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DETECTION OF AUTISM SPECTRUM DISORDER USING DEEP LEARNING

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Abstract - Social interaction, conduct, and cognitive ability are all impacted by the neuro developmental illness known as autism spectrum disorder (ASD). Even though ASD diagnosis can be difficult and time-consuming, early detection and intervention can improve long-term results. Early childhood is when autism spectrum disorder first manifests, and it eventually leads to issues with social, academic, and occupational functioning in society. Within the first year, autism signs are frequently visible in children. Some infants display autistic spectrum disorder symptoms as early as infancy, including decreased eye contact, a lack of responsiveness to their name, or a lack of interest in carers. To identify the presence of disorder at an early stage, use a deep learning system like LSTM. Self-Stimulatory Behaviours Dataset (SSBD) was used to collect the datasets, and video dataset was used to construct the system. The feature extraction algorithm is the Blaze Pose algorithm. The model file has been constructed, and the datasets will be trained using the deep learning technique. When a disease prediction input image is provided, the severity of the disease is determined as a result. Using the children's activity, the proposed system offers an effective way to more effectively anticipate the presence of autism spectrum disorder

Key Words: Autism Spectrum Disorder, Long-Short Term Memory, Blaze Pose, Batch Normalization, ReLu, Softmax

1.INTRODUCTION

Detecting childhood autism involves identifying a neurological variation known as autism spectrum disorder (ASD), a deviation from typical neural functioning. This condition significantly impacts how an individual perceives and interacts with others, resulting in challenges related to social interaction and communication. Recognizable indicators of this disorder encompass restricted and repetitive behavioral patterns. The term "spectrum" in autism spectrum disorder encompasses a broad range of symptoms and varying severity levels.

Previously, Asperger's disorder, childhood integrative disorder, and an unspecified form of pervasive developmental disorder were viewed as distinct conditions constituting the spectrum of autism disorders. Although "Asperger's disorder" is widely perceived to be on the milder end of the autism spectrum disorder, the term is still occasionally used. Early on-set of autism spectrum disorder results in difficulties with social, cognitive and occupational functioning. Signs of autism are often noticeable in children within their first year, and a small percentage of them may exhibit typical development up to 18 to 24 months, after which autism symptoms begin to manifest.

Individuals with autism may experience a period of relapse. Despite the absence of a known cure for autism spectrum disorder, early and intensive intervention can significantly improve the lives of many children [1]. Autism spectrum disorder is characterized by challenges in social interaction and communication. Some common indications include not responding to their name, resistance to physical touch or cuddling, preference for solitary play, limited facial expressions, weak eye contact, difficulty engaging in conversation, slow or impaired speech, inability to initiate or maintain conversations, or difficulty expressing needs or categorizing things. They may also use an unusual tone or rhythm while speaking, engage in verbatim repetition of words or phrases without comprehension, struggle to understand simple instructions or questions, show limited or no signs of emotion, and appear indifferent to others' feelings. They may not bring objects to demonstrate interest or point at them, behave inappropriately in social situations by being passive, aggressive, or disruptive, struggle to interpret nonverbal cues from others such as facial expressions, body language, or tone of voice [2].

Identifying potential signs of autism is possible by distinguishing between the behaviors and activities of typically developing children and those of children with autism. While each child is unique, some common differences can be observed:

Typically developing children gradually acquire language skills, starting with gestures and babbling before progressing to words and sentences. They understand and respond to both verbal and nonverbal communication. However, language development in autistic children may be delayed or atypical, leading to challenges in initiating and sustaining conversations, comprehending non-literal language like sarcasm, or using a limited and repetitive set of words.

Autistic children often exhibit repetitive or stereotypical behaviors, such as repetitive movements (e.g., hand flapping), intense focus on specific objects or topics, adherence to strict routines, or a strong fixation on particular subjects. While typically developing children may also engage in some repetitive behaviors, they are typically not as pronounced or intense as in autistic children.

Children with autism often display heightened or diminished sensitivities to sensory stimuli. They might experience sensory overload or meltdowns due to extreme sensitivity to sounds, textures, or lights. Alternatively, they may seek sensory input and engage in repetitive actions like spinning or tapping to self-regulate. Typically developing children may exhibit normal sensory responses but may have specific preferences or aversions to certain sensory stimuli.

2.LITERATURE SURVEY

Junxia et al. created a strategy to identify extreme introvertedness by planning two-step multimodal highlight learning and demonstrated a combination based on a commonplace profound learning calculation namely stacked de-noising auto-encoder (SDAE) [1]. Within the first step, two SDAE models are outlined for highlight learning from EEG and ET methodology, separately. Also, a third SDAE was utilized within the second step outlined to perform multimodal combination with learned EEG and ET highlights in a concatenated way. This multimodal recognizable proof shows that it can naturally capture relationships and complementarity from conduct methodology and neurophysiological methodology in a latent highlight space and produce instructive highlight introductions with better discrimination ability and generalization for improved recognizability. They collected a multimodal dataset containing 40 ASD children and 50 normal children to evaluate their proposed strategy. The strategy accomplished better accuracy compared with two unimodal methods and a straightforward feature-level combination method, which has promising potential to supply an objective and precise determination to help clinicians. However this has two drawbacks: EEG and ET modalities may not be accessible at all times, and it requires much more computational costs.

Sakib et al. focused on the extreme introvertedness. They planned brain network-based highlights for the conclusion of ASD. Particularly, they utilized the 264 districts based parcellation from imaging (fMRI) [2]. They characterized 264 crude brain highlights by the 264 eigenvalues of the Laplacian framework of the brain organize and another three highlights by arranging centralities. By applying a calculation, they obtained 64 separate highlights. Vector Machine was utilized for diagnosing ASD with the obtained highlights on Extreme introvertedness Brain Imaging Information Exchange dataset. In any case, it is exceptionally complex to discover the eigenvalues.

Nasibeh et al. proposed a framework to identify extreme introvertedness utilizing ANN and developed a causal relationship estimator called “nCREANN” (nonlinear Causal Relationship Estimation by Manufactured Neural Organize) that recognized both direct and nonlinear components of effective network within the brain [3]. Moreover, it was able to recognize between these two sorts of network components by calculating the direct and nonlinear parts of the input-output mapping. The nCREANN execution has been verified using synthesized information, and after that, it has been applied to EEG information collected amid children with extreme introvertedness range clutter (ASD) and Typical Developing (TD) children. This strategy has diminished clumsiness within the dataset by removing more than 80% repetitive information and keeping more than 98% of the important data with negligible misfortune. This helped in discovering unused biomarkers for early location of this neurodevelopmental clutter. Though nCREANN helps early identification of ASD it incurs increased computational cost.

Akshay proposed a framework for detecting autism using physiological arousal in the presence of movement [4]. Physiological arousal refers to the excitement-related features reflected by physiological responses, such as increases in blood pressure, breath rate, and reduced activity of the gastrointestinal system. Anxiety represents a significant clinical concern in autism spectrum disorder (ASD) due to its detrimental impact on physical and mental well-being. The treatment of anxiety in ASD remains a challenge due to difficulties in self-awareness and communication of anxiety symptoms.

To overcome these treatment barriers, physiological markers of autonomic arousal, collected through wearable sensors, have been suggested as real-time, objective, and language-free measures of anxiety. A specialized Kalman-like filter has been proposed to integrate heart rate and accelerometry signals. This filter tracks user heart rate under different movement assumptions and selects the appropriate model for anxiety detection based on user movement conditions. These methods include supervised learning approaches such as linear discriminant analysis, K-Nearest Neighbors (KNN), AdaBoost, decision trees, logistic regression, random forests, and support vector machines (SVM). This approach can effectively reduce false detections due to user movement and accurately identify arousal states during developmental periods. While supervised approaches can offer highly accurate detection in controlled settings, their application may not always be feasible in typical circumstances where limited training data is available.

ZhongZhao et al. (2019) proposed a framework to identify autism using KNN [5]. To develop a rapid diagnostic tool with high precision, machine learning (ML) approaches have been explored to determine the feasibility of detecting ASD with a limited number of features extracted from behavioral assessment, neuroimaging, and kinematic data. Despite restricted and repetitive behaviors (RRB) being cardinal symptoms of ASD, no study has been conducted to explore whether limited kinematic features (RKF) could be used to identify ASD. Twenty children with high-functioning autism and twenty-three children with a typically developing (TD) group were enrolled. They were instructed to perform a motor task that required the execution of movements with the utmost variation. Entropy and 95% range of movement effectiveness, speed, and acceleration were calculated as RKF indices (Repeated K-fold cross-validation). K nearest neighbor (KNN) was trained and tested. The results showed that the KNN algorithm (k = 1) achieved the highest classification accuracy with four kinematic features, yielding an accuracy of 88.37%. The study demonstrated that RKF can robustly assist in distinguishing ASD. It was inferred that applying ML to genetic, neuroimaging, psychological, and kinematic features might pose a significant challenge to the current diagnostic criteria of ASD and could potentially lead to an automated and objective diagnosis of ASD. However, this motor task would not be suitable for children under 2 years old, suggesting its limitations in early ASD screening.

3. PROBLEM STATEMENT

The Autism detection methods employed by the existing systems have their own weaknesses. EEG and ET modalities may not be available at all the time and requires much more computational costs. The Eigen values are very difficult to find out. nCREANN is able to follow slow dynamics, and this may increase computational cost. Supervised approaches may not always be possible in everyday situations where only limited training data are available. KNN motor task would not work for children less than 2 years old. Some of the techniques use Deep neural network for autism detection by detecting speech abnormalities but this will not be possible for the children who are all unable to speak and dumb children. Generative Adversarial network (GAN) based neural networks for autism detection requires a large amount of training data in order to produce good results.

To address these challenges, this study focuses on autism detection utilizing videos and deep learning networks. This objective has been realized through the application of the LSTM (Long Short-Term Memory) algorithm to train on video data. As a preprocessing step, frames are extracted from the videos and resized to a standardized dimension. Feature extraction is carried out using the Blaze Pose algorithm. The resulting features are utilized to train the LSTM model. The SoftMax activation function is then employed to transform a set of raw predictions into probabilities. These probabilities signify the likelihood of the video indicating the presence of autism.

4.PROPOSED ASD USING LSTM

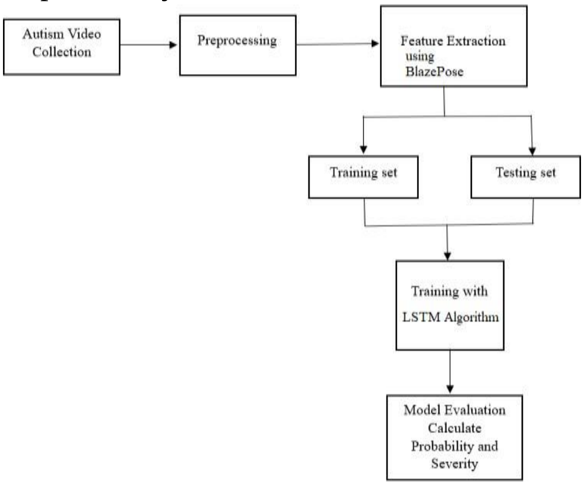

Figure 1. Proposed ASD using LSTM

The proposed autism detection technique utilizes advanced deep learning method namely LSTM to assess video based behavioral patterns and to potentially identify traits associated with autism, contributing to improve diagnostic insights.

4.1 Dataset Collection

The Self-Stimulatory Behaviors Dataset refers to a specific dataset that captures and documents self-stimulatory behaviors in individuals. This repository contains scripts to clip Self-Stimulatory Behaviors Dataset (SSBD) dataset. The SSBD dataset is downloaded from https://rolandgoecke.net/research/datasets/ssbd/.

4.2 Dataset Pre-Processing

The OpenCV library is used to extract frames from video files in a directory and resize them to a desired output size. The resized frames are then saved as JPEG images in another directory. The necessary libraries, OpenCV and OS are imported. Then, the paths to the directory containing the video files, the output directory where the resized images are saved, and the desired output size of the images are defined. Then a loop is iterated over all the video files. For each video file, the script loads the video file using OpenCV and extracts each frame of the video as a resized image. The script uses a while loop to read each frame of the video until there are no more frames to read. For each frame, the script resizes the frame to the desired output size using the cv2.resize() function and saves the resized frame as a JPEG image in the output directory using the cv2.imwrite() function. Finally, releases the video capture object and moves on to the next video file.

4.3 Feature Extraction and Representation

The BlazePose method is utilized by the proposed system for feature extraction. Google created BlazePose (Full Body) [7], a posture detection model that can calculate the (x,y,z) coordinates of 33 skeleton key points. It has a detector namely BlazePose. The human portion of the input image is removed by the detector, and BlazePose produces the 33 key points in the following order.

Angle between three Joints

= arccos((y2 + z2 - x2) / (2 * y * z)) ..……….Eq.(1)

Using the law of cosines the angle between the three pose markers that correspond to the three joints in the body are calculated. The lengths of the sides across from the appropriate joints are denoted by the letters 'x', 'y', and 'z'. Then the following steps are performed:

i. Pose identification: Location and identification of human poses in each video frame using a pose identification model. A set of pose landmarks or key points that represent the locations of particular bodily joints or body parts are normally the output of the pose detector.

ii. Pose Landmark Extraction: From the output of the pose detection model, extract the pose landmarks. The coordinates or placements of each pose marker correspond to a particular body joint or body portion.

iii. Feature Calculation: To represent various facets of the body posture or movement patterns, numerous features can be calculated based on the retrieved pose landmarks. These characteristics may include joint angles, length-to-length ratios, joint velocities, or any other pertinent measurements.

iv. Feature Representation: Each video frame's extracted features will be translated into a text file. Save it as a csv file after that.

The posture locator has two primary strategies: findPose and findPosition. The findPose strategy takes a picture as input and returns the picture with the posture points of interest drawn on it. The findPosition strategy takes an picture as input and returnsa list ofthe x and y arranges of the posture points of interest. The findPose strategy to begin with changes over the input picture from BGR arrange to RGB arrange,which is the organize anticipated by the Media pipe library. In case the posture landmarks are recognized, the strategy employments the Draw strategy to draw the points of interest on the picture At last, the strategy returns the picture with the posture points of interest drawn on it.

The findPosition method first initializes an empty list to store the x and y coordinates of the pose landmarks. It thenchecks if the pose landmarks were detected in the image. If the landmarks were detected, the methoditerates through the landmarks and calculates the x and y coordinates of eachlandmark relative to the size of the image. The x and ycoordinates are then added to the list. If the draw parameter is set to True, the method draws a small circle ateach landmark position on the input image. Append the coordinates in the list. Finally, the method returns the list of x and y coordinates of the pose landmarks.

This will iterate for each frame to read video file using the cap.read() function. If the function returns False, indicating that there are no more frames to read, the loopis exited. This will iterates through the list of pose coordinates and writes them to the text file using the write method of the file object. The loop then writes a newline character to the text file to separate the pose coordinates for each frame. The to _csv () function is usedto save the data frame as a CSV file.

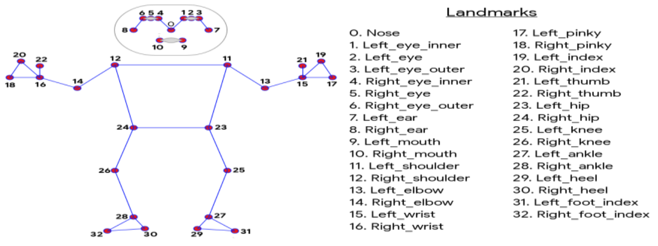

Figure 2 Blaze Pose Ordering Convention [8]

After the inclusion of extraction handle, these highlights are given to learning calculation whichcan prepare the highlights and yield precision [8]. At this point, the highlights hauled out are utilized to prepare the LSTM. Long short-term memory (LSTM) is an artificial Recurrent Neural (RNN) design utilized within the fieldof profound learning. A common LSTM unit is composed of a cell. The cell recalls valuesover subjective time interims and thethree doors direct the stream of data into and out of the cell [8]. LSTM systems are well-suited to classifying, preparing and making expectations based on time varying information, since there can be slacks of obscure term between critical occasions in atime arrangement.

5.PROPOSED LSTM BASED ON ASD SYSTEM TRAINING

The features extracted as described in the previous section are given to the Long short-term memory (LSTM) algorithm for training with the features. LSTM is a deep learning algorithm that follows Recurrent Neural Network (RNN) architecture and has feedback connections. It can process entire sequences of data such as speech or video apart from single data points such as images. A cell, an input gate,an output gate and a forget gate are the major components of LSTM. The job of the cell is to remember values over random time interval. The information flow is regulated by the input and output gates. LSTM networks are well-suited to classifying, processing and making predictions based on time series data, since there can be lags of unknown duration between important events in a time series. Figure 3 [9] depicts the LSTM architecture.

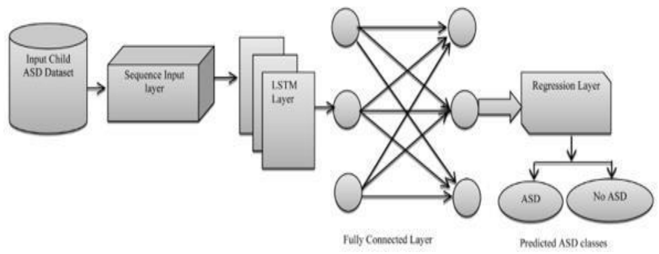

Figure 3 LSTM Architecture

The following modules play a crucial role in constructing and preparing deep learning models:

Sequential from keras.models: This class facilitates the creation of a linear stack of layers within the deep learning model.

Dense and Dropout from keras.layers: These classes define fully connected layers and dropout regularization in the model.

BatchNormalization, MaxPooling1D, Conv1D, and Flatten from tensorflow.keras.layers: These classes define essential layers like batch normalization, max pooling, 1D convolution, and flattening in the model.

Adam from tensorflow.keras.optimizers: This class defines the Adam optimization algorithm, vital for effectively training the model.

Load_model from keras.models: This function is instrumental in loading a pre-trained model from a file.

In a typical neural network architecture, the activation functions ReLU (Rectified Linear Unit) and Softmax are commonly employed to introduce meaningful outputs.

5.1 ReLU (Rectified Linear Unit) Activation Function

The ReLU activation function is applied element-wise to each neuron in the dense layers. The calculation can be summarized as follows:

For a given input value x, the ReLU activation function is defined as: $f(x) = \max(0, x)$ …………………. Eq. (2)

For each layer:

First Dense Layer (81 units): The output value of each neuron in this layer is calculated by adding a bias term to the dot product of the input features and their respective weights. The ReLU activation function is then applied element-wise. If a neuron's output value is non-negative, it remains the same (f(x) = x). Otherwise, it is set to zero (f(x) = 0).

Second Dense Layer (27 units): The output values of each neuron are calculated similarly to the first dense layer. The ReLU activation function is applied element-wise.

Third Dense Layer (9 units): Once again, the output values of each neuron are calculated using the dot product of the input features, weights, and bias term. The ReLU activation function is then applied element-wise.

5.2 SoftMax Activation Function

SoftMax is a popular activation function normally used in the output layer of neural networks that are employed for multi-class classification. SoftMax calculates the probability of an input belonging to each class "i" based on its corresponding output value "x_i" using the following function:

f(x)=e^(x_i)/Σe^(x_j) ………………… Eq. (4)

e^(x_i): The exponential work is connected to the yield esteem x_i for a particular lesson i. This exponentiation guarantees that the yield esteem ispositive.

Σ e^(x_j): This denominator is calculated by summing the exponentiated yield values over all classes j.

f(x):The Softmax normalizesthe exponentiated yield values, partitioning each esteem by the whole of all theexponentiated values.This guarantees that the probabilities sum up to 1,making it a substantial likelihood conveyance.

In this work, theSoftMax actuation function is utilized within the yield layer of a neural network to dole out probabilities to distinctive classes, such as "extreme introvertedness" and “non-autism”

5.3 Batch Normalization

To add a batch normalization layer in a neural network the necessary libraries and modules are first imported. Then a batch normalization layer is created and added after the fully connected layer before an activation function. The batch normalization layer is inserted into the modelarchitecture at the desired position by connecting the previous layer’s output to the input of thebatch normalization layer. While doing this, it is necessary to ensure that the number of features or channels matches the expected input size of the batch normalization layer. Rather than doing the standardization within the crude information, bunch standardization isdonebetween the layers of a neural arrange. Ratherthan utilizing the whole information set, it is done in mini-batches. It encourages learning by quickening preparing and using higher learning rates.

$Z^N = (z-m_z)/ s_z$ …………………… Eq. (3)

where m_z is the mean of the neurons’ output and s_z the standard deviation of the neurons’ output.

This is depicted in Figure 4. [9].The inputs are xi, the neurons' yields are z, the actuation functions’ yield may be, a and the network'syield is y.

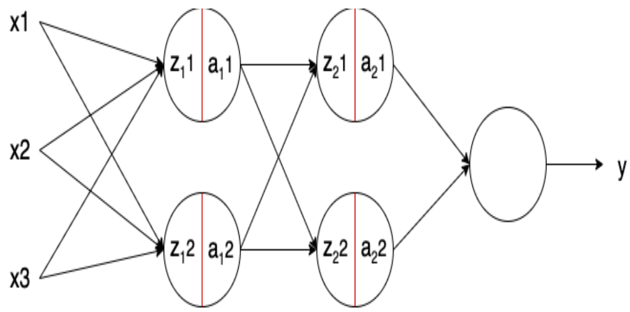

Figure 4. Batch Normalization

The proposed LSTM based ASD system creates a Keras Sequential model function creates four dense layers and three batch normalization layers. The first dense layer has 81 units and uses the ReLU activation function. The first batch normalization layer is added after the first dense layer. The second dense layer has 27 units and uses the ReLU activation function. The second batch normalization layer is added after the second dense layer. The third dense layer has 9 units and uses the ReLU activation function. The third batch normalization layer is added after the third dense layer. SoftMax activation function is utilized by the fourth dense layer which has 3 units. The SoftMax activation function is used to ensure that the output of the model is a probability distribution over the three classes. Finally, the function returns the created model.

6. MODEL EVALUATION:

P(A) = e^(scorea) / Σ(e^(scorei)) for all classes……...Eq. (5)

Where P(A) represents the probability of the input belonging to the "Autism" class. e^(x) represents the exponential function applied to the input value x. scorea is the output score representing "Autism" class from the Softmax layer. scorei is the output score reepresenting each class from the Softmax layer.

In this Eq 3, the numerator calculates the exponential of the score associated with the "Autism" class. The denominator sums up the exponential values of the scores for all classes. Dividing the numerator by the denominator provides the probability of the input belonging to the "Autism" class.

The higher the probability, the more severe the autism may be perceived.

For example:

- If P(Autism) is close to 1 (e.g., 0.9 or higher), it may indicate a high likelihood of severe autism.
- If P(Autism) is around 0.5, it may suggest a moderate probability of autism with a moderate level of severity.
- If P(Autism) is close to 0 (e.g., 0.1 or lower), it may indicate a low likelihood of autism or a milder form of autism.

Four measures namely accuracy, F-1 score, precision, recall are used to assess the performance of the proposed system. All of these evaluation measures can be calculated using those following equations:

Accuracy = $\frac{TN+TP}{TN+TP+FN+FP}$ …………..Eq.(6)

Precision = $\frac{TP}{FP+TP}$ ...………….Eq.(7)

Recall=$\frac{TP}{FN+TP}$ ……………Eq.(8)

F-1 Score = $\frac{2TP}{FN+FP+2TP}$ …………..Eq.(9)

Where,

TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative

7. RESULTS AND DISCUSSION

The videos are downloaded from Self-Stimulatory Behaviours Dataset. Some of the sample videos are provided in the following Figure 5.

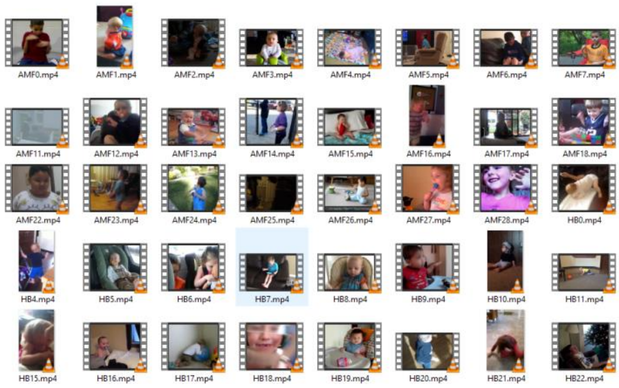

Figure 5. Sample Videos from SSB Dataset

The images are extracted from the videos and are pre-processed by converting the images into required size so that it can be made ready for feature extraction. The Figure 6 shows simple pre-processing.

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Random size Pre-processed

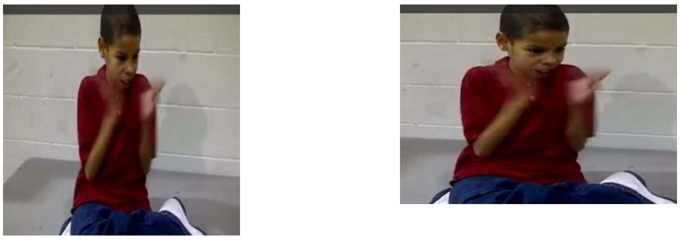


Figure 6. Pre-processing

The skeletal joint features are extracted from the images using BlazePose algorithm as shown in Figure 7.

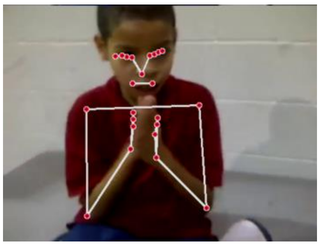


Figure 7. Feature extraction

After extracting features, training is performed using LSTM algorithm and the screen shot of the same is provided in Figure 8.

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 81)                5427

 batch_normalization (BatchN  (None, 81)               324
 ormalization)

 dense_1 (Dense)             (None, 27)                2214

 batch_normalization_1 (Batc  (None, 27)               108
 hNormalization)

 dense_2 (Dense)             (None, 9)                 252

 batch_normalization_2 (Batc  (None, 9)                36
 hNormalization)

 dense_3 (Dense)             (None, 3)                 30

=================================================================
Total params: 8,391
Trainable params: 8,157
Non-trainable params: 234
_________________________________________________________________
```

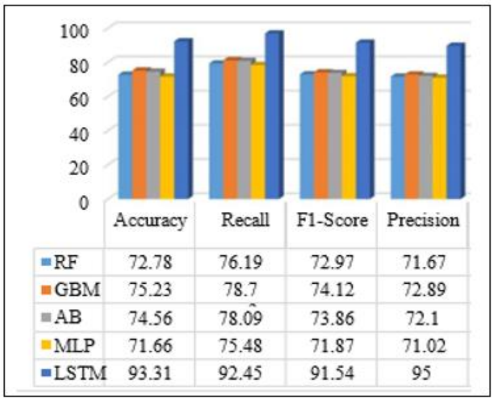
Figure 8. LSTM training

The performance of the proposed LSTM based ASD detection system is evaluated using the metrics such as precision, recall, f1-score

	precision	recall	f1-score
armflapping	0.92	0.93	0.93
headbanging	0.89	0.92	0.91
spinning	0.95	0.92	0.93
accuracy			0.93
macro avg	0.92	0.93	0.92
weighted avg	0.93	0.93	0.93

Figure 9. Performance of the Proposed ASD Detection System using LSTM

The performance of the proposed LSTM system is compared with other existing systems that use RF (Random Forest), GBM (Gradien Boost Method) , AB(Ada Boost) and Multi Layer Perceptron (MLP) in terms of Acurracy, Recall, F1-Score and Precision.



	Accuracy	Recall	F1-Score	Precision
RF	72.78	76.19	72.97	71.67
GBM	75.23	78.7	74.12	72.89
AB	74.56	78.09	73.86	72.1
MLP	71.66	75.48	71.87	71.02
LSTM	93.31	92.45	91.54	95

Figure 10. Performance comparison of the proposed LSTM based ASD system with other systems

8. CONCLUSION

Autism is a developmental disorder affecting brain growth, leading to abnormal behaviors in children. Detection of autism often leverages video analysis. The dataset of Self-Stimulatory Behaviors provided valuable video resources for training and evaluating the proposed ASD detection model. An essential preprocessing step involved resizing images for optimizing computational efficiency and reducing computational demands during training. By utilizing the BlazePose pose detection technique, relevant features were extracted from video frames, capturing body movement patterns that are indicative of autism. Incorporating the ReLU activation function in the hidden layers was key to capturing complex patterns and enhancing the model's ability to learn from the data. The proposed detection system based on LSTM showed promise in accurately identifying autism. Looking forward, future plans involve exploring advanced recurrent neural network (RNN) architectures, such as Gated Recurrent Units (GRUs) or Transformer-based models, to capture long-term temporal dependencies in the data. These advancements aim to better understand complex temporal patterns and further enhance the model's overall performance.

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