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# Deep Learning Based Facial Emotion Recognition for Analysing the Effectiveness of Online Class

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**Abstract:** Online classes break down barriers of distance and time, allowing students from different geographical locations and backgrounds to access quality education. However, monitoring student engagement and emotional well-being during online classes presents a unique challenge. This study aims to analyze the facial expressions of students during online classes, in order to assess their emotional states and evaluate the performance of a fine-tuned MobileNet V2 architecture. To conduct this study, we utilized the CK+ dataset, which consists of labeled facial expressions captured in controlled laboratory settings. To specifically identify the emotions shown by students during online classes, the MobileNet V2 model is first pre-trained on ImageNet, a large-scale picture classification dataset, and then refined on the CK+ dataset. Preprocessing techniques such as image augmentation and normalization are applied to enhance the model's generalization capability. Before fine-tuning, the pre-trained model achieved moderate level of performance. After fine-tuning, the performance of the model achieved higher accuracy of 98.40% compared to the base model, indicating its enhanced ability to detect and classify facial emotions during online classes. By leveraging deep learning-based tools like the proposed model, educators can gain valuable real-time feedback on the effectiveness of their online teaching methods and make data-driven decisions to optimize the learning experience for their students.

***Keywords:*** *: Mobile Netv2, Online class, Fine tuning, Performance metric, ImageNet Dataset*

## 1. Introduction

With the rapid advancements in technology and changing job market dynamics, education has become essential for individuals to adapt and thrive in their careers. Education not only empowers individuals with knowledge and critical thinking skills but also fosters innovation, creativity, and social development, playing a crucial role in driving economic growth and societal progress [1].

Moreover, education instills a sense of curiosity, lifelong learning, and continuous improvement, empowering individuals to stay relevant and competitive in their chosen fields. It offers a basis for personal growth [2], gives people the ability to make wise decisions, and gives them the means to make a significant contribution to their communities and society as a whole.

Additionally, schooling is critical in developing social and emotional competencies [3], such as empathy, cultural sensitivity [4], and teamwork, all of which are necessary for creating a peaceful and inclusive community and establishing good relationships. Education plays a pivotal role in the development and progress of societies. Well-educated individuals contribute to the overall social and economic development of their communities [5]. Moreover, education empowers individuals to become active and informed citizens, capable of participating in democratic processes [6], advocating for social justice [7], and driving positive societal change. By promoting inclusivity and equal opportunities, education helps break down barriers and address systemic inequalities [8], leading to a more equitable and cohesive society. Through education, individuals gain knowledge, skills, and critical thinking abilities that enable them to address complex challenges, make informed decisions, and contribute to sustainable development. By investing in education, societies can foster innovation, promote economic growth [9], and create a more equitable and prosperous world for all.

In addition to accessibility, online classes offer a dynamic learning environment that encourages active engagement and collaboration among students [10]. Through virtual discussions, interactive assignments, and multimedia resources, online classes promote critical thinking, problem-solving, and digital literacy skills necessary for success in today's interconnected world. Moreover, online classes provide a flexible learning environment that accommodates diverse schedules and lifestyles [11]. Students can access course materials, participate in discussions, and submit assignments at their convenience, allowing them to customize their learning experience and overcome barriers of time constraints and geographical limitations [12].

The need for online classes has been magnified by recent global events, such as the COVID-19 pandemic, which disrupted traditional educational systems worldwide.

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Online classes became essential in ensuring continuity of education during times of crisis when physical classrooms were not accessible [13]. They provided a means for teachers and students to connect remotely, engage in interactive learning experiences, and maintain academic progress. Online classes have proven their value in fostering resilience, adaptability, and innovation in the education sector, serving as a viable alternative to traditional classroom-based learning and meeting the evolving needs of today's learners in an increasingly digital world [14].

Despite the physical separation, online classes promote collaboration and interaction among students. Virtual classrooms [15] often include discussion boards, chat features, and group projects, allowing students to engage with their peers and exchange ideas. Through these cooperative exercises, students can learn from one another's viewpoints and experiences while also fostering a sense of community. Moreover, online classes facilitate global connections, as students from different geographical locations [16] can come together and participate in discussions, cultural exchanges, and collaborative projects.

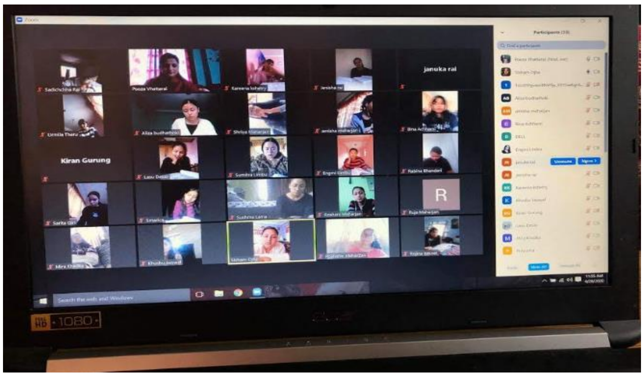

**Fig 1** Conducting online class to facilitate learning

Assessing the effectiveness of online classes through facial emotions has the potential to revolutionize the way educators evaluate students' engagement and emotional experiences in virtual learning environments [17]. By leveraging facial expression recognition technology, teachers can analyse real-time reactions displayed on students' faces, providing valuable insights into their level of attentiveness, interest, and overall emotional state. The ability to detect emotions such as enthusiasm, confusion, boredom, or frustration can help educators tailor their instructional strategies and interventions to better meet students' needs [18]. This form of assessment can enhance online teaching practices by facilitating timely feedback and fostering a more engaging and supportive learning environment.

One of the primary advantages of assessing online classes through facial emotions is the immediate and non-intrusive nature of the data collection [19]. Unlike traditional assessment methods, which often rely on self-reporting or post-session surveys, facial expression analysis can capture students' genuine emotional responses in real-time. This allows for timely interventions and targeted support, as teachers can quickly identify when students may be struggling, disengaged, or in need of additional clarification [20]. By leveraging facial emotion analysis, educators can proactively address potential learning barriers and create a more responsive and personalized online learning experience.

## 2. Literature Review

Veli Batd et al [21] conducted a mixed-methods study, which included a pre-experimental study and a qualitative study, to investigate the reactions and outcomes of the rapid transition to online education. An investigation by Sitti Hardiyanti Arhas et al. [22] used qualitative descriptive research. In this study, data were gathered from 10 informants through observation, interviews, and documentation. Tarika Nandedkar and Nidhi Jhawar [23] attempt to determine whether the goal of knowledge enlargement was achieved through online learning or if it was merely a betrayal. The article also tries to pinpoint the elements that significantly contribute to online learning's efficacy. A questionnaire was used as the survey instrument by Noradila Nordin et al. [24] with the participation of 31 students. According to Rana Saeed Al-Maroof et al. [25], the study's objective was to ascertain whether or not students would like to keep using online learning platforms in traditional face-to-face classes in a way that is comparable to how they do so in online virtual classes.

The goal of Julia Yu-Fong Chang et al. [26] was to compare the efficiency of learning for dental care education in physical classrooms with online classes. In this study, dentistry students tended to hold the opinion that online learning was more beneficial than learning in a traditional classroom. Instead, they tended to hold the belief that a physical exam taken in a classroom was more convenient and fairer than an online exam. The effectiveness of online nursing instruction was investigated from the viewpoints of nursing professors and students by Yvonne Smith et al [27]. In order to gauge the degree of readiness, involvement, and online classroom activities during the pandemic, Md. Al-Amin et al. [28] conducted a survey of over 844 students from many universities in Bangladesh.

A survey conducted by T. Muthuprasad et al. [29] with 307 agricultural students revealed that 70% of respondents were willing to opt for online courses for their curriculum. The study highlighted that students preferred using smartphones, favored recorded lessons with quizzes, and acknowledged the challenges of internet connectivity in rural areas. By extending TAM, Ferhan ahin et al. [30] suggested a study to identify the factors influencing instructors' intentions to use ITs and investigate the contributions of individual characteristics in the proposed model. Taher Farahat et al. [31] proposed a study to investigate the factors influencing students' acceptance of online learning and how those factors affect their intention to use online learning. Investigating the factors influencing college students' behavioural intentions about the usage of e-learning during the COVID-19 epidemic was the aim of Mailizar Mailizar et al's [32] study. Zhou Liqiu and associates [33] The theoretical underpinning of this study was the Technology Acceptance Model, which was extended to investigate the factors influencing learners' intentions to use an online learning platform by including additional external variables and one perceived variable. To determine what influences students' intentions to study online, Greeni Maheshwari [34] suggests conducting a study. The suggested method includes a brand-new research variable that is described as extrinsic elements that subtly affect students' intentions to learn online.

It is important to recognize the shortcomings of current methods for evaluating the efficacy of online courses. The use of self-reported data from surveys and feedback forms, which might be skewed by recall bias, is one drawback.. Additionally, the use of self-reported data may be limited in capturing real-time emotional fluctuations and may not provide a comprehensive picture of students' engagement throughout the entire class session. Another drawback is the lack of standardized metrics for assessing the effectiveness of online classes. This variability makes it difficult to establish a unified framework for evaluating the effectiveness of online classes. Lastly, there is a need for more sophisticated and accurate emotion recognition technologies. While facial expression analysis can provide insights, current algorithms may have limitations in accurately detecting and classifying complex emotions or accounting for individual and cultural variations. Improvements in these areas are necessary to enhance the reliability and validity of existing approaches for analyzing the effectiveness of online classes.

## 3. Materials and Methods

In this section a comprehensive description of the dataset, model architecture, and training optimization provides a solid foundation for conducting the study and analyzing the effectiveness of online classes using facial emotions accurately. The dataset collection process involved gathering a diverse range of samples, ensuring representation from different demographics and capturing a wide array of facial expressions relevant to the analysis of online class effectiveness. Pretrained models are trained on the CK+ dataset after having previously been trained on large-scale datasets such as ImageNet. This improves the model's performance in accurately recognizing and classifying facial expressions in the context of online class analysis, as well as its capacity to learn complex facial features. Following dataset collection, the collected data underwent preprocessing and augmentation techniques to enhance the quality, diversity, and generalization capabilities of the dataset for subsequent analysis and model training.

To assess the effectiveness of online classes, the proposed fine-tune architecture was utilized as a key component in the evaluation process. This architecture, specifically tailored for analyzing facial emotions, played a crucial role in accurately classifying and interpreting the emotional responses of students in online learning environments. The MobileNet V2 convolutional neural network (CNN) model was chosen as the proposed architecture for the study. It was utilized to divide the CK+ images into seven distinct groups based on the type of facial expression exhibited in each image. This categorization allowed for a comprehensive analysis of different emotional responses within the context of online classes.

To optimize and improve the performance of the MobileNet V2 model, fine-tuning techniques [35] were employed by adjusting the layers and learning rate. In the context of online classes, transfer learning was used to improve the model's capacity to identify and categorize facial expressions accurately by utilizing the features taken from the ImageNet dataset. By leveraging pre-trained features, the model could effectively adapt to the specific task at hand and achieve improved performance. Following the fine-tuning process, the MobileNet V2 model was trained and evaluated using the CK+ images.

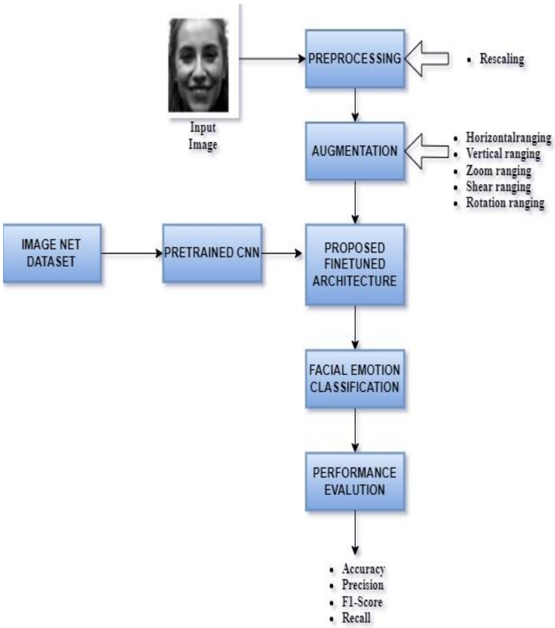


**Fig 2** Block Diagram of the Proposed Approach

During the evaluation phase, the model was presented with individual images, and classified each image into one of the seven predefined emotions based on the learned patterns and features. This classification process allowed for a comprehensive analysis of emotional responses in the context of online classes using the proposed model.

### 3.1 Dataset Description

The CK+ dataset was used to assess how effective the online class was. There are 1076 photos in the dataset, aged 18 to 50, representing a range of genders and ethnicities. Each image shows a facial shift from the neutral expression to a targeted peak expression. Data is already reshaped to 48x48 pixels in grayscale format and noisy images were adapted.


**Fig 3** Sample images from Dataset

The dataset contains two classes and each class contains seven subclasses. One of seven expression classes—angry, disdain, disgust, fear, happiness, sadness, and surprise—is assigned to each of these pictures. Most people agree that the CK+ database is the most widely utilized laboratory-controlled facial expression classification database out there.

**Table 1** Dataset description

| | |
|---|---|
| Total Number of Images | 1076 |
| Image for Training | 873 |
| Image for Testing | 203 |

### 3.2 Data preprocessing and Augmentation

By using techniques for denoising, strengthening the edges of picture structures, and enhancing image contrast, image pre-processing aims to improve data quality. "Image preprocessing" is a technique that modifies digital photographs to extract pertinent information or improve their visual quality. Augmentation is the practice of artificially producing additional images from the original photos; it is used to expand datasets. This is particularly helpful for applications involving computer vision and artificial intelligence that require training on large datasets. The techniques for image augmentation include horizontal ranging [36], vertical ranging, zoom ranging, shear ranging, rotation ranging [37]. Images are frequently preprocessed before being utilized in learning systems by combining image processing and augmentation.

### 3.3 Convolutional Neural Network and TL Approaches

CNN (Convolutional Neural Network) is a deep learning framework designed specifically for processing and analyzing visual data, such as images. They apply a set of learnable filters to the input data in order to detect local patterns and features. Convolutional layers are designed to capture spatial hierarchies by scanning the input with sliding windows. Pooling layers are used to down sample the spatial dimensions of the data, reducing its spatial resolution while preserving important features. By adding non-linearities to the network, activation functions help the network acquire intricate representations. Rectified Linear Unit (ReLU) is a common activation function in CNNs [38].

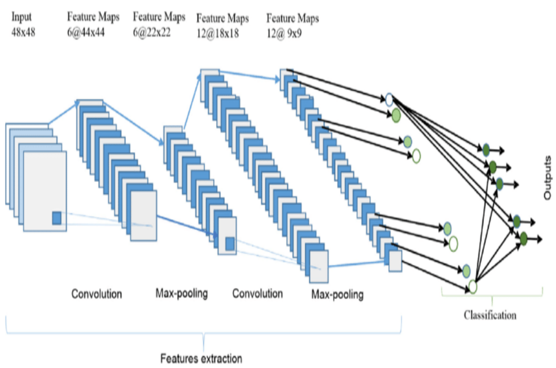


**Fig 4** CNN Framework

Fully connected layers, also known as dense layers, are typically placed at the end of a CNN. They link each neuron in the current layer to every neuron in the preceding layer. High-level features can be captured and predictions can be made using fully connected layers and learnt representations. The loss function calculates the discrepancy between the ground truth label and the CNN's anticipated output. It quantifies the model's performance during training and is used to update the network's parameters through backpropagation. CNNs use Adam optimization algorithms to iteratively update the model's parameters and minimize the loss function. These algorithms use the gradients calculated during backpropagation to modify the network's weights and biases. These components together form the foundation of a CNN framework. CNNs can learn hierarchical representations of visual input by stacking numerous convolutional layers, pooling layers, and fully connected layers. This enables them to extract relevant features and produce accurate predictions on tasks like object detection and image classification, among others.

### 3.4 Proposed Finetuning Architecture

Fine tuning is a deep learning technique that allows a neural network that has already been trained to adapt to a new task or dataset. It comprises modifying or retraining a model—like a convolutional neural network—on a fresh dataset after it has previously been trained. The pre-trained model has previously accumulated a set of generic features from a substantial and diverse dataset, which is the fundamental idea behind fine tuning. The lower layers' weights record these fundamental characteristics; by freezing these weights and retraining the higher layers on a fresh dataset, the model can be adjusted to perform a new task with fewer training time and training samples. Fine tuning can be a particularly effective strategy for adapting previously learnt models for new tasks when the new dataset is small or the training period is limited. Selecting the pre-trained model and the fresh dataset with care, together with fine-tuning the hyperparameters, is essential to achieve optimal performance.

Pre-trained MobileNetV2 models are fine-tuned by retraining them on a smaller, task-specific dataset after they have already been trained on a larger dataset. Fine-tuning enables the model to specialize and adjust its knowledge to the new dataset by utilizing the learned features and weights from the pretrained model, leading to increased performance and generalization. During fine-tuning, the model's parameters are updated based on the new dataset, typically with a smaller learning rate to avoid overfitting. This process helps the model to better understand and classify specific features related to the target task, making it more effective and accurate in the desired application.

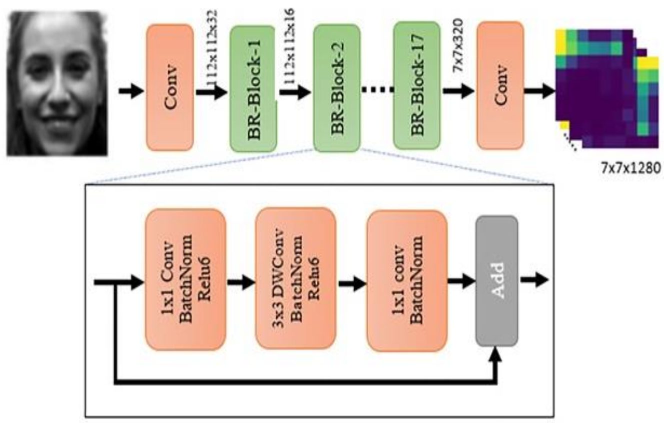


**Fig 5** MobileNetV2 Architecture

Hyperparameters in deep neural networks are typically set empirically, and they play a crucial role in determining the learning process and overall performance of the model. To maximize the model's performance and prevent problems like overfitting or underfitting, hyperparameters including learning rate, batch size, number of layers, activation functions, and regularization approaches must be carefully selected.

**Table 2** Hyper parameters

| Parameters | Before Fine-tuning | After Fine-tuning |
|---|---|---|
| Optimizer | Adam | RMSprop |
| Activation Function | ReLu, Softmax | ReLu, Softmax |
| Learning Rate | 0.0001 | 0.00001 |
| Loss | Categorical Crossentropy | Categorical Crossentropy |
| Batch Size | 32 | 32 |
| Number of Epochs | 20 | 50 |

Experimentation and fine-tuning of these hyperparameters are essential to achieve the best results for a specific task or dataset. The comprehensive listing of experimented hyperparameter values and corresponding classification performance in Table 2 provides valuable insights for determining the optimal configuration that yields the best classification performance for the given task or dataset.

**Table 3** Model summary of Fine-tuned MobileNetV2 Model

| Parameters | Before Fine-tuning | After Fine-tuning |
|---|---|---|
| Total Parameters | 34,265,991 | 34,265,991 |
| Trainable Parameters | 32,008,007 | 34,017,991 |
| Non-trainable Parameters | 2,257,989 | 248,000 |

## 4. Result and Discussion

### 4.1 Hardware and Software Setup

To guarantee a reliable computing environment, the study used the Microsoft Windows 10 operating system and the Google Colaboratory platform.. The fine-tuned structures of the proposed models were designed to receive preprocessed and enhanced CK+ images as input, enabling accurate classification of the emotional expressions captured in the images. Using what they had learned, the models classified the input photos into one of seven pre-established classes: Anger, Contempt, Disgust, Fear, Happy, Sadness, and Surprise. This allowed for a thorough examination of the emotional reactions that students might have in the setting of online learning.

### 4.2 Performance Parameters

The performance parameters are used to assess the suggested model's efficacy. Among the often used performance metrics are F1-Score, Accuracy, Precision, and Recall. With the help of these performance indicators, the model's classification performance is thoroughly assessed, enabling a quantitative evaluation of its recall, accuracy, precision, and F1-Score to accurately categorize the emotional expressions recorded in the dataset.

The degree to which a model's predictions correspond with the actual values of the training data is referred to as accuracy. It is typically stated as a percentage of correct predictions made by the model out of all of its forecasts. The ability of a model to accurately discern between positive situations and those that it has classified as positive is referred to as its accuracy. It is determined as the ratio of real positives to all cases labeled as positive. Recall is the attempt to determine the percentage of actual positives that were incorrectly detected. When there is an imbalance in the classes or when both FP and FN are expensive, the F1-score can be helpful because it offers a compromise between precision and recall.

**Table 4** Performance Parameters

| Parameters | Equation |
|---|---|
| Accuracy | (TP+TN)/(TP+TN+FP+FN) |
| Precision | (TP)/(TP+FP) |
| Recall | (TP)/(TP+FN) |
| F1-Score | 2* (Precision×Recall)/(Precision+Recall) |
| TP=True Positive<br>TN=True Negative<br>FP=False Positive<br>FN=False Negative | |

By training and evaluating the proposed model on the CK+ dataset, its efficiency and effectiveness in accurately classifying emotions within the context of online classes were revealed, providing insights into its performance and potential for practical applications. The suggested model, which was based on the MobilenetV2, had the best accuracy of 98.40%, according to the experimental results. Figure 7's train and validation loss illustrates how the model was trained over a number of epochs. The graph shows that accuracy increases proportionately with the number of epochs. Furthermore, as training progressed, the loss reduced proportionately with the number of epochs until it reached its lowest point, signifying that the model was sufficiently trained and that the classification could be completed.

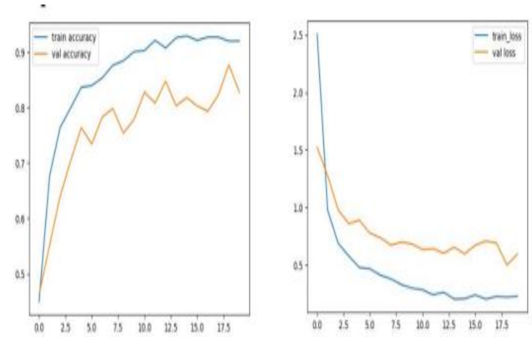


**Figure 6** Accuracy loss curves for training and validation data before fine tuning

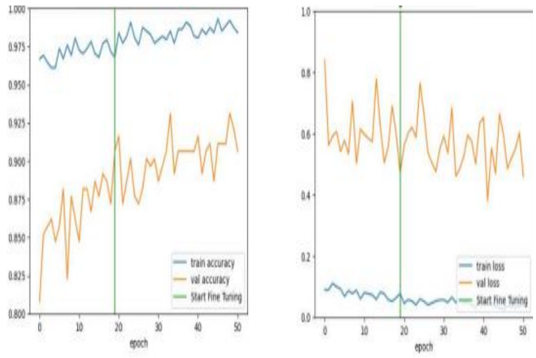


**Fig 7** Accuracy loss curves for training and validation data after fine tuning

Classification reports for the recommended fine-tuned architectures provide insightful details on how well the model performs for each individual emotion class. By providing information on parameters like precision, recall, and F1-score, they enable a thorough evaluation of the model's dependability and possible areas for development. Analyzing these classification reports aids in understanding the strengths and weaknesses of the model's predictions and facilitates further refinement and optimization of the proposed architectures.

**Table 5** Classification report of Fine-tuned MobileNetV2

| Parameters | Before Fine-tuning | After Fine-tuning |
|---|---|---|
| Accuracy | 91.98 % | 98.40 % |
| Precision | 93.24 % | 99.42 % |
| Recall | 94.84 % | 99.54 % |
| F1-Score | 93.81 % | 99.08 % |

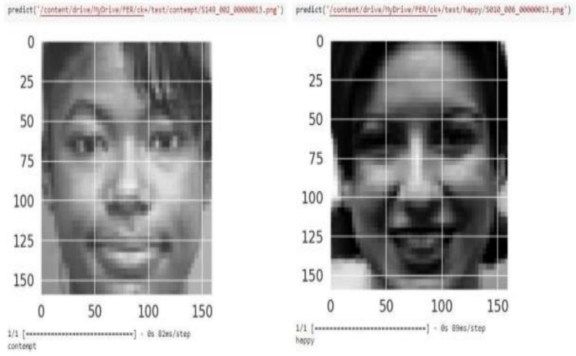

**Fig 8** Random Sample of Test Images

The model's performance was improved after fine-tuning, according to the categorization reports of the recommended fine-tuned architectures. The visual representation of a random sample from the dataset allows for a visual inspection of the model's predictions, providing insights into the accuracy of the classification results and revealing any potential misclassifications or patterns that can further inform the model's performance evaluation and refinement. An evaluation of the model's ability to correctly identify the emotional expressions in the test dataset can be seen visually thanks to the plot of the random sample of two test photos and the predicted and true labels displayed in Figure 8. By contrasting the expected and true labels, we may learn more about the accuracy of the model and identify possible areas for improvement.

## 5. Conclusion

In online classes, students have the opportunity to actively participate in discussions, share ideas, and collaborate with their peers, fostering a dynamic learning environment that promotes interactive and engaging learning experiences. Distance and time restrictions are eliminated via online learning, giving students from all backgrounds and regions access to high-quality education. As online learning becomes more prevalent, there is a growing need to assess engagement of students in virtual classrooms. Using DL approaches, this paper examined various strategies for analyzing the effectiveness of online class. Transfer learning was utilized in this paper to create and verify a DL model based on a pre-trained CNN MobileNet V2. The proposed method was evaluated and validated using a publicly available dataset, CK+. The use of transfer learning and MobileNetV2 with fine tuning had been demonstrated to be a promising approach. With an accuracy rate of up to 98.40%, this approach has proven to be an effective technique for analyzing the effectiveness of online class.

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