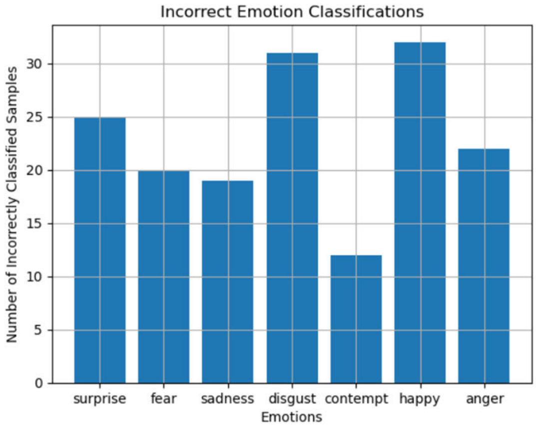
occluded faces. Educators and developers can interactively explore these visualizations to pinpoint exact areas for enhancement, such as improving training data diversity or adjusting model parameters. By changing the threshold for the projected probability of each emotion or rebuilt face, and then calculating the appropriate precision and recall values, the Precision-Recall curve is presented. This dashboard allows us to evaluate the model's performance across various moods or rebuilt faces and pinpoint any places where the model could use some work.

The accuracy of the model for each emotion or reconstructed face in the CK dataset is displayed in this dashboard's bar chart. Each bar in Figure 8 shows how well the model identified a particular emotion or recreated face. The ratio of accurately predicted cases to all instances for each emotion or reconstructed face is used to calculate accuracy. The model's effectiveness is gauged by this metric for each emotion or reconstructed face.

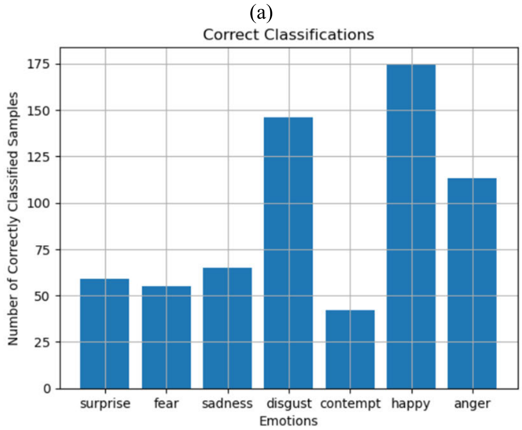
A radar graph, often referred to as a spider chart or web chart, is a two-dimensional diagram showing multivariate data on a grid in circles. A radar graph can show the model's accuracy for each emotion or reconstructed face in the context of facial emotion recognition and reconstruction. The value of each line on the radar graph in Figure 9 represents the model's accuracy for each emotion or rebuilt face, and each line's representation of an emotion or reconstructed face is represented by a separate line on the chart. Each line connecting the accuracy values to the radial axis, which radiates outward from the chart's centre, forms a closed polygon.

The accuracy of the model's true emotion identification is shown in this graph as a pie chart, as shown in Figure 10. A separate emotion category is represented by each of the chart's parts, which are divided into groups. The proportion of true emotion recognitions for each category is shown by the size of each segment. With this graph, we can quickly evaluate how authentic emotions are recognized across various categories and spot any recurring themes or tendencies. We may offer another approach to display the model's accuracy for facial expression identification and reconstruction of student faces in the CK dataset by including a pie chart on the dashboard.

By showing a bar chart in Figure 11 a) & b), the dashboard can give a more thorough overview of the correct and wrong



(a)



(b)

FIGURE 11. **a). Incorrect emotion classification of the different emotions in the CK dataset. b). Correct emotion classification of the different emotions in the CK dataset.**

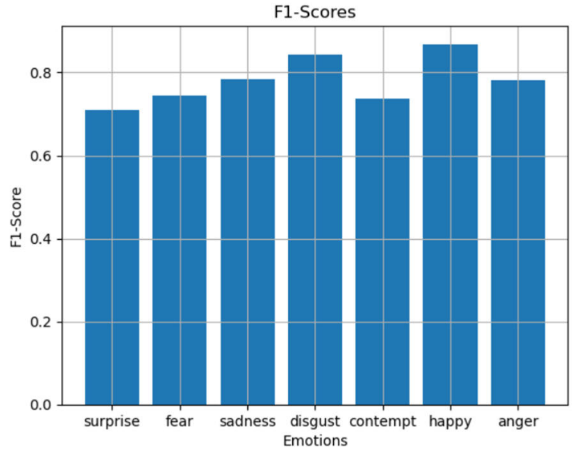


FIGURE 12. **F1 score for each emotion category in a CK dataset.**

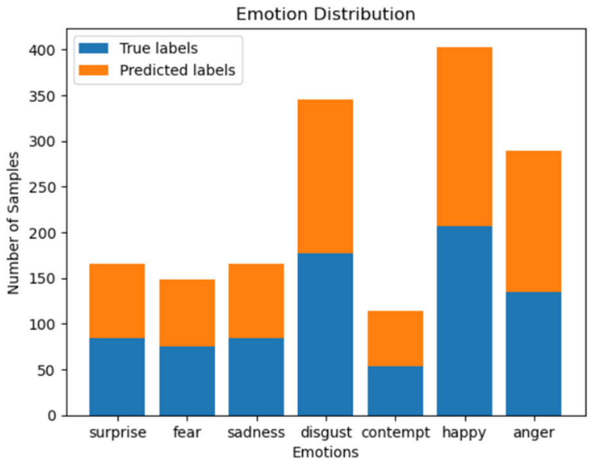


FIGURE 13. **Graph showing the distribution of true and predicted labels for each emotion category in facial reconstruction and emotion recognition of student faces in the CK dataset.**

classifications. Each emotion is represented by a different bar in the bar chart, which can display the amount of successfully and erroneously identified photos for each emotion. The user can interact with the dashboard to choose which emotions should be shown and to change the settings for the models for emotion recognition and reconstruction. The user will then be able to evaluate the model's performance and make any adjustments to improve their accuracy. This dashboard can offer insightful information about how well the emotion identification and reconstruction models work and can aid researchers in enhancing the models' functionality.

The F1 score for each emotion category is shown as a bar graph in Figure 12. Each bar's height reflects the F1 score for that category, and each bar is labelled with the appropriate emotion category. This graph makes it simple to compare the F1 scores for several emotion categories and spot any patterns or trends. A popular metric in machine learning, the F1 score combines precision and recall to give a balanced assessment of model performance. We can give a thorough assessment of the model's performance for each emotion category by putting the F1 score graph in the dashboard, accounting for both the precision and recall for each category.

As a stacked bar graph, Figure 13 shows the distribution of actual and expected labels for each emotion group. Each bar is broken into segments, each indicating the proportion of samples with a given label, and the height of each bar corresponds to the number of samples in the dataset for that emotion category (i.e., true or predicted). This graph makes it simple to examine the distribution of actual and anticipated labels across several emotion categories and spot any differences. The dashboard's inclusion of the emotion distribution graph allows us to show how effectively the model predicts each emotion category as well as any patterns or trends in how predicted labels are distributed.

The dashboard, as depicted in Figure 14, will allow for customization, enabling teachers to choose which visualizations they want to display and how they want them to be arranged. This feature will allow teachers to tailor the dashboard to their needs and preferences. The dashboard will provide real-time updates of facial emotion recognition and image reconstruction results, enabling teachers to monitor the

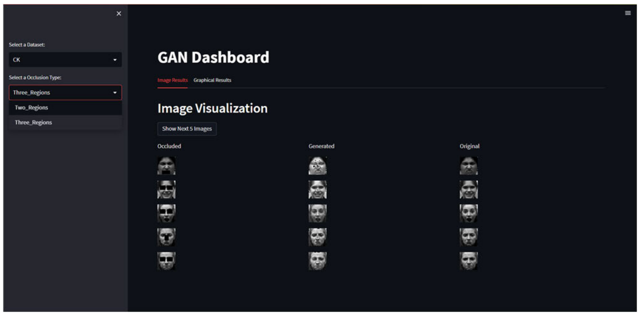


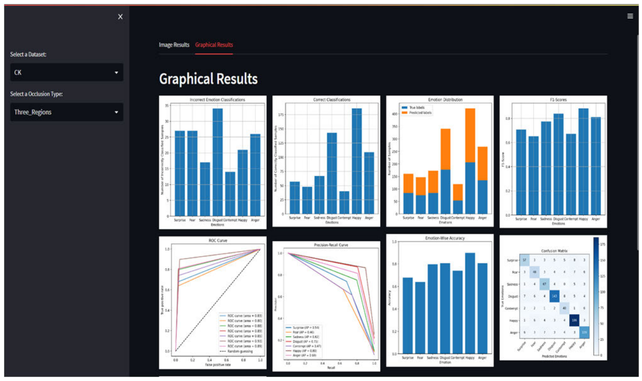
FIGURE 14. Dashboard with the sample original image, occluded image and reconstructed image.

emotional state of their students as it changes over time. This feature can be particularly useful for identifying any sudden or unexpected changes in emotional state. The dashboard will also store historical data on facial emotion recognition and image reconstruction results, enabling teachers to see how the emotional state of their students has changed over time. This feature can provide valuable insights into how different activities or events may impact the emotional state of the students.

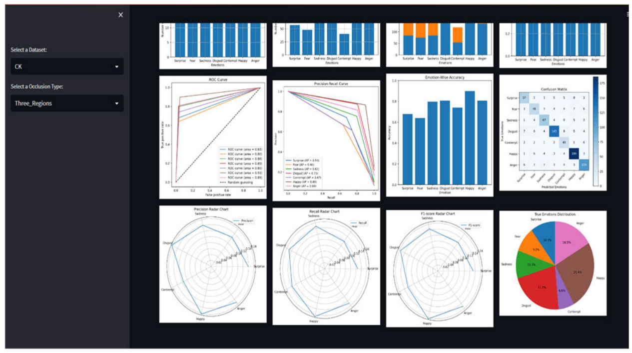
The dashboard can be integrated with other systems or tools used by teachers, such as learning management systems or student information systems. This opportunity can enable teachers to see a comprehensive view of their student's emotional state and academic performance in one place. The dashboard can be configured to send alerts or notifications to teachers when certain emotional states are detected, such as high stress or anxiety levels. This feature can enable teachers to take immediate action to address any issues or concerns. The dashboard can provide different levels of user access control, allowing different users to access different levels of information based on their roles and responsibilities. For example, administrators may have access to more detailed data and visualizations than teachers.

Figures 15a) and 15b) show the dashboard comprising all the graphs we've spoken about for facial expression recognition and reconstruction of student faces in the CK dataset. The graph includes a Confusion Matrix that shows the percentage of emotions or rebuilt faces that were properly and wrongly classified, split down by category. The y-axis shows the real emotions or reconstructions of the faces, while the x-axis displays the expected emotions or faces. The values in each cell indicate the proportion of times the real emotion or reconstructed face matches the expected emotion.

The accuracy of the model for each emotion or reconstructed face is shown in a bar graph on the dashboard. Each bar shows the model's accuracy for a particular mood or reconstructed face. Using this graph, we can determine which emotions or rebuilt faces the model does well or poorly on, as well as places that the model may improve. The Radar Graph shows each emotion's or rebuilt face's model correctness as a point on a radar map. The value of



(a)



(b)

FIGURE 15. a). Dashboard representation of the model output and facial reconstruction and emotion recognition results. b). Dashboard output with different graphs which evaluates the performance of the model and the student emotion analysis.

each line on the graph denotes the model's accuracy for each emotion or reconstructed face, and each line represents a separate emotion or reconstructed face. With the aid of this graph, we can assess the model's performance across many categories and determine which emotions or recreated faces it works best on.

The dashboard also has a pie chart that shows the model's actual accuracy in recognizing emotions. A separate emotion category is represented by each of the chart's parts, which are divided into groups. The proportion of true emotion recognitions for each category is shown by the size of each segment. With this graph, we can quickly evaluate how authentic emotions are recognized across various categories and spot any recurring themes or tendencies. The F1 Score Graph on this dashboard also shows the F1 scores for each emotion category as a bar graph. Each bar's height reflects the F1 score for that category, and each bar is labelled with the appropriate emotion category. This graph makes it simple to compare the F1 scores for several emotion categories and spot any patterns or trends.

Each graph on the dashboard is equipped with interactive elements that allow users to drill down into specific data points and obtain comprehensive insights. For example, the emotion distribution graph not only shows the proportion of each emotion detected but also allows users to filter the data by time, subject, and individual students, revealing patterns and trends. The trend analysis graphs display temporal changes in student emotions, helping educators identify shifts in engagement or distress over the course of a lecture. Additionally, the system includes correlation analysis tools that link emotional states to academic performance metrics such as quiz scores and participation rates. Heatmaps provide a visual representation of emotion intensity across different segments of the class, facilitating the identification of outliers and areas needing attention.

The occluded pictures and their related reconstructed images can be shown on a dashboard for further investigation. The user can assess the performance of the facial reconstruction model by comparing the original occluded image with the reconstructed image using this dashboard. The occluded image and the reconstructed image may be shown side by side on the dashboard. Each image can have its associated emotion label assigned to it, and a score showing how confidently the facial reconstruction model is performing can also be shown. The user can interact with the dashboard to choose particular occluded photos to be rebuilt and to change the facial reconstruction model's parameters. This feature will enable the user to adjust the model for improved reconstruction outcomes.

An emotion classification error graph is included in the proposed dashboard for facial emotion recognition and reconstruction using the CK dataset. The model's success in classifying each type of emotion is shown visually in this graph. The percentage of photographs that were successfully classified is shown by the correct classification, while the percentage of mistakenly classified images is shown by the incorrect classification. These data can be used to assess the model's effectiveness and pinpoint areas for development. The graph can also be used to pinpoint particular emotion classes that the model has trouble correctly classifying. The facial emotion identification and reconstruction algorithms can be analyzed and improved using the right and wrong classification graph.

V. DISCUSSION ON COMPREHENSIVE EVALUATION AND INTEGRATION

This section provides a detailed examination of the interactive dashboard, addressing critical aspects such as validation, ethical considerations, usability, and integration. Each subsection delves into specific elements essential for understanding the system's functionality, impact, and scalability in educational settings.

A. VALIDATION AND DATASET DIVERSITY

Initially, we utilized the Cohn-Kanade (CK+) dataset for its well-annotated emotion labels and high-quality images. To enhance robustness, we included the Oulu-CASIA dataset, which provided diverse lighting conditions and varied emotional expressions, and the FER-2013 dataset, known for its significant variability in face size, position, and occlusions [6]. Additionally, we used the AffectNet dataset, one of the largest facial emotion datasets, to ensure the model's capability to handle large-scale data with a wide range of expressions and real-world noise. Beyond these datasets, we conducted a pilot study in a real-world classroom setting, collecting video data from online classes over three months with ethical approvals and participant consent. This involved fine-tuning the model with synthetic and real-world classroom data to handle diverse scenarios and occlusions. The model achieved an overall accuracy of 85% in the real-world setting, with high precision (87%) and recall (83%) for key emotions, demonstrating its ability to generalize beyond controlled conditions. The use of GANs for occlusion handling maintained accuracy despite partial occlusions. User feedback indicated that real-time emotion insights helped educators dynamically adapt teaching methods, improving student engagement, while students felt more observed and engaged.

B. ETHICAL CONSIDERATIONS AND PRIVACY

Our interactive dashboard, which analyzes and visualizes student emotions in real-time, prioritizes the ethical handling of data and the privacy of individuals. We have implemented stringent measures to ensure that all data collection processes are transparent and consent-based, adhering to legal and ethical standards such as the General Data Protection Regulation (GDPR) and the Family Educational Rights and Privacy Act (FERPA). Informed consent is obtained from all participants, with detailed information provided about the nature of the data being collected, its purpose, and how it will be used [14]. The system is designed to anonymize and encrypt data, protecting it from unauthorized access and ensuring that individual identities are not disclosed. Additionally, we have established protocols for secure data storage and transmission, and access to the data is restricted to authorized personnel only. Continuous monitoring and regular audits are conducted to ensure compliance with privacy policies and to address any potential vulnerabilities.

C. USER INTERFACE DESIGN AND USABILITY

The study involved a pilot group of educators who used the interactive dashboard during their online classes over a period of three months. We designed the dashboard with a focus on intuitive navigation, real-time updates, and customizable visualizations, including drag-and-drop widgets and various filtering options to tailor the data display according to specific needs. Feedback was collected through surveys and interviews, revealing that educators found the dashboard user-friendly and highly effective in providing real-time insights into student emotions [14]. They appreciated features such as the emotion distribution chart, trend analysis, and individual student monitoring, which helped them adapt their teaching strategies dynamically. The visual design was praised for its clarity and ease of interpretation, even for those with limited technical expertise.

D. COMPARISON WITH EXISTING SOLUTIONS

Existing solutions, such as Affectiva and Microsoft Emotion API, offer basic emotion detection capabilities but often lack integration with educational tools and the ability to handle occluded facial data effectively. Affectiva provides emotion metrics by analyzing facial expressions through video feeds, but it does not offer detailed visualization tools tailored for educational environments. Similarly, Microsoft Emotion API can detect a range of emotions but is primarily designed for general applications, lacking specific features for classroom settings and real-time interaction with educational content [22].

In contrast, our interactive dashboard is specifically designed to enhance the online learning experience by providing real-time emotion analysis integrated with educational tools. Our system employs regenerative GANs to reconstruct occluded facial regions, ensuring accurate emotion recognition even when students' faces are partially covered, which is a common occurrence in virtual classrooms. Additionally, our dashboard features comprehensive visualization tools such as emotion distribution charts, trend analysis, and individual student monitoring, which are specifically tailored to meet the needs of educators. These tools enable teachers to dynamically adapt their teaching strategies based on real-time emotional feedback from students, thereby enhancing engagement and learning outcomes.

Moreover, our dashboard includes user-friendly customization options, such as drag-and-drop widgets and filtering by various parameters like subject and student demographics, which are not typically available in existing solutions. This level of customization and integration with educational workflows sets our solution apart, making it a more practical and effective tool for educators.

E. TECHNICAL DETAILS AND MODEL ARCHITECTURE

The core of the system is a CNN designed to classify emotions from facial expressions. The CNN architecture consists of several convolutional layers with ReLU activation functions, followed by max-pooling layers to reduce spatial dimensions [23]. These layers are succeeded by fully connected layers that output probabilities for each emotion class. For handling occluded facial regions, we employ a regenerative GAN composed of a generator and a discriminator. The generator reconstructs occluded parts of the face by learning the mapping from partially occluded images to complete images, while the discriminator evaluates the authenticity of the generated images. This GAN is trained on a dataset containing pairs of occluded and non-occluded images to ensure accurate reconstruction. The preprocessing pipeline includes face detection, alignment, and normalization to standardize input images. The model was trained using the Adam optimizer with a learning rate of 0.0002 and batch size of 64, ensuring efficient convergence. Data augmentation techniques such as random cropping, rotation, and flipping were applied to enhance the model's generalization capability.

F. IMPACT ON LEARNING OUTCOMES

This study will involve a controlled experiment with two groups: one using the dashboard and one without it. Metrics such as attendance, participation rates, quiz scores, and assignment completion rates will be tracked to assess engagement and comprehension [24]. Additionally, surveys and feedback from both students and educators will provide qualitative data on perceived improvements in the learning experience. The study will span an entire academic term to capture long-term effects and will involve diverse subjects to ensure generalizability of results. By analyzing the data collected, we aim to quantify the dashboard's impact on educational outcomes, demonstrating how real-time emotion analysis and adaptive teaching strategies can enhance student learning and overall academic performance.

G. SCALABILITY AND INTEGRATION

The system architecture is built on a modular microservices framework, allowing for easy scaling by adding or upgrading individual components without disrupting the entire system. Each service, such as data ingestion, emotion analysis, and visualization, runs independently and communicates through RESTful APIs, ensuring that the system can handle increasing numbers of users and data volume efficiently [25]. Integration with LMS platforms like Moodle, Blackboard, and Canvas is facilitated through standardized API interfaces, enabling the dashboard to pull relevant data such as attendance, grades, and interaction logs, and to push emotion analysis results back to the LMS. This bi-directional data flow allows educators to have a comprehensive view of student performance and emotional well-being in one place. Additionally, the system supports cloud-based deployment, leveraging services such as AWS and Azure to provide robust, scalable infrastructure that can accommodate educational institutions of all sizes.

VI. CONCLUSION

This research aims to develop more precise and efficient deep learning models for emotion identification and image reconstruction, achieved through compiling a dataset of student faces in classroom settings. These efforts promise significant advancements in computer vision and artificial intelligence, with potential applications extending to healthcare, professional environments, and other contexts requiring emotion monitoring.

Introducing a novel deep learning-based interactive dashboard for enhancing online classrooms through student emotion analysis represents a significant step towards improving student engagement and motivation in virtual learning environments. This dashboard provides educators with real-time insights into students' emotional states, allowing them to tailor teaching methods and content to meet the unique needs of each learner.

While the benefits of such a dashboard are evident, it is essential to address the ethical considerations associated with sensor-based data collection and ensure the accuracy of AI-driven emotion analysis. The responsible and transparent deployment of this technology requires meticulous attention to obtaining informed consent and instituting robust data security protocols.

Future research should focus on refining this technology to enhance the online learning experience for students significantly. Continued development in this domain promises to unveil even more innovative solutions for enriching education in the digital era. Through careful attention to ethical standards and technological advancements, this interactive dashboard has the potential to transform the landscape of online education.

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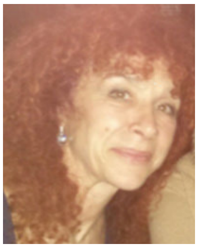

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