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Upset or Collapse Detection System for ASD Children Using Smart Watch with Machine Learning Algorithm

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Abstract— 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 research work intends to develop and implement a non-invasive real-time Upset or Collapse Detection System (UCDS) for people with ASD. With a certain model of smart watch, the non-invasive biological indications such as Pulse Rate (PR), Skin Temperature (ST), and Galvanic Skin Reaction (GSR) can be artificially captured. In order to create the UCDS, deep learning algorithms like CNN, LSTM, and the hybrid of CNN-LSTM are given the physiological signals that are captured to a server. The deep learning algorithm could recognise aberrant upset or collapse states from real-time physiological signs after being trained. Deep learning algorithms including CNN, LSTM, and CNN-LSTM are used to train and test the proposed UCDS system, and it is discovered that hybrid CNN-LSTM beat them all with an average training and testing accuracy of 96% and a low mean absolute error (MAE) of 0.10 for training and 0.04 for testing. Furthermore, the suggested UCDS system is supported by 93% of the ASD caretakers.

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

1. INTRODUCTION

Children with ASD typically fail to describe their own mental and emotional states, despite the fact that the changes to their expressions and other psychological features may be a very crucial signal of the emotional changes in these children [1-3]. At least one challenging behaviour, such as damaging objects, yelling, shouting, or kicking, may be displayed by a person with ASD. This type of disruptive conduct might be disturbing and harmful to ASD persons or others [4]. The presence of inciting, triggering, and sustaining factors like sensory stimulation, need frustration, and parental criticism may result in upset or collapse [5].

The restless state, such as upset or collapse, is called in ASD as major challenge of disputes and discomfort, in which powerful and dangerous eruptions of problematic behaviours might occur on a regular basis. ASD upset or collapse may be one of the most difficult aspects of autistic people and their guardians [6]. Individuals with ASD are more likely than the general population to exhibit difficult behaviour because collapses or upsets connected with poor outcomes resulted in a lower quality of life [7, 8]. It is very essential that correctly recognise and monitor such anomalous behavior in ASD patients on a regular basis.

Non-invasive physiological indicators can be capable of providing a sensitive and easy assessment of changes in sympathetic arousal linked with emotions, intellect and concentration. During hyperactivity, upset or collapse-related situations several visible physiological changes such as body perspiration, irregular heart rate and elevation in body heat can be observed [9]. In addition, an effective system may be needed to represent and retrieve all the evidences from various visible physiological inputs. Due to the diverse character of autistics, it is extremely difficult to get real-time physiological data using connected devices. IoT architecture is used for Healthcare Monitoring System (HMS) by easily accessible clinical applications with quick access flexibility and hence it is planned to develop a modern smart HMS to gather health associated data with IoT. [10 -13].

Several researchers have suggested employing machine learning and deep learning methods while considering the comprehensive data from physiological datasets in order to overcome the limitations. [14-17]. "BioSenHealth 1.0," an effective internet-connected HMS, is installed and recognized as a more accurate system at low cost [18]. Non-invasive devices and effective deep learning algorithms based on physiological signals may be able to give adequate details regarding agitated emotional characteristic of upset or collapse conditions in ASD persons. The objective of this paper is to offer an effective Upset or Collapse Detection System (UCDS) for people with ASD. The suggested data collection method enables the proposed UCDS system to acquire physiological signals including Skin Temperature (ST), Pulse Rate (PR), and Galvanic Skin Response (GSR).

A novel UCDS is proposed for monitoring the conditions of ASD people with the deep learning algorithm using the parameters including PR, GSR and ST. The technique described in this paper is able to continuously monitor and refresh the data in regular periods and can provide an alarm if an Upset or Collapse condition occurred. The interactive graphical interface of the proposed scheme is meant to make it easier for doctors and parents to comprehend and access upset or collapse related behaviour. Personalized sensor readings are sent to an UCDS-implemented server and will be accessed whenever required.

2. RELATED WORKS:

One of the toughest challenges facing families and care takers is dealing with autistic children. Recently, there has been a lot of interest in creating systems that use the Internet of Things. ASD therapy and diagnosis are the focus of various research literatures but only a few relevant studies have been presented to examine ASD in truthful method.

The authors of [19] describe the conception and application of a smart device dubbed "Things That Think" (T3) that transforms common objects into smart ones that encourage interaction through entertainment. Smart things can help the teachers in facing issues that arise during the training of autistic students in object recognition.

The focus of the authors in [20] is to save women or children in danger by giving a notice alert through a wearable gadget. This system tracks the location of the user by using a GSM or GPS module, and it makes use of various sensors, such as a motion sensor, temperature sensor, and pulse rate sensor, to track the user's heart rate and assess their general health.

Shi et al. [21] developed a mechanism to enhance relationships amongst kids with ASD and address the lack of contact among kids with autism. The main goal of the author is to provide data-driven services for ASD kid screening, treatment, intervention, and monitoring. The objective is to identify the interactions between the autistic children using a sensor framework consisting of sensor badges worn by child and teacher participants in the pockets of the custom T-shirt.

In their study on a variety of smart systems, sensors, and gadgets related to health issues, Badotra et al. [22] addressed a number of challenges. According to [23], Internet of Things (IoT) has become a prominent form of contemporary information technology. Storing the data gathered from observing physiological factors like heart rate is one of the most intriguing uses for the expanding number of wearable sensors in healthcare. The main elements of this technology are wireless body area networks (WBAN), cloud computing, and the Internet of Things (IoT). In [24], the authors proposed an Assistive Companion for Hypersensitive Individuals (ACHI) as a supportive intermediate for assisting individuals with ASD with their overloaded sensory responses. Also, the ACHI equipment can help calm down of autistic kids. PandaSays, a ML-based smartphone application, was developed and integrated with an Alpha 1 Pro robot by Popescu et al. [25]. They also covered performance evaluation using CNN and residual neural networks.

Farooqi et al. [26] employed data mining techniques like classification, regression, and clustering to make an early diagnosis of ASD. Early diagnosis of ASD is essential for providing patients with the right support and education for their careers. They discovered that categorization algorithms are the best for the most precise diagnosis. Wong et al. [27] have investigated the influence of autism treatments on appropriate behaviour using data mining technologies. Using this approach, it is possible to foresee and comprehend autistic children better. These methods allowed them to discern between acts that were regarded as acceptable and inappropriate.

Westeyn et al. [28] and Albinali et al. [29] have reported the research that is most pertinent to our work. A pattern recognition technique was utilised by Westeyn et al. [28] to identify stereotyped motor behaviours frequently seen in ASD youngsters. A recruited adult imitated seven typical self-stimulatory actions of autistic people (drumming, hand flapping, hand striking, pacing, rocking, spinning, and toe walking). Three specifically built accelerometer sensors that were placed at the wrist, waist, and ankle collected data. 69% of those seven activities could be found using a pattern recognition technique based on hidden Markov models (HMM).

Building bots with artificial intelligence (AI) in order to aid in the treatment of autism was the main goal of Palestra et al. [30]. They have created the Behavior Management (BM) and Robot Intelligence Module (RIM). The RIM consists of four elements: body posture, eyes, facial expression, and head position. The two components of the BM are the treatment protocol and the NAOqi API. Machine learning (ML)-based ASD detection was provided by Tariq et al. [31]. By analysing the 30 behavioural features from the video, they developed a mobile/web app for diagnosing ASD.

Galvanic Skin Response (GSR), Skin Temperature (ST), and Pulse Rate (PR) are examples of physiological indicators that are regarded as significant data sources that can help diagnose and cure diseases [32]. Goodwin et al. [33] noted that an autistic person's physiology could appear to be different from what was actually recorded inside the body.

With the assistance of wearable technology, changes in physiological signals could be noninvasively observed, helping to forecast anxiety levels and instances of self-harm as well as

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raising self-awareness of one's own internal emotional state to assist people control their emotions. According to Koo et al. [34], 72% of parents of children with ASD were willing to watch for changes in their children's physiological signals or behavioural parameters in order to better understand their breakdowns, tantrums, or other emotions..

3. SYSTEM DESIGN AND IMPLEMENTATION

In this paper the UCDS based on deep learning is proposed for identifying ASD people, and it is implemented using different physiological data associated with GSR, PR, and ST. This suggested solution will monitor the biological condition of the ASD child and update the data continuously and give an alert in the event of a collapse or temper outburst.

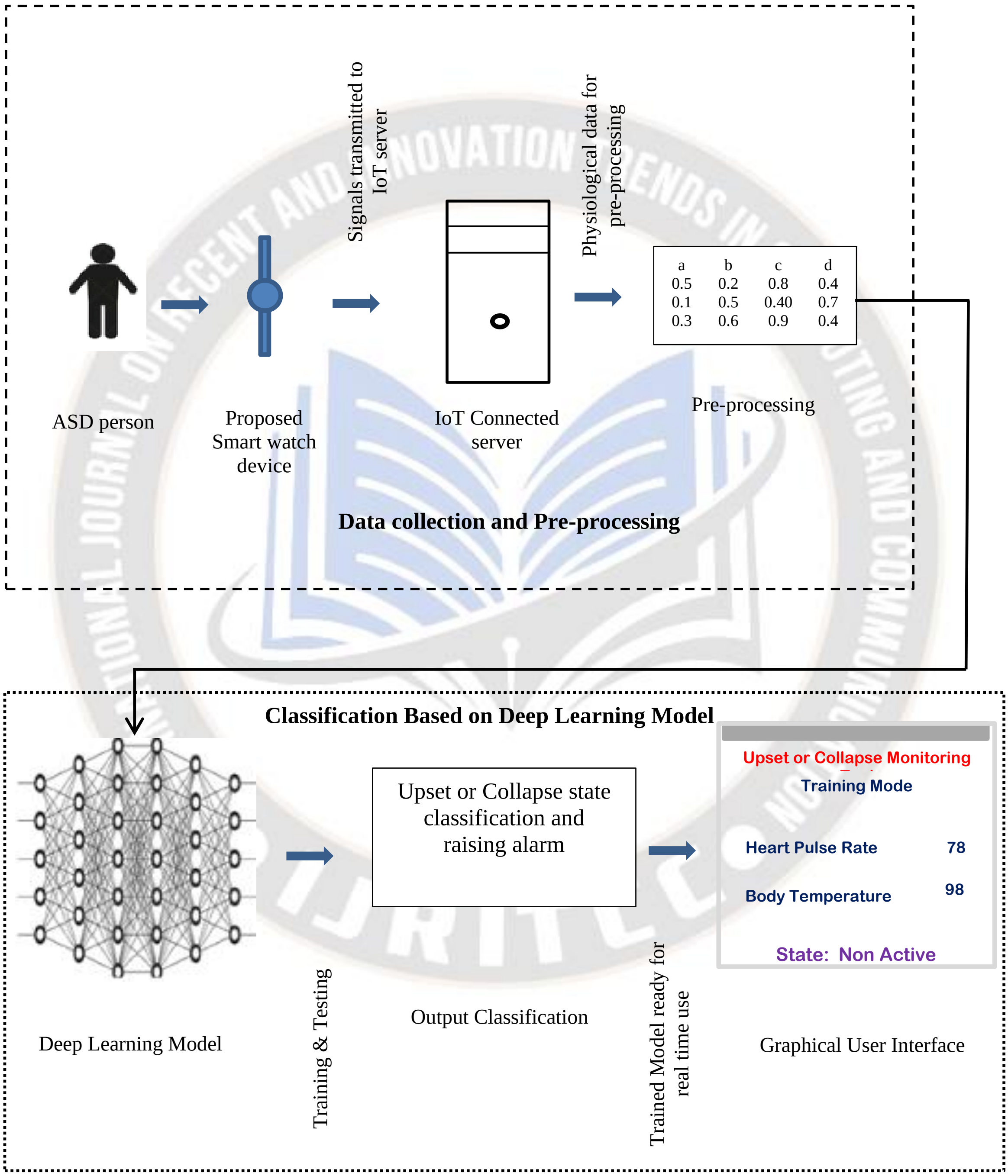

Figure 1. UCDS Block diagram

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The interactive graphical environment is created to make it simple for clinicians and parents to comprehend and access the behaviour associated to upset or collapse. The unique personalized sensor readings are transmitted to a remote server so that the data can be accessible by any authorised person. The internet-connected graphical monitoring tool, which could be accessed remotely by physicians and parents at anytime and anywhere, is helpful for observing and classifying current physiological data. The suggested design is able to identify the upset or collapse state of people with ASD, which may then be used to help with behaviour-related problems.

A smart watch with sensors is used to gather the required health related signals such as PR, ST, and GSR and communicate data to an internet-connected server. To detect the Upset or collapse condition, the deep learning model is applied to the gathered personalised physiological data at the IoT server. The suggested design's distinguishing feature is a remotely available and user-friendly graphical interface for physicians and parents to obtain runtime detection. These characteristics were made possible in order to give early treatment and to determine the cause of often recurring severe and hazardous incidents. Figure 1 depicts the block diagram of the entire system.

3.1 Hardware design

Many types of smart watches with built in sensors available in the market to monitor the parameters such as PR, GSR and ST. In our prototype we have used the "Fitbit Sense" model smart watch to monitor and update the above mentioned parameters. A battery-operated Arduino Nano is used to process and transmit the acquired physiological signals to the server through a wireless network.

3.2 Data Gathering and Pre-processing

The physiological signals, including PR, ST, and GSR from the smart-watch are recorded to include multimodal physiological signals, and then sent to the cloud server. The simulated sessions are conducted for 30 minutes in order to properly record the data. Pre-processing is done to two phases. In the first phase, null values are eliminated from the stored data. Then in the second phase, Min-max scaling method is used to normalize the data without affecting the original structure of the data. The Min-max technique divides the feature's minimum values by the difference between its original maximum and minimum values. Each parameter (xi) is scaled using the MinMax formula as given below:

$$\text{MinMaxScalar (xi)} = \frac{\text{xi} - \text{minimum of x}}{\text{maximum of x} - \text{minimum of x}} \quad (1)$$

Using the Isolation Forest outlier detection method, the primary pre-classification method is created to determine the necessary classification labels with a low or high state of acquired data. As a threshold for the upset or collapse condition, the sensitivity of the outlier system was pre-adjusted at 1% to obtain the top 1% outlier from multifactor health data including PR, GSR, and ST. The process of data collection and pre-processing is given in algorithm 1.

3.3 Combining CNN with LSTM

A collection of sequentially captured digital signals over a predetermined time period is referred to as a time series data and the same is used to predict real-time observations. In this work, acquired time series data are analysed using a hybrid CNN and LSTM algorithm, and the CNN-LSTM algorithm's performance is compared to that of CNN and LSTM. A one-dimensional signal is fed into the initial convolutional layer of the CNN-LSTM model. Every convolution layer is convoluted with its corresponding kernel (filter) size as:

$$x_n = \sum_{K=0}^{N-1} YkFn - k \quad (2)$$

Where Y represents the input signal, F represents the filter, N repreents the total number of signals, and xi are the corresponding output vectors. Next, to recover the original characteristics of the data, the CNN-LSTM method first created a shallow CNN. Also, its output turned into a pool of data with small amplitude. A Leaky ReLU function is given as:

$$\text{f(x)} = \begin{cases} x, \text{ if } x > 0 \\ 0.01 \text{ otherwise} \end{cases} \quad (3)$$

The Softmax function is given as:

$$p_j = \frac{e^{x_j}}{\sum_1^k e^{x_k}} \text{ for } j = 1,2,3,\ldots \quad (4)$$

```
Algorithm 1: //Data collection and pre-processing
Begin
    Initiate the UCDS system;
    Start recording;
        Collect the physiological signals from smart-watch;
        Transmit the signals to the IoT server;
    Stop recording;
    Remove redundant and null values;
    Use MinMax scaling algorithm to scale the data from 0 to 1;
    Classify the PR, GSR and ST values to LOW or HIGH;
    Represent LOW value as 0 and HIGH value as 1;
End
```

```
Algorithm 2: Training and testing the system
Begin
    Input the system with preprocessed data
    Training is conducted with pre-classified data
    For K = 10 to 25
        Validate the DL algorithm for K times
        (Accuracy will be more with maximum K value)
    End for
End
```

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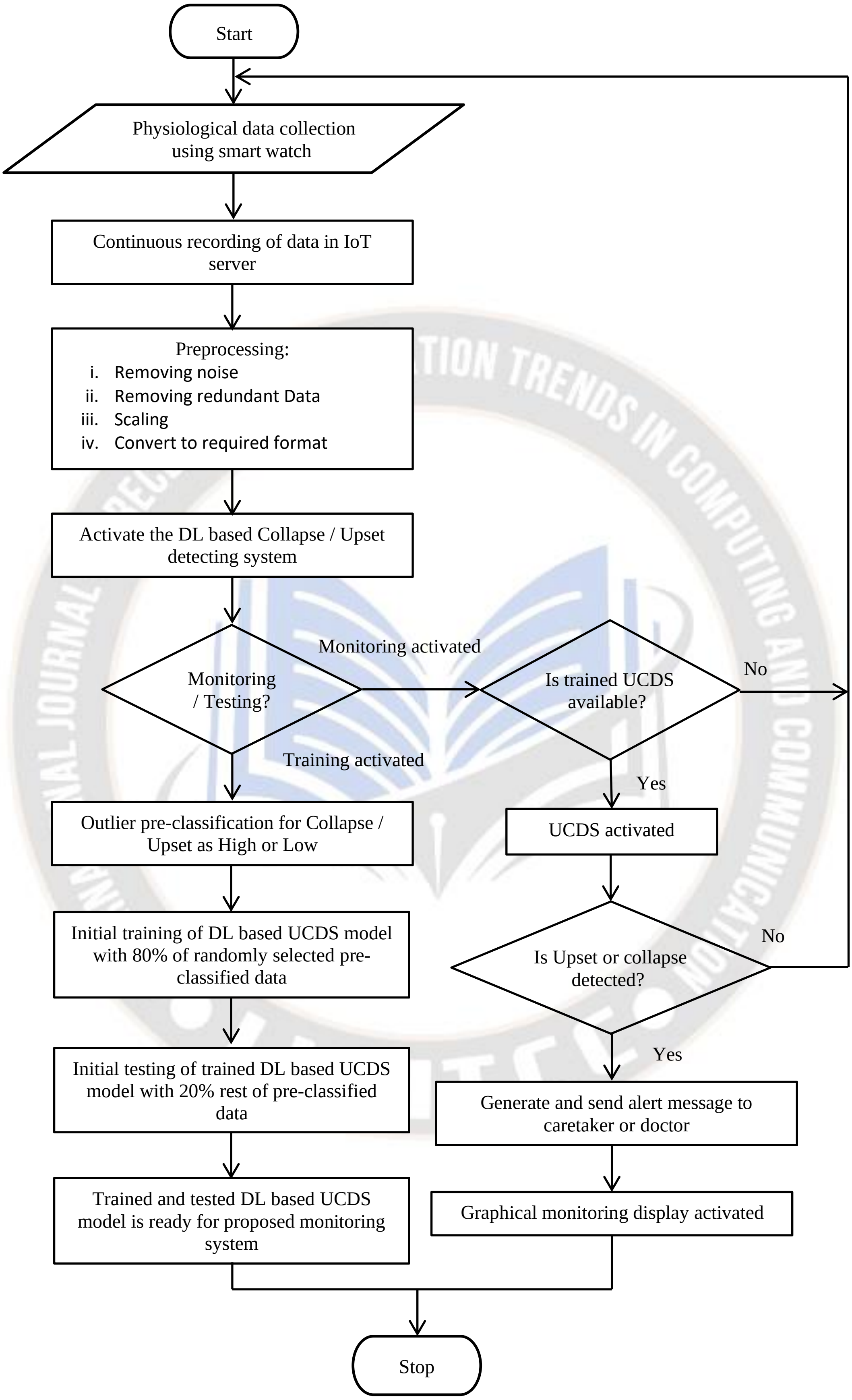

Figure 2. Flow chart of the proposed UCDS framework

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Algorithm 3: Upset or Collapse detection and warning
Begin
Deploy the trained USCD system
Collect the signals from the smart watch for an individual
Transmit the data to the server
Start recording
Fix the threshold level for PR, GSR and ST as PR_{thr} , GSR_{thr} , ST_{thr}
If PR >= PR_{thr} AND GSR >= GSR_{thr} AND ST >= ST_{thr}
Then detect Upset and Collapse of the individual
Generate alert message and pass to the caretaker
Store the data
End

For feature fusion, the retrieved features are transformed into matrix form and fed to the LSTM. In the fused CNN-LSTM model, the LSTM layer employed the ordering of the local features that were recovered from the convolutional layer. Algorithm 2 gives the process of training as well as testing of the proposed UCDS, whereas algorithm 3 provides the upset and collapse detection process. The flow diagram of UCDS framework for training and testing processes is depicted in figure 2.

4. Comparison of LSTM, CNN, and Hybrid CNN-LSTM

An efficient UCDS system for detecting ASD person's upset / collapse state was created using DL algorithms such as CNN, LSTM, and hybrid CNN-LSTM. For 300 iterations, the effectiveness of UCDS is assessed, and comparison analysis is done using DL algorithms including CNN, LSTM, and CNN-LSTM. To find an enhanced algorithm for the proposed UCDS system, performance analysis is done based on training and testing accuracy as given in Table 1 and 2 respectively. Figure 3 and 4 depicts the graphical representation of the training and testing accuracy of the system as given in Table 1 and 2. While detecting the upset and collapse states using the UCDS, it is shown that the CNN-LSTM hybrid algorithm outperformed CNN and LSTM separately.

The accuracy and MAE (Mean Absolute Error) parameters are used to examine the training and testing efficiency of the CNN-LSTM based UCDS. The results are shown in Figures 5 and 6, respectively. As shown in Figure 7 and 8, more detailed results of the UCDS for upset or collapse identification in ASD were performed using 80% of the training dataset and 20% of the testing dataset that had been gathered. These fundamental metrics included precision and F1-score.

Table 1 Accuracy of training of CNN, LSTM, CNN-LSTM

Iterations	Training Accuracy		
	CNN	LSTM	CNN-LSTM
1	55	64	72
10	59	75	95
25	62	83	96
50	68	87	97
75	73	89	98
100	75	92	98
125	82	91	97
150	86	93	98
175	85	93	97
200	86	92	97
225	85	93	98
250	86	92	98
275	86	93	98
300	86	92	98

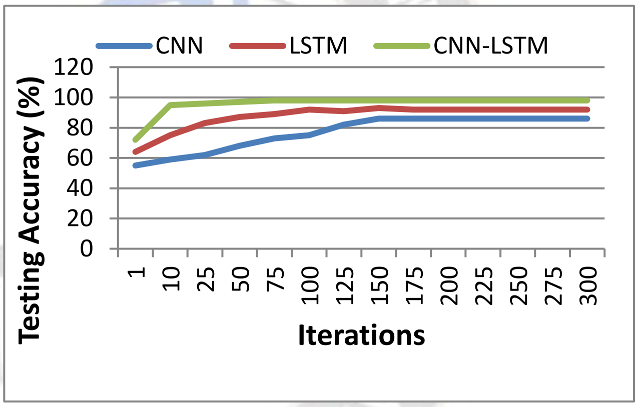

Figure 3. Accuracy of training of CNN, LSTM, CNN-LSTM

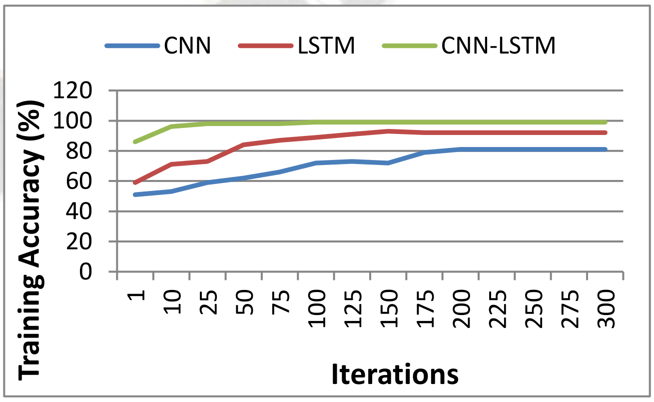

Figure 4. Accuracy of testing of CNN, LSTM, CNN-LSTM

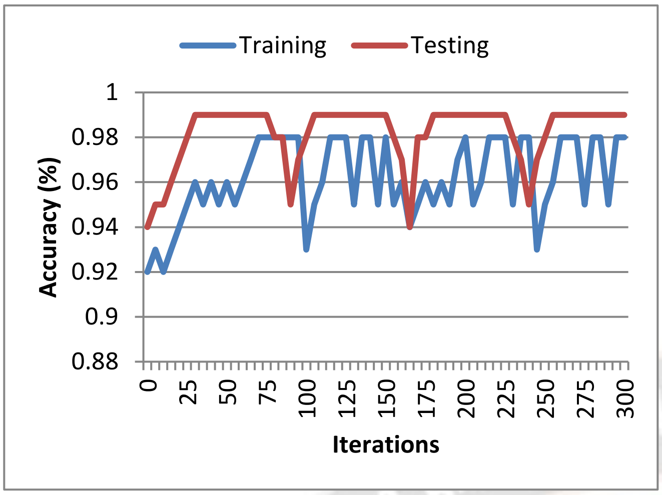

Figure 5 Training and Testing accuracy

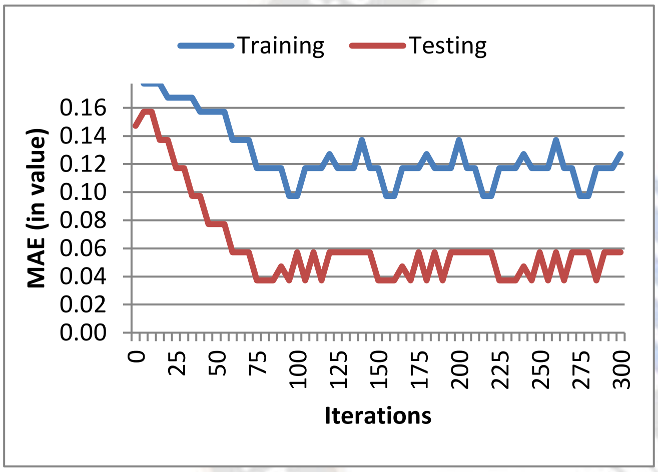

Figure 6 MAE for training and testing of UCDS

Table 2 Accuracy of testing of CNN, LSTM, CNN-LSTM

Iterations	Testing Accuracy		
	CNN	LSTM	CNN-LSTM
1	51	59	86
10	53	71	96
25	59	73	98
50	62	84	98
75	66	87	98
100	72	89	99
125	73	91	99
150	72	93	99
175	79	92	98
200	81	92	99
225	82	93	98
250	81	92	99
275	82	93	98
300	81	92	99

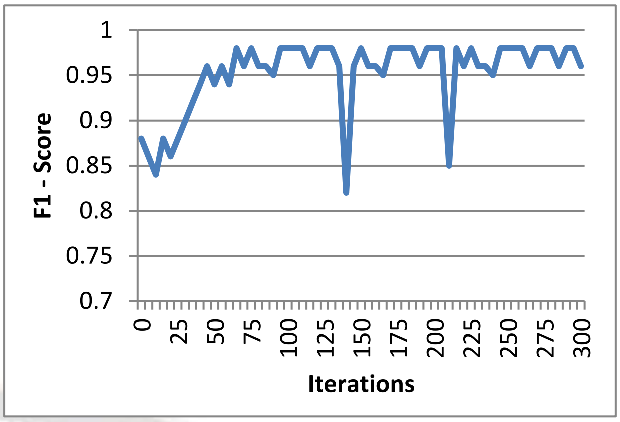

Figure 8. F1-score

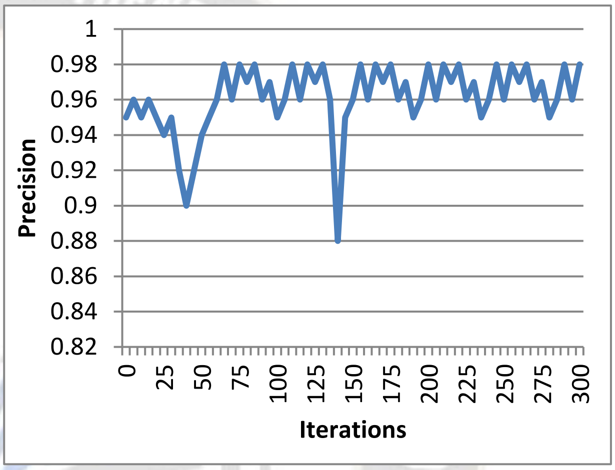

Figure 7. UCDS precision

Table 3. Responses of the caretakers about UCDS

Caretaker Details			Evaluation parameters (Scale: 0 - 10)				
No	Level	Group	UI	MS	DS	AS	Overall
1	AK	ASD	7	8	7	7	7.25
2	AK	ASD	8	9	5	7	7.25
3	LK	ASD	7	6	5	6	6
4	HK	ASD	8	8	5	8	7.25
5	LK	ASD	6	5	4	6	5.25
6	LK	ASD	6	4	4	6	5
7	HK	ASD	8	9	7	9	8.25
8	LK	ASD	6	7	6	5	6
9	AK	ASD	8	7	7	5	6.75
10	AK	ASD	6	8	7	6	6.75
11	AK	TD	7	8	6	8	7.25
12	HK	TD	8	8	7	9	8
13	AK	TD	7	7	4	5	5.75
14	AK	TD	8	7	6	6	6.75
15	LK	TD	6	7	7	6	6.5
Above average: (i.e 6% of satisfaction level) =							93.3

4.1 Validation based on the caretakers' response

We have conducted experiments by using various parameters which include the caretakers' response. Several degrees of autism knowledge, including, Low Knowledgeable (LK), Average Knowledgeable (AK) and Highly Knowledgeable (HK) are analysed by caretakers of both ASD and TD (Typically Developed) group of participants. Caretakers' only responsibilities in this situation are to comprehend the suggested framework and verbally evaluate it. The design of User Interface (UI), Monitoring System (MS), Detection System (DS), and Alerting System (AS) are the four parameters used to evaluate the efficiency of the suggested UCDS system on a scale of 0 to 10. Table 3 and Figure 9 give the average ratings of the specified parameters for the proposed system.

5. DISCUSSIONS

The hybrid CNN-LSTM outperforms the training and testing analyses with an average training and testing accuracy of 96% and low MAE (0.10 for training and 0.04 for testing). The proposed CNN-LSTM model's accuracy and F1-score values were 0.98 and 0.97, respectively. The hybrid CNN-LSTM's accuracy is very good and had minimal losses. Moreover, analysis of the caretaker responses from the ASD and TD groups is done using variables such UI, MS, DS, and AS. This analysis produced 93.3 above-average (more than 6) favourable responses on a scale of 0 to 10. ASD and TD caretaker response to the proposed MTDS were identical, according to the statistical analysis that was undertaken. The comparative research revealed that the suggested CNN-LSTM based UCDS has a better accuracy than the existing technologies.

6. CONCLUSION

Due to the complexity of neurological developmental issues, it may be challenging to identify upset or collapse in people with ASD. Since only facial emotions or behaviour are the indicators of upset or collapse conditions of ASD children, well-known and expertise knowledge were essential to correctly identify the state of breakdown or tantrum. In order to address this issue, in this research work a CNN-LSTM based MTDS system has been developed and a specific model of smart watch is used to collect the brain signals from the ASD people and evaluated. The graphical interface is also created to make it simple for physicians and caregivers to use this design. It could simply reflect real-time data from physiological signals and classify the ASD people for upset or collapse as active or inactive.

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