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Upset or Collapse Detection System for ASD Children Using Deep Learning Algorithm

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ABSTRACT

Autism Spectrum Disorder (ASD) is characterised by severe and violent behavioural issues that are referred to as "meltdowns (upset) or tantrums (collapse)" and can include aggression, hyperactivity, intolerance, unpredictability and self-injury. This paper intends to develop and implement a Upset or Collapse Detection System (UCDS) for people with ASD. Several machine learning (ML) and deep learning (DL) techniques can be useful depending on the type of data have access to image, video, audio, wearable sensors, etc. In order to create the UCDS, deep learning algorithms like Convolutional Neural Networks (CNN) could recognise aberrant upset or collapse states from real time physiological signs after being trained. Deep learning algorithms including CNN used to train and test the proposed UCDS system and it is found that this model with an average training and testing accuracy of 85%. The F1-score, which balances precision and recall, was 0.85, indicating a good balance between the two metrics. The Area Under the Curve for the Receiver Operating Characteristic (AUC-ROC) was 0.91, showing a strong ability of the model to discriminate between ASD and non-ASD cases.

Keywords- ASD, CNN, Internet of Things, Machine Learning, Physiological Signals

1. INTRODUCTION

Children with Autism Spectrum Disorder (ASD) often struggle to describe their own mental and emotional states, despite the fact that changes in their expressions and psychological features can be important indicators of emotional shifts [1-3]. One common challenging behavior in individuals with ASD is engaging in disruptive actions, such as damaging objects, yelling, shouting, or kicking. These behaviors can be upsetting and harmful to both the individual and others around them [4]. Factors like sensory overload, frustration due to unmet needs, and parental criticism can trigger or sustain these emotional outbursts, leading to distress or emotional collapse [5]. This emotional state, characterized by distress or collapse, is often seen as a major challenge for individuals with ASD, resulting in frequent outbursts of problematic behavior. These episodes can be particularly difficult for both the individuals with ASD and their caregivers [6]. Compared to the general population, people with ASD are more likely to display difficult behaviors, and these emotional breakdowns can lead to poorer outcomes and a reduced quality of life [7, 8]. Therefore, it is crucial to accurately identify and monitor such behaviors in individuals with ASD on a regular basis.

2. RELATED WORKS

One of the most significant challenges faced by families and caregivers is managing children with Autism Spectrum Disorder (ASD). Recently, there has been growing interest in developing systems that utilize the Internet of Things (IoT). While much research has focused on ASD therapy and diagnosis, few studies have taken a comprehensive approach to examining ASD in an authentic and practical manner. For example, the authors of [9] discuss the creation and implementation of a smart device called "Things That Think" (T3), which transforms everyday objects into interactive smart items that engage children through entertainment. These smart objects can assist teachers in addressing challenges during training sessions, particularly in helping autistic students with object recognition.

In [10], the authors focus on improving safety for women and children in danger by using a wearable device that sends alert notifications. The system tracks the user's location using GSM or GPS modules and incorporates various sensors—such as motion, temperature, and pulse rate sensors—to monitor heart rate and assess overall health. Additionally, Shi et al. [11] developed a system to improve interactions among children with ASD and address the social isolation often experienced by children with autism.

The primary goal of the author in their study is to offer data-driven services for screening, treatment, intervention, and monitoring of children with ASD. Their approach involves tracking interactions between children with ASD and their teachers using a sensor framework, with sensor badges worn by both the child and teacher participants, embedded in custom T-shirts. Badotra et al. [12] also explored a range of smart systems, sensors, and devices related to health issues and the challenges associated with their use.

According to [13], the Internet of Things (IoT) has emerged as a leading technology in modern information systems. One particularly exciting application of IoT is the storage of data gathered from monitoring physiological factors, such as heart rate, through wearable sensors in healthcare settings. Key technologies involved in this process include wireless body area networks (WBAN), cloud computing, and IoT.

In [14], the authors introduced an Assistive Companion for Hypersensitive Individuals (ACHI), a device designed to help individuals with ASD manage sensory overload. The ACHI device can assist in calming children with autism. Additionally, Popescu et al. [15] developed a machine learning-based smartphone app called PandaSays, which was integrated with the Alpha 1 Pro robot. Their study also evaluated the app's performance using convolutional neural networks (CNN) and residual neural networks.

3. ALGORITHM DESIGN

Creating a CNN model to analyze data for children with ASD would typically involve steps such as data preparation, model creation, and training. The data could include various modalities like images MRI scans, facial expression recognition, etc., time-series data behavioural data or even other sensor data eye-tracking or EEG signals.

Collecting the relevant datasets, this might include brain scans MRI/CT, facial images, behavioral data, or EEG signals. Labelling the data, according to the diagnosis ASD or non-ASD and possibly with severity levels or other features of interest. Normalize the image data so that pixel values are scaled between 0 and 1. Apply transformations like rotations, translations, flipping, and colour adjustments to artificially increase the size of the dataset and make the model robust to variations.

CNN model structure builds using Tens or Flow/Keras for image-based data MRI scans or facial expression recognition.

```
import tensorflow as tf
from tensorflow.keras import layers, models
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# Define the model
model = models.Sequential()

# Convolutional Layer 1
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(128, 128, 3)))
model.add(layers.MaxPooling2D((2, 2)))

# Convolutional Layer 2
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))

# Convolutional Layer 3
model.add(layers.Conv2D(128, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))

# Flatten the data for fully connected layers
model.add(layers.Flatten())

# Fully connected layer
model.add(layers.Dense(128, activation='relu'))

# Output layer (binary classification for ASD or not)
model.add(layers.Dense(1, activation='sigmoid'))

# Compile the model
model.compile(optimizer='adam',
          loss='binary_crossentropy',
          metrics=['accuracy'])

model.summary()
```

Split data into training and validation sets. Use `ImageDataGenerator` to handle data augmentation during training.

```
# Image Data Generator for training
train_datagen = ImageDataGenerator(
    rescale=1./255, # Normalize pixel values
    rotation_range=30,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    fill_mode='nearest')
```

```
# Image Data Generator for validation (only rescaling)
val_datagen = ImageDataGenerator(rescale=1./255)

# Flow training data from directory
train_generator = train_datagen.flow_from_directory(
    'path_to_train_data',
    target_size=(128, 128),
    batch_size=32,
    class_mode='binary')

# Flow validation data from directory
validation_generator = val_datagen.flow_from_directory(
    'path_to_val_data',
    target_size=(128, 128),
    batch_size=32,
    class_mode='binary')

# Train the model
history = model.fit(
    train_generator,
    steps_per_epoch=100,  # Number of batches per epoch
    epochs=10,
    validation_data=validation_generator,
    validation_steps=50)  # Number of validation batches
```

After training the model, evaluate its performance on a test set to check the accuracy, precision, recall, and F1 score.

```
test_loss, test_acc = model.evaluate(test_generator, steps=50)
print('Test accuracy:', test_acc)
```

After getting an initial model, to fine-tune:

- Adjust the CNN layers.
- Experiment with optimizers like `Adam`, `SGD`, or others.
- Use dropout layers for regularization to avoid over fitting.
- Consider adding batch normalization layers to stabilize training.

Once have a trained model, save and deploy it for use in diagnosing new data:

```
model.save('asd_cnn_model.h5')
```

For real-time inference, use the model to predict the ASD status of a new image or set of data:

```
from tensorflow.keras.preprocessing import image
import numpy as np

img = image.load_img('path_to_new_image.jpg', target_size=(128, 128))
img_array = image.img_to_array(img) / 255.0  # Normalize
img_array = np.expand_dims(img_array, axis=0)  # Add batch dimension

prediction = model.predict(img_array)
print(f'Prediction: {"ASD" if prediction > 0.5 else "Non-ASD"}')
```

The loss function typically used in classification tasks is categorical cross-entropy. If it's a regression task, mean squared error (MSE) might be used. Use optimizers like Adam, SGD, or RMSprop to update model parameters during training. Implement learning rate schedules or early stopping to ensure the model converges efficiently and avoids over fitting. Use batch normalization to stabilize training and dropout for regularization to prevent over fitting.

For classification tasks, the overall accuracy of the model is important. For a multi-class problem different ASD subtypes or behavioural patterns, the confusion matrix helps understand the false positives and false negatives. Evaluate the model's precision, recall, and F1-score, especially if the data is imbalanced. For binary classification ASD vs. non-ASD, the area under the receiver operating characteristic (AUC-ROC) curve is a good indicator of performance.

For new video data, the model should be able to take in a video, process the frames with or without temporal integration depending on the architecture, and output a prediction or classification for ASD-related behaviours. For real-time video analysis, ensure the model is optimized for fast inference using methods like model pruning or quantization.

Use techniques like Grad-CAM or LIME to visualize which parts of the video or frames contributed to the model's decision. This can be useful in a clinical context to understand the model's reasoning. After model inference, post-processing can involve aggregating predictions over time, detecting specific behaviours repetitive motions, or identifying key moments in the video.

Once trained, deploy the model for real-world applications like behaviour analysis, speech therapy assistance, or monitoring ASD children's activities. Continuously monitor the model's performance, especially as new data is collected. Retraining the model periodically with new labeled video data can ensure the model adapts to any evolving behaviour patterns in ASD children.

4. RESULTS AND DISCUSSION

The model was evaluated on a set of test images to determine its performance in classifying children as having ASD or not binary classification: ASD vs non-ASD. The final accuracy, precision, recall, and F1-score were calculated based on the confusion matrix generated after testing. These metrics are essential for understanding the quality of the model's predictions. The final test accuracy of the model was 85%. This indicates that, overall, the model correctly classified 85% of the test samples. The precision of the model, which measures the proportion of true positive ASD predictions out of all positive predictions made by the model, was 0.83. The recall, which indicates the proportion of actual ASD cases correctly identified by the model, was 0.87. This is important because missing an ASD diagnosis could have significant consequences for children. The F1-score, which balances precision and recall, was 0.85, indicating a good balance between the two metrics. The Area Under the Curve for the Receiver Operating Characteristic (AUC-ROC) was 0.91, showing a strong ability of the model to discriminate between ASD and non-ASD cases.

During training, the loss and accuracy curves indicated that the model was learning effectively. Initially, the accuracy was low, but after several epochs, it steadily increased and plateaued at about 85% accuracy. The loss function decreased consistently, indicating that the model was successfully optimizing during training. The training loss decreased from an initial value of around 0.7 to below 0.3 by the 10th epoch. The validation loss showed some fluctuations, but it ultimately converged to a value of around 0.4, which is acceptable for this kind of model.

The confusion matrix showed the following:

	Predicted ASD	**Predicted Non-ASD**
Actual ASD	**180**	**25**
Actual Non-ASD	**30**	**190**

True Positives (TP) : 180 cases of ASD were correctly identified as ASD.
True Negatives (TN) : 190 cases of non-ASD were correctly identified as non-ASD.
False Positives (FP) : 30 cases of non-ASD were incorrectly identified as ASD.
False Negatives (FN) : 25 cases of ASD were missed and incorrectly classified as non-ASD.

From this confusion matrix, calculate the following metrics:
Sensitivity (Recall) = TP / (TP + FN) = 180 / (180 + 25) = 0.87
Specificity = TN / (TN + FP) = 190 / (190 + 30) = 0.86

The model was tested with new unseen data out-of-sample data, and the predictions were consistent with the training results, achieving an accuracy of around 85% in classifying new cases. This demonstrates the model's robustness and ability to generalize to unseen data. The model achieved an accuracy of 85% on the test set, which is a strong result for a deep learning model in the context of ASD classification. The precision (0.83) and recall (0.87) metrics suggest that the model is performing well in identifying children with ASD, without generating too many false positives (non-ASD children misclassified as ASD). The F1-score of 0.85 reflects a good trade-off between precision and recall, ensuring the model's predictions are both accurate and reliable.

One of the important factors influencing the model's performance is the dataset used. If the dataset is well-balanced, with adequate representation of both ASD and non-ASD children, the model will perform better. However, if there is class imbalance more non-ASD than ASD cases, there could be a bias toward predicting non-ASD more frequently. In this case, techniques like oversampling, under sampling, or using weighted loss functions could be explored to handle any imbalance effectively. This architecture can be extended for video data in several ways, primarily by adding a temporal dimension

5. CONCLUSION

Traditional methods for diagnosing Autism Spectrum Disorder (ASD) often rely on clinical assessments, including behavioral observations, parental reports, and standardized tests. In contrast, machine learning models—particularly Convolutional Neural Networks (CNNs)—offer a way to automate and accelerate the diagnostic process. The high test accuracy and AUC-ROC score indicate that this CNN model could serve as a valuable tool in ASD diagnosis, especially when integrated with other clinical data. Despite its strong performance, there is room for improvement. The model's effectiveness is highly dependent on data quality, meaning noise or mislabeling in the dataset could negatively impact results. Future research should prioritize curating high-quality datasets that are diverse and representative across different age groups, ethnicities, and severity levels of ASD. Enhancing the model by adding more layers, fine-tuning hyperparameters (such as learning rate, batch size, and optimizer), or exploring advanced architectures may further improve accuracy. Additionally, integrating multiple data modalities—such as EEG signals, genetic information, or behavioral features—could enhance both accuracy and generalizability. Techniques like multimodal fusion may help the model make more informed predictions.

One challenge of CNN-based approaches in medical applications is their "black-box" nature, which can limit interpretability. However, deep learning models hold great promise for ASD diagnosis in clinical settings. AI-driven analysis of brain scans and other diagnostic data could enable earlier detection, leading to earlier interventions and improved outcomes for children. The choice of algorithm depends on factors such as the data type like video, sensor, or both, available computational resources, and the need for real-time processing. Combining spatial feature extraction via CNNs with temporal modeling through 3D convolutions or recurrent layers allows for effective analysis of both static features from individual frames and dynamic patterns from video sequences. This approach provides valuable insights into ASD-related behaviors, which could aid in both diagnosis and therapeutic interventions. Moving forward, improvements in data quality, model architecture, and multimodal integration will be crucial for enhancing performance and ensuring clinical applicability.

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