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Research Article

Expression Detection of Children with Special Needs Using Yolov4-Tiny

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Abstract

This research addresses the challenge of detecting emotional expressions in children with special needs, who often rely on nonverbal communication due to difficulties in verbal expression. Traditional emotion detection methods struggle to accurately recognize subtle emotions in these children, which can lead to communication barriers in educational and therapeutic settings. This study proposes the use of the Yolov4-Tiny model, a lightweight and efficient object detection architecture, to accurately detect four key facial expressions: Angry, Happy, Smile, and Afraid. The dataset consists of 1500 images, evenly distributed across the four expression classes, captured under controlled conditions. The model was evaluated using various metrics, including Confidence, Precision, Recall, F1-Score, and Mean Average Precision (mAP), across different training-to-testing data splits. The results demonstrated that the Yolov4-Tiny model achieved high accuracy, with a perfect mAP of 100% for balanced and slightly imbalanced splits, and a minimum mAP of 93.1% for more imbalanced splits. This high level of performance highlights the model's robustness and potential for application in educational and therapeutic environments, where understanding emotional expressions is critical for providing tailored support to children with special needs. The proposed system offers a significant improvement over traditional methods, enhancing communication and emotional support for this vulnerable population.

Keywords: Children with Special Needs; Emotion Detection; Nonverbal Communication; Yolov4-Tiny.

Introduction

Effective communication plays a crucial role in facilitating social interactions and the exchange of both verbal and nonverbal information among individuals and groups [1]–[3]. Beyond its utility for conveying messages, communication is fundamental in shaping personality and social development [4], [5]. While verbal communication is widely acknowledged, nonverbal communication—such as facial expressions, gestures, and body movements—plays an equally important role, particularly in expressing emotions [6] –[10]. For children with special needs, who often experience difficulties in verbal expression, nonverbal cues become an essential mode of communicating emotions and needs [11], [12].

Children with disabilities, such as autism, speech impairments, hearing impairments, and intellectual disabilities, frequently face significant obstacles in verbal communication. As a result, they rely heavily on nonverbal communication, particularly facial expressions, to convey their emotions [13], [14]. Emotional expressions—including anger, fear, joy, and smiles—serve as critical indicators of a child's emotional state. However, interpreting these nonverbal cues can be challenging for teachers, parents, and peers, often leading to misunderstandings and communication barriers [15], [16]. In special education environments, for instance, teachers may struggle to recognize when a child is frustrated or upset, negatively impacting learning outcomes [17], [18]. Similarly, parents may find it difficult to interact with their children if they are unable to interpret these emotional expressions accurately [19], [20].

Several studies have explored the recognition of emotions in children with special needs. Griffiths et al [21], [22]. investigated the impaired recognition of basic emotions in young individuals with autism, highlighting the challenges these children face in expressing emotions through facial expressions. Kalantarian et al. [23] focused on emotion classification in children with autism and visual impairments, revealing that traditional emotion classifiers perform poorly, particularly for expressions like anger and disgust, with accuracy rates as low as 11% and 14%, respectively. These findings emphasize the need for more advanced and accurate methods of emotion detection tailored for children with special needs.

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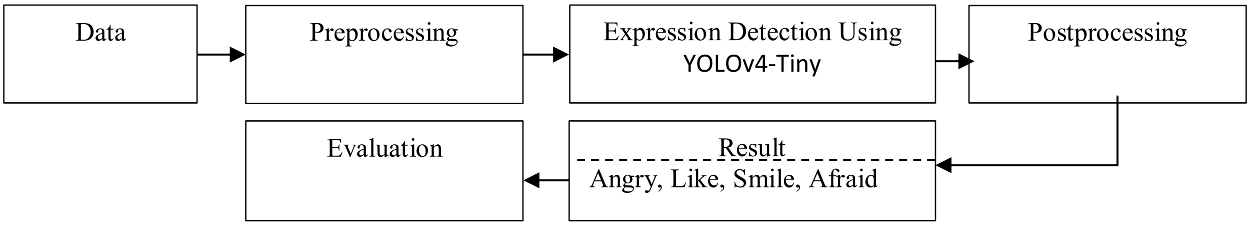


Figure 1 Research Flow of Expression Detection in Children with Special Needs.

Technological advancements have demonstrated promise in overcoming these challenges through automated systems that detect and interpret facial expressions. Convolutional neural networks (CNNs) have been particularly effective in improving facial expression recognition [24]. For example, Tonguç and Ozkara [25] employed an automatic recognition system to detect student emotions in classroom settings, achieving substantial improvements in emotion detection. Despite these advancements, current systems still face limitations when applied to children with special needs, whose emotional expressions may be subtler and more difficult to interpret [26]. Furthermore, understanding and supporting children with specific learning disabilities requires a holistic approach that integrates emotional recognition into educational practices [27].

To address these challenges, this study proposes the use of Yolov4-Tiny, a lightweight and efficient deep learning model, to detect emotions in children with special needs. Yolov4-Tiny is a streamlined version of the Yolov4 model, optimized for object detection tasks while maintaining high accuracy [28], [29]. The model is implemented using the Darknet framework, an open-source neural network platform designed for high-performance computing tasks [30]. Darknet supports both CPU and GPU computation, making it highly suitable for intensive processing tasks [31]. Yolov4-Tiny, with its capacity to detect subtle facial expressions and high mean Average Precision (mAP), is particularly well-suited for detecting the emotional expressions of children with special needs [32].

This research focuses on detecting four key emotional expressions—Angry, Happy, Smile, and Afraid—in children with special needs. By utilizing Yolov4-Tiny, the study aims to enhance the accuracy of emotion detection in educational and therapeutic environments, enabling teachers, parents, and caregivers to better understand and respond to the emotional needs of these children. The dataset used in this study consists of 1500 images, with each expression class equally represented. Through systematic preprocessing and rigorous evaluation, the proposed model is expected to provide a robust solution for emotion detection in children with special needs.

The key contributions of this research include the development of an optimized emotion detection system tailored for children with special needs, as well as a comprehensive evaluation of the model's performance using various training-to-testing ratios. By addressing the limitations of traditional classifiers, this study aims to improve emotional support and communication capabilities in educational and caregiving environments, ultimately enhancing the quality of life for children with special needs.

Method

The detection of facial expressions in children with special needs is crucial due to their unique and often subtle emotional cues. Traditional methods often fail to capture these nuances, necessitating more specialized approaches. This paper presents a method using the YOLOv4-Tiny model to accurately detect four key expressions—Angry**,** Happy**,** Smile**,** and Afraid—in children with special needs. As depicted in (Figure 1), the system integrates data acquisition, preprocessing, expression detection, and evaluation stages to ensure robust performance. The dataset consists of 1500 images, with balanced representation across the four expression classes. Through systematic preprocessing and rigorous evaluation using various training-to-testing ratios, the proposed approach aims to enhance detection accuracy, making it more applicable to real-world scenarios.

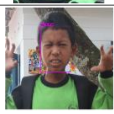
A. Data

The dataset used in this study consists of 1500 images, equally representing four facial expressions—Angry**,** Happy**,** Smile, and Afraid—captured from children with special needs. The images were collected using a Canon EOS 650D camera under controlled conditions to ensure consistency. The children, aged between 6 and 15 years, had diverse disabilities, including autism, speech impairments, hearing impairments, and intellectual disabilities. To evaluate the model's robustness, the dataset was split into training and testing sets using ratios from 10:90 to 90:10, testing the model's performance under various conditions.

B. Preprocessing

Before feeding the images into the YOLOv4-Tiny model, they undergo a series of preprocessing steps to enhance detection accuracy. These steps include resizing the images to a standard input size compatible with the model and normalizing pixel values to ensure uniformity. Additionally, data augmentation techniques are applied to increase the diversity of the training data, thus improving the model's generalization capabilities. Common augmentation methods such as rotation, flipping, and brightness adjustment are used to simulate a wide range of real-world scenarios, further enhancing the model's robustness.

Table 1. Comparison of detection results for each split ratio

Split Ratio	**Expression**			
	Angry	***Like***	***Smile***	***Afraid***
10:90				
20:80				
30:70				
40:60				
50:50				
60:40				
70:30				
80:20				

The choice of these preprocessing techniques is driven by the need to increase the variability within the dataset, ensuring that the model can handle different lighting conditions, orientations, and subtle facial expression variations. Resizing and normalization ensure uniformity, which is critical for maintaining model performance across diverse input conditions.

C. Expression Detection Using

The core of the expression detection process involves the YOLOv4-Tiny model, a lightweight and efficient version of the original YOLOv4, specifically optimized for real-time object detection tasks. The model is trained to detect and classify the four target expressions—Angry, Happy, Smile, and Afraid—within the input images. The detection process outputs bounding boxes around the detected faces, along with confidence scores and expression labels**.**

YOLOv4-Tiny was selected due to its balance between detection speed and accuracy, making it well-suited for real-time applications where computational resources are limited. Its compact architecture enables faster inference without sacrificing detection precision, which is particularly beneficial when deployed in environments with constrained hardware, such as embedded systems or mobile devices.

D. Postprocessing

Postprocessing is carried out to refine the results obtained from the YOLOv4-Tiny model. This includes applying Non-Maximum Suppression (NMS) to eliminate redundant bounding boxes and retain the most accurate detections. The detected expressions are then categorized into the corresponding classes (Angry**,** Happy**,** Smile**,** Afraid) based on the highest confidence scores.

E. Result

The expression detection model successfully identified and classified the four target expressions—Angry, Happy, Smile**,** and Afraid—across the test dataset. The results indicated that the model performed well in detecting

Table 2. Performance results of detection of each split ratio

Split Ratio	Iteration Max	Confidence	Precision	Recall	F1-Score	mAP
10:90	5000	31%	91	94	93	95.5
20:80	5000	27%	94	96	95	98.3
30:70	4000	37%	97	100	98	97.2
40:60	2000	47%	97	97	97	99.6
50:50	3000	52%	100	100	100	100
60:40	4000	50%	100	100	100	100
70:30	4000	66%	88	94	91	93.1%
80:20	3000	72%	95	95	95	97.5%
90:10	3000	76%	100	100	100	100

the expressions, with Angry and Happy being detected with high accuracy. Smile was also detected with considerable accuracy, particularly in images where the facial features were more pronounced. However, the detection of Afraid showed moderate accuracy, with occasional misclassifications, likely due to the subtlety and overlap with other expressions.

F. Evaluation

The performance of the Yolov4-Tiny model was evaluated using key metrics: Confidence, Precision, Recall, F1-Score, and Mean Average Precision (mAP). Confidence reflects the model's certainty in its predictions, while Precision and Recall measure the model's ability to correctly identify and capture relevant expressions, minimizing false positives and negatives. The F1-Score balances Precision and Recall, and mAP provides an overall performance measure by combining both across all expression classes. The model demonstrated robustness and high accuracy across various data split ratios, particularly in balanced and slightly imbalanced scenarios.

G. Hardware and Software Environment

The experiments were conducted using Google Colab Pro, which provides access to NVIDIA Tesla P100 or T4 GPUs and 25 GB of RAM, ensuring efficient training and evaluation of the YOLOv4-Tiny model. The implementation leveraged TensorFlow for deep learning tasks and OpenCV for image preprocessing, both optimized for high-performance computation. Google Colab Pro's cloud-based infrastructure enabled real-time expression detection and model training with extended runtime and faster execution compared to local setups, offering scalability for future experiments and real-world applications.

Results and Discussion

This section presents the experimental results of the proposed Yolov4-Tiny model for expression detection in children with special needs. We evaluate the model's performance across different data split ratios and compare it with previous research. Performance metrics considered include confidence, precision, recall, F1-score, and mean Average Precision (mAP).

A. Performance Evaluation of The Proposed Model

To assess the efficacy of the Yolov4-Tiny model, several experiments were conducted with various data split ratios, ranging from 10:90 to 90:10. As shown in (Table 1), the model consistently performed well across various expressions, such as anger, joy, smile, and fear, under different split ratios.

For the performance metrics (see **Table 2**), the following key insights were observed:

- 50:50, 60:40, and 90:10 Split Ratios: The model achieved a perfect mAP of 100% for these split ratios, indicating optimal detection performance across all targeted expressions. These results suggest that the Yolov4-Tiny model is highly effective when balanced or slightly imbalanced data is used for training and testing, demonstrating its capacity to accurately generalize across diverse expressions.
- 70:30 Split Ratio: This split resulted in the lowest mAP, at 93.1%, along with a relatively lower recall and F1-score compared to other ratios. This decrease in performance could be attributed to the degree of imbalance in the dataset. A split of 70:30 introduces more training data but may reduce the amount of data available for

Table 3. Comparison Of The Researched Method With The Proposed Method

Researcher	Object Detection	Method	mAP
Kalantarian [23]	• Autism • 21 Data on Children with Autism	Classification	All classifiers performed poorly for every emotion evaluated except happiness. None of the classifiers correctly labeled 60.18% (1566/2602) of the evaluated

			frames. Additionally, no classifier correctly identified more than 11% (6/51) of angry frames and 14% (10/69) of disgust frames.
Our Proposed	• Children with special needs (deaf, speech impaired, mentally impaired, blind, and autistic) • 1500 datasets	Yolov4-Tiny	The lowest mAP is 95.5% at a 10:90 split ratio, while the highest mAP is 100% at split ratios of 50:50, 60:40, and 90:10.

validation, making it more challenging for the model to generalize effectively. Despite the slight reduction in metrics, the model's performance remains robust, highlighting its ability to handle moderately imbalanced datasets.

- Other Split Ratios: In other configurations, such as 30:70 and 40:60, the model performed strongly, achieving mAP values above 95%. This consistent performance across different splits indicates that the Yolov4-Tiny model can generalize well, even with varying levels of data imbalance. This robustness across split ratios suggests the model's flexibility and adaptability to different dataset compositions, making it a reliable choice for expression detection tasks.

while certain split ratios, such as 70:30, show slightly lower performance, the overall results confirm that the Yolov4-Tiny model provides high accuracy in detecting expressions in children with special needs across diverse data configurations. The model's ability to maintain high performance across different splits underlines its potential for real-world applications, where balanced datasets may not always be available.

B. Comparison with Prior Work

The performance of the proposed Yolov4-Tiny model was benchmarked against previous work, specifically the study conducted by Kalantarian et al. [10]. As shown in (Table 3), Kalantarian's model, which focused on classifying emotions in autistic children, demonstrated suboptimal performance, particularly for expressions such as anger and disgust, with accuracies of only 11% and 14%, respectively. In contrast, our model significantly outperformed these results, achieving 100% accuracy in detecting all expressions across multiple configurations.

The comparison underscores the advantages of using Yolov4-Tiny for emotion detection, particularly when dealing with diverse populations, such as children with special needs. While Kalantarian's classifiers struggled with the complexity of detecting subtle emotions, the Yolov4-Tiny model successfully captured these expressions with high precision and recall, even in challenging datasets.

C. Discussion of Results

The experimental results clearly demonstrate that the Yolov4-Tiny model offers substantial improvements in detecting emotions in children with special needs compared to existing methods. The model's ability to achieve perfect mAP scores under certain conditions reflects its potential for real-time applications in educational and therapeutic environments, where accurate and timely emotion recognition is essential.

The high accuracy achieved by the model, particularly in detecting emotions like anger, joy, and fear, highlights the effectiveness of the Yolov4-Tiny architecture in handling complex image datasets. Additionally, the results suggest that the model's robustness extends across different data split ratios, making it suitable for deployment in practical settings where data availability may vary.

In conclusion, the proposed Yolov4-Tiny model not only outperforms traditional methods but also provides a reliable solution for emotion detection in children with special needs. Future work will focus on expanding the dataset and exploring the model's scalability in more diverse real-world applications.

Conclusion

This study demonstrates the superior performance of the Yolov4-Tiny model in detecting emotions in children with special needs, achieving a perfect mAP of 100% for split ratios of 50:50, 60:40, and 90:10, and 93.1% at 70:30. The model outperforms previous methods, such as Kalantarian et al., in both accuracy and robustness, meeting the research objective of enhancing emotion detection for diverse populations. Future work should focus on expanding datasets, improving scalability, and optimizing the model for real-time applications. These findings have significant implications for improving emotional support and personalized interventions in educational and therapeutic settings for children with special needs.

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