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ORIGINAL STUDY

Facial Expression Recognition and Classification for Autism Spectrum Disorder based on SDFT Images using Deep Learning

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ABSTRACT

Autism spectrum disorder (ASD) is a prevalent condition in childhood, affecting around 1 in 44 individuals. Approximately 53% of children with ASD exhibit one or more challenging behaviors (CBs), which include aggression, self-injury, property destruction, elopement, and more. This percentage is significantly higher compared to their typically developing peers or those with other developmental disorders. Cognitive-behavioral therapy (CB) has numerous detrimental effects on the individual, all of which are linked to an unfavorable long-term result. When it comes to caregivers of children with ASD, the presence of Challenging Behaviors (CB) is a more dependable indicator of stress than the intensity of the child's primary ASD symptoms. This study examines the use of fixed facial traits extracted from photographs of autistic children as a biomarker for distinguishing them from healthy children.

This research extracts characteristics from the power spectrum density (PSD) got using t-f (SDFT) analysis of each autism face image. The acquired characteristics are then input into a convolution neural network (CNN) to classify the face image as autistic (happy, angry,..etc.) or not. The accuracy of this study's given result that used the SDFT of the image is 52%, and that of the original face image is 44%, and if used the transfer learning for the original face image, it has up from 44% to 85%.

Keywords: Computer vision, Machine learning, SDFT, CNN, Autism spectrum disorder, Behavioral science

1. Introduction

Autism spectrum disorder (ASD) is a group of neurodevelopmental diseases defined by a lack of verbal and nonverbal communication during the first three years of life. Atypical social behaviors include eye contact avoidance, emotional management or empathy issues, and a narrow range of interests and activities [1]. ASD currently affects between 1% and 2% of the population, according to recent large-scale surveys [2, 3]. ASD has been more common during the previous two decades [4]. Although the average age of diagnosis has decreased and the DSM diagnostic criteria have changed, an increase in risk variables cannot be entirely excluded [5, 6]. According to research [2, 3, 7], males are two to three times more likely than women to have ASD. The under recognition of female ASDs might be the source of this diagnostic bias in favor of males [8]. Furthermore, several studies have proposed that women may have unique protective effects against ASD [9].

The DSM-4 previously classified autism into four distinct disorders: Asperger Syndrome, Autistic Disorder, Pervasive Developmental Disorder Not Otherwise Specified (PDD-NOS), and Childhood Disintegrative Disorder. The diagnosis of autism spectrum disorder (ASD) is formed by combining these four classes in the Diagnostic and Statistical Manual of Mental Disorders-5 (DSM-5). ASD was categorized into severity levels by the DSM-5 based on the extent

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of deficits in social communication and repetitive and limited activities. As for the categorization, the severity levels are as follows: Level 1 (requiring support), Level 2 (requiring substantial support), and Level 3 (requiring major support) [10]. Even though clinicians use standardized diagnostic instruments to diagnose ASD, one key disadvantage of the technique is that using diagnostic tools takes a significant amount of time "to complete the evaluation and interpret the results" [11]. An innovative machine-learning strategy has been proposed to address this issue. The primary objective of machine learning research in ASD diagnosis is to improve diagnostic accuracy while decreasing diagnostic time. Reduced diagnostic time enables ASD patients to get timely intervention. The machine learning approach seeks to discover the top ASD features by lowering the dimensionality of relevant input data. The motivation of this research is a study of using Sliding Discrete Fourier Transform for images and the effect on classifying ASD by depending on facial expression deep learning method approach. And improve this method by using transfer learning.

1.1. Literature review

According to the study, the random SVM cluster approach has the potential to aid in the auxiliary diagnosis of ASD using resting-state functional magnetic resonance imaging (fMRI) data [12]. The study used brain imaging data from the Autism Brain Imaging Data Exchange (ABIDE) dataset to detect ASD. A multilayer perceptron with a backpropagation method was utilized here [13]. The article focuses on mobile autism risk assessment tools. The application, designed for mobile devices, detects children who are at risk of developing autism spectrum disorder early on. They employ the binary firefly technique and achieved 91–92% accuracy [14]. The researchers employed crowdsourcing to obtain information. A comprehensive collection of clinical tests and behavioral observations was conducted on individuals diagnosed with autism and ADHD, as well as on individuals exhibiting typical developmental patterns. The SVM method is employed with an accuracy ranging from 60% to 90% [15]. The SVM random method was employed in these investigations, achieving an accuracy of 89% [16–18]. The study offers a machine-learning method for accurately forecasting autism symptoms at any stage of life. The study introduces a novel and improved machine learning technique that combines the Random Forest-CART and Random Forest-ID3 algorithms to enhance the prediction of autism with higher efficiency and accuracy. We developed a smartphone application with this framework. We conducted an evaluation of the proposed model using the AQ-10 dataset and 250 authentic datasets collected from individuals with and without autism [19]. The study explores techniques for learning graph representations and utilizing deep neural networks to identify people with Autism Spectrum Disorder (ASD) by analyzing the functional connectivity patterns in their brains. AWE, Node2vec, Struct2vec, multi-node2vec, and Graph2Img are all methods used to represent the ABIDE I and II databases. Among these methods, Graph2Img is considered the most effective. The paper demonstrates an accuracy of 80% for leave-one-site-out cross-validation by utilizing PCA for feature vector extraction and a latent deep neural network for classification [20]. This work introduces a pragmatic approach for detecting autism spectrum disorder (ASD) by analyzing facial photographs. We employ VGG16 transfer learning-based deep learning methods on a unique dataset of clinically diagnosed children with Autism Spectrum Disorder (ASD) that we have collected [21]. This study presents the Mobile Net, a deep learning model that utilizes facial photos to accurately assess youngsters as either healthy or potentially autistic. This study employs a dataset sourced from Kaggle [22]. Applying a Deep Convolutional Neural Network (CNN) to categorize emotional expressions in individuals with and without Autism Spectrum Disorder (ASD) by analyzing electroencephalography (EEG) signals. The study revealed that CNN effectively detected facial emotions in both ASD and non-ASD groups, suggesting that brain signals of individuals with ASD contain information about face emotions [23]. The research explores the application of machine learning methods for the automated detection of autism spectrum disorder (ASD) through the analysis of brain imaging data. The research explores the utilization of machine learning techniques for the early identification of Autism Spectrum Disorder (ASD), along with the difficulties involved in combining machine learning with various brain imaging data [24]. This study employed transfer learning techniques using pre-trained MobileNetV2 and MobileNetV3-Large models trained on the ImageNet dataset to accurately detect and classify facial expressions in children with autism [25]. This research assessed several deep learning configurations using the VGG19 model to categorize face photos as either autistic or non-autistic. The configuration that yielded the greatest overall accuracy of 75.85% was RMSprop + LSTM + Dropout [26]. This work presents ResNet-50 and DeepLabV3 + segmentation for face recognition in datasets of children with autism and shows that DeepLabV3 + segmentation may enhance facial recognition accuracy [27]. The

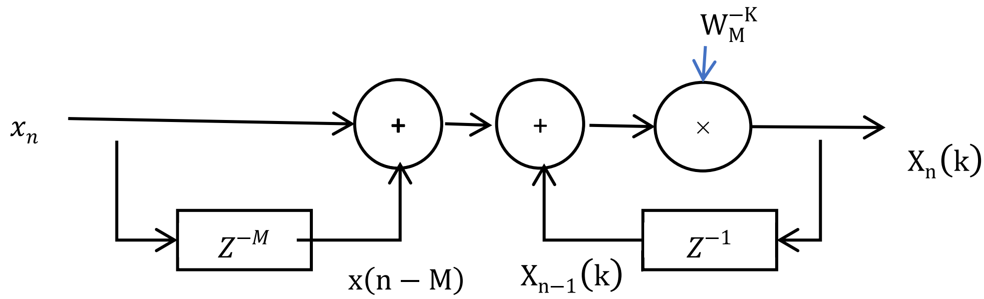


Fig. 1. The construction of the IIR filter that may be used to calculate SDFT from the ASD video frame data.

paper proposes a deep learning approach for facial emotion recognition and detection using CNN-10 and ViT, data augmentation to improve robustness, and high accuracy in extracting facial features and classifying expressions into 6 categories [28]. The study discusses a research that employed pre-trained convolutional neural network models to diagnose autism spectrum disorder from face photos. The ResNet50 model outperformed state-of-the-art methods with 92% accuracy [29]. The researchers developed an autism classifier utilizing deep learning methodologies. A computer vision model was developed using video data obtained from a mobile game application [30]. The research explores the progress of artificial intelligence (AI) models in diagnosing autism spectrum disorder (ASD) by evaluating facial expressions and cues. The study examines the use of convolutional neural network (CNN) models with XGBoost and RF algorithms in hybrid systems [31]. The research explores the development of a real-time system that employs deep learning and Internet of Things (IoT) technology to accurately detect emotions in children with autism. The objective of the system is to detect and recognize emotions in children with autism and assist in the management of pain or intense anger. The document highlights the importance of assistive technology in improving the quality of life for individuals with autism. The essay emphasizes the significance of selecting appropriate assistive technology that is in line with individual needs and characteristics. Furthermore, the document explores the use of facial expression recognition as a means of promptly identifying autism [32]. The main goal was to develop a deep learning model for classifying ASD facial expression based on the original image with SDFT image. The remainder of the paper is arranged as follows: Section 3 offers the suggested system modelling and the central database, Section 4 presents the experiment, and Section 5 and Section 6 contain the discussion and conclusion.

2. Suggested system modeling and the major database

2.1. Sliding Discrete Fourier Transform (SDFT)

Jacobsen and Lyons created SDFT as a DSP method for real-time spectrum analysis that requires fewer calculations and gives results sample by sample, with the rate of the spectral bin output being the same as the rate of the input data [33].

The SDFT algorithm is utilized to process a signal window of fixed length in the SDFT situation. Let's examine a complex input signal x(n), where n = 0,1,2,..., that will be divided into M overlapping windows. Let k represent the index in the frequency domain, where k is greater than or equal to 0 and less than M. The kth bin of an M-point Discrete Fourier Transform (DFT) is computed at time index n according to the following procedure [34].

$$X_n(k) = \sum_{m=1}^{M-1} x(\hat{n}+m)\ W_M^{-km} \tag{1}$$

where m is the index, n is the time domain index, M is the length of the window, $\hat{n} = n - M + 1,\ W_M^{-km} = e^{-j2pi/M}$.

Equation (1) can be rewritten according to the circular shift property as following:

$$X_n(k) = W_M^{-km}\left(X_{n-1}(k) + x(n) - x(n-M)\right) \tag{2}$$

where $W_M^{k+M} = W_M^k$ because it is a periodic signal.

Equation (2) states that the SDFT outputs will be updated after each input sample based on the SDFT output's prior value and the time series' current value; this approach may be implemented using Infinite Impulse Response (IIR) (Fig. 1).

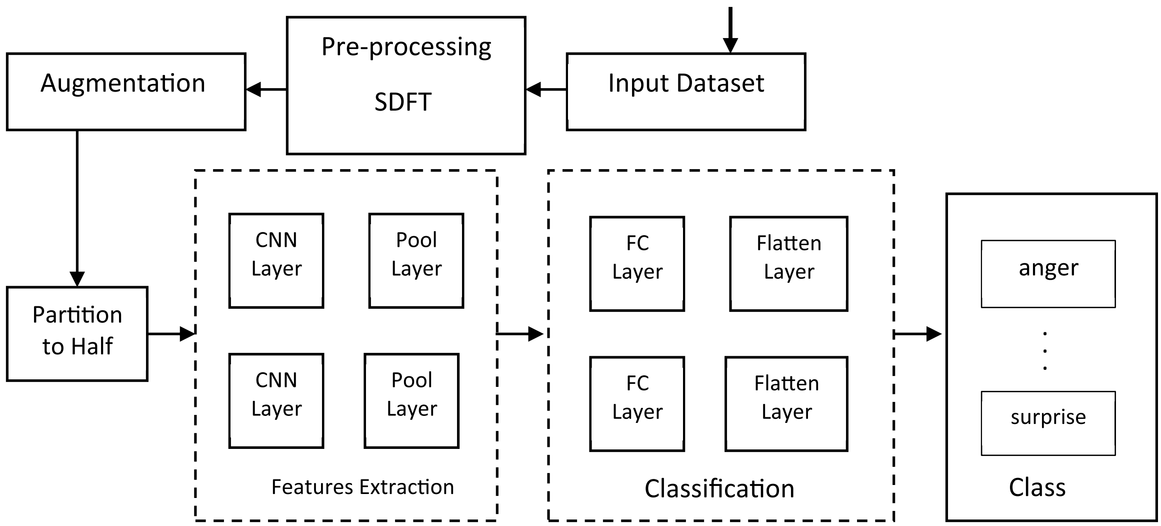


Fig. 2. Schematic diagram of the proposed system.

3. Proposed method

CNNs have demonstrated extraordinary performance in various computer vision applications, outperforming traditional approaches in many situations. Their capacity to automatically learn hierarchical features from raw input data enables them to extract meaningful information from photos and movies. A convolutional neural network (CNN) is a deep learning system that processes and analyses visual input like photos and videos. It is commonly used for computer vision applications such as picture classification, object identification, and image segmentation. They comprise several layers: convolutional, pooling, and fully linked. Convolutional layers utilize convolutional filters to extract information from input pictures. These filters recognize patterns and edges in pictures, eventually learning more complex information as the network grows more profound. Pooling layers are used to down-sample the feature maps generated by the convolutional layers. They minimize the spatial dimensions of feature maps, allowing for extracting the most important characteristics while offering some translation invariance. Finally, fully linked layers are employed to perform classification or regression tasks. They transfer the high-level characteristics learnt in preceding layers to the required output classes or values. Fig. 2 shows a flowchart of the suggested system.

3.1. Dataset

The dataset used to train and test this model was obtained from the Kaggle website and comprises face photos of autistic children [35]. This dataset is the only one that has been made accessible to the general

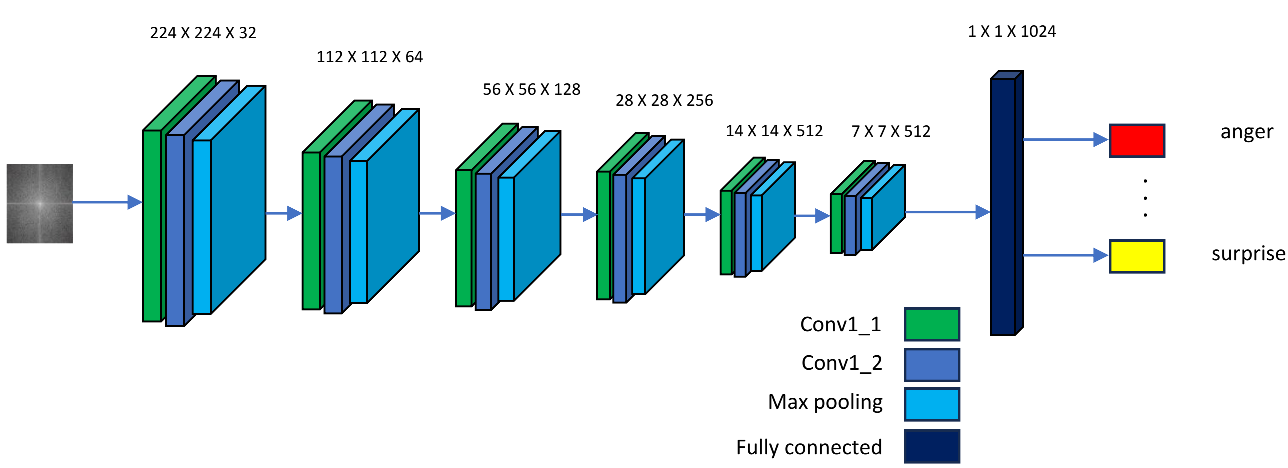


Fig. 3. A framework of the proposed classification system.

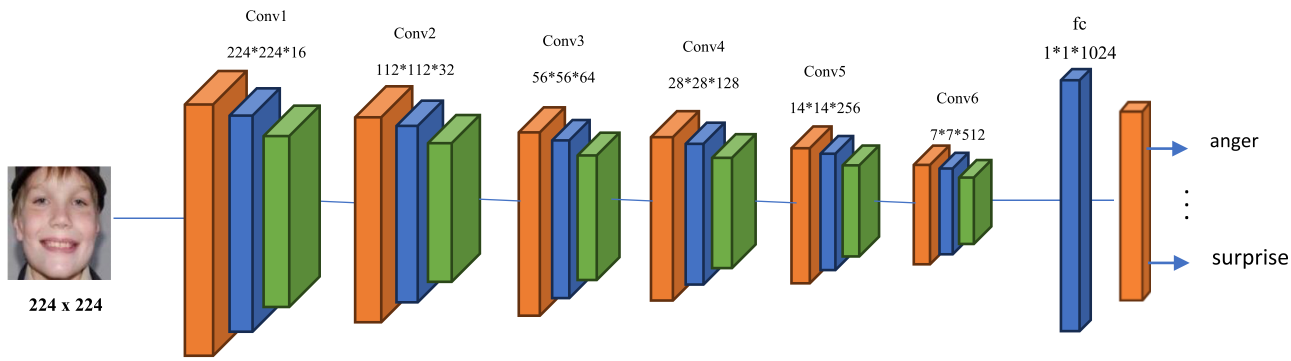


Fig. 4. A framework of the first case.

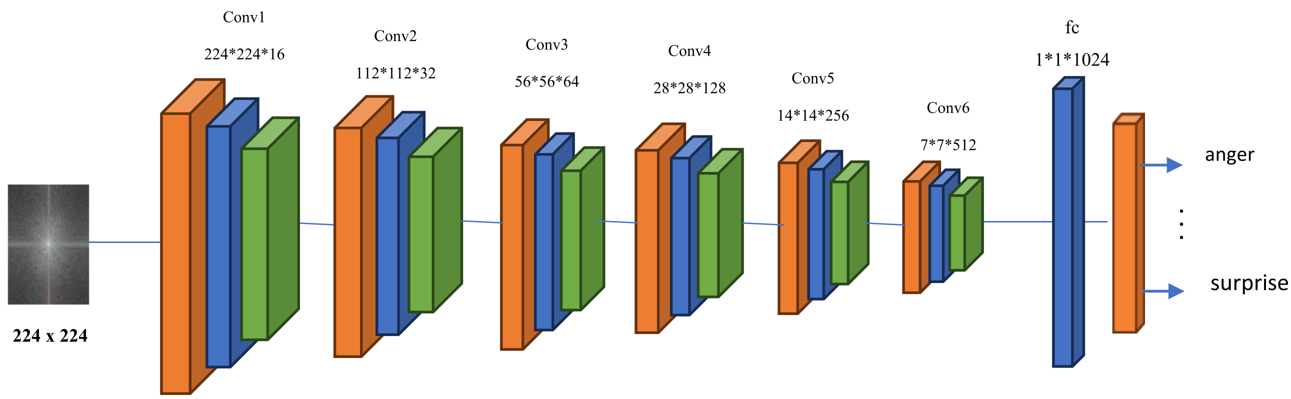


Fig. 5. A framework of the second case.

public. For this study, 758 photographs were chosen for each of the following labels: (Anger: 67, Fear: 30, Joy: 350, Natural: 48, Sadness: 200, Surprise: 63). The collection consists of facial photos of kids with autism, featuring both boys and girls.

3.2. Methodology

The proposed model comprises a Convolutional Neural Network (CNN). The spatial CNN network uses original facial image, paralleled by a CNN network for SDFT images taken from the original image. Our deep learning model is shown in Fig. 3.

In this work, we used three cases to input the deep learning model. As shown in Fig. 4, the original image is taken and preprocessed through scaling and clipping in the first case to make it suitable for CNN to classify facial emotion for ASD. In the second case, according to the image in the first case, after converting to SDFT, the magnitude value for the image is taken and then passed to CNN, as shown in Fig. 5. In the third case, we work in a parallel network by taking two images and passing them to a paralleled hybrid CNN network, where one is the original image and the other uses the SDFT image. This is shown in Fig. 6.

3.3. Transfer learning

Transfer learning is a machine learning technique that involves repurposing or transferring a model trained on one activity to another similar task. This is achieved by leveraging the knowledge acquired from the initial model's training process. To increase the accuracy of the method in this paper, we used Integrating VGG19 with transfer learning, a prevalent approach in computer vision applications, wherein the pre-trained VGG19 model is further refined on an original dataset tailored to the specific job at hand. This method offers time and computing resource efficiency, as training a deep neural network from the beginning causes a substantial quantity of labeled data and computer capabilities.

4. Experiments

Data augmentation is a more robust support technique used in machine learning and computer vision, with applications for ASD classification and detection. The procedure comprises making various changes to the initial dataset to generate additional augmented samples. Augmentation increases data

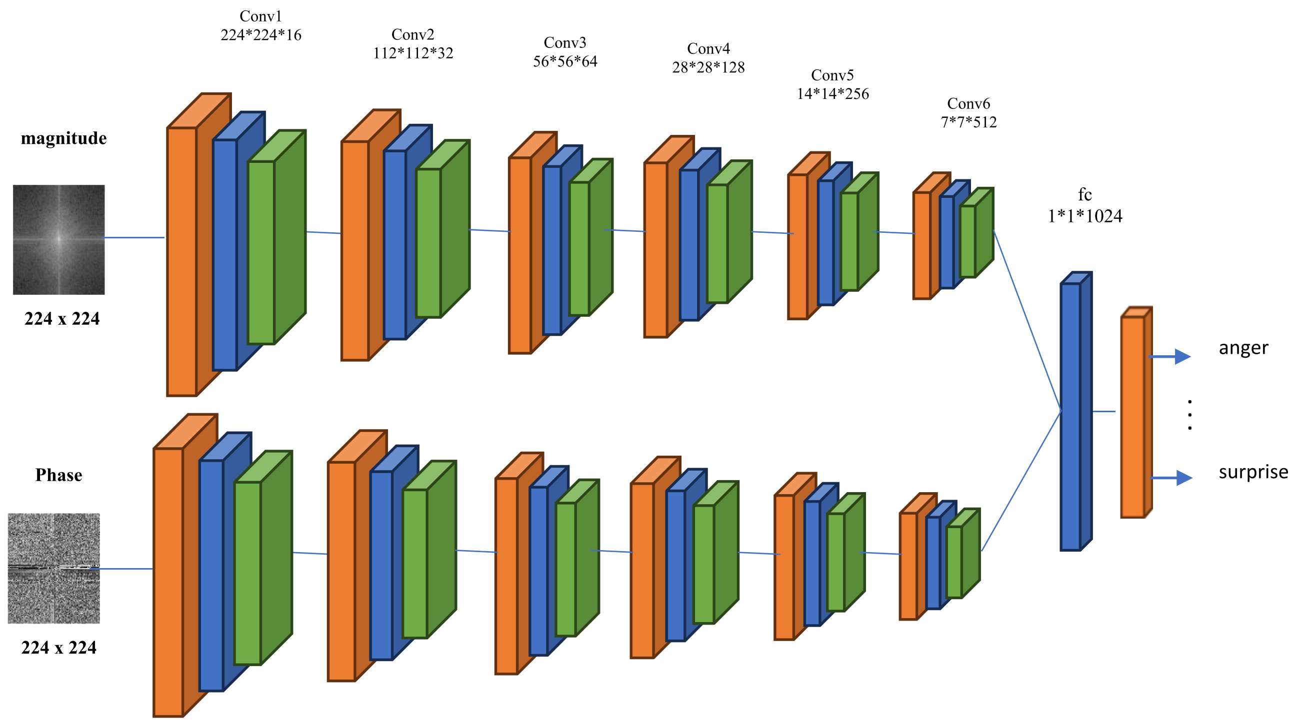


Fig. 6. A framework of the third case.

diversity, reduces overfitting, and improves the model's generalization capacity. Facial feature analysis for people with autism benefits substantially from augmentation since it allows the model to learn from a wider range of pictures, resulting in better performance and more trustworthy results. The dataset included 758 facial feature images taken from people with autism spectrum disorder (ASD).

There were chosen for each of the following labels: (Anger: 67, Fear: 30, Joy: 350, Natural: 48, Sadness: 200, Surprise: 63).

The MATLAB application was employed to facilitate the training of the learning models. A limited range of data visualization and analysis tools were employed to evaluate the effectiveness of the models. We conducted a performance comparison of three case models that were trained using different optimizers. The training was done with a batch size of 90 and a learning rate of 0.0001, across 15 epochs. We used a standard set of hyperparameters with the specified values. The dataset had 758 photographs. As stated in Table 1.

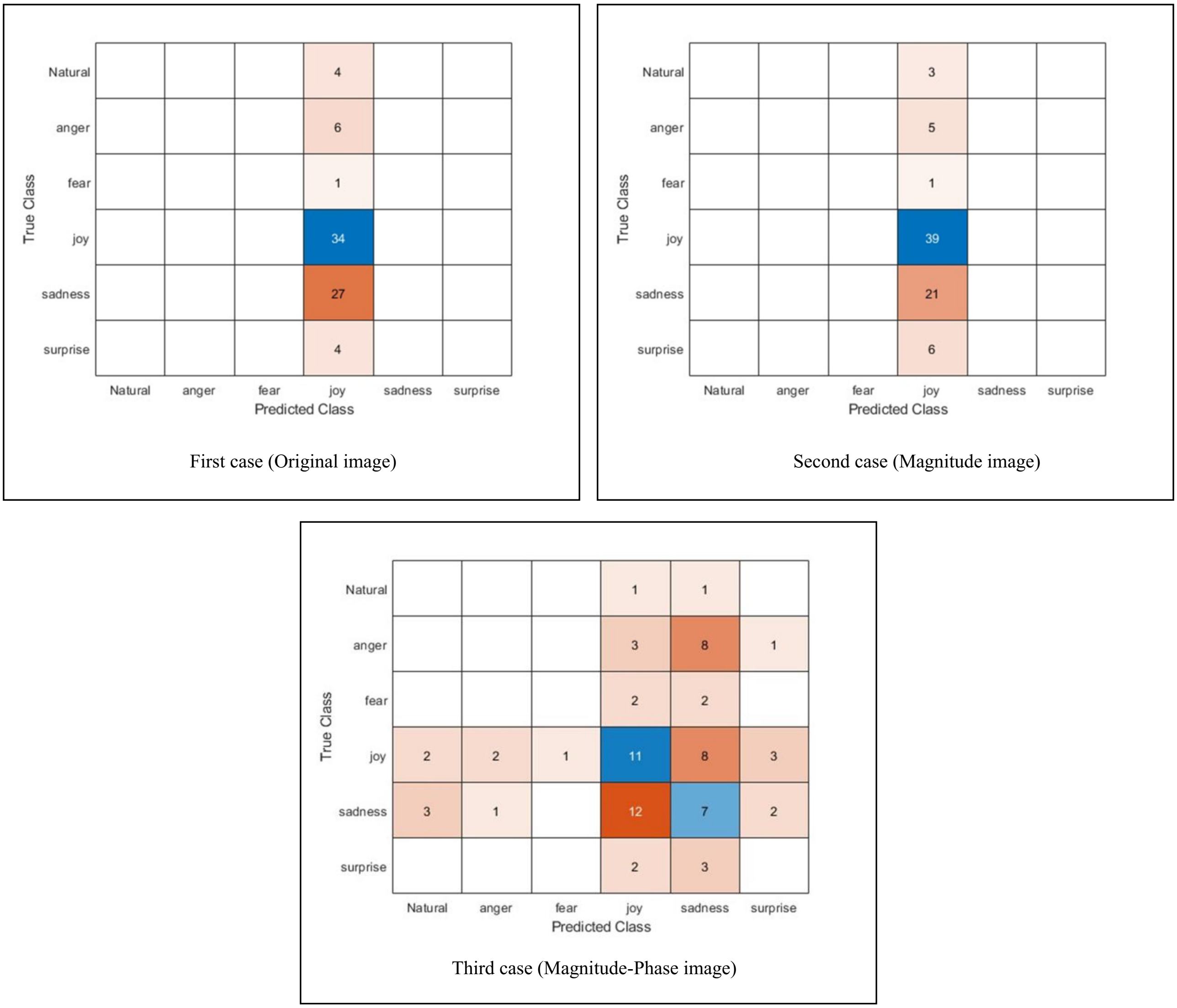
The accuracy of the first case model which uses the face images was 44%, the second case model which uses the magnitude value that result from SDFT of the face images was 52%, and the third case model that uses the magnitude and phase was 45%, which mean that the phase value does not contain any important information compared with magnitude. From the result we noted that the accuracy does not exceed the threshold, because the little volume of the dataset, and the SDFT needed a huge dataset. While using Transfer Learning for case 1 (used original images for face), the accuracy increased from 44% to 85%. And because there is no available transfer learning model for the SDFT dataset because of this situation, you can visualize an enhanced to the other cases that used magnitude values.

Table 1. Results of three case.

Image	Accuracy	Misclassification rate
Original-Image (First case)	0.4474	0.5526
Magnitude (Second case)	0.5200	0.4800
Magnitude–Phase (Third case)	0.4533	0.5467

The confusion matrix in Fig. 7 displays the true-negative and false-positive rates and the valid-positive and false-negative indications for the first, second, and third cases. The second case model demonstrated the best accuracy outcomes based on the evaluation measures more than others.

Fig. 8 visually represents the three loss situations of training, validation, and testing. The X-axis represents the number of iterations, namely 15 epochs, while the Y-axis represents the model's loss percentage. In order to obtain an accurate assessment of the training system's effectiveness, we examined the performance of the validation system.



First case (Original image)

Second case (Magnitude image)

Third case (Magnitude-Phase image)

Fig. 7. Confusion matrix of the third case.

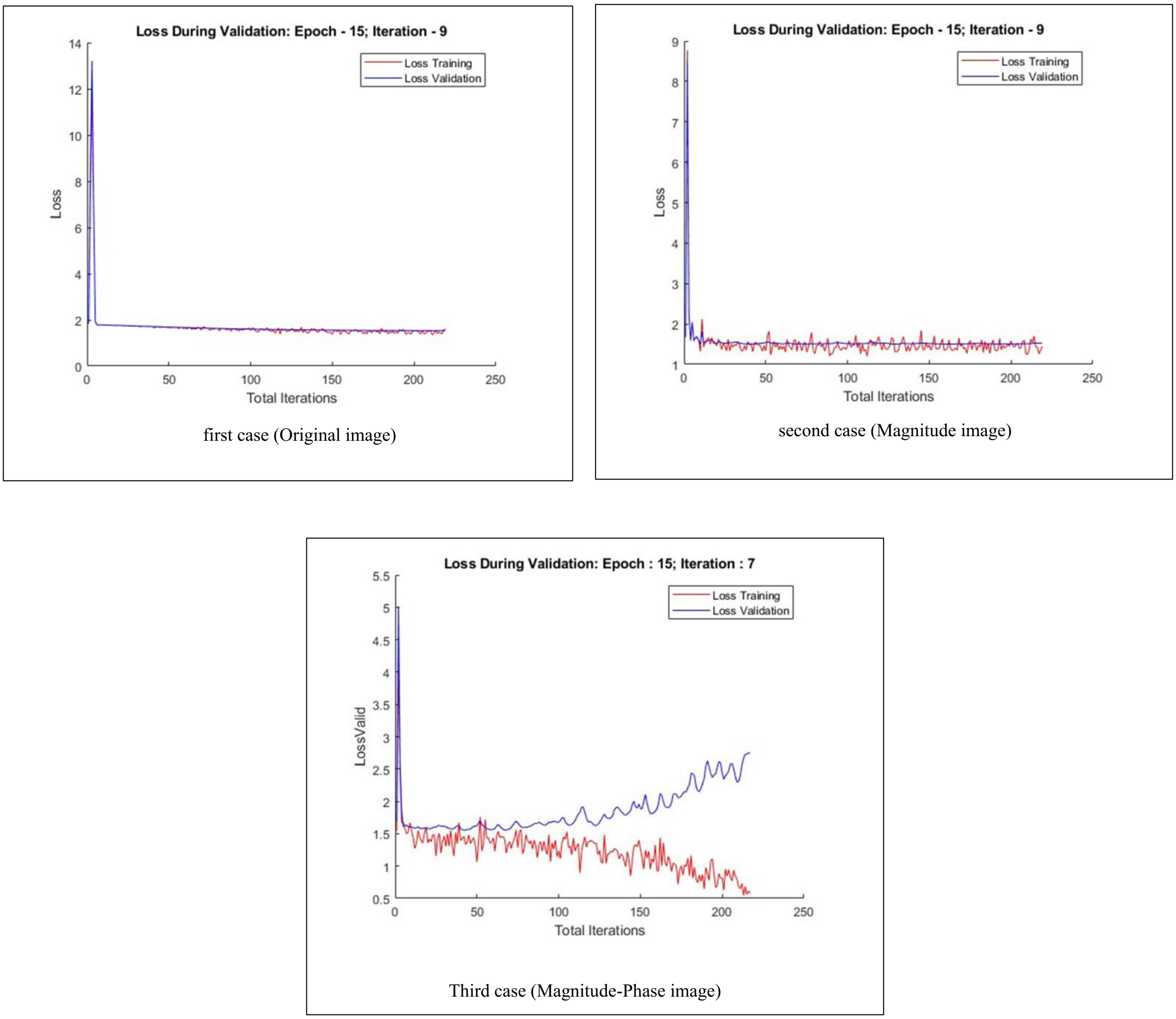
The Fig. 8(first case original image) demonstrates the progression of training and validation loss during the model's training phase, displayed against the total number of iterations. Below is an extensive analysis of the outcomes:

The first training and validation loss has a high value and thereafter experiences a rapid decline throughout the initial iterations. The sharp decline suggests that the model rapidly acquires knowledge from the original data.

Following the first decrease, the both loss reaches a stable state with a value slightly below 2.0. This indicates that the model is continually acquiring and improving its parameters throughout the training phase.

The training loss exhibits a consistent level of stability, with minor variations, suggesting that the model is still acquiring knowledge, although at a reduced pace, and is not excessively adapting to the training data.

The findings shown in the Fig. 8(second case Magnitude image) suggest that the training procedure was carried out effectively and skillfully. The model demonstrates proficient initial acquisition, efficient extrapolation, and consistent performance throughout the iterations. Indicating that the model is not suffering from either overfitting or underfitting, the training and validation losses are both minimal and closely matched. This shows a strong model that effectively manages the trade-off between bias and variation. We notice the match in the two forms (first and second case) is clearly visible; we conclude that using SDFT for the original images is or gives similar results as if we use the original images.



first case (Original image)

second case (Magnitude image)

Third case (Magnitude-Phase image)

Fig. 8. Performance of the third case (Loss during train and validate).

While the model Fig. 8(third case Magnitude-Phase image) initially exhibits favorable learning behavior, the discrepancy between the training and validation loss underscores the problem of overfitting. To guarantee the model's effectiveness with unfamiliar data, we must address this problem.

We notice that the similarities between the two figures are easily discernible. Therefore, we may infer that using SDFT for the original photos yields comparable outcomes to utilizing the original images themselves.

It is worth mentioning that the loss value of both the training and validation data consistently stays around value 2, which may be attributed to the limited size of the dataset. Compelling us to use transfer learning in order to enhance the accuracy.

After applying the transfer learning on first case (original images), the value of the confusion matrix, accuracy, loss train and validation are shown graphically in Fig. 9, with each iteration of 70 epochs (X-axis) and the model's percentage accuracy and loss expressed in % (Y-axis).

The use of transfer learning seems to be successful in this situation. In a very short amount of time during the training phase, the model is able to swiftly adjust to the new data and acquire a high level of accuracy.

The data shown in the figure demonstrates that the transfer learning strategy has been effective, which has led to a satisfactory level of model performance and an accuracy of validation score of 85.36%. The training process is consistent, and there are few indications of overfitting. Furthermore, the accuracy and

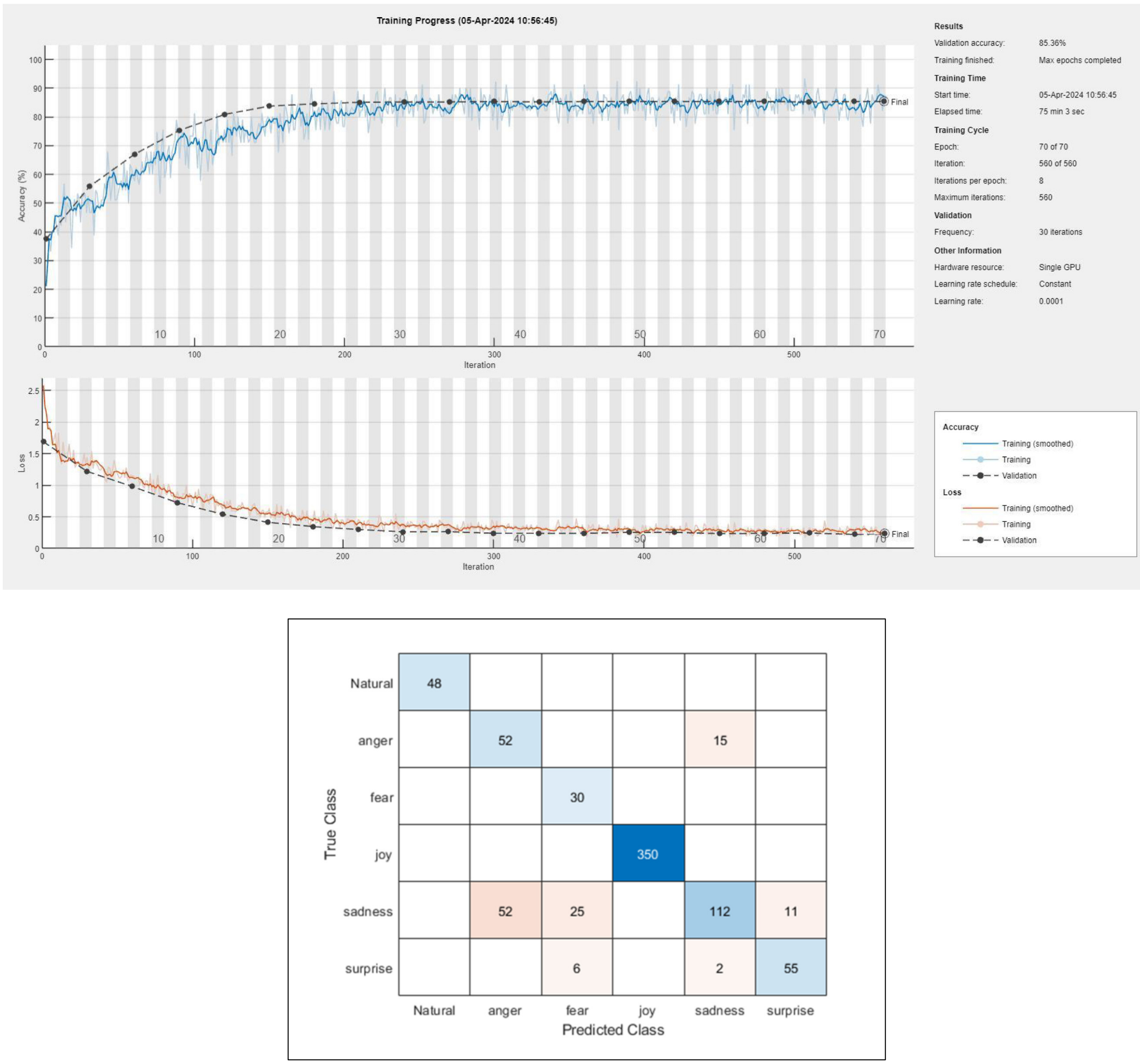


Fig. 9. Performance of the first case with transfer learning (VGG19) (Accuracy and Loss during train and validate) Confusion matrix of the first case.

loss metrics indicate that the model is well-tuned and performs well for the job that has been presented to it. The performance might be improved with more modifications and perhaps even more data, but the results that have been obtained thus far are encouraging.

5. Discussion

Face expressions or emotions could help identify ASD. Working with kids requires an unambiguous ASD diagnosis to address issues. Because ASD patients have complex attentional behaviors, making these tools is challenging. Autism Spectrum Disorder (ASD) sufferers benefit most from early detection and treatment. ASD diagnosis in children has traditionally required hospitalization, which is expensive and time-consuming. This study presents an impartial, practical, and effective way of diagnosing Autism Spectrum Disorder (ASD) in children by evaluating their facial expressions and emotions.

We fill the gap between classifying people with autism and analyzing their faces. This makes AI-based autism classification cheaper and faster. Our deep convolutional neural network model uses different imaging scenarios to reach both goals.

The model was trained and verified using 758 photos, 80% for training and 20% for validation and testing. Our study found that the SDFT image may be not enough to diagnose autism in children. This diagnostic approach may work good if available dataset enough for SDFT image for face. Your findings reveal that the transfer learning model achieved an accuracy up to 85% for original face image. The finding from this study proven that used the SDFT of image does not achieve or give the desired results, so we do not recommend using SDFT as dataset as input to CNN to classification and detection process.

6. Conclusion

This study looked into the utility of facial features as a biomarker for accurately distinguishing autistic children depending on face emotion or expression. We used a publicly available dataset that included face images for children ASD distinguish with (Anger, Fear, Joy, Natural, Sadness and Surprise). Three convolutional neural network (CNN)-based binary autism spectrum disorder (ASD) classifier models were constructed and assessed using three distinct datasets to evaluate the performance of each model. By using the transfer learning model for the original face image had superior performance, with an accuracy rate of 85%. The results indicate that specific features of autism spectrum disorder (ASD) may be effectively extracted from still images of a child's face, enabling a rapid and precise method for screening ASD. On the other hand, this study given indicator not good, when used SDFT image for the original face image so we advise against using SDFT for cases where the dataset is few.

Conflicts of interest

Authors declare that there is no conflict of interest.

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