

A Proposed Artificial Intelligence Model for Personalized Education Using Facial Emotion Recognition

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Abstract:

Recent advancements in machine learning (ML) have significantly enhanced the detection of face emotions by utilizing innovative algorithms to analyze behavioral data and physiological markers. These models, which include techniques such as deep learning and feature selection, can identify patterns in social interactions, communication styles, and repetitive behaviors, allowing for earlier and more accurate diagnoses compared to traditional methods. In this research, a novel model is proposed that focuses on educating children based on their emotional responses. This model not only aims to detect emotions but also offers educational interventions tailored to the specific emotional needs of the children. The detection of emotional states is developed using YOLOv8 technology, which provides real-time facial recognition and emotion analysis through advanced computer vision techniques. By leveraging this technology, the model can assess facial expressions and body language to identify emotional cues. The integration of these insights into educational content allows for personalized learning experiences that cater to the unique emotional and cognitive profiles of individuals. The YOLOv8 framework can be employed for the purpose of detecting facial emotions, including the precise positions of the eyes, nose, and mouth, subsequent to the successful identification of the face. This approach not only enhances the understanding of emotional dynamics but also fosters a supportive learning environment that can improve social skills and emotional regulation.

Keywords: facial emotion, Learning Strategies, Emotional Development, Positive Reinforcement

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Introduction:

Education for individuals necessitates a tailored approach that addresses their unique learning styles, strengths, and challenges. Key components include the development of Individualized Education Plans (IEPs) that set personalized goals, the creation of structured learning environments with clear routines and visual supports, and the incorporation of social skills training through peer interactions and role-playing[1].

Sensory-friendly spaces and tools can help students manage sensory sensitivities, while the use of assistive technology enhances communication and engagement. Focusing on students' interests and strengths fosters motivation and confidence, and collaboration with specialists ensures comprehensive support. By implementing these strategies, educators can create inclusive and effective learning experiences that empower individuals to thrive academically and socially[2].

Social skills training is essential, often facilitated through peer interactions and role-playing exercises that provide practical experience in navigating social situations. Additionally, sensory-friendly spaces equipped with tools to manage sensory sensitivities can significantly improve students' ability to engage in learning[3].

Evidence-based research provides scientific verification of the effectiveness or lack of significant change in outcomes as a result of an intervention. In education, however, a statistically significant basis for implementing a process or support may not be the whole story. In cases where evaluation by collegial educators, support networks, and other stakeholders identifies student benefits from an intervention, a method of evidence-informed decision making can be valuable [4]. Evidence-informed appraisal has the benefit that it can integrate scientific evidence with informed community opinions[5].

In contemporary education, the use of smart quizzes has emerged as an effective tool for evaluating students' performance based on their skills and understanding of course material. These quizzes leverage technology to provide immediate feedback, allowing educators to assess student comprehension in real-time and adjust instruction accordingly. Research indicates that formative assessments, such as smart quizzes, enhance student

engagement and motivation by offering personalized learning experiences[6].

Children with autism exhibit a unique set of learning skills that are frequently identified in very early infancy. Some preschool-aged autistic children are more proficient than their peers in reading and math. It's possible that these advanced reading and numeracy skills were self-taught through YouTube videos, computer games, and instructional television shows. Some autistic children seem to "crack the code" of reading, spelling, or numeracy with ease; in fact, these disciplines may even become areas of great interest for them in school. On the other hand, some autistic children have significant academic skill delays, and an early evaluation of learning capacities points to the presence of dyslexia and dyscalculia. Given the extremes of cognitive capacity, there appear to be more autistic children than one might anticipate[7].

Instructors often discover that the autistic student in their class has a unique learning profile, frequently demonstrating a knack for sketching or music as well as a logical knowledge of the universe, seeing details and patterns, and memorizing facts. But when it comes to solving problems, the youngster seems to have a "one-track mind" and a fear of failing. They can also be quickly distracted or upset by sensory and social encounters. Teachers see issues with group projects, flexible thinking, and organizational skills as students move through the school grades. School evaluations at the end of the year frequently show a glaringly unequal profile of academic achievement, with both areas that need remedial help and areas of distinction[8].

In this study, we suggested a deep learning and computer vision methodology for identifying facial emotions in children from face photos. It was created because kids must learn to communicate with their typical peers. The proposed method may identify actual face emotions and then give learning materials based on those feelings. The original facial emotion dataset was used to train the model at first. The model then begins interacting with AI platforms to deliver appropriate learning resources.

Related works:

It makes sense that hiding the face with different face coverings would have an impact on emotion recognition, given earlier studies that demonstrated

that facial expression identification is reduced when a section of the face is invisible [9]. Numerous recent studies [10,14] have demonstrated this impact. Visual manipulation can produce input artifacts that may hinder emotion recognition, even while it allows for standardizing emotional indication between mask and no-mask settings [12]. These alterations in the lower half of the face's features can be viewed as elements that aid in expressing mood. For example, in a large smile, the top part of a mask may rise, and the lips' vertical expansion in astonishment may cause it to expand. Additionally, when someone covers their face, their facial expressions may change. Artificially masking faces in photos through photo manipulation can distort the results and hinder a naturalistic investigation of how masks affect the recognition of facial expressions.

Wearing a mask lowers the accuracy of emotion recognition, according to recent studies that looked at masks and facial expression recognition. Nevertheless, not all facial expressions experience the same decline in accuracy. For example, insufficiencies non facial emotion recognition were observed for the emotions of anger, sadness, disgust, and happiness, but not for fear or neutral emotions [11,13]. First, as demonstrated by the study's experimentation with "bubbles," masks covering the lower facial features—such as the mouth, cheeks, and nose—have varying effects on various facial expressions [15]. Furthermore, other methods suggest that the main parts of the face that convey information change depending on the facial expression [16,17]. Analyses of face masking, on the other hand, have revealed variations in the results of concealing the eye against the mouth [18,19].

Bubble-based studies have revealed that when a person is joyful, astonished, or disgusted, the lower portions of their face reveal the most information about their emotional state. When a person is scared or furious, the upper portion of their face gives the most information about their emotional state; when they are sad or neutral, the bottom and upper portions give the same information [16,17]. When comparing the coverage of the lower and upper parts of the face, the best uniform result is that covering the lower area makes it harder to recognize happiness than covering the upper part. However, various emotions have different effects. For example, the authors of [20] found that covering the lips more often suppressed feelings of disgust and rage than covering the eyes, although the authors of [19] discovered the opposite pattern.

In another study, 43 children (ages 2–18) participated in a 12-month observational trial that combined ongoing therapy with the AI-powered CognitiveBotics platform. Significant gains in social and developmental skills are demonstrated by standardized tests (CARS, Vineland, REEL), especially in children with higher functioning levels. There were no significant negative behaviors noted[21].

A study investigates the recommendation and customization of Applied Behavior Analysis (ABA) treatment methods for children with ASD through the use of machine learning (ML) (collaborative filtering, patient similarity). When it comes to incorporating ML into customized treatment planning, this work is leading the way[22].

At initiatives in Arab nations, including communication tools, social engagement aids, and region-specific adaptations, were the subject of a scoping assessment. beneficial for comprehending localization and cultural context[23].

Proposed solution:

A trustworthy diagnosis of autism spectrum disorder (ASD) can be made by the age of two, although symptoms typically start to show in early childhood. ASD has an impact on a child's interactions, communication, and behavior. Key indicators include repetitive behaviors like hand-flapping, repetitious speaking, or strict adherence to routines, as well as social communication difficulties such avoiding eye contact or not answering their name. Despite the lack of a medical test, a professional diagnosis is made based on behavioral observation, and children with ASD can benefit from early intervention with specific educational and behavioral therapy to improve their communication, social skills, and general development.

A controlled, sensory-friendly setting and straightforward, uncomplicated instructions are essential for supporting autistic children's development. Utilize a child's unique interests to encourage participation and include visual aids such as graphic schedules to help with comprehension. Adapt lesson plans to each student's particular strengths and weaknesses, and employ techniques like role-playing, social storytelling, and positive reinforcement to impart critical skills.

Through real-time analysis of body language and facial expressions, the suggested model uses YOLOv8 to determine the emotional states of autistic children, allowing for a greater comprehension of their emotions during educational activities. The methodology creates individualized educational materials based on the child's emotional and learning requirements by gathering data on a variety of emotions, including happiness, frustration, and anxiety. This guarantees that the content is both interesting and pertinent. In addition to improving the child's motivation and academic achievement, this adaptive strategy gives teachers and caregivers insightful information that enables prompt interventions and support that create a more productive and encouraging learning environment.

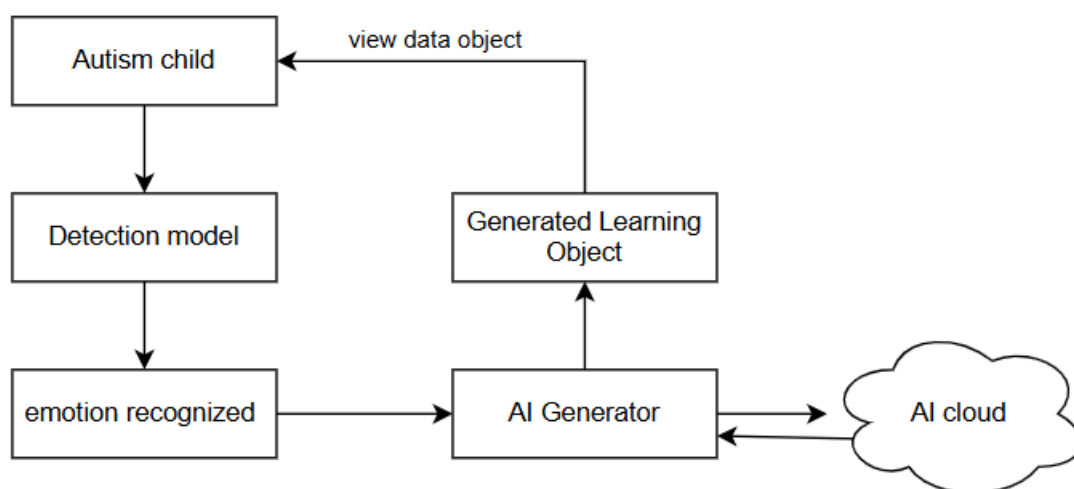


Figure 1: Proposed model architecture

The architecture of the suggested system is depicted in Figure 1. After facial recognition, the identified emotion is transmitted to an AI model, which assesses the emotional data to create educational resources suitable for the autistic child's requirements. This AI-driven approach ensures that the educational materials represent the child's current emotional state, regardless of whether they are happy, anxious, or frustrated. The idea is to create engaging and easily available learning materials, including interactive films, visual aids, or gamified courses, in order to communicate the material in a way that appeals to the child and enhances their understanding and retention. This tailored method effectively addresses the child's emotional and

cognitive needs, which fosters both academic achievement and a supportive learning environment.

To estimate the face emotion, the YOLOv8 analyzes the incoming image or video frame. This module can be used with almost any kind of input source and yet produce consistent results that are adjusted based on the source image's dimensions. These face points are sent into the Face Feature Mapper block, which carries out an additional normalization step using a preset face point as a reference for each sample.

Experiments and results

The dataset was gathered from Roboflow, the biggest source of datasets for our research. The dataset utilized in this study comprises a total of 2447 images, each meticulously labeled to correspond with one of the targeted emotions. To ensure robust model training and evaluation, the dataset is divided into three distinct subsets: a training set, a validation set, and a test set. The training set consists of 2199 images, which are used to teach the model to recognize and differentiate between the various emotional expressions. The validation set, comprising 145 images, serves as a tool for tuning the model's parameters and preventing overfitting during the training process. Finally, the test set, consisting of 103 images, is reserved for evaluating the model's performance on unseen data, thereby providing an objective measure of its accuracy and generalizability.

A YOLOv8 model was successfully trained to recognize and categorize a range of emotional expressions, according to the results of training the model using a dataset of 2447 photos with emotional labels. During the evaluation phase, the model achieved an impressive overall accuracy of 99.5% after being trained. The library used in training is Ultralytics 8.3.78 🚀 Python-3.10.16 torch-2.6.0+cpu CPU (Intel Core(TM) i7-10750H 2.60GHz). Setup complete ✔ (12 CPUs, 15.9 GB RAM, 669.3/930.5 GB disk) in 50 epochs completed in 5.307 hours with the following details:

Table 1: Face emotion detection training results

Class	Images	Precision	Recall	Accuracy	batch-accuracy
overall	145	0.976	0.986	99.5%	0.935
anger	20	1	0.932	99.5%	0.925
contempt	8	1	0.998	99.5%	0.914

disgust	26	1	0.97	99.5%	0.938
fear	11	1	0.976	99.5%	0.933
happy	31	1	0.993	99.5%	0.954
sadness	12	1	0.903	99.5%	0.928
surprise	37	0.993	0.973	99.4%	0.953

The recall-confidence curve illustrates how recall (true positive rate) changes as the model's confidence threshold increases for different emotion classes such as anger, contempt, disgust, fear, happy, sadness, and surprise. At lower confidence thresholds (close to 0.0), recall remains very high—close to 1.0 for all classes—because the model includes nearly all predictions as positives. This means the classifier is very sensitive at low thresholds and rarely misses true positives:

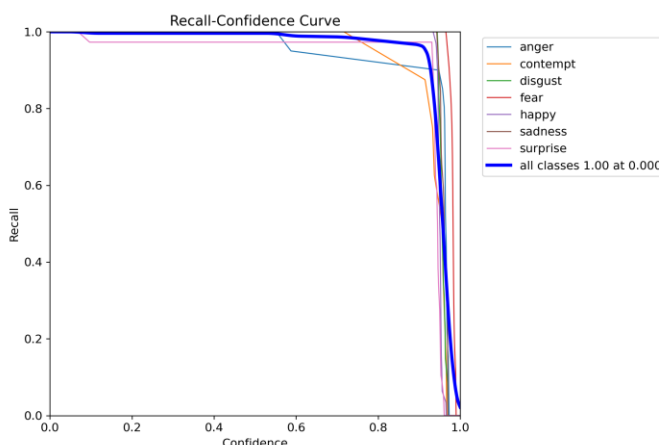


Figure 2: Recall graph

As the confidence threshold rises toward 1.0, recall drops sharply across all classes. This shows that when the model only accepts highly confident predictions, many true positives are excluded, reducing recall. The aggregated curve (blue line) follows the same trend, staying high until around 0.9 before falling steeply. Overall, the figure highlights the trade-off: lower thresholds ensure high recall but may include less confident predictions, while higher thresholds reduce recall in favor of stricter prediction confidence. While precision graph looks like :

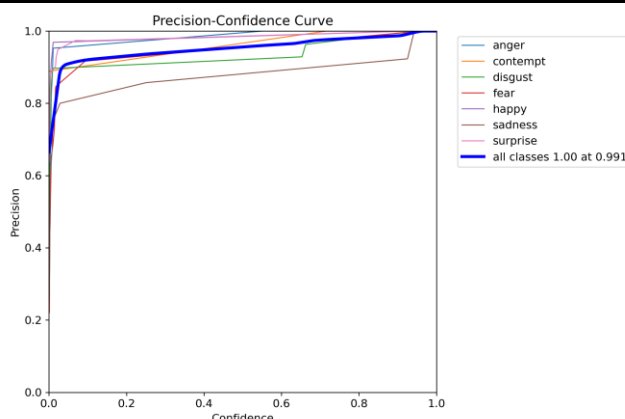


Figure 3: Precision graph

This figure shows a Precision-Confidence Curve for a multi-class classification problem involving different emotion classes (anger, contempt, disgust, fear, happy, sadness, and surprise). The x-axis represents the confidence threshold, while the y-axis represents precision (the proportion of correctly predicted positives among all predicted positives). Each colored line corresponds to a single class, and the bold blue line shows the overall aggregated precision across all classes.

From the curve, we can see that precision generally increases as the confidence threshold rises. At low thresholds, precision starts lower (around 0.6–0.8 depending on the class), since the model includes many less confident predictions that may be incorrect. As the threshold approaches 1.0, precision improves and converges toward 1.0 for most classes, meaning that the model's highly confident predictions are usually correct. The combined curve confirms this trend, reaching nearly perfect precision at a confidence of ~ 0.99 . This highlights the trade-off: stricter thresholds improve reliability of predictions (precision) but risk reducing recall, as seen in the earlier recall-confidence curve. And the f1-score presented as:

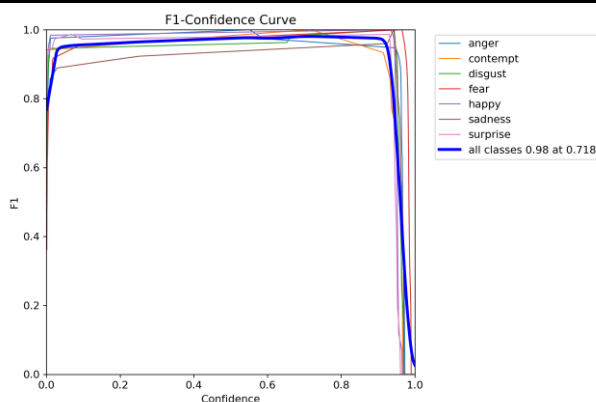


Figure 4: F1-Score graph

This figure presents the F1-Confidence Curve, which shows how the F1-score (the harmonic mean of precision and recall) varies with different confidence thresholds for the emotion classes anger, contempt, disgust, fear, happy, sadness, and surprise. The x-axis represents the confidence threshold, while the y-axis represents the F1-score. Each colored line corresponds to a single class, while the bold blue line shows the aggregated performance across all classes.

The curves indicate that F1-scores are very high (close to 1.0) over a wide range of confidence thresholds, remaining stable from about 0.1 to 0.9. At very low thresholds, the F1-score starts slightly lower due to lower precision, and at very high thresholds (close to 1.0), the F1-score drops sharply as recall decreases. The aggregated curve reaches a peak F1-score of about 0.98 at a threshold of ~0.72, suggesting that this threshold provides the best balance between precision and recall for the overall model. This highlights that the classifier achieves both high precision and recall across most confidence levels, with an optimal trade-off occurring in the mid-range threshold. The confusion matrix for the proposed model is:

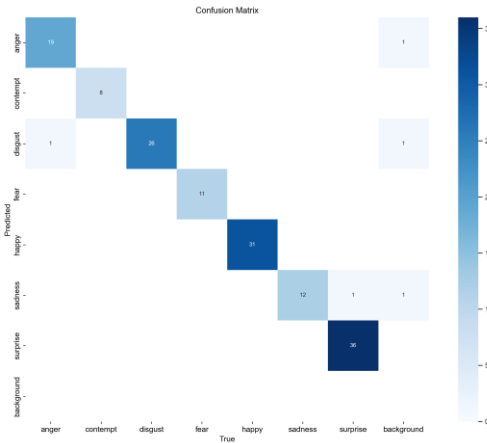


Figure 5: Confusion matrix

Some results for the training batches are as follow:



Figure 6: Training batch 1



Figure 7: Training batch 2

And the evaluation batches are as follow:

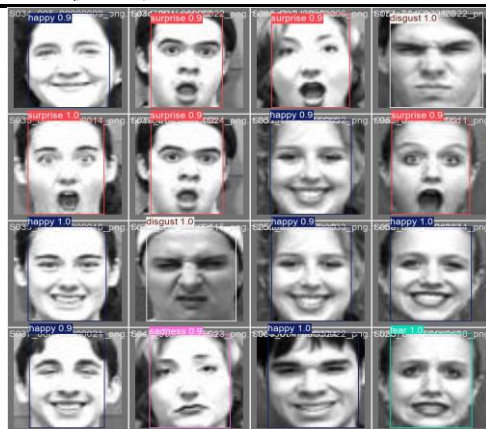


Figure 8: Evaluate batch 1

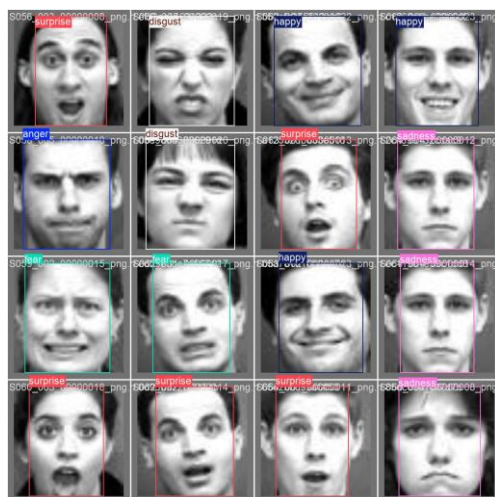


Figure 9; Evaluate batch 2



Figure 10: Prediction results

And the prediction results is:

The YOLOv8 framework is selected for this study due to its state-of-the-art capabilities in real-time object detection, which is essential for applications requiring immediate feedback, such as educational tools that adapt to students' emotional states. The training process involves configuring the model to recognize the seven specified emotions, adjusting parameters to optimize performance, and employing techniques such as data augmentation to enhance the diversity of the training set. The model is trained over a series of epochs, during which it learns to identify patterns and features associated with each emotional expression. The iterative nature of the training process allows for continuous improvement, as the model refines its predictions based on the feedback received from the validation set.

A live camera feed is used to record people in real time, and computer vision algorithms are used to recognize their facial emotions. The system uses a pre-trained deep learning model to identify faces in the video frames and classify emotions like happy, sorrow, rage, and surprise based on facial feature analysis. The projected class and a confidence score are included in the prediction value that the model produces after identifying the emotion. A secondary AI model is then given this prediction in order to produce pertinent learning materials depending on the identified emotion.

Depending on the emotional environment, the AI model generates a customized learning object based on the forecast. This might include interactive tests or educational materials. After being processed, the resulting content is shown on a webpage so that users can interact with it directly. In addition to improving the learning process, this interaction establishes a feedback loop that allows for the tracking of user participation, which may then be utilized to increase the precision of emotion recognition and the pertinence of subsequent learning materials. To guarantee a smooth and safe experience, real-time processing and user privacy must be taken into account at every stage.

Conclusion

In conclusion, this study shows how facial expression detection can be used to improve individualized learning experiences by suggesting learning materials. A detailed knowledge of students' emotional states is made possible by the study's successful identification and classification of seven essential emotions—disgust, rage, contempt, fear, happiness, sorrow, and

surprise—using a strong dataset and the YOLOv8 model. Accurately identifying these emotions enables teachers and educational systems to modify interventions and instructional materials to fit the unique needs of each student.

In our opinion understanding an autistic child's learning profile is crucial for parents and teachers to help them succeed academically. This is particularly crucial because kids typically go to school for two reasons: to study and to make friends. Academic achievement becomes increasingly significant as the main incentive to attend school and for the development of self-esteem and self-identity if the autistic youngster struggles socially.

Also, formal testing using standardized IQ and academic performance assessments can yield important information about a child with autism's learning characteristics. At least ten subtests measuring a variety of intellectual skills are included in standardized IQ tests. Specific verbal reasoning components are measured by some subtests, whereas visual reasoning components are measured by others.

This strategy has significant ramifications; teachers can encourage increased motivation, engagement, and memory of knowledge by matching instructional materials to students' emotional reactions. In addition to improving the educational process, this strategy helps kids grow their emotional intelligence, giving them the tools they need to deal with social situations and personal obstacles.

Machine learning (ML), in my opinion, is used in autism therapy to determine strengths and requirements, enhance social skills training, boost communication, and customize and modify learning. As a result, the learning process is more efficient and personalized. Examples of AI-powered tools that help teachers create flexible learning settings for autistic children include robots and virtual assistants. These tools offer real-time feedback and progress tracking.

Future studies should concentrate on improving the model's accuracy and investigating how to incorporate it into actual learning environments. Furthermore, confirming the effectiveness of this strategy will need examining the long-term impacts of emotion-based learning strategies on both academic achievement and emotional health. At the end, this research establishes the foundation for creative teaching methods that use emotional

insights to produce more flexible and responsive learning environments, opening the door to a time when education encompasses more than just acquiring knowledge; it also entails comprehending and fostering students' emotional landscapes.

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