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A Facial Emotion Recognition System for Children with Autism, Based on The Integration of 3D-CNN and LSTM

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Abstract

Detecting autism spectrum disorder (ASD) is a difficult task for medical experts and healthcare providers, as the medical diagnosis is based primarily on the presence of a malfunction in brain functions that are reflected in the behavior of children. Facial expressions can be an effective alternative to diagnosing ASD. This is because children with ASD usually have specific patterns and behaviors that set them apart from other children. A key intervention enhanced the quality of medical home care for children on the autism spectrum by utilizing assistive technology. In this study, an emotion recognition system was developed for children with autism spectrum disorder. Face recognition, facial feature extraction, and feature classification are the three main stages of the proposed emotion recognition system. The system detects six facial emotions: fear, anger, sadness, neutral, surprise, and joy. The proposed system uses the mixing of Long Short-Term Memory (LSTM) and 3D convolutional neural network (3D-CNN) technologies to extract spatiotemporal features from pre-processed video templates. Findings reveal that the combination of the two techniques achieved an accuracy of 99.82%, which is better than other techniques.

Keywords: ASD, HAR, HealthCare, Monitoring, Deep Learning, Machine Learning, CNN, LSTM.

1 Introduction

Human activity recognition systems are based on machine learning and deep learning, which is a very effective way to monitor health and safety, especially for those needing health care. In these systems, data is collected by sensors, wearable devices, and cameras, which are later analysed to detect activity changes, behavioural patterns, and social interactions. These systems can help evaluate many health risk factors that patients face, such as unexpected changes in their daily behavior when exposed to abnormal conditions. Therefore, many researchers have applied different cyber-physical systems for these purposes (Ganesan et al., 2022). Over the past few years, there have been tremendous advancements and significant work toward developing systems based on innovative computer vision for various domains.

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Behind the spread of these systems, several aims were discovered to assist individuals living with autism. Abnormal social interaction and communication characterize autism or autism spectrum disorder (ASD), along with repetitive and restricted behaviors (Jarraya et al., 2021; Piedra et al., 2025). We can give an overview of the human activity recognition system through Figure 1. The human activity recognition system consists of five main parts. First are sensors, which collect data. Second, data processing, in other words, deletes corrupted and duplicated data and removes the noise associated with this data. Third, data segmentation is classified into two main categories: test and training data. Fourth, data analysis should be done in a descriptive, diagnostic, predictive, and prescriptive manner. Fifth and finally, data classification according to the result of foregoing processes for understanding and predicting the health condition of the subject and for provision of needed aid [(Afzali Arani et al., 2021; Xie & Fang, 2024; Latha & Narasimhulu, 2025).

Over the past years, information and communication technology (ICT) has been widely used in the healthcare industry. Research has been done on using smartphones, wearable devices, and other mobile devices to support those who benefit from this industry, whether they are patients or healthcare providers (Koumpouros & Kafazis, 2019). Researchers have focused their attention on human activity recognition because of its broad application prospects. Human activity recognition is used in medicine, entertainment, sports, education, security, and surveillance, among other areas. For example, real-time monitoring of a patient's activity status is standard in the medical field (Li et al., 2020). Researchers used different techniques to detect stress and anxiety in individuals with ASD. However, these sample collection tools may face some challenges in detecting behavior changes in real-time and daily use. The emergence of wearable assistive technologies is a means by which emotional changes can be detected non-invasively. Wearable technology can be a highly valuable asset for individuals with ASD as well as those who care for them (Taj-Eldin et al., 2018).

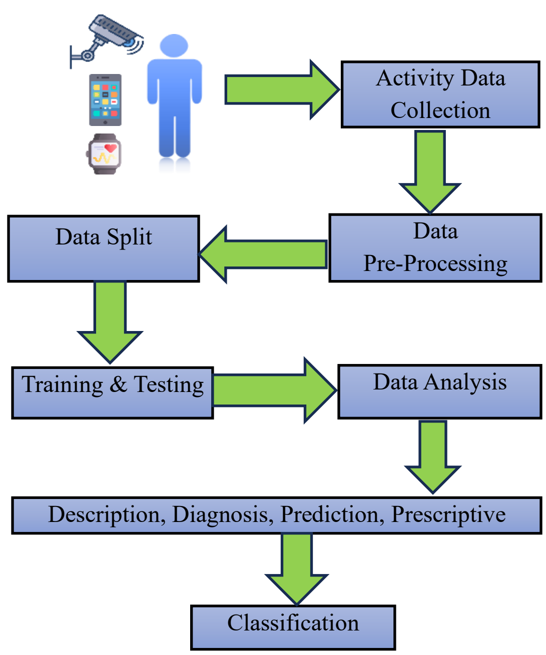

Figure 1: Outline of Human Activity Recognition System

Current advancements incorporating the Internet of Things (IoT), machine learning, and artificial intelligence have demonstrated the capacity to assist in health care purposes, particularly for those suffering from autism. Accurate detection of sudden changes in the behavior of patients can ensure timely assistance and may avoid cases of ASD (Ghosh et al., 2021; Vatandoust et al., 2017). This can be achieved through the processing power of artificial intelligence. IoT device-based systems offer numerous beneficial features that enable patients' remote monitoring. Consequently, IoT device-based healthcare applications have gained popularity over the past few years (Hosseinzadeh et al., 2021). IoT devices and Sensors like Cameras, GPS, and heart rate are usually embedded in wearable devices such as smartwatches. To date, no statistics are measuring the increase in improvements to the detection and diagnosis of autism disease, so the disease is an increasing challenge for healthcare providers responsible for caring for affected children with autism (Alhalabi et al., 2014).

Artificial intelligence has proven its potential in many fields, especially in health care. Researchers have used different algorithms of artificial intelligence, such as machine learning algorithms (logistic regression (LR), decision tree (DT), support vector machine (SVM), etc.) to inspect and categorize different kinds of spectrum disorders (Biswas et al., 2021). Much research has shown that children with autism show some signs of spasticity and meltdown, sometimes called the “rumble phase”. So, it is possible to identify and alert these behaviors by deep learning before they become worse and can help healthcare providers control, treat, or avoid these behaviors (Patnam et al., 2017). Generally, we would be referring to assistive technology as a device or piece of equipment that has been customized with a view to improving and fine-tuning people with autism's ability to function. These systems or devices are intended to be used by children with autism to help them (Fazana et al., 2017).

The general aim of the present paper is to identify the most suitable characteristics that help us devise an integrated system that does not allow children with autism to injure themselves in case of a meltdown emergency by recognizing that a meltdown is happening and warning health providers.

The remaining part of the paper is structured as an overview of the literature on monitoring children with autism during a meltdown episode, which is presented in the second section. The next section describes the proposed framework, the design and components of the system, and its working mechanism. In the following section, the results are described and discussed. Finally, we wrap up the paper by summarizing the suggested work and outlining potential prospective study avenues for system development.

2 Related Works

Children's families and caregivers face the greatest difficulties when dealing with autistic children. Monitoring and treating children on the autism spectrum has gained significant attention over the past years. Numerous articles have been written about the treatment and diagnosis of ASD, while the number of papers concerning the monitoring of ASD has been quite small. Several reviews of the literature have already appeared related to this work's topic of interest, analyzing the possible technologies allowing remote monitoring of the body and emotional state of children utilizing various sensing modalities.

Computer vision methods of monitoring individuals with ASD are in the infancy stage. Numerous studies have focused on this subject. In the following sections, we outline some existing work that attempts to offer automatic basic emotion recognition and physiological cues evident in individuals with autism during meltdown episodes. The mentioned work shall be tabulated based on the methods and tools utilized to acquire the data.

The study (Manocha & Singh, 2023) proposes a deep activity prediction methodology based on a convolutional neural network (CNN) and long short-term memory (LSTM) for physical irregularity recognition. The 3D CNN network extracts spatiotemporal characteristics of the templates of a video and is utilized in predicting the subject location. The magnitude of irregularity in feature maps is calculated with the help of the LSTM model. In work (Strobl et al., 2019), the researchers relied on the two algorithms. The first is a CNN. On a smartphone screen, employ the second Eye-Tracker algorithm to distinguish between gaze directed toward the eyes and the mouth. Gaze aversion behaviors have been tracked by using this technology over time among people who have ASD. Research workers have proposed in (Shahamiri & Thabtah, 2020) a framework involving a cell phone application that offers a user interface that captures questionnaires and a smart web service for detecting ASD. The system also depends on a CNN. As well as a base of data that enables CNNs to be trained from users' knowledge of a system. In work (Li et al., 2020), they also proposed a system that depends on a three-layer LSTM that helps diagnose children with ASD through video data captured using deep learning technology. The system relies on tracking eye movement in each video. The system relies on tracking two paths: length and angle. Next, the system calculates a cumulative histogram for each component. The study (Mohammed et al., 2021) aims to detect ASD using machine learning methods. In this work, the researchers experimented with feature selection methods using the Adult Autism Screening Dataset. They used several classifiers. One is the CNN, which has default parameters. They utilized a simple convolution layer in 1D with a subsequent pooling layer, a dense layer, along with an output layer for the CNN. The proposed system by (Talaat, 2023) depends on deep CNNs for real-time emotion identification for autistic youth. The system detects six facial emotions and consists of three layers: fog, cloud, and IoT (Vatandoust et al., 2017). The proposed system also includes an Emotion Detection Assistant (EDA) application for parents to receive alerts when their child experiences negative emotions. The system uses enhanced deep learning (EDL) technology for sentiment classification and image segmentation (Mohammed et al., 2025).

Hasan Al Banna et al In the study (Al Banna et al., 2020), researchers proposed an artificial intelligence-based automated control system. The envisioned system includes a smart wristband (SWB), an interactive display, and a camera device mounted on the display to monitor children and adolescents with ASD. These wearable devices are connected to a wearable app that monitors them around the clock without any intervention by the caregivers. The authors of the article (Tomczak et al., 2020) suggested a comparable system that caters to the needs of a specific group of people with ASD and a monitoring system for stress. The stress monitoring system also includes a wearable device (wristband). The system also contains a software application dedicated to data analysis and creating reports evaluating therapeutic effects. In work (Akinloye et al., 2020), the researchers also developed a wearable emotion-based electronic healthcare controller. Technology uses speech recognition sensors and electrodermal activity (EDA) to get physiological information from autistic children. This system includes an emotional and electronic health care module. A wearable system called the Emotion Module detects, evaluates, and categorizes data into different states of emotion. The e-Health Care Module is a web-based program that provides access to therapists or medical specialists. What was mentioned in the study (Fioriello et al., 2020) is similar to previous studies; the researchers developed a small wearable chest belt suitable for children. The belt includes several sensors, including three electrocardiograph devices and a piezoelectric sensor, to monitor cardiorespiratory activity in children with ASD and learning difficulties. Moreover, after data is collected, a microcontroller with a wireless interface transmits the data to a personal computer for analysis. In work (Mohammadian Rad et al., 2018), Researchers have proposed a wearable sensor system. Sensor data models and distribute regular human movements and abnormal movements observed in patients with ASD. Researchers used a SVM algorithm to analyze and classify the data. An autoencoder was also used to reduce noise and identify the natural human movements from accelerometer signals. The paper (Sumi et al., 2018) proposes a helpful system for infants with ASD or autism. This system also depends on wearable devices, especially smartwatches. The current system's primary objective is to decrease children's dependency on healthcare providers and parents to receive help. The system takes input from a set of four detectors and generates appropriate alerts to parents, caregivers, and children with ASD. In work (Fadhil & Mandeel, 2018), a system has been proposed for monitoring children with autism remotely and analyzing the data collected by the sensors. The system comprises a Node MCU (Micro Controller Unit), a smartphone or personal computer, a wearable galvanic skin response (GSR) sensor, and a server. The system monitors people's reactions to different emotions. In the last stage of the system, a comparison is made between the data obtained for children with autism and those without autism. The proposal in work (He, 2022) includes a four-part health monitoring system: a wearable data gathering module, a cellphone monitoring data, an intelligent medicine container module, an alert-receiving application, and a remote monitoring server module used in a medical context. This work suggested that behavioral training in autism for children be investigated under music therapeutic intervention with intelligent monitoring of health. The system uses several algorithms to analyze and classify data, comprising the QR analysis method, the modal strain energy (MSE) method, the effective independence (EFI) method, the Guian model reduction method, and the modal kinetic energy (MKE) method. In the study (Cantin-Garside et al., 2020), a framework is proposed. It also depends on wearable devices that include three-axis accelerometers. Accelerometers are placed on the child's body. Up to six accelerometers were applied to each child. Each child was also recorded on video by utilizing a series of three cameras. These devices are used to detect self-injurious behaviors.

Mehmet Baygin et al (Baygin et al., 2021) used electroencephalogram (EEG) signals for children suffering autism to create and implement a model for automatic autism prediction. The signal-to-image conversion model was presented, features extracted using a one-dimensional local binary pattern (1D_LBP), and the produced characteristics were used as input for short-time Fourier transform (STFT) to produce spectral photos. In this work, deep characteristics are extracted using a set of pre-trained MobileNetV2, ShuffleNet, and SqueezeNet models. Then, a two-layer ReliefF algorithm was used to classify and select features. The suggested system in (Sivasangari et al., 2024; Zakaria & Zaki, 2025) monitors and identifies individuals who have a spectrum disorder of autism, utilizing a machine-learning algorithm along with sensors. The system has a neural sensor to gather EEG information and a Q-sensor to determine stress levels. The system recognizes the face and, through it, detects emotions and informs the user and caregiver about the incident at home. The proposed system consists of three main stages: mobile, web service, and sensing. This unit needs an Internet connection to receive requests and information gathered via the sensors. Lastly, this information is retained, analyzed, and concluded here.

Past authors have offered numerous methods through which we can recognize a meltdown crisis in children with autism, but these studies also have many challenges that require deep analysis to overcome them.

3 Proposed Methodology

The purpose of this research is to improve home health care for children with autism through artificial intelligence technologies. Medical artificial intelligence techniques in the modern sense are the collection and flow of electronic data between the caregiver and the patient, remote processing techniques, and artificial intelligence algorithms that include deep learning, machine learning, and intelligent neural networks to process medical data.

Under normal conditions, healthy youngsters with autism never lose their ability to make facial expressions like everyone else. However, with a meltdown predicament, an autistic person undergoes a rapid and sensitive mix of distinct feelings like fear, disgust, sadness, and anger. Due to this fact, an investigation of compound feelings displayed while under a meltdown crisis was put forward.

The distinct feelings observed in children with autism, whether in their ordinary condition or during nervous breakdowns, are detected through video frames recorded in various situations in which the child experiences a variety of complex emotions, or through sensors embedded in wearable smart bracelets or smartwatches. This section of our research will present the steps necessary to build a prototype for facial emotion analysis.

A. Problem Description

This section proposes a system for recognizing the emotions of autistic children on the ASD. The system proceeds in three stages: the first involves facial recognition, the second involves feature extraction, and the third involves feature classification. The proposed system detects six facial emotions: anger, fear, joy, neutrality, sadness, and surprise. This research presents a hybrid architecture for facial expression recognition, combining a 3D-CNN and a LSTM architecture.

B. Proposed System

The proposed model comprises six stages: Data Collection, Pre-processing, Feature Extraction, Classification, Results, and Decision. As shown in Figure 2, the suggested system acts to detect and monitor children with ASD, along with making the user, caretaker, or any other individuals aware of it.

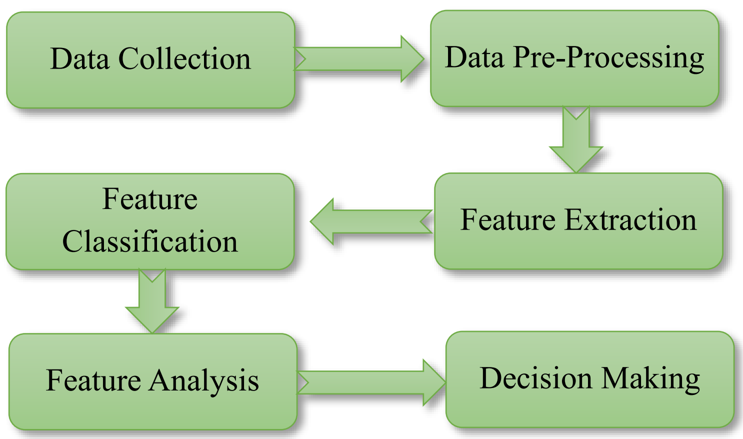

Figure 2: Stages of the Proposed System

The proposed system consists of three layers: the sensor unit, the data processing unit, and finally, the application unit, which is shown below with a block diagram in Figure 3.

The sensor layer consists of several cameras. These cameras are used to detect the emotions of autistic children that appear through facial expressions when ASD.

The monitoring application module is installed on the smart devices of parents and caregivers. The system processes the data to determine what to do if an abnormal change in the child's emotions occurs and then sends alerts or notifications to parents and caregivers.

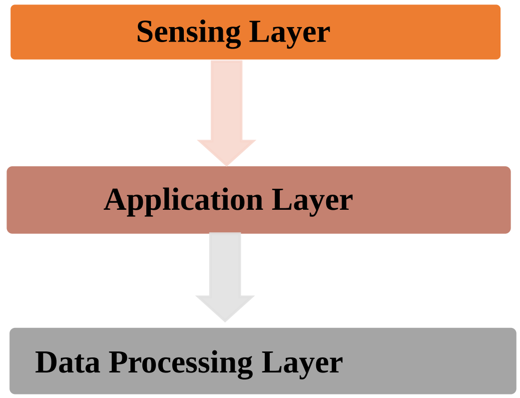

Figure 3: Architecture Diagram of the Proposed System

Expert systems and databases make up the data processing layer. The expert system processes the data received from the sensor layer. The function of this layer is to collect data and send it from the sensor layer to the data processing layer to process it and make the appropriate decision. After the decision is made, it will be sent to the application as an alarm or notification.

C. Proposed Model

This section proposes a Hybrid Deep Learning model (HDL) for emotion classification by combining two technologies: a 3D-CNN and LSTM. The overall architecture of the proposed model is shown in Figure 4. The system consists of several parts. The system also includes an autoencoder that extracts features from the input frames to improve the proposed system's efficiency in data classification.

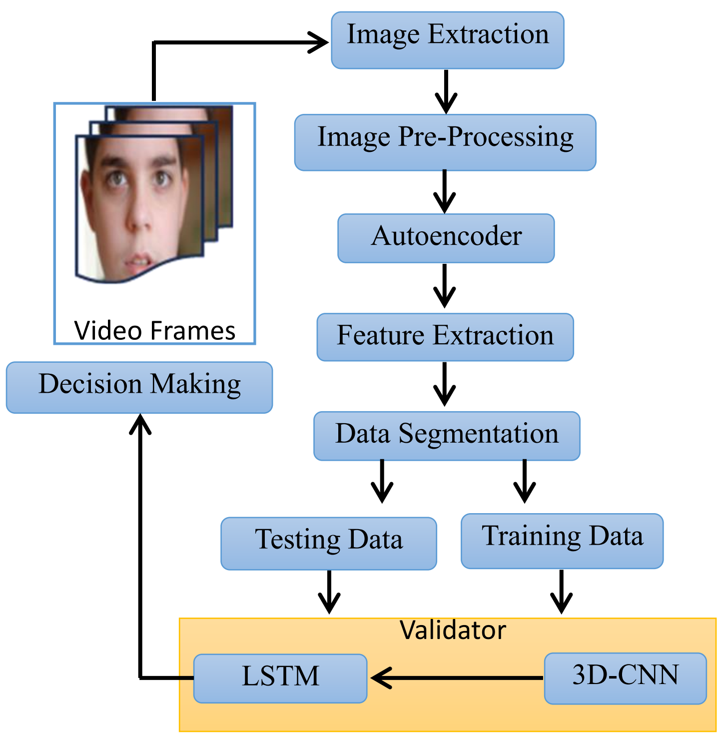

Figure 4: The Proposed HDL Model

D. Emotion Recognition

Optical sensors are one of the sources of data for this investigation. Optical sensors continuously capture data on emotions and gestures (irregular and regular). The proposed model combines two technologies, 3D-CNN + LSTM, for sequential frame analysis to recognize emotions in real time. Spatiotemporal attributes are extracted from pre-processed video templates employing a 3D-CNN. The LSTM network then addresses temporal characteristic modeling in a time-structured form to compute the intensity of irregular events. 3D-CNN architecture based on video frame processing. A 3D-CNN is fed input data generated by video templates. It will be possible to extract temporal and spatial information from the sequence of frames by constructing a vector group. Then addresses characteristics by an LSTM network to obtain final, evaluable values.

E. Video Frame Pre-Processing

Video frame pre-processing is a quality improvement process that removes degradation, distortions, and noise from blurry frames. The straightforward capture of frames by sensors and cameras brings extraneous noise from data acquisition mechanisms. So, some pre-processing to refine the frame features before moving on to further analysis was needed, see Figure 5.

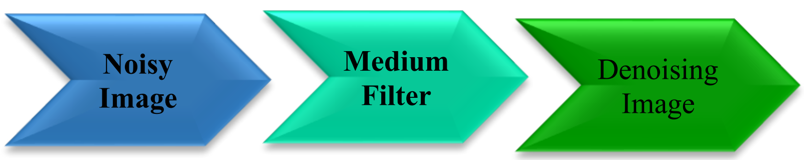

Figure 5: Noise Removal Steps

The data undergoes some prior pre-processing before being fed into the framework's next stage of the model for emotion identification. The templates must be categorized into two broad classes for a thorough analysis. The system is supposed to recognize and identify abnormal emotions and gestures by analyzing a series of frames. The system divides the frame sequence into non-overlapping parts named video templates. Using the suggested procedure, video templates are formed with identical frame counts. Video template (V) is a frames' collection with a mean frame time of one second each, described as:

$V_t = \{F_1, F_2, F_3, \ldots, F_n\}$

A video template of (n) frames can be formulated by using the equation:

$$(F_e - F_s) \bmod n = 0 \quad (1)$$

To understand the equations, see below.

V_t: The video template.

F_s: The first video frame in a video template.

F_e: The last video frame in a video template.

F_n: The overall video frames in a video template.

If a segment of a frame cannot be divided by the overall number of frames or if there isn't a zero remainder, an even division is achieved by appending zeros after the segment's last frame. The system further compresses the video templates in the next phase to lessen template processing costs. Once the template reformulation compression has been achieved, the video templates are passed to the next phase to analyze gestures and emotions.

F. Three-Dimensional Convolutional Neural Network

A category of deep neural networks known as 3D-CNNs uses characteristics extracted from photos as input to carry out certain missions like image semantic systems, image classification, and face recognition. Convolution layers exist in a CNN to detect basic yet meaningful attributes.

In mathematics, convolution networks use convolution functions, which are mathematical operations between two functions that yield a third function describing how one's shape is altered by that of another. The issue lies that convolution networks' job is to simplify images so that they become easy to process without erasing vital characteristics, so that a good prediction is achieved.

The 3D-CNN architecture contains three CNN layers. The initial layer receives the frame set input that has already been pre-processed and sends it to the mini-feature map. The input from the first lessened feature map is transferred back to the second lessened characteristic map by the second convolutional layer. And so on for the last layer. Then, the CNN generates the result vectors and is transferred to the fully connected layer for anomaly analysis of the recorded values.

We calculate the compression ratio of video templates through the following equation:

$$A_i = \frac{V_c}{V} \tag{2}$$

To understand the equations, see below

A_i: The compression ratio of the video template.

V_c: A template's size after compression.

V: The video template's original size.

The 3D-CNNs have an input layer, an output layer, and three principal hidden layers' types: convolutional layers, pooling layers, and FC, or fully connected layers, and a huge group of parameters, allowing them to learn complex objects and patterns. Furthermore, CNNs often use pooling operations to reduce the spatial dimensions of feature maps, resulting in a more manageable output size, and feature maps can be calculated through the following equation:

$$\text{Feature Map} = \text{Input Image x Feature Detector} \tag{3}$$

The input data is filtered and information is found using layers of convolution. The image size can be calculated after the process of convolution through the following equation:

$$I_{out} = \frac{I-F+2P}{S} + 1 \tag{4}$$

To understand the equations, see below:

I_{out} : Image size after convolution.

I: Original image size.

F: Filter.

P: Padding.

S: Stride.

Like the convolutional layer, the pooling layer reduces the spatial size of convolutional features. This reduces the computational power required to process the data by reducing dimensions.

The Max-pooling Layer selects the most important element from the feature map. It is the most popular method because it produces the best results. Basically, Max Pooling finds the maximum pixel value of the kernel-covered part of the image. Additionally, Max Pooling cancels out noise. It eliminates loud activations and removes noise with dimensionality reduction.

The image size can be calculated after the process of pooling through the following equation:

$$I_{out} = \frac{I-F}{S} + 1 \tag{5}$$

To understand the equations, see below:

I_{out} : Image size after Pooling.

I: Original image size.

F: Filter.

S: Stride.

G. Long Short-Term Memory (LSTM)

The LSTM is a robust architecture of Recurrent Neural Networks (RNN) used in deep learning. Networks of LDTM are a kind of deep learning artificial recurrent neural network that enables the retention of information over extended periods. The network consists of three independent LSTM modules. One component focuses on retaining the information acquired at the preceding timestamp, while another component analyses the link between the information from the previous timestamp and the present information, as well as the potential for its obsolescence. In the second ingredient, the cell tries to gather new data from its inputs. Within the third component, the cell carries forward the new data for the present time stamp to the following timestamp. This LSTM is executed just once as a single pass, referred to as a one step.

There is a composition of three components that form the gates of the LSTM module. Both incoming and outgoing information within any memory (cell) layer/block of the LSTM cell are governed by gates. The first gate is referred to as a forgetting gate while the second one is referred to as an input gate. The final gate is referred to as an output gate.

Similar to a basic RNN, the LSTM likewise has a concealed state, where the concealed state of the present timestamp is denoted by H_t and the concealed state of the previous timestamp by (H_{t-1}). Besides, for the preceding and present timestamps, respectively, LSTM's cell state is denoted by (C_{t-1}) and (C_t). In this context, short-term memory refers to the concealed state, while long-term memory refers to the state of the cell. It is noteworthy to observe that the cell state contains the information together with the timestamps. The LSTM cell can remember values at random intervals of time, through three gates that flow information Cross it into and out of the cell. In the following sections, we will explain the work of the gates in more detail.

- Input gate: Input gating is utilized for determining the relevance of incoming information being sent by the input. As shown in the equation of input gate.

$$i_t = \sigma\,(X_t * U_i + H_{t-1} * W_i) \tag{6}$$

Again, the sigmoid function on (i_t) has been used. Consequently, at timestamp (t), the (I) value will lie between 0 and 1.

Currently, the function of the state concealed at the previous timestamp (H_{t-1}) and the entry (X) at timestamp (t) are the new data that must be supplied to the cell state. The function of activation here is (tanh). Owing to this function, the new information value will range between (-1) and (1). When (N_t) value is negative, that means information is being taken from a state of the cell, while if (N_t) value is positive, it is being added to a state of the cell at the present time stamp. Nevertheless, there is no direct addition of (N_t) to the state of the cell. As shown in the updated equation.

$$N_t = \tanh\,(X_t * \ U_c + H_{t-1} * W_c) \quad \text{(new information)} \tag{7}$$

Here, the cell's state at the present stamp of time is represented by (C_{t-1}), and the remaining states are the values we earlier estimated. As shown in the following equation:

$$C_t = F_t * C_{t-1} + i_t * N_t \quad \text{(update cell state)} \tag{8}$$

To understand the equations, see below:

i_t : The input entry.

X_t : The input at the current timestamp t.

U_i : The input weight matrix.

H_{t-1} : A concealed public at the preceding timestamp.

W_i : The input weight matrix is related with the concealed state.

N_t : The new information of the present stamp of time t.

C_t : The cell state of the current timestamp t.

U_c : The weight matrix related with the current input.

W_c : The weight matrix related with the previous hidden state.

- **Forget gate:** In the cell of the neural network based on LSTM, the initial task is to determine whether we forget or retain data from an earlier time interval based on the equation given below.

$$F_t = \sigma\,(X_t * \ U_f + \ H_{t-1} * \ W_f) \tag{9}$$

Afterward, (F_t) is analyzed with a sigmoid function. It will result in a number between 0 and 1 for (F_t). The following equations illustrate how this $(F_t)$is later multiplied by the cell state of the preceding timestamp.

$$C_{t-1} * F_t = 0 \qquad \text{if } \ F_t = 0 \ \text{(entirely forgotten)} \tag{10}$$

$$C_{t-1} * F_t = C_{t-1} \quad \text{if } \ F_t = 1 \ \text{(nothing to be forgotten)} \tag{11}$$

To understand the equations, see below:

F_t : forget gate

X_t : The present timestamp input.

U_f : Matrix of weight related with input.

H_{t-1} : The preceding timestamp's concealed state.

W_f : Matrix of weight related with the concealed state.

C_{t-1} : Preceding timestamp's cell state.

- Output gate: This is the output gate equation, which is very similar to the previous two gates. The output gate regulates the output and establishes the final cell output. This is shown by equations:

$$O_t = \sigma(X_t * U_o + H_{t-1} * W_o \tag{12}$$

A sigmoid function will also result in a value between 0 and 1 for (O_t). Using (O_t) and (tanh) for the updated cell state, we can calculate the current concealed state. As shown below.

$$H_t = O_t * \tanh(C_t) \tag{13}$$

Interestingly, the output current and long-term memory (C_t) are both factors for the hidden state. A concealed state (H_t) can be activated to output the present timestamp by applying (SoftMax) activation. As shown below.

$$\text{Output}=\text{SoftMax}(H_t) \tag{14}$$

The prediction token has the highest number of points in the output.

To understand the equations, see below:

O_t : The output gate.

X_t : The current timestamp input.

U_o : The matrix of weight related with the present input.

H_{t-1} : The state that was hidden at the preceding timestamp.

W_o : The matrix of weight related with the preceding concealed state.

C_t : The present timestamp's cell state.

σ : The sigmoid function, this function makes the result value between (0) and (1).

tanh : The function of activation, this function makes the result value between (-1) and (1).

G. Intelligent Alerts to Make Wise Decisions

In health care and ancillary care, warning and emergency signals play a necessary role in notifying caregivers or physicians of the present condition of the person being monitored. There are two classifications for the monitoring process: monitoring built on alerts and continuous monitoring. In this case, the monitoring services were incorporated into this work to enhance efficiency in the proposed system. Ongoing monitoring constantly sends data into the suggested categorization methodology to examine the emotional data employed in the suggested system. Alarm-based monitoring alerts physicians and caregivers when the system detects disordered emotions from a patient. Lastly, the system assists the physician or parents in managing the emotional upheaval of the child at an early stage to propagate early precautions.

H. Data Collection Process

The system is designed to deal with data collected in real time or based on available datasets to evaluate the system's performance and the proposed methodology. This methodology targets six principal emotions: surprise, sadness, natur, joy, fear, and anger. This prediction helps caregivers and coaches of people with autism to treat them accordingly.

4 Results and Discussion

This part addresses the pragmatic implementation and testing to identify and classify autism spectrum symptoms using a hybrid deep learning model incorporating LSTM networks with 3D-CNN. The method intends to effectively differentiate behavioral patterns linked to autism using spatiotemporal features acquired from sequences of facial expression images. Python gained popularity since it offers deep learning frameworks and image processing capabilities among other computer languages. The development and testing stages were conducted in the PyCharm Integrated Development Environment (IDE), thanks in significant part to strong debugging, code management, and visualization features.

A. Dataset

The "Autistic Children's Emotions" dataset, which is available on Kaggle and was developed by Dr. Fatima M. Talaat, is a critical resource for researchers interested in identifying facial expressions in children with ASD. This collection is meticulously organized into six categories—normal, wrath, fear, joy, sorrow, and surprise—and includes various emotionally charged and filtered images. Four one-to-one relationships. Duplicate and cached images were eliminated to ensure the veracity and quality of the data, thereby providing a more accurate representation of the genuine emotional expression of children with autism. The systematic design of the dataset allows for its integration into machine learning processes, particularly in the training and testing of 3D convolutional neural networks (3DNNs) and LSTM. These models are fit for studying the nuanced facial expressions that define ASD, as they are good at capturing spatial and temporal aspects. Using this information may help researchers create and enhance algorithms meant for early autism identification and intervention tactics, thereby perhaps improving therapy results.

Moreover, the dataset is available at https://www.kaggle.com/datasets/fatmamtalaat/autistic-children-emotions-dr-fatma-m-talaat.

Motivates cooperative study and result comparison, thus promoting affective computing and autism research. Its use goes beyond scholarly study; it provides possible advantages in clinical environments, teaching materials, assistive devices to help people with ASD, and other spheres.

B. Training and Testing

Dividing the dataset into two subsets, one to assess the performance of the deep learning model and another to train it, is part of the training and testing step. The 3DCNN+LSTM model is learning in training to extract temporal and spatial elements from sequences of facial expression photographs of autistic youngsters. The model changes its core settings to reduce misclassified results. Its accuracy, generalization, and efficacy are assessed using unseen data after training. It names six emotional states: normal, anger, fear, pleasure, sorrow, and surprise.

A confusion matrix, Figure 6, helps one assess the performance of categorization models. This matrix displays the correct rather than projected classifications for a multi-class classification task with six emotional classes—anger, fear, pleasure, normal, sorrow, and surprise. While each column shows the expected categorization, each row of the matrix reflects the actual (right) classification. The diagonal elements show valid predictions that the expected categorization corresponds with the appropriate one. The off-diagonal components reflect misclassifications. With 41 correct predictions and just one misclassification as sorrow, Joy is the most accurate feeling in categorization from the matrix. Sadness follows with one misclassification as happiness and 13 proper categories. Normal had seven accurate predictions free from misclassification. Surprise got six accurate guesses and no misclassifications, either. With 3 and 2 accurate predictions, respectively, anger and fear exhibited somewhat poor accuracy. There was one misclassification of fear, as happiness was noted.

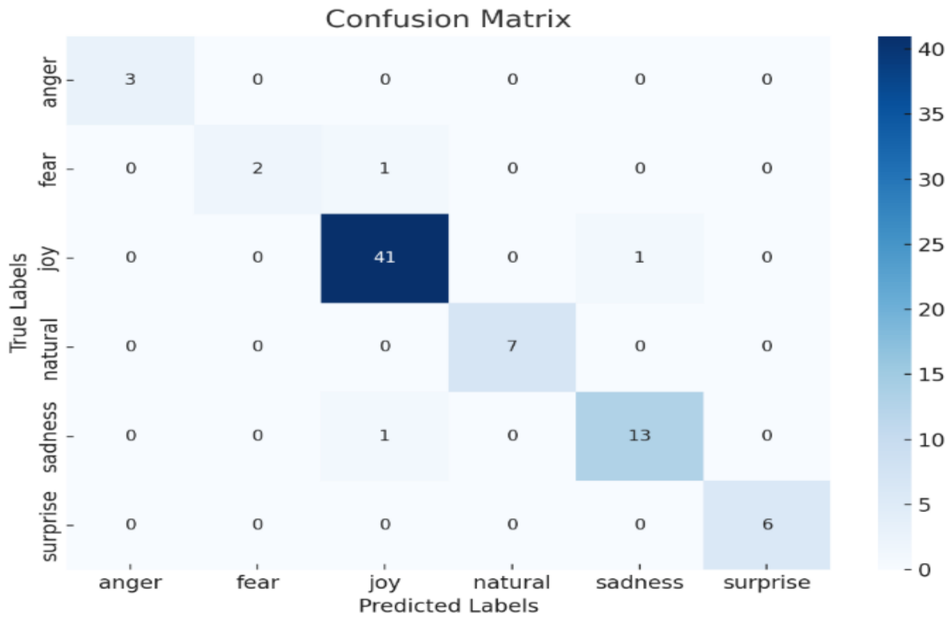

Figure 6: Confusion Matrix

Particularly, the model performs better overall for emotions with more training occurrences, suggesting a probable class imbalance in the dataset. Between fear and pleasure and between joy and sorrow, misclassifications show overlapping traits or emotions that the model finds difficult to separate. With deeper tones implying more values, the color gradient—light blue to dark blue—visually emphasizes the frequency of predictions. The side color bar rises to 40, matching the highest count of accurate predictions for the joy class. Through data balance or feature optimization, this confusion matrix helps pinpoint strengths and shortcomings in the classifier's performance and directs further development.

Figure 7 shows the accuracy development throughout 100 training cycles for both the training and validation datasets. Training accuracy is shown by the yellow line; the red line shows validation accuracy. Both accuracies start below 0.6, meaning the model starts with somewhat modest performance. Both graphs indicate a constant rising trend as training continues, indicating that the model is learning from the data successfully. Accuracy rises over 0.90 for both sets by around epoch 50; after training, both almost approach 0.98–0.99, showing strong classification performance. The near closeness of the two curves across the training phase suggests an effective generalization of the model with little overfitting. Training and validation accuracy show no appreciable difference, which is encouraging for model resilience and a well-optimized learning process. This graph confirms that the model performs successfully on unseen validation data and fits the training data well.

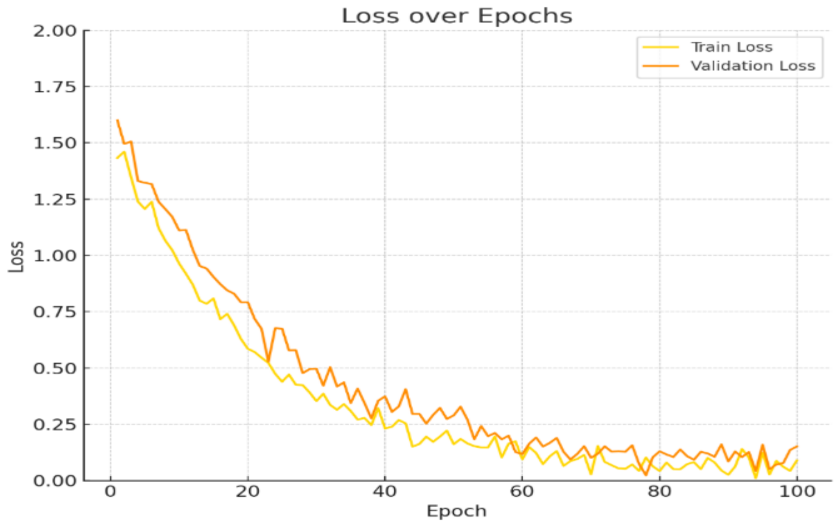

Figure 7: Accuracy Over Epoch

Measuring over 100 epochs, Figure 7 displays the loss across epochs for a machine learning model's training and validation stages. The training loss is shown by the yellow line; the orange line shows the validation loss. Both losses start high, between 1.5 and 1.6, indicating early in training, significant mistakes in the model. Both loss numbers continuously drop as training continues, indicating that the model is learning and improving its predictions. Training and validation losses drop below 0.1 by around epoch 60, suggesting a significant prediction error. As predicted, the training loss stays somewhat smaller than the validation loss during training. Still, their modest and persistent difference suggests that overfitting is low. The convergence of both losses toward comparable low values at the endpoints of the model not only remembers the training set but also effectively generalizes unprocessed input. Normal fluctuations in the validation loss curve are reflections of variance in the validation dataset. Without significant variation, the constantly decreasing trend in both curves suggests that the training of the model is successful and the learning process is steady and well-optimized.

C. Training and Testing

Using quantitative indicators, the section on Metrics and Evaluation evaluates the 3DCNN+LSTM model to guarantee correctness and dependability in categorizing the emotions of autistic children. Accuracy, precision, recall, and F1-score are essential measures that provide a whole picture of the model's performance. The confusion matrix shows how well the model distinguishes every emotional type. Excellent performance on all criteria, especially the 0.99 accuracy, attests to the strength of the model. This part also addresses the model's generalization capacity, guaranteeing that it functions regularly on unprocessed data—a necessary condition for practical use and implementation.

Table 1 lists the assessment measures used to evaluate the 3DCNN+LSTM model in six emotion classifications for children with autism. These measures include accuracy, recall, F1 score, and support—sample count per category. Reflecting good performance across most emotional categories, the model had a high accuracy of 0.99. For instance, anger, normalcy, and surprise were categorized with flawless accuracy, recall, and F1 scores—that is, the model predicted these categories without mistake.

Table 1: Classification Report of 3DCNN+LSTM Model for Each Emotion Category

Emotion	Precision	Recall	F1-Score	Support
Anger	1	1	1	3
Fear	0.67	0.67	0.67	3
Joy	0.97	0.98	0.98	42
Natural	1	1	1	7
Sadness	0.93	0.93	0.93	14
Surprise	1	1	1	6

With an accuracy of 0.97 and a recall of 0.98, Joy—the category with the most support (42 images)—also showed outstanding performance, proving the model's resilience in managing well-used categories. While fear exhibited the lowest values (0.67), sadness also performed well, scoring 0.93 across all three measurements.

This is especially vulnerable to misclassification as the limited number of three test samples allows for, still, the model's performance was confirmed by the generally good F1 ratings. This thorough examination of the measures guarantees that the model generalizes well. But also maintains balanced performance across high and low emotional support categories, which is essential for practical uses involving sensitive populations, including children with autism.

Table 2 Based on six important performance metrics— Accuracy (Acc), Precision (P), Recall (R), F1-score (F1), Cohen's Kappa (K), and Area Under the Curve (AUC)—four deep learning models—MobileNet, ResNet, Xception, and the proposed 3DCNN+LSTM model—are compared in this table). Every statistic has a standard deviation number that shows the consistency of the model's performance across many folds or trials. Xception performs best among the pre-trained models: 95.23% accuracy and an F1-score of 93.31%. With routinely excellent accuracy, recall, and area under the curve (AUC) scores, it provides a robust foundation for emotional classification in autistic children. Though they perform generally well, ResNet and MobileNet lag somewhat in Cohen's Kappa and AUC, two indices of the model's agreement with real labels and discriminative skills, respectively.

The suggested 3DCNN+LSTM model surpasses its predecessors on every assessment metric. With a precision of 98.54%, accuracy of 99.01%, and recall of 98.72%, it can remarkably detect low misclassification of emotional expressions. Although an F1-score of 98.63% indicates a reasonable mix of accuracy and recall, a Cohen's Kappa value of 0.961 reveals remarkable agreement outside chance.

An AUC of 0.9912 further supports the fantastic ability of the model to differentiate among several emotional states. Inspired by facial emotion sequences, these results illustrate how well 3D CNNs improved with LSTM layers collect spatial and temporal data. With great accuracy and dependability, the suggested method's outstanding performance confirms its fit for autism-related emotion identification challenges. In clinical and educational environments, this paradigm may greatly support early identification and tailored intervention plans.

Table 2: Comparative Performance of Pretrained Models and Proposed 3DCNN+LSTM Architecture

Model	Acc.	P.	R.	F1.	K.	AUC.
MobileNet	0.8812 ± 0.0231	0.9138 ± 0.0281	0.9027 ± 0.0101	0.9002 ± 0.0256	0.813 ± 0.0264	0.892 ± 0.0312
ResNet	0.9143 ± 0.0338	0.9028 ± 0.0335	0.9311 ± 0.0050	0.9162 ± 0.0227	0.802 ± 0.0315	0.8625 ± 0.0103
Xception	0.9523 ± 0.0278	0.932 ± 0.0318	0.9421 ± 0.0134	0.9331 ± 0.0219	0.853 ± 0.0312	0.9134 ± 0.0121
3DCNN+LSTM	0.9901 ± 0.0052	0.9854 ± 0.0061	0.9872 ± 0.0078	0.9863 ± 0.0049	0.961 ± 0.0098	0.9912 ± 0.0065

5 Conclusions and Future Works

Human activity recognition is broadly utilized in security, surveillance, education, sports, entertainment, medicine, and other fields. What interests us in our research is the medical field. In this field, Doctors may utilize the activity status of patients in actual time to prevent mishaps. Re-searchers in this field use different techniques to detect anxiety and stress in people with ASD. These technologies can provide very significant benefits to people with ASD and their care providers. Therefore, in this context, researchers may face several challenges.

The current paper, combining two technologies, 3D-CNN+LSTM, was presented as a method to recognize facial expressions. A significant innovation in improving the home care of children with autism has been the development of assistive technology. It is crucial to establish an emotion detection system in real-time for kids with ASD to recognize their feelings as well as help them in case of pain or anger.

A real-time automatic emotion recognition system was designed for children with autism in the present investigation. Three stages of emotion recognition were involved: facial feature extraction, face recognition, and feature classification. The emotion recognition system identifies six facial emotions: sadness, surprise, neutral, joy, fear, and anger.

One of the main challenges of using 3D-CNNs or any other algorithm for image classification is computing the spatial structure of the image. Therefore, many image classification processes have been implemented in various applications using image classification algorithms. Our study found inferential results based on previous studies that the Merge between 3D-CNN+LSTM achieved a classification accuracy of 99.82%, while the other artificial neural network achieved a classification accuracy rate of 99.69%.

In general, since they can be used to extract the spatial structure of images and selectively extract informative features automatically, a model of this kind is often favorable as an alternative to ANNs in the classification of images. In addition, 3D-CNNs are more suitable for large datasets and complex image classification tasks than ANNs because they are more efficient and scalable. Overall, 3D-CNNs have revolutionized the field of image classification and remain a focus of research.

In future work, we will work on implementing the framework and the proposed methodology while training the proposed system to classify images and analyze the associated time and spatial series. In addition to analyzing the other data related to the vital signs of children with autism. To achieve the best results that contribute to helping healthcare providers and patients. In addition, it will shorten the path for researchers in this field and help them achieve better results.

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