Modeling Facial Recognition in Atypical Emotional Processing Using Neural Networks

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Abstract

Emotion recognition is essential for effective social communication, yet this ability can be impaired in neurodivergent conditions such as autism spectrum disorder, psychopathy, and alexithymia. This project uses a biologically inspired neural network model to simulate facial emotion recognition and investigate how these conditions may alter emotional processing. A baseline feedforward neural network was first developed using the extended Cohn-Kanade (CK+) dataset, which contains grayscale images categorized by seven primary emotions. The model was trained on preprocessed 48×48 pixel images and initially used a single hidden layer with sigmoid activation. Performance was then improved through architectural modifications, including switching to ReLU activation, adding hidden units, applying dropout regularization, and the Adam optimizer, and eventually converting the model to a convolutional neural network (CNN). Finally, the network is adapted to simulate emotion recognition deficits observed in individuals with Autism Spectrum Disorder (ASD), psychopathy, and alexithymia, such as reduced sensitivity to subtle expressions or emotional class biases. The resulting models revealed distinct recognition patterns, demonstrating how machine learning can be used to explore and simulate atypical cognitive and affective processing.

1 Introduction

Animals have evolved to develop many different forms of communication [9]. From birds singing songs to releasing chemicals to ward off predators, each species has its own unique way of conveying messages for various purposes. In the same way. humans have developed diverse methods of communication, such as verbal speech, physical body signals, and emotional cues [9]. A particularly significant form of human communication, and the focus of this paper, is the use of facial expressions [9]. Facial expressions serve as a nonverbal visual cue that conveys emotion and information, allowing individuals to communicate their feelings and intentions without words [10]. This paper explores how facial expressions are used to communicate emotions, specifically in the context of emotion recognition systems and the role they play in both human interaction and computational models designed to interpret these expressions [6].

Understanding and recognizing facial emotions is a fundamental aspect of human social interaction [9]. However, individuals with neuro-divergent conditions such as autism spectrum disorder (ASD) and psychopathy often exhibit impairments in processing and recognizing emotions, particularly subtle facial expressions [1], [2]. These difficulties can significantly impact social functioning, communication, and interpersonal relationships [1]. As a result, there has been growing interest in leveraging computational models to simulate and analyze facial emotion recognition, not only for diagnostic purposes but also for developing potential therapeutic interventions [11].

Prior research has explored a wide range of computational methods for facial emotion recognition [4]. Early studies used shallow feedforward neural networks to classify emotional states from static images, achieving moderate success by mapping raw pixel input to discrete emotional categories [3].

More recent work has adopted convolutional neural networks (CNNs), which are able to extract spatial features from facial images and improve classification performance on datasets like CK+, JAFFE, and FER-2013 [5]. In a recent research journal [5], research on facial emotion recognition systems highlighted that positive emotions like happiness and surprise are typically recognized with the highest accuracy, while negative emotions such as anger and disgust remain more challenging for AI models [5]. Their review also found that complex hybrid models, such as the Generalized Feedforward Neural Network (GFFNN), which achieved 100% accuracy in some cases, outperformed traditional approaches [5]. Importantly, CK+ was identified as one of the most widely used datasets across studies, although it did not yield the highest mean accuracy when compared to alternatives like SAVEE [5]. The study also emphasized the relevance of artificial network systems in healthcare applications, such as mental health monitoring, pain detection, and emotional support in elderly care [5]. In addition to performance-focused models, other researchers have explored how modifying network design or training constraints can simulate atypical emotional processing, such as in autism or alexithymia, providing a bridge between computational modeling and cognitive neuroscience [8].

In this project, the use of artificial neural networks (ANNs) for emotion recognition are examined, using the CK+ dataset, which contains images of facial expressions corresponding to different emotional states [5]. Our baseline approach employs a simple biologically inspired neural network that mimics early affective processing in the brain [5]. This network utilizes sigmoid activation functions and a simple architecture to classify facial expressions. To assess the potential for improvement, this baseline model is compared with a Convolution Neural Network (CNN), a more advanced architecture that is specifically designed to take advantage of spatial patterns in image data for more accurate classification [6].

By comparing the performance of these models, the aim of this experiment is to investigate how the complexity of the neural network architecture affects the accuracy of emotion recognition. This comparison is particularly relevant in the context of understanding atypical emotional processing in individuals with conditions such as autism, alexithymia, and psychopathy, which are often associated with difficulties in recognizing emotional signals [8].

2 Methodology

This project used the extended Cohn-Kanade (CK+) dataset, which contains grayscale facial images labeled by emotion [7]. The dataset includes 910 png images categorized into eight emotion classes: anger, disgust, fear, happiness, sadness, surprise, neutral, and contempt [7]. For consistency in training, all images were resized to 48×48 pixels and converted into normalized tensors [7].

Figure 1: Samples of Each Emotion in the Cohn-Kanade (CK+) dataset

The experiment began with the creation of a simple baseline feedforward neural network aimed at classifying images into one of the seven primary emotions [5]. The dataset was randomly split into training and testing sets in an 80/20 ratio. The architecture consisted of one hidden layer with sigmoid activation, a dropout layer to reduce overfitting, and a final linear output layer. The model was trained using stochastic gradient descent (SGD), and then tested how varying the number of hidden units (16, 32, 64, 128) affected validation accuracy.

To improve the model's performance, several modifications were introduced. First, the sigmoid activation function was replaced with the Rectified Linear Unit (ReLU), which allowed for faster convergence and mitigated the vanishing gradient problem. The optimizer was also changed to Adam, known for its adaptive learning rate and efficient training. Dropout regularization was retained, and the number of hidden units was increased to enhance the network's ability to learn more complex patterns. Finally, the model was converted into a Convolutional Neural Network (CNN) by incorporating convolutional and pooling layers followed by dense layers, allowing it to better extract spatial features from facial expressions [6].

To simulate differences in emotion perception seen in certain neurodivergent populations, specific constraints were introduced to the neural network architecture. For Autism Spectrum Disorder (ASD), the model's responsiveness to social emotions such as fear and surprise was intentionally dampened by reducing the learning rate for those emotion classes, mimicking reduced sensitivity to social cues [1]. In the case of psychopathy, the network was modified to show selective insensitivity to emotions like fear and sadness by adjusting the loss contribution or suppressing output activations linked to those categories [2]s. For alexithymia, the model's capacity to distinguish between closely related emotions was impaired by increasing class confusion through label smoothing or added weight decay, reflecting challenges in emotional awareness and verbal expression [3].

3 Results

3.1 Baseline Neuron Model

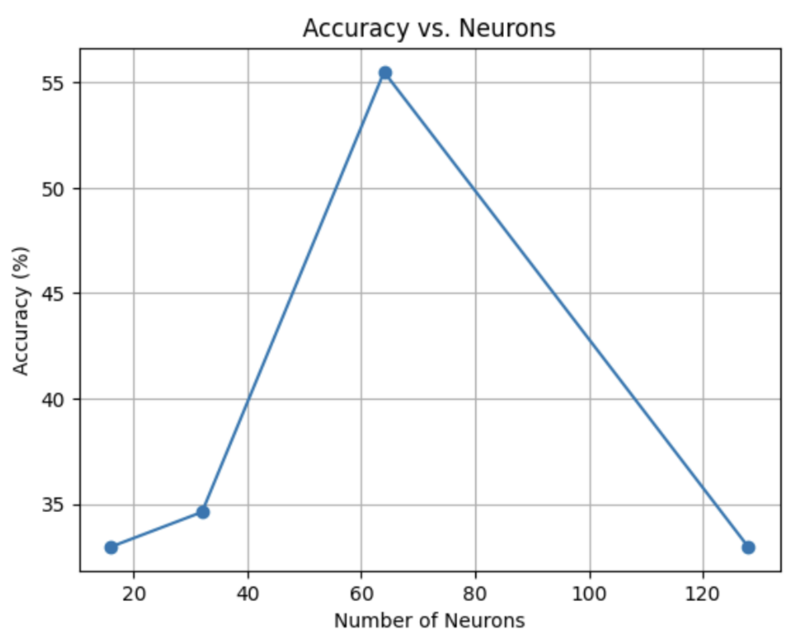

Figure 2: Emotion Recognition Accuracy Under Different Network Sizes

The figure above shows the accuracy of emotion recognition for the baseline neuron model, implemented as a simple, biologically inspired feedforward neural network with a hidden layer and sigmoid activation. The model was trained on grayscale images from the CK+ facial expression dataset, resized to 48×48 pixels and normalized. The number of neurons in the hidden layer was varied 16, 32, 64, and 128, to evaluate how network capacity influences performance. As shown in Figure 2, classification accuracy ranged from approximately 33.0% to 55.5%. Performance peaked around 60 to 70 units at 55.49% accuracy, indicating that even shallow networks can begin to extract emotional features with success.

3.2 Improvements

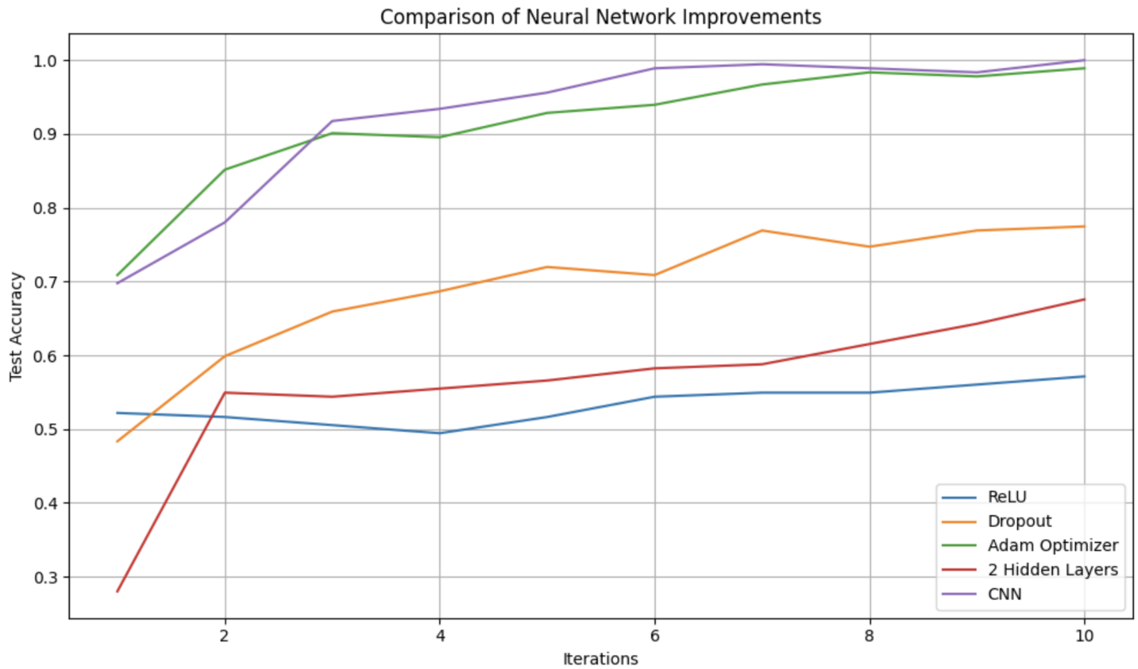

Figure 3: Accuracy Improvements from Neural Network Adaptations

The figure above displays the testing accuracies of emotion recognition for a series of improvements made to the baseline model. These improvements included a conversion from sigmoid to ReLU activation, the addition of dropout regularization, switching the optimizer from SGD to Adam, adding two hidden layers, and finally converting the architecture into a Convolutional Neural Network (CNN).

3.3 Atypical Emotion-Processing Modifications

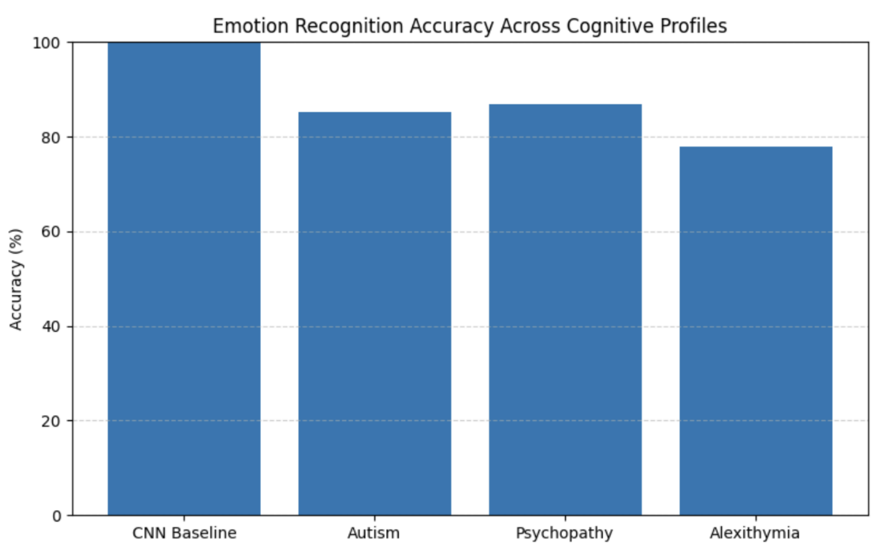

Figure 4: Comparative Accuracy of Emotion Recognition Across Neuro-cognitive Profiles

The model was adapted to simulate emotion recognition challenges associated with autism, psychopathy, and alexithymia. For autism, sensitivity to subtle emotions like sadness and fear was reduced. In psychopathy, weights associated with distress-related emotions such as fear and sadness were reduced, while recognition of dominant expressions like anger remained high. For alexithymia, emotional categories were merged or flattened. Figure 4 represents a comparison of maximal accuracies across the neurodivergent conditions with the modified CNN. The modifications did not significantly reduce the model's accuracy, with the lowest accuracy observed in the alexithymia condition at approximately 78.02%.

Model type	Accuracy (%)
Baseline	55.49
ReLU	57.14
Dropout	77.47
Adam optimizer	98.90
Hidden layers	67.58
CNN	100.00
Autism	85.16
Psychopathy	86.81
Alexithymia	78.02

Table 1: Maximal Performance Across Neuron Model Variants

This table presents a comparison of different neural network configurations used for emotion recognition in facial expressions, including a baseline model, enhanced versions with various improvements, and models adapted for neurodivergent conditions such as autism, psychopathy, and alexithymia. The table summarizes the maximal accuracies achieved by each model variant during testing, providing insights into the performance of each approach and highlighting the impact of model adjustments on emotion recognition accuracy.

4 Discussion

In this paper, the baseline model served as a foundational benchmark for emotion recognition from facial images. It consisted of a single hidden-layer neural network with sigmoid activation and dropout for regularization. The performance of this model highlighted the limitations typically associated with shallow architectures and sigmoid activations, specifically slower convergence and difficulty in capturing complex features due to vanishing gradients [5].

After training, the baseline model achieved moderate classification accuracy, with a final testing accuracy that plateaued at around 33%. This result is significantly lower than human-level performance in emotion recognition, which typically ranges from 78% to 100% [12]. These accuracies remain relatively low compared to typical human behavior in similar tasks, suggesting that the baseline model is limited in its ability to emulate human-like emotional perception [12]. Notably, only a single training pass was performed per configuration, simulating early-stage neurobiological processing with minimal optimization. This approach emphasized raw learning potential, reinforcing the need for further architectural and functional improvements in later stages of the project [5]. While the model could capture basic emotional patterns from the dataset, it lacked the representational power needed to generalize effectively across all emotion categories [5].

Following these insights, various adaptations were implemented to improve the model's performance, leading to dramatic increases in accuracy, with the modified models reaching up to 100% accuracy [6]. Each modification was applied sequentially to assess its effect on performance. The ReLU activation function enabled better gradient propagation, addressing issues with vanishing gradients. Dropout helped mitigate overfitting, and the Adam optimizer provided adaptive learning rates, enhancing training efficiency. The addition of hidden layers increased the model's representational power. Lastly, the incorporation of a Convolution Neural Network (CNN) enabled more effective spatial feature extraction from facial images [5]. Of the models tested, the CNN model achieved the highest accuracy at 100%, while the Adam Optimized model followed closely with an accuracy of 98.9%.

The CNN model emerged as the best-suited model, achieving the highest overall accuracy and demonstrating consistent performance across repeated runs [6]. Its ability to extract spatial features effectively, combined with its stability and strong empirical support in literature, made it the most appropriate choice for further applications, such as the atypical emotional processing simulations [6]. Additionally, CNNs are more widely supported by well-documented research, making them a more reliable choice for further analysis [6]. Consequently, the CNN architecture was chosen for continued experimentation, particularly in simulations involving neurodivergent conditions [6].

When applied to neurodivergent conditions such as autism, psychopathy, and alexithymia, the accuracy of the model was reduced as expected but not significantly [8]. Modifications to the model, aimed at reducing detection accuracy for specific emotions typically observed in these conditions, did not completely interfere with the model's capacity to recognize certain facial expressions and emotion [11]. This suggests that while the model's efficiency in emotion recognition may decrease for these conditions, it can still learn and identify emotional cues, albeit at a lower efficiency [11]. Additionally, the model can also provide a framework for understanding how emotional recognition differs in individuals with neurodivergent conditions [11].

This work has practical implications for understanding emotion recognition in neurodivergent individuals. By simulating conditions like autism, psychopathy, and alexithymia, the improved models offer insights into the challenges these individuals face when interpreting emotional cues. Moreover, these models provide a more objective way to study emotional processing in neurodivergent populations and could inform the development of assistive technologies or interventions aimed at improving social interactions. Overall, the findings contribute to the broader understanding of emotion recognition, with potential applications in areas such as healthcare, therapy, and social support.

5 References

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