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STUDENT EXPRESSION DETECTION IN E-LEARNING PLATFORMS

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ABSTRACT

Our research suggests a deep learning method for determining how engaged students are with their online courses. Our method makes use of convolutional neural networks (CNNs) to interpret facial expressions that are recorded via webcams during online conversations. To provide the best possible model input, we preprocess face photos and select a varied dataset. The CNN architecture captures both spatial and temporal dependencies, enhancing engagement level detection accuracy. Our model performs well in classifying expressions that indicate curious, distracted, enthusiastic, observant, uninterested through training and validation. In conclusion, that the online learning experience may be enhanced by using deep learning algorithms for engagement detection, making it more advantageous and successful for students.

KEYWORDS – *CNN, Webcams, Engagement level, Online learning, Deep Learning, Facial expressions*

I. INTRODUCTION

The emergence of online education has completely changed how people can access educational possibilities, providing unprecedented flexibility and accessibility. Nonetheless, evaluating student participation is a significant difficulty for teachers in this digital age. Online classrooms don't have the same instant feedback systems as traditional classroom settings, which make it easier for teachers to assess student involvement and reactions.

Our study explores the field of deep learning to provide a novel way for gauging student participation in online courses in response to this difficulty. We want to use facial expression recognition to predict students' involvement levels during virtual learning sessions, taking use of the advances in deep learning, especially in computer vision.

In addition to addressing the pressing need for efficient engagement assessment in online courses, this research establishes the groundwork for the creation of intelligent systems capable of customizing instructional strategies in response to each student's unique reaction. Our goal is to build a dynamic and interactive learning environment that encourages active participation, collaboration, and knowledge retention by incorporating deep learning algorithms into the foundation of online education. This deep learning project emphasize the value of employing facial expression detection to evaluate students' degree of participation in online courses

II. OBJECTIVES

1. Create a deep learning technique to identify facial emotions in online courses by utilizing CNNs.
2. Select a varied collection of images and prepare them for the best possible model input.
3. Create a CNN architecture that can recognize the temporal and spatial relationships found in expressions.
4. To effectively distinguish different engagement levels, train and evaluate the model.
5. Assess how well the approach enhances the quality of online learning.
6. Examine possibilities for e-learning platform integration.
7. Adjust the model to make it more accurate and user-friendly.

III. LITERATURE SURVEY

[1] Student engagement is considered to be synonymous with educational quality and is positively correlated with a student's perseverance, satisfaction, learning efficiency, and degree completion.
[2] Kahu mentioned that student engagement is a reflection of a student's internal psychological state, which includes behavior,

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cognition and emotion.
[3] The face is the most expressive and communicative part of a human being.
[4-5] A face alignment is performed, and the aligned image crops the face to obtain the entire face area as input. In the training process of the macro-expression detection model, an attention mechanism is added to allow the model to focus only on the facial regions that are helpful for the emotion classification results and enhance the generalization ability of the model.
[6] In Whitehill proposed an approach that recognizes engagement from student's facial expressions. The approach uses Gabor features and SVM algorithm to identify engagement as students interacted with cognitive skills training software. The authors obtained labels from videos annotated by human judges
[7] Then, the authors in used computer vision and machine learning techniques to identify the affect of students in a school computer laboratory, where the students were interacting with an educational game aimed to explain fundamental concepts of classical mechanics.
[8] Unauthorized Access: Using malware to gain access to data for a deep learning project without proper authorization is illegal and unethical. It violates the privacy rights of individuals and the terms of service of the online platform.
[9] In the authors proposed a system that identifies and monitors student's emotion and gives feedback in real-time in order to improve the e-learning environment for a greater content delivery. The system uses moving pattern of eyes and head to deduce relevant information to understand students' mood in an e-learning environment
[10] developed a Facial Emotion Recognition System (FERS), which recognizes the emotional states and motivation of students in videoconference type e-learning. The system uses 4 machine learning algorithms (SVM, KNN, Random Forest and Classification & Regression Trees).
[11]A Convolutional Neural Network (CNN) is a deep artificial neural network that can identify visual patterns from input image with minimal pre-processing compared to other image classification algorithms. This means that the network learns the filters that in traditional algorithms were hand-engineered.
[12] Pooling Layer reduces the dimensionality of each feature map but retains the most important information.

IV. METHODOLOGY

During this project work the approach followed can be described in the following steps. They are

1. Data Collection
2. Data Preprocessing
3. Model Selection
4. Model Training and evaluation

Data Collection

For the data collection process, the dataset is collected from the Kaggle, the dataset is FER (Facial Expression Recognition). The data consists of 48x48 pixel grayscale images of faces. From this data we have collected the appropriated that needed for our project and placed under 7 labels named as Apprehensive, Curious, Distracted, Enthusiastic, Irritated, Observant,

Fig.1: Labels

Data Preprocessing

In deep learning projects, data preparation is an essential phase that entails getting the raw data ready for model training. It includes a range of procedures and methods designed to enhance the efficiency and efficacy of the learning algorithms by cleansing, converting, and organizing the data.

In this project the crucial data processing steps are

Resizing: Resizing is a popular preprocessing method utilized in many deep learning tasks, especially in computer vision applications. Before supplying photos to the model for training or inference, resizing entails adjusting their dimensions to a uniform size. The resizing helps in the standardization of the input and reduce overfitting.

Grayscale Conversion of images: Grayscale color photos are converted, which lowers the dimensionality of the data and makes processing easier. Only intensity information is present in grayscale photos, which can be sufficient for some tasks and reduce computer complexity.

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Model Selection
The model or algorithm used in this project is Convolution Neural Networks (CNNs) which is well know for the processing of the images. As the project mostly relays on the image processing to identify the engagement level of the student, CNN algorithm is taken to train the data samples.

Algorithm
Start:
Import necessary libraries
Initialize Model:
Create a Sequential model.
Add Convolutional Layers:
Create a Sequential model
Add a Conv2D layer:
- Filters: 16
- Kernel size: (3, 3)
- Activation: ReLU
- Strides: (1, 1)
- Input shape: (48, 48, 1)

Add a MaxPooling2D layer (default parameters)
Add a Conv2D layer:
- Filters: 32
- Kernel size: (3, 3)
- Activation: ReLU
- Strides: (1, 1)

Add a MaxPooling2D layer (default parameters)
Add a Conv2D layer:
- Filters: 16
- Kernel size: (3, 3)
- Activation: ReLU
- Strides: (1, 1)

Add a MaxPooling2D layer (default parameters)
Flatten the output
Add a Dense layer with 256 units and ReLU activation
Add a Dense output layer with 7 units and softmax activation
Compile the model:
- Optimizer: Adam
- Loss: Sparse categorical cross-entropy
- Metrics: Accuracy

Train the model on the training dataset
Evaluate the model on the test dataset

Display the test accuracy
Pooling Layers: Convolutional layers are usually followed by pooling layers in order to minimize the spatial dimensions of the feature maps without sacrificing the most crucial information. The pooling operation performed is max pooling, which reduces the feature map
Activation Function: The CNN model gains non-linearity from activation functions, which helps it recognize intricate patterns and correlations in the data. The activation function used is ReLU (Rectified Linear Unit).
Flattening layer: Feature maps are flattened into a one-dimensional vector before being passed from the convolutional layers to the fully connected layers.
Fully Connected Layers: Dense layer serves as the final part of the network where the learned features are reflected as predictions or decisions.

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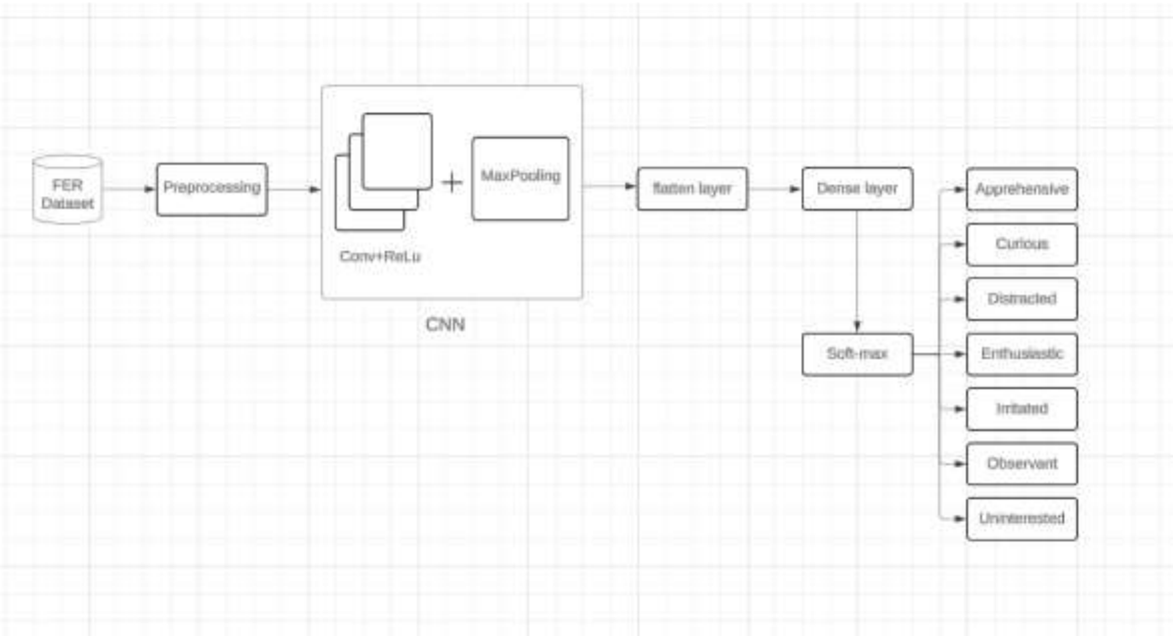

Fig.2: System Architecture

V. RESULTS

And our output screens are as follows:

1. Login for Student and Faculty

Fig.3: Home Page

Fig.4: Login Page

2. Select whether to detect Single Image or Live Detection(using webcam or system camera)

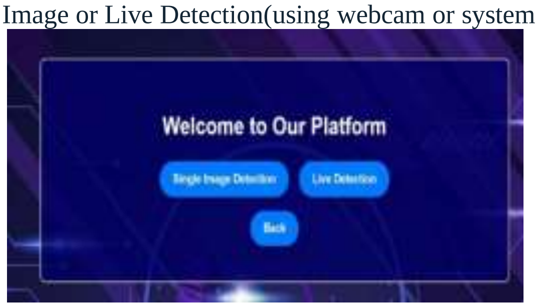

Fig.5: Selection

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- **Expression Detection of Static Image**




Fig.6: Distracted **Fig.7: Enthusiastic** **Fig.8: Observant** **Fig.9: Apprehensive**

The figures 6,7,8,9 represents the expressions of the Static images.

- **Expression Detection using Live-Cam:**



Fig.10: Curious **Fig.11: Irritated** **Fig.12: Enthusiastic**

- **Faculty dashboard:**
  The faculty dashboard gives teachers a thorough picture of how well their online students are performing and how engaged they are. It provides several features to help with efficient instruction and progress tracking for students. The following are some salient characteristics Engagement metrics, Tracking of student's performance. All things considered, the faculty dashboard is a useful tool that helps teachers oversee their online courses, keep tabs on their students' progress, and offer tailored assistance to improve the learning process.

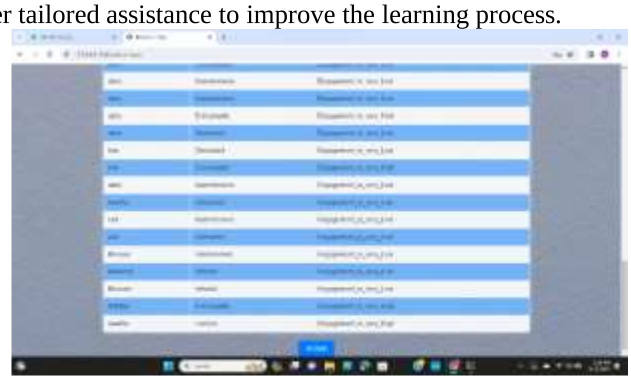

Fig.13: Faculty Dashboard

VI. CONCLUSION

In brief, our CNN system employs facial feature analysis to measure student involvement, delivering real-time information classified into output labels such as apprehensive, curious, irritated, uninterested, observant, enthusiastic, and distracted Teachers can maximize student involvement by dynamically adapting their teaching tactics by collecting tiny details. With the help of this cutting-edge strategy, teachers may design meaningful learning experiences that are individualized for each student, completely changing the dynamics of the classroom and improving student results. Our research seeks to rethink conventional educational paradigms for the contemporary period by fusing cutting-edge technology and pedagogical skills.

VII. FUTURE SCOPE

Feedback systems: Self-directed learning and metacognitive awareness may be encouraged by putting in place feedback systems that let students evaluate their degrees of engagement and get tailored advice on how to become more attentive.

Parental Involvement: Using family engagement programs or parent-teacher communication platforms, parents can participate in the tracking and analysis of student engagement data, which can encourage teamwork to promote learning at home and in the classroom.

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Multimodal Analysis: Investigating the incorporation of extra data modalities, including textual or audio inputs, in addition to face features may offer a more thorough comprehension of student participation and improve prediction accuracy.

VIII. GRAPHS

The model's performance is monitored by the accuracy graph, and training convergence is shown by the loss graph. The precision graph illustrates how well the model can recognize pertinent instances. Faculty can improve student learning experiences by optimizing engagement prediction models through the analysis of these graphs.

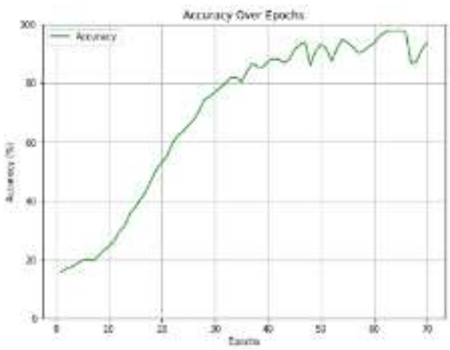


Fig.14: Accuracy

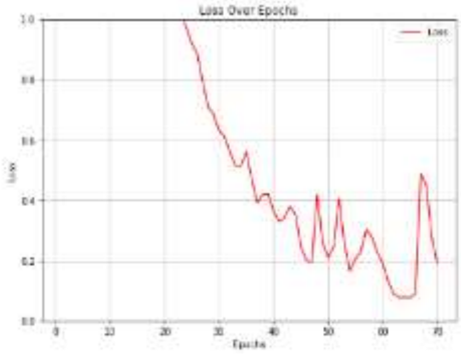


Fig.15: Loss

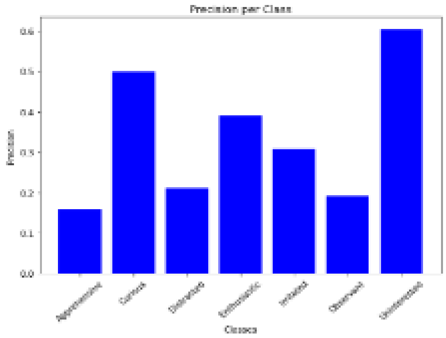
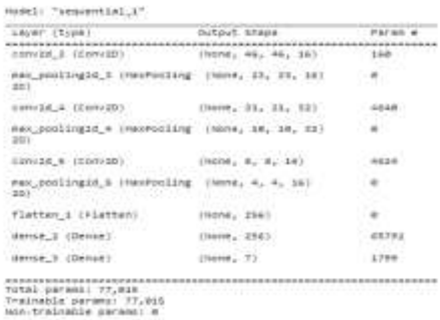


Fig.16: Precision



Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_3 (Conv2D)	(None, 46, 46, 16)	160
max_pooling2d_3 (MaxPooling2D)	(None, 23, 23, 16)	0
conv2d_4 (Conv2D)	(None, 21, 21, 32)	4640
max_pooling2d_4 (MaxPooling2D)	(None, 10, 10, 32)	0
conv2d_5 (Conv2D)	(None, 8, 8, 16)	4624
max_pooling2d_5 (MaxPooling2D)	(None, 4, 4, 16)	0
flatten_1 (Flatten)	(None, 256)	0
dense_2 (Dense)	(None, 256)	65792
dense_3 (Dense)	(None, 7)	1799

Total params: 77,015
Trainable params: 77,015
Non-trainable params: 0

Fig.17: Model Summary

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