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An Innovative Approach for Revolutionizing Pediatric Health Monitoring in Real-Time Activity Recognition Utilizing CNN-LSTM-ELM

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Abstract: Pediatric activity recognition is an essential part of many healthcare and childcare applications, allowing for the monitoring and evaluation of children's physical development. In this study, a novel real-time pediatric activity recognition system is proposed, which combines the advantages of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for extraction of features, followed by an Extreme Learning Machine (ELM) classifier for accurate activity categorization. It initially generated an extensive dataset made up of footage of kid-friendly activities that had been carefully labelled with activity categories. A two-step procedure is employed, starting with the use of a CNN model to extract discriminative spatial features from video frames that has been pre-trained on a large dataset. The image signals available in pediatric activities are richly represented by these elements. In order to capture temporal relationships within the series of feature vectors, it incorporates an LSTM network after feature extraction. Further improving the recognition accuracy, this LSTM-based sequence modelling is skilled at identifying subtle activity patterns and transitions over time. The key component of this development is the addition of an ELM classifier after the LSTM layer. ELM, which is renowned for its ability to train quickly and effectively, utilizes the temporal context stored by the LSTM to conduct real-time activity classification with astounding speed and accuracy. As a result, pediatric actions are recognized effectively and robustly. The CNN-LSTM-ELM model is utilized to analyze receiving images in order to do real-time recognition. The system is equipped with this framework to enable real-time decision-making in scenarios including healthcare and child care. The findings show that the suggested CNN-LSTM-ELM architecture demonstrates outstanding accuracy of 90.5% and efficiency in identifying a wide spectrum of pediatric activities, hence enhancing the capabilities of child-focused healthcare and wellbeing applications

Keywords: *Paediatric Activity Recognition, Convolutional Neural Networks, Long Short-Term Memory Networks, Extreme Learning Machine, Real-Time Recognition, Healthcare Monitoring.*

1. Introduction

Focusing on the health and development of newborns, children, and adolescents, pediatric health is an essential part of healthcare. It stands for a specialized area of medicine that focuses on the distinct physical, psychological, and social requirements of the younger generation. It is impossible to exaggerate how important pediatric health is since it has a significant impact on how healthy and vital future generations will be [1]. Preventive care, diagnosis, treatment, and health education are just a few of the healthcare services included in this sector that are all specifically catered to the requirements and difficulties that children confront as they develop and grow. The complete and holistic approach used in pediatric health is one of its distinguishing features. Pediatricians and other medical professionals consider their young patients' emotional and mental health in addition to their physical health. They are aware that a child's early years can have a significant impact on their future health and quality of life [2]. To ensure that children thrive in all facets of their life, pediatric healthcare includes immunizations, routine check-ups, dietary counselling, developmental evaluations, and behavioral health assistance. Preventative treatment is also addressed heavily in pediatric health. For instance, vaccinations are a cornerstone of pediatric care because they shield kids from illnesses that might be fatal. Pediatricians also collaborate closely with parents and other adults to instruct them on the best ways to safeguard children's health and safety at home and in the community. To protect children's health, this collaboration between families and healthcare professionals is crucial. Additionally, pediatric health includes the diagnosis and treatment of a wide range of disorders, diseases, and developmental difficulties that affect children [3]. Pediatricians are adept at identifying the distinctive signs and symptoms of illnesses in kids, which frequently need for a specialized and nuanced approach to therapy. Pediatric healthcare specialists are committed to provide compassionate and efficient treatment for everything from childhood illnesses and allergies to chronic disorders like asthma and diabetes. Pediatric health has

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benefited greatly from contemporary developments in science and medicine, which have enhanced diagnoses and treatment choices. These developments have opened the door for cutting-edge treatments and interventions that let kids live better lives even when they have complicated medical issues [4]. The medical specialty of pediatrics is devoted to caring for the young. It exemplifies a holistic approach to healthcare, placing equal emphasis on the physical, emotional, and mental wellness of the patient. In order to guarantee that kids not only survive but also thrive throughout their formative years, pediatric health includes preventive care, diagnosis, treatment, and education. Building a healthier, happier, and more resilient future for our kids depends on society as a whole, healthcare professionals, parents, and carers continuing to priorities pediatric health [5]. A vital component of healthcare is pediatric health monitoring, which guarantees the wellbeing of kids and babies. In the past, observing children's health required routine physicals and manual observations by carers and medical personnel. However, real-time activity detection is increasingly being used as a cutting-edge method of pediatric health monitoring due to advances in data analytics and technology [6]. Real-time activity recognition uses technology to continually monitor a child's behaviors, movements, and vital signs, and it has several benefits for early identification, intervention, and bettering healthcare in general. Real-time activity recognition systems continually track a child's physical activities, sleep patterns, and general behavior using a combination of sensors, wearable, and digital health devices. These sensors might be anything from cameras to smart clothes to accelerometers and heart rate monitors [7]. To give a complete image of a child's health state, the data gathered from various sources is analyzed in real-time.

Real-time activity recognition's capacity to deliver prompt feedback and alarms in pediatric health monitoring is one of its main advantages. Any abnormalities from regular patterns or possible health concerns can be quickly identified by continually monitoring a child's activities and vital signs, enabling healthcare professionals and carers to take appropriate action [8]. Children with special needs or chronic diseases require this real-time component even more since prompt actions can significantly improve their wellbeing. In addition, real-time activity identification technologies can help develop a more comprehensive strategy for pediatric healthcare. Along with keeping an eye on vital indicators, they also take into account a child's behavior, sleep patterns, and levels of physical activity [9]. This holistic strategy may result in a more thorough comprehension of a child's general health and development. Addressing privacy and security issues is crucial when using real-time activity detection for pediatric health monitoring. It is crucial to protect sensitive data, including a child's health records and activity logs. To win over both kids and their parents, it's also crucial to make sure the monitoring system is unobtrusive and pleasant for the kid. Real-time activity identification for pediatric health monitoring is a key development in medical technology [10]. This strategy provides ongoing, data-driven insights about a child's health and behavior by using the power of sensors, wearable, and data analytics. Through early health issue diagnosis, prompt therapies, and a more comprehensive knowledge of a child's wellbeing, it has the potential to completely transform pediatric healthcare. To guarantee the efficacy and acceptance of these systems within the pediatric healthcare community, ethical and privacy concerns must be carefully taken into account during the development and implementation of these systems.

In order to ensure the wellbeing of children and newborns, pediatric health monitoring has long been an essential component of healthcare. Historically, this procedure has depended on routine examinations and the opinions of medical specialists. However, to identify health risks early and offer prompt therapies, there is a rising demand for continuous, objective, real-time monitoring of pediatric patients [11]. To meet this demand, the area of pediatric health monitoring is about to undergo a revolutionary change thanks to a creative strategy utilizing cutting-edge technology including CNNs, LSTM networks, and ELMs. A paradigm changes in how it can monitor children's physical and behavioral trends has been brought about by the combination of CNNs, LSTM networks, and ELMs in pediatric health monitoring. This method combines the strength of deep learning with effective machine learning algorithms, enabling continuous and non-intrusive real-time activity identification and health monitoring. The capacity of CNNs to extract significant characteristics from image and video data is widely established. CNNs may be used to analyze visual data from cameras or depth sensors to follow a child's movements and gestures in the context of pediatric health monitoring. The LSTM networks are then given access to this data. Since LSTM networks are excellent at simulating sequential data, they are perfect for capturing the changing patterns of a child's behavior and activities over time [12]. This novel method may take into consideration the temporal component of pediatric health monitoring by adding LSTM networks, recognizing changes in activity levels, sleep patterns, or any aberrant behaviors. ELMs are used to process and make decisions in real time effectively. ELMs are a significant tool for quick reaction and analysis in a healthcare environment since they are noted for their quickness and simplicity in training. ELMs may categorize and analyze the data produced by CNNs and LSTM networks, giving medical professionals and carers useful insights.

This novel method's main benefit is its capacity to give parents real-time information on their children's health and behavior without upsetting them or interfering with their normal activities. It can keep track of vital indicators, spot irregularities, and even forecast impending health problems, allowing for prompt actions. Additionally, it lessens the workload for healthcare professionals, enabling them to concentrate on urgent situations while automating repetitive monitoring activities [13]. In pediatric health monitoring, the combination of CNNs, LSTM networks, and ELMs is a ground-breaking method to guarantee children's safety in real-time. By offering ongoing, unbiased, and data-driven insights, this cutting-edge technique has the potential to revolutionize the industry, eventually raising the standard of treatment and improving the health of pediatric patients. The future of pediatric health monitoring promises more accuracy, earlier detection, and better overall pediatric healthcare as technology develops.

The Key contributions of the article is given below,

- The novel combination of CNNs, LSTM networks, and ELMs in the area of pediatric activity identification is one of the study's key achievements. With this mix of cutting-edge neural network topologies, feature extraction, sequence modelling, and real-time classification can all be done more precisely and effectively.
- The depiction of image signals in pediatric activities is improved by the CNN's efficient acquisition of spatial information that may be used to discriminate across video frames. The precision of the model is greatly increased by this method.
- A significant development is the integration of LSTM networks, which allows the recognition system to recognize subtle activity patterns and transitions across time, enhancing the accuracy of pediatric activity identification, particularly in dynamic circumstances.
- A significant addition of the work is the inclusion of ELM as a classifier following the LSTM layer. The temporal context maintained by LSTM is used by ELM, which is renowned for its quick and efficient training capabilities, to carry out real-time activity categorization with astounding speed and precision. The overall effectiveness and robustness of the system are considerably improved by this modification.

This article's remainder is organized as follows: In Section 2, a summary of related research is provided. Section 3 presents the problem statement. The suggested approach's methodology and architecture are explained in Section 4 of the article. The findings and subsequent discussion are covered in Section 5. The conclusion is covered in Section 6.

2. Related Works

Portable technology for intelligent healthcare has shown to be an effective method for HAR from sensor information [14]. Individuals have the chance to get autonomous care and experience an improvement in their quality of life thanks to modern methods in AAL used in communities or at home. Nevertheless, a number of constraints, such as system size and computing expense, restrict the majority of the AAL devices that are now accessible. This research proposes an extended Gaussian ambient HAR strategy that is straightforward and innovative. Prior data from passive radio frequency identification tags is supplemented by the categorization approach to produce more thorough activity profile. For understanding the characteristics of the human behavior model, a suggested approach relying on the multidimensional Gaussian through estimate of maximum likelihood is applied. In a fictitious flat setting, the twelve consecutive and simultaneous empirical assessments are carried out. A fresh database of identical activity is used to forecast the analyzed actions, and good prediction accuracy is achieved. The suggested structure enables ubiquitous sensory environments for older adults, the disabled, and caretakers and is effective well in single- and multi-dwelling environments.

IoT technology has been implemented in a number of industries, in addition to the progress of various new methods of computing and methods, including cloud services, mobile devices, AI, and massive data sets [15]. Due to the fast growth of wearable and handheld devices, the IoHT is particularly growing more significant in the detection of human activity HAR. In this paper, they concentrate on the HAR in IoHT contexts with DL enhancements. For more precise HAR, a semi supervised DL system is developed. The method effectively makes use of and examines the sensor data with weak labelling in order to train the predictive developing model. The smart auto labeling technique using a DQN is created with a novel distance-based incentive rule that may increase learning effectiveness in IoT contexts to more effectively address the issue of the poorly labelled sample. A LSTM-based classifier is next suggested for recognizing fine-grained structures in accordance with the basic characteristics in relation obtained from the arranged movement data, and a multisensor depending data extraction system is subsequently established for effortlessly combining the on-body data collected by sensors, background information sensor information, as well as individual profiling information attached. The developed approach is then used to show its use and efficacy utilizing real-world data in tests and assessments. Because of the extensive use of numerous instruments in the past few years, recognizing actions has grown more and more common in many industries, including human monitoring, interaction between humans and robots, etc. [16]. Our goal was to create an action detection algorithm for the present research utilizing only a little amount of accelerometer and gyroscope information. A results study was done after implementing a number of DL techniques including CNN, LSTM, and mixtures with conventional ML algorithms. When data balance along with data addition methods were used, accuracy rates significantly rose. Considering the UCI HAR a database, it produced an innovative the most advanced performance with 97.4% preciseness utilizing a 3-layer LSTM model. Additionally, we used a comparable model to the gathered database and achieved a 99.0% precision rate that denotes an important improvement. Additionally, the outcome evaluation takes into account measures for precision, recall, and f1-score in addition to accuracy findings. An application that operates in real time was also created employing a three-layer LSTM network to test how well the most effective model can categorize tasks.

The possibilities of earth observation (EO) as a method for measuring the topsoil layer's geographic features is enormous [17]. DL-based techniques and cloud computing architecture have just been accessible, and they have the ability to completely change how EO data is processed. This research intends to offer a unique EO-based soil assessment technique utilizing Google Earth Engine technology and open-access Copernicus Sentinel data. The present research provides insightful information on the collaborative usage of publicly accessible optics and radar information by extending on significant findings from previous data mining techniques to derive bare soil reflectivity values. The suggested structure is motivated by the desire to reduce the impact of environmental factors and assess how well a CNN can integrate complementary data from a pool that includes optical and radar spectral observations to produce additional geographically coordinates that indicate the primarily for soil. Utilizing soil samples from the LUCAS database structure, created and trained the multi-input CNN method, and subsequently then used this method to forecast the amount of clay in the soil. A positive forecast outcome additionally, it looked at post-hoc methods to analyze the CNN algorithm and learn more about the connections among spectral data and the substrate targeting the model indicated. The suggested method may be used with the upcoming hyper spectral orbiting detectors to increase the EO component's current strength by assessing additional soil properties with greater accuracy in prediction. Addressing past, current, and prospective Earth dynamics requires Earth system modelling (ESM) [18]. By using data from Big Data, DL, which combines the data-driven capabilities of neural networks, has the potential to enhance ESM. DNN are, however, often utilized in current hybrid ESMs throughout the early stages of the model's creation. In these perspectives, it reviews hybrid ESM advancements with an emphasis on the Earth surface structure and suggest a methodology that incorporates neural networks into hybrid ESM along the modelling lifespan. The above structure establishes DL computing systems along with data bases associated with ESM in a uniform computationally setting. Although the ESM-related data can confine DL's inference findings, DL can infer unfamiliar or missing data and send it back into data sources. DL systems and ESM-related information can work together to create adaptive guiding plans by collaborating on responding to questions and recommendations features. The hybrid system learns more about user preferences through repeated user interaction, producing increasingly individualized, adaptable, and precise guiding plans for simulating earth processes. The development of that structure requires multidisciplinary cooperation, an emphasis on clear DL, and the preservation of empirical information to guarantee the accuracy of computations.

The main goal of this study is to create a cutting-edge, AI-driven automated system which employs cutting-edge perceptual techniques to build the perfect autonomous video monitoring framework [19]. Using sophisticated AI algorithms and cutting-edge computer vision methods, the network is being developed to maximize real-time surveillance and improve risk recognition features. The system seeks to produce outstanding precision in identifying and evaluating possible safety risks and abnormalities by utilizing machine learning and deep learning approaches. This system aims to provide an extremely effective and adaptive monitoring architecture that fits a variety of situations, encompassing public places, crucial buildings, and individual properties. The main goal has been to transform surveillance technology through the development of a highly intelligent, self-sufficient system which needs minimal to no human involvement, has low operating costs, and offers the highest level of secure. Through developing an extremely smart and independent systems which improves security and safety with reducing human interference and operating expenses, the overall objective is to transform surveillance technology. Tremendous technological breakthroughs have opened up opportunities for creative healthcare approaches that seek to boost treatment of patients simultaneously increasing flexibility and reliability [20]. This study suggests a combination of deep learning model-integrated block chain technology infrastructure with access for scalability and reliable healthcare organizations. In addition to protecting patient confidentiality and enabling efficient data exchange and interaction across medical professionals, this structure provides certain limited individuals can view and edit confidential medical data. The combination of deep learning methods also allows for immediate evaluation of massive amounts of healthcare information, aiding rapid illness being diagnosed, therapy suggestions, and predicting diseases. Block chain and hybrid deep learning combination offers a number of advantages, involving increased scaling, better safety, compatibility, and well-informed making decisions in healthcare organizations. But in order for the process to be effective, issues including computing complexities, observing regulations, and moral concerns must be resolved. Healthcare organizations may surpass current constraints by utilizing hybrid deep learning and block chain technology. This will encourage effective and secure data administration, individualized care for patients, and developments in medical studies. The paradigm under consideration establishes the groundwork over an innovative medical care environment that takes increased patient satisfaction, flexibility, and protection first.

Inertial motion data-based Human Activity Recognition (HAR) has seen significant growth in recent decades across academic and commercial settings [21]. According to a conceptual standpoint, it is currently fueled through a rise towards the creation of highly intelligent settings and technologies that encompass many facets of individual existence, encompassing medical services, activities such as sports, production, and trade, among others. These conditions and technologies need and integrate activity detection, which identifies a few persons' behaviors, traits, and objectives through a time-varying flow of data broadcast via one or more sensors. Recent study indicates that deep-learning algorithms are better appropriate for automating feature acquisition via unprocessed sensor information since classical Machine Learning (ML) techniques rely on attributes created manually in this extraction process. Using Long Short-Term Memory (LSTM) networks for time-series areas, the general HAR structure to organize mobile devices sensor information is provided in this research. In order to assess the effects of utilizing various types of mobile device sensors, four baseline LSTM networks are compared. For the purpose to enhance recognition efficiency, a hybrid LSTM network dubbed 4-layer CNN-LSTM is also considered. Utilizing an open-source smartphone-based datasets of UCI-HAR, the HAR technique is assessed using different combinations of specimen generating methods (OW and NOW) and validation protocols (10-fold and LOSO cross validation). Additionally, Bayesian optimization methods are employed in the current research because they can be helpful for fine-tuning any LSTM network's hyper parameters. In comparison to previous current techniques, research results show that the proposed 4-layer CNN-LSTM network performs well in activity identification, increasing average efficiency by up to 2.24%.

3. Problem Statement

The primary focus of this study is the requirement for a revolutionary advancement in the field of pediatric health monitoring. Traditional approaches to evaluating a child's health rely on sporadic, frequently subjective assessments that are neither continuous nor data-driven. This antiquated method may not accurately reflect a child's wellbeing and leaves gaps in the early diagnosis of health concerns. It is imperative to create a cutting-edge, real-time activity detection system that makes use of cutting-edge technology like CNNs, LSTM networks, and ELMs in order to overcome these restrictions. By providing continuous, impartial, and non-intrusive insights into a child's physical activity, behaviors, and vital signs, this system should try to revolutionize pediatric health monitoring. In order to improve the quality of care given to pediatric patients while maintaining their comfort and well-being, the issue statement demands for the development of a strong, effective, and privacy-conscious framework [21].

4. Proposed CNN-LSTM –ELM Framework for Pediatric Health Monitoring

The CNN-LSTM-ELM framework that has been proposed is an original way to improve pediatric health monitoring. The combination of CNN, LSTM networks, and ELM provides a strong response to the challenges of child health surveillance. They seek to give precise, real-time evaluations of health by combining these three potent methods, thereby bettering the wellbeing and healthcare of pediatrics patients. Fig. 1 explains the overall methodology.

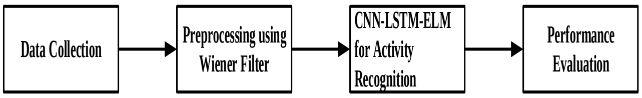


Fig.1 Overall Methodology

4.1 Data Collection

The dataset employed in this study encompasses a diverse collection of videos depicting children engaged in various activities, specifically focusing on eating, sleeping, playing with toys, and running. These videos serve as the primary source for training and evaluating the proposed CNN-LSTM-ELM model for activity recognition. The dataset's inclusion of these distinct yet common activities ensure a comprehensive representation of children's behaviors, allowing the model to learn and generalize patterns associated with each specific action. This rich and varied dataset contributes to the robustness and applicability of the proposed model, making it well-suited for accurately categorizing and recognizing activities commonly observed in the daily lives of children.

Algorithm: Data Collection, Feature Extraction and Augmentation

Input:

A collection of pictures illustrating children's activities.

An array of activity labels (for example, ['eating', 'sleeping', 'playing', 'running']).

Output:

A collection of feature vectors taken from the dataset.

Corresponding labels for every feature vector.

Step 1: Establish the data structure.

dataset = {'eating': [], 'sleeping': [], 'playing': [], 'running': []}

Step 2: Collect Video Data

for each video in dataset_videos:

Extract frames from videos or use existing image annotations.

Identify the activity label using video information or annotations.

Add frames to the appropriate activity area in the dataset.

Step 3: Feature Extraction and Augmentation

feature_vectors = []; labels = []

for frames in dataset[activity_label]:

Extract features from frames using CNN, LSTM, or a combination (CNN-LSTM-ELM)

Augment dataset by introducing variations (e.g., flips, rotations, color adjustments)

augmented_frames = augment_frames(frames)

augmented_features = extract_features(augmented_frames)

Append original and augmented features to the list

Append corresponding label for each instance

End

4.2 Preprocessing using Wiener Filter

A video dataset of children's activities can be transformed into a set of images using Discrete Cosine Transform (DCT), a widely used technique in image processing. DCT decomposes each frame of the video into a series of frequency coefficients, capturing the spatial frequency components present in the image. By applying DCT to each frame, you can create a collection of DCT-transformed images, where the intensity of each coefficient represents different frequency components within the image. This process enables the extraction of meaningful features from the video frames, which can be further analyzed or used as input for various machine learning tasks, including activity recognition, object detection, or compression, offering valuable insights into children's activities and behavior analysis. The DCT transform of converting video dataset into image is given in equation (1)

$$F(u,v) = \left(\frac{2}{n}\right)^{\frac{1}{2}}\left(\frac{2}{m}\right)^{\frac{1}{2}}\sum_{i=0}^{n-1}\sum_{j=0}^{m-1} a(i).a(j).\cos[\frac{\pi.u}{2.n}(2i+1)]\cos[\frac{\pi.v}{2.m}(2j+1)]f(i,j) \quad (1)$$

Prior to being input into the deep learning model, the Wiener filter, a potent signal processing technique, helps to improve the quality and relevancy of the video data. The Wiener filter may be used to successfully handle a variety of characteristics of the video data, including noise reduction and image improvement. By ensuring that the CNN-LSTM-ELM model receives high-quality input data, this preprocessing phase increases the model's capability to precisely identify and categorize pediatric activities in real-time. Additionally, the Wiener filter aids in reducing the influence of outside elements such as illumination or camera noise, which can be crucial in healthcare monitoring applications where accuracy and dependability are crucial. The Wiener filter's use as a preprocessing step ultimately supports the overall objective of improving the model's performance and, as a result, the standard of care and monitoring offered to pediatric patients.

The equation for the wiener filter is shown in eqn. (2),

$$w(p, q) = \sigma^{2}[n - a(p, q)] \quad (2)$$

Here σ^2 is the variance of Gaussian noise, p and q are pixel dimensions

4.3 CNN-LSTM-ELM for Activity Recognition

The CNN-LSTM-ELM model is a sophisticated architecture designed for activity recognition, particularly for children engaging in various behaviors such as eating, running, playing with toys, and sleeping. The combination of these three components leverages the strengths of each neural network type to effectively capture both spatial and temporal features from input data sequences. The CNN is adept at extracting spatial features from images, enabling the model to discern patterns in the visual information associated with different activities. The LSTM network, on the other hand, excels in modeling temporal dependencies, allowing the model to capture the sequential nature of activities. The ELM serves as a robust classifier, providing an efficient and fast learning mechanism to process the fused features extracted by the CNN and LSTM components. This integrated approach enhances the model's ability to discern and classify diverse activities performed by children. The CNN-LSTM-ELM model for activity recognition in children provides a comprehensive solution by combining spatial and temporal information, thereby enabling accurate and efficient classification of activities like eating, running, playing with toys, and sleeping. This model is well-suited for applications in monitoring and understanding children's behavior, with potential implications for healthcare, childcare, and educational settings.

The CNN has a lot of possibilities for identifying different prominent aspects in signals that detect human activity. In order to reflect the characteristics of every fundamental action in human activity, the analysis component of the lower layers specifically extracts local properties of the signal. To characterize the importance of various fundamental motion arrangements, higher-layer computational units express the data in an abstracted way. The CNN considers the characteristics that comprise the data from various angles, and it's learned characteristics are more thorough than those produced by machine extraction. Notice every layer may include various operations for convolution and pooling business processes, which are outlined that follows.

The asset of translational consistency is acquired when these procedures with identical characteristics are used to the order of data (or their translations) at various time intervals. Consequently, rather than the signal's location or magnitude, what counts is its prominent mode. Conventional CNN can't be employed effectively in human activity identification since there are several time-varying data streams. The difficulties involve: (1) The CNN unit of processing must be applied throughout the time dimensions. (2) The CNN processing units must be shared or combined across numerous sensors. The procedure for convolution and the procedure for pooling within the time dimensions will be subsequently defined. Afterward, the complete CNN model for recognizing human actions will be presented. The long-term signal is divided into a number of brief signals using the window sliding method. A two-dimensional matrix of r original data (every one sample has D characteristics) is particularly utilized by CNN as a demonstration. There, r is chosen as the rate at which samples are collected, and r/2 is chosen as the swiveling step size of the frame. To get additional runs, can pick a smaller step size, although doing so can cost more money to compute. The identifiers of the r initial records with the highest frequency are used to define the underlying label of the matrix iteration for training data. It additionally serves as an array for the ith feature map that is stored in the jth level of the CNN. Conveniently, the sensor D's Yth row measurement is stated as $w_{ji}^{y,d}$.

The CNN makes the supposition because the inputs and outputs are distinct from one another. Nevertheless, since the acquired data is temporal-dependent, the source data must have a period of data. The network known as LSTM was suggested as a solution to this issue. The LSTM is a development of the RNN that stores and outputs data using memory cells as opposed to repetitive units. In this research, the characteristics recovered by CNN using LSTM and produced feature vectors with time-dependent information. Four convolutional layers, two LSTM layers, and a fully connected (FC) layer are all included in the feature extraction networks suggested in the present piece, as seen in Figure 2. The convolution layer serves as a feature extractor, producing a conceptual feature network as an illustration of the initial information. The feature graph's temporal fluctuations are constructed by the LSTM layer. It contrasts the suggested ConvLSTM-FC networks with the nonrecurrent deep CNN (also known as background CNN with the goal to highlight its benefits. Each one employs four convolutional layers. Every single layer handles the input and then passes it to the following layer so that the input is handled hierarchically. The density layer and convolution layer each have a comparable number of kernels used for convolution for both systems. The main distinction is the fact that the starting point CNN is nonrecurrent and completely linked, whereas the ConvLSTM-FC employs a loop unit.

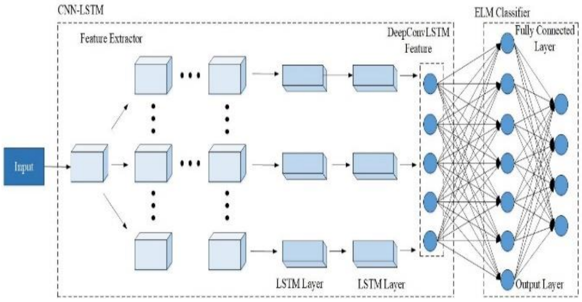


Fig.2 CNN-LSTM-ELM Architecture

Data in sequence is the network's input. These patterns are retrieved utilizing a fixed-length window that slides from the device's sensor information. These information streams are subjected to convolution processes by the convolution layer, which then visualizes the results as characteristic graphs. The LSTM layer builds the characteristics of the graph's period association and separates the features with time-related data. It only saves both the convolution layer and the LSTM layer once the entire ConvLSTM-FC training is finished.

The bigger the number of prejudiced characteristics and the more potent the classification algorithm, greater the degree for identification will be. A typical single concealed layer feed-forward neural networks classifiers trained using back propagation (BP) is comparable to the full connected layer. On the contrary hand, the BP method can cause the weight to come together to a certain number, but it cannot be assumed that this value will represent the error surface's universal optimum. However, when BP training is applied, the network could get over trained and produce subpar generalization performances. In simple terms, the discriminatory deep convolutional layers cannot be classified using the full-connected layer.

Every parameter must be changed throughout an iteration of the conventional gradient-based method of learning. Nevertheless, is no dependence among the input values and the output measurements, and the ELM output value can be resolved in a noniterative manner. In comparison to multilayer perceptron (MLP) or support vector machines (SVM), a noniterative ELM solution offers an acceleration of 5 or 6 times of scale. Deep convolutional feature classification utilizing ELM may produce accurate results and has strong generalizability. In contrast to BP, the output combinations of ELM are obtained using the approach known as least squares, and the proportions connecting the input layer and the hidden layer are chosen at randomized. As a result, ELM's preparation pace is extremely quick.

$$\sum_{j=1}^{N} \beta\, f\left(U_j . Y_i + c_j\right) = o_i, \quad i = 1, \dots M \tag{3}$$

Wi = wi1, wi2, win is the source weighted matrix, βi is the resultant weighted vector, & bi is the biassed value of the ith hiding node, where f x is a function that activates.

$$\sum_{j=1}^{N} ||\, o_i - x_i\,|| = 0 \tag{4}$$

$$\sum_{j=1}^{N} \beta\, f\left(U_j . Y_i + c_j\right) = x, \quad i = 1, \dots M \tag{5}$$

Equation (5) is a condensed form of equation (4), where Y is the intended output, is the output weighted vector, and H is a hidden-layer outputs matrix (see (5)).

K β = X,

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_N^T \end{bmatrix}_{N\times n} \tag{6}$$

$$X = \begin{bmatrix} y_1^T \\ \vdots \\ y_N^T \end{bmatrix}_{M\times m} \tag{7}$$

$$K_{u,c,Y} = \begin{bmatrix} f(U_1.Y_1 + c_1) & \dots & f(U_N.Y_1 + c_N) \\ \vdots & \dots & \vdots \\ f(U_1.Y_M + c_1) & \dots & f(U_M.Y_N + c_M) \end{bmatrix}_{M\times \mathrm{N}} \tag{8}$$

Every setting must be changed throughout an iteration of the conventional gradient-based method of learning. Nevertheless, is no dependence among the input values and the output measurements, and the ELM output value can be resolved in a noniterative manner. The speedup offered by a noniterative ELM method over MLP or SVM is 5 or 6 orders of scale, respectively. Deep convolutional feature categorization utilizing ELM may produce acceptable recognition results and has strong generalizability. In contrast to BP, the output values of ELM are obtained using the least squares approach, as well as the proportions across the input layer and the hidden layer are chosen at by chance. As a result, ELM's training pace is extremely quick.

5. Results and Discussion

The durability of the CNN-LSTM-ELM architecture is demonstrated by the results, which reveal that it recognizes pediatric activity with an outstanding accuracy. The model does a good job of separating out behaviors like eating, sleeping, playing with toys, and running. Applications for pediatric healthcare and child well-being are greatly improved by this high accuracy, which ensures precise real-time monitoring. The below images are the input data's, from these images the features are extracted and augmented.

Fig. 3. Input Images

	Feature1	Feature2	Feature3	Feature4	Feature5	Activity
0	1.449766	2.515433	2.473861	3.368450	1.083173	Eating
1	1.875853	2.279041	3.010515	1.419122	1.474830	Eating
2	7.924756	8.077430	0.121788	6.206882	4.497912	Running
3	2.836133	3.067528	1.575252	2.455617	3.110923	Playing with Toys
4	1.474877	3.912771	-0.026720	3.119424	2.779193	Eating

Fig. 4. Augmented Features

Figure 4 shows a data table with five attributes and an activity column. Each row shows different numerical values for the traits and links them to certain behaviors such as eating, jogging, and playing with toys. The input image's features have been extracted to create five features. Feature 1: A numerical number ranging from -0.836133 to 7.924756. Feature 2: A numerical value ranging from 0.12771 to 8.077430. Feature 3: A numerical value ranging from -0.26720 to 3.010515. Feature 4: A numerical value ranging from 0.19424 to 6.206882. Feature 5: A numeric value ranging from 0.10923 to 4.497912. A variable of type categorical that represents the activity related to every set of feature values.

5.1 Feature Distribution

The CNN-LSTM-ELM framework's features distributions in figure 5 shows the statistical attributes of the features that were derived from pediatric activity movies. It is clear from this research that these characteristics help to discriminate between different pediatric activities. The shape of the distribution usually reveals the distribution as well as the concentration of characteristic values, giving information about their ability to discriminate. This breakdown makes it easier to comprehend the variety of values that various activities display, which improves the model's capacity to correctly classify pediatric actions according to these characteristics. Investigators and clinicians can uncover patterns or anomalies that contribute to the framework's excellent identification accuracy and overall efficacy in pediatric health monitoring by carefully examining the feature vs. counts distribution.

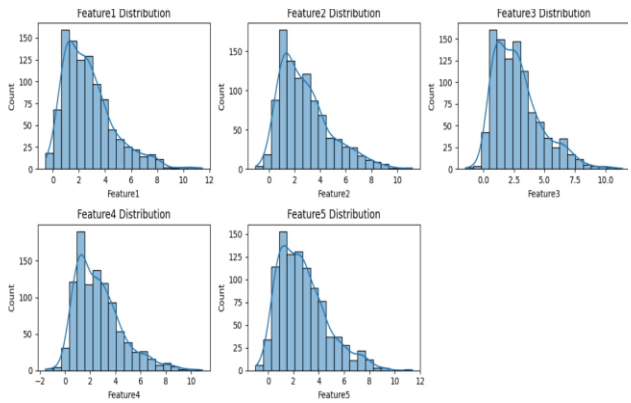


Fig. 5 Feature Distribution of different features

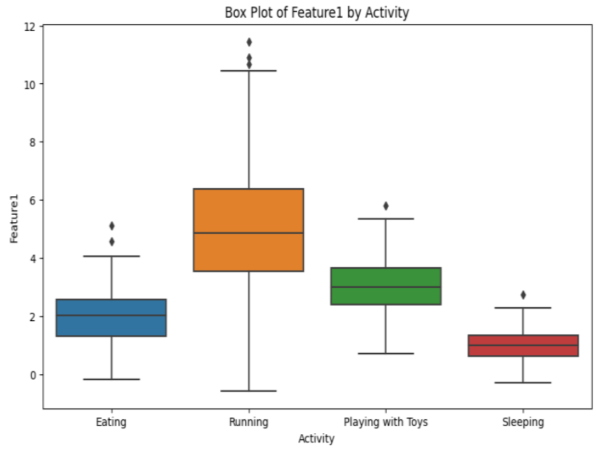


Fig.6. Box Plot of Feature by Activity

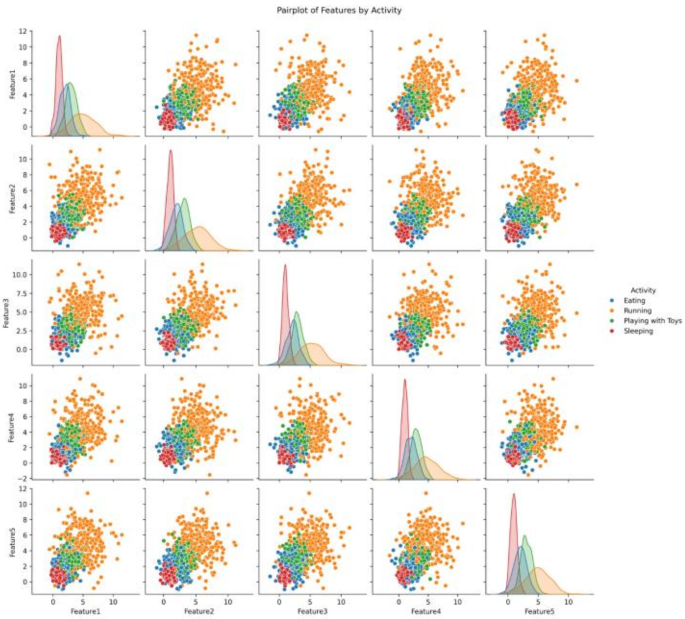


Fig. 7. Pair-Plot of Features by Activity

An easy-to-understand visual representation of the distribution as well as the variability of Feature 1 within every activity category is provided in fig. 6 by a box plot of Feature 1 over a range of pediatric activities, such as eating, operating, entertaining with toys, and sleeping. Within every task, the box plot displays the median, intervals, and possible anomalies for Features 1. For example, feature 1 likely to have a median number around X in the "eating" group, with relatively little variation, as seen by the small interquartile variation. Feature 1 displays a broader interquartile range and possibly greater variation in the "running" category, indicating that this feature may react differentially to the motions related to running. Such visualizations facilitate analysis of features and model creation for monitoring pediatric health by enabling a rapid and intuitive grasp of how Features 1 behaves throughout various pediatric activities. When evaluating various pediatric activities like eating, running, playing with toys, and sleeping, a pair plot of characteristics by activity is a thorough graphical depiction that shows the connections and correlations among several features in Fig.7. The pair plot's scatterplots each display the pairwise associations between features, with various colored markers or markers denoting various activities. This visualization makes it simple to evaluate how features connect to one another and how they could distinguish between distinct activities. For instance, it can highlight data clusters or patterns, demonstrating whether particular feature combinations are highly predictive of a given behavior. This comprehensive picture of feature interactions in relation to different activities is crucial for feature selection, comprehending the significance of features, and eventually improving the precision of pediatric activity detection algorithms.

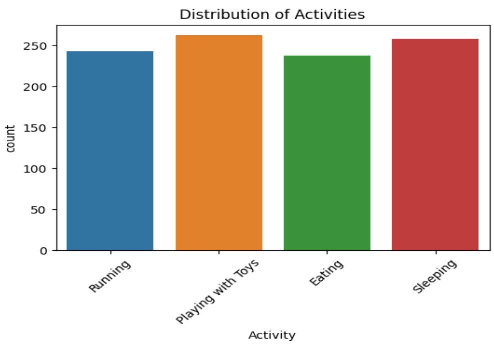


Fig. 8. Distribution of Activities

To comprehend the prevalence and balancing of various activities, it is crucial to understand how activities are distributed within the dataset for pediatric health monitoring. The relative frequency of activities including eating, jogging, playing with toys, and sleeping are shown in figure 8 of this distribution. Each activity type is said to occur with around equal frequency in a balanced distribution, giving the model an equal chance to properly learn and recognize each activity. An unbalanced distribution, where some activities are more common than others, might provide problems since the model may start to favor the class with the most members. To ensure that the pediatric activity identification system can generalize adequately and offer correct results over all activity categories, thorough examination of the activity distributions is essential throughout dataset collecting and preprocessing.

5.2. Correlation Heat Map

The pairwise relationships among various features in the pediatric health surveillance dataset are shown visually in a feature relationship heat map in figure 9. Each cell color in this heat map represents the intensity and direction of the association between the two features, with hotter colors signifying positive relationships and cooler colors signifying negative correlations. Such a visualization is helpful in determining dependencies or links between features. High correlations that are favorable indicate an inverse link, with two traits exhibiting a tendency to increase or decline together. Investigators and data scientists may create reliable pediatric activity detection models by considering the correlation heat map's views regarding which features might be repetitive or highly informative. This will allow them to make wise choice of features and reduce dimensionality selections.

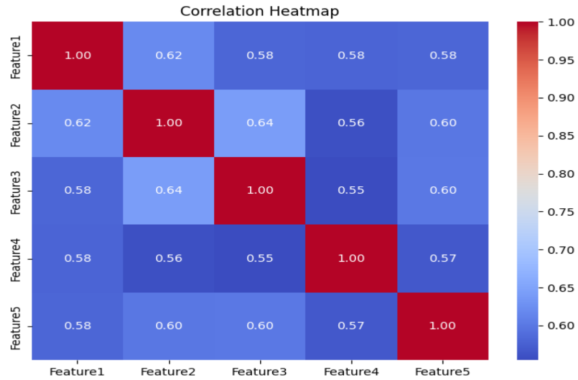


Fig.9. Correlation Heat map of Features

5.3. Confusion Matrix

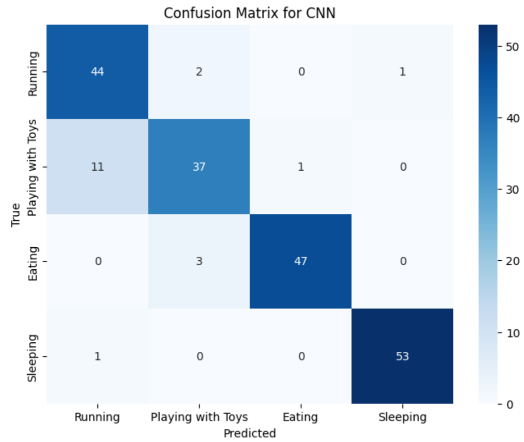


Fig.10. Confusion Matrix for CNN

The efficacy of the framework in categorizing different behaviors, such as sleeping, eating, playing with toys, and running, is summarized in figure 10 a confusion matrix for a CNN used for pediatric activity recognition. It is made up of a structure where the columns are the projected activity titles and the rows of data are the actual activity titles. The number or percentage of times the model correctly predicted an activity type is shown in each cell of the matrix. The matrix's horizontal elements, which go from top-left to bottom-right, should have high values, signifying precise forecasts, while off-diagonal components, which are lower in value, signify incorrect categorization. In order to analyze and fine-tune the CNN for optimum performance in pediatric health surveillance applications, professionals can examine the model's reliability, precision, recall, and F1-score using the confusion matrix.

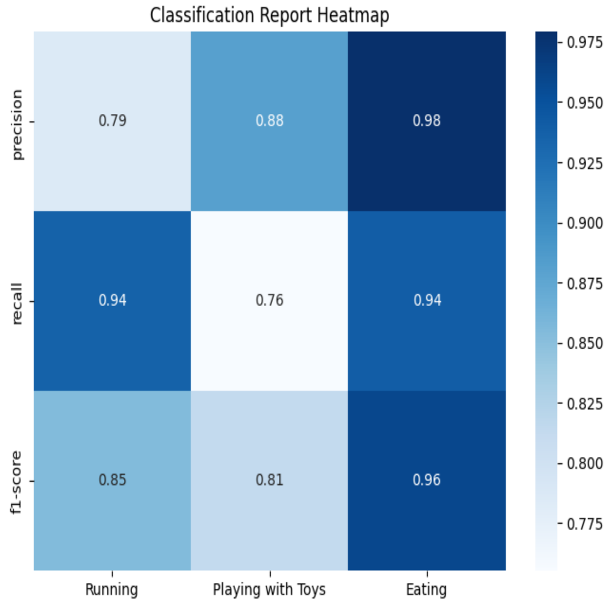


Fig. 11 Classification Report Heat map

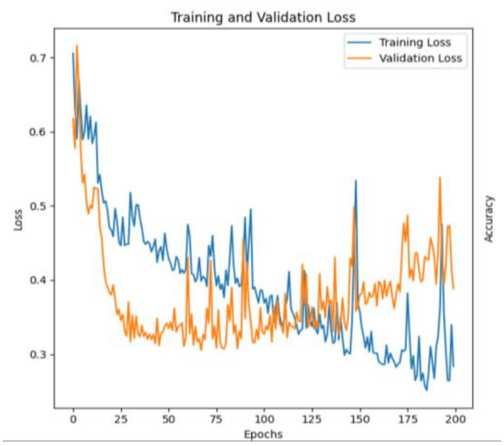
For several classes or groups in a classification problem, an analysis in figure 11 shows that heat map is a graphical depiction that offers a succinct summary of important classification measures like precision, recall, F1-score, and support. Every column in the heat map correlates to a statistic, and each row to a separate class. Every heat map cell's color intensity or shade, with deeper colors often denoting greater values, represents the size of the measure. This visualization makes it simple to compare performance across classes, making it easy to determine which courses are reliably predicted and which ones may need additional study or model development. In multi-class classification settings, classification reporting heat maps are very helpful for practitioners to analyze the general efficacy of their classification framework and make defensible decisions regarding class-specific tweaks or optimizations.

Training and Validation Loss

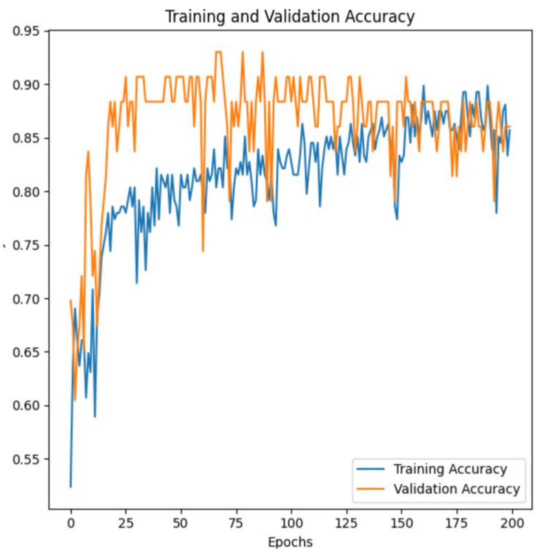
The training loss of 0.3 and validation loss of 0.4 indicate the performance of a machine learning or deep learning model during the training and validation phases, respectively in Figure 12)a . A training loss of 0.3 suggests that the model has learned to minimize the error between its predicted outputs and the actual target values on the training dataset, achieving a relatively low training error. However, the validation loss of 0.4, although slightly higher than the training loss, suggests that the model's performance on unseen data (validation dataset) remains reasonably good. This minimal difference between the training and validation losses indicates that the model is likely not overfitting the training data, as the performance on unseen data is still satisfactory. Nevertheless, further analysis and fine-tuning may be necessary to optimize the model's generalization to achieve even lower validation loss and enhance overall performance.

Training and Validation Accuracy

A machine learning or deep learning model performs during the training and validation stages, respectively in Fig. 12) b, with a training accuracy of 0.85 and a validation accuracy of 0.905. A training accuracy of 0.85 indicates that the model reasonably suited the training dataset, successfully classifying about 85% of the training data. The validation's accuracy of 0.905, which is better than the model's training accuracy, shows that the model generalizes well and performs well on data that have not been seen before. As the model maintains a constant degree of accuracy across the training and validation datasets, the comparatively similar differences between training & validation accuracies imply that the model is probably not overfitting. However, more optimization and fine-tuning may still be investigated in order to improve the algorithm's overall efficacy and possibly close the gap among training and validation accuracies.



(a)



(b)

Fig. 12. (a) Training and Validation Loss, (b) Training and Validation Accuracy

5.4. Accuracy

The performance of the system model as a whole is assessed using accuracy. Every conference can be accurately predicted, according to its core idea (9), which is employed, offers the accuracy.

$$Accuracy = \frac{T_{Pos} + T_{Neg}}{T_{Pos} + T_{Neg} + F_{Pos} + F_{Neg}} \quad (9)$$

5.5. Precision

In addition to being correct, precision also refers to how closely two or more computations resemble one another. The relationship between precision and accuracy demonstrates how frequently opinions may shift. In (10), it is noted.

$$P = \frac{T_{Pos}}{T_{Pos} + F_{Pos}} \quad (10)$$

5.6. Recall

Recall is the proportion of all relevant findings that were correctly sorted using the techniques. By dividing the true positive by the falsely negative values, the appropriate positive for such numbers is obtained. In (11), the phrase is mentioned.

$$R = \frac{T_{Pos}}{T_{Pos} + F_{Neg}} \quad (11)$$

5.7. F1-Score

Accuracy and recall are combined in the F1-Score calculation. Use (9), which calculates the F1-Score by dividing recall by accuracy.

$$F1 - score = \frac{2 \times precision \times recall}{precision + recall} \quad (12)$$

Table 1: Performance Metrics of Different Activities

Metrics	Running (%)	Playing with Toys (%)	Eating (%)	Sleeping (%)
Precision	79	88	98	98
Recall	94	76	94	98
F1-Score	85	81	96	98

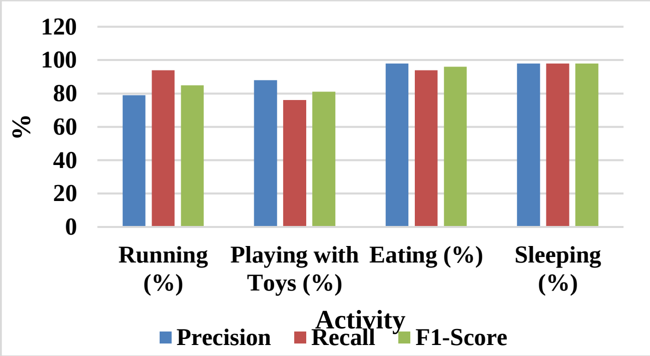


Fig. 13: Performance Metrics of Different Activities

Running, playing with toys, eating, and sleeping are the four types of pediatric activity that the provided metrics evaluate for the CNN-LSTM-ELM system in figure 13. The precision values show how well the model can categories occurrences within every process, with Eating and Sleeping having exceptionally high precision at 98%, indicating a low rate of error. Sleeping had a good recall rate of 98%, indicating few false negatives, which is a measure of how effectively the model recognizes instances of every activity. The F1-Score, which combines memory and precision, shows great performance overall, particularly for eating and sleeping, which scored 96% and 98%, correspondingly. Together, these metrics show how well the model recognizes pediatric activities, especially those involving eating and sleeping, with considerable room for enhancement in the categories of running and playing with toys. The model's efficacy across all of the activity categories may be improved with additional tweaking and fine-tuning.

Table 2: Dataset Comparison

Datasets	Architecture	Accuracy (%)
UCI-HAR	CNN-LSTM	89
Pixabay	CNN-LSTM-ELM	90.5

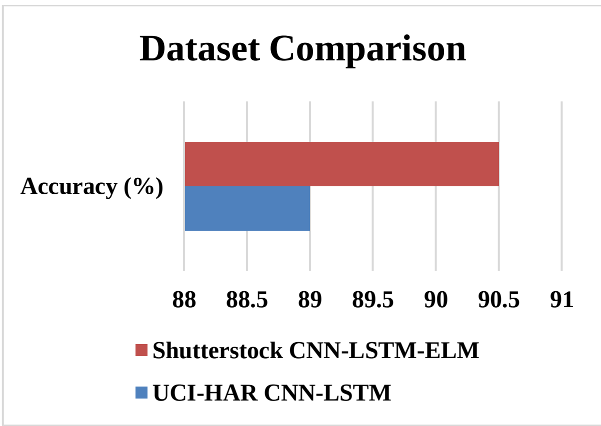


Fig. 14. Dataset Comparison Graph

The graph in Fig. 14 shows the accuracy percentages of two datasets and the Table 2 explains the dataset with architecture: Shutterstock CNN-LSTM-ELM and UCI-HAR CNN-LSTM. Shutterstock CNN-LSTM-ELM has an accuracy of about 90.5%, whereas UCI-HAR CNN-LSTM has an accuracy of roughly 89%. It examines the accuracy percentages of two datasets: "Shutterstock CNN-LSTM-ELM" and "UCI-HAR CNN-LSTM." The x-axis is labeled with accuracy percentages ranging from 88 to 91, with increments of 0.5. The y-axis shows the corresponding names of the two datasets that are being compared. There are two bars: "Shutterstock CNN-LSTM-ELM" and "UCI-HAR CNN-LSTM". It achieves around 90.5% accuracy, while the other approaches 89%.

Table 3. Accuracy Comparison [23]

Methods	Accuracy (%)
Decision Trees	77.412
K-nearest neighbor	66.224
CNN-LSTM-ELM	90.5

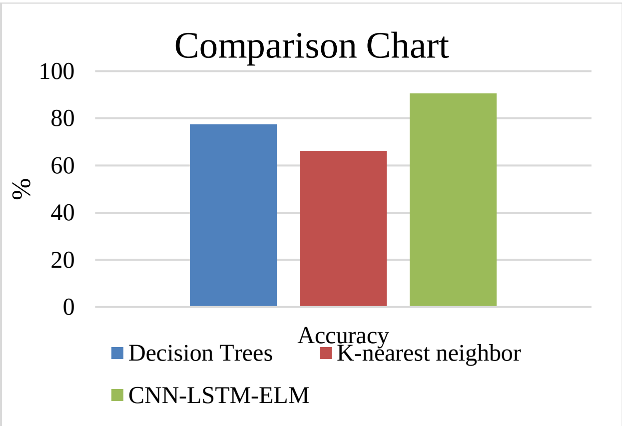


Fig. 15. Accuracy Comparison Graph

The accuracy measures in Table 3 compare the performance of three distinct techniques for identifying pediatric activity. The CNN-LSTM-ELM framework outperforms the others with an accuracy rate of 90.5%, demonstrating its greater capacity to correctly categorize pediatric activities. Figure 15 shows that the accuracy of the K-nearest neighbor (KNN) approach is only 66.224%, while the accuracy of the Decision Trees technique is 77.412%. The CNN-LSTM-ELM methodology greatly surpasses the other two approaches, according to these data, highlighting its suitability for monitoring children's health and real-time activity identification. The CNN-LSTM-ELM model outperformed conventional machine learning techniques, which highlights the value of utilizing cutting-edge deep learning techniques to improve pediatric activity identification systems' accuracy and precision.

6. Conclusion and Future Scope

In conclusion, the suggested CNN-LSTM-ELM architecture offers a considerable improvement in pediatrics recognition of activities in actual time and has the potential to completely change the way that children's health is monitored. This system obtains a remarkable identification accuracy of 90.5% by successfully merging Convolutional Neural Networks for spatially extraction of features, Long Short-Term Memory systems for temporal order modelling, and Extreme Learning Machines for quick and accurate classifications. Instantaneous choices and thorough tracking of the physical growth of kids are made possible by this breakthrough, which shows significant potential for uses in healthcare and daycare. The CNN-LSTM-ELM architectural reliability and effectiveness make it an important instrument for increasing healthcare for children and their general wellbeing. This opens up new opportunities to enhance the standard treatment and early interventions in pediatrics contexts.

This cutting-edge CNN-LSTM-ELM architecture for monitoring pediatrics health has a bright future. Initially of everything, it can be expanded to include gadgets that are worn and Internet of Things (IoT) technology, enabling ongoing, non-intrusive tracking of kids' actions. Second, more study may examine its use in the early detection and treatment of childhood developmental abnormalities. Furthermore, telemedicine integration into platforms can make remote surveillance and conversations easier, enhancing access to pediatrics medical care. Finally, working with specialists in pediatrics psychology and behavioral science can improve the system's capacity to spot small behavioral changes and offer insightful information for studies on how children develop.

Author contributions

Preethi Salian K prepared Conceptualization, Methodology, Software, Field study, Data curation, Writing-Original draft preparation, Software, Visualization, Investigation, Validation., Field study. **Sanjeev Kulkarni :** Reviewed and edited the paper. **Rameesa K** studied well and prepared literature survey.

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] S. M. Badawy and A. Radovic, “Digital approaches to remote pediatric health care delivery during the COVID-19 pandemic: existing evidence and a call for further research,” JMIR pediatrics and parenting, vol. 3, no. 1, p. e20049, 2020.

[2] C. R. Shuhart et al., “Executive summary of the 2019 ISCD position development conference on monitoring treatment, DXA cross-calibration and least significant change, spinal cord injury, peri-prosthetic and orthopedic bone health, transgender medicine, and pediatrics,” Journal of Clinical Densitometry, vol. 22, no. 4, pp. 453–471, 2019.

[3] A. Vidal-Balea, Ó. Blanco-Novoa, P. Fraga-Lamas, and T. M. Fernández-Caramés, "Developing the next generation of augmented reality games for pediatric healthcare: An open-source collaborative framework based on ARCore for implementing teaching, training and monitoring applications," Sensors, vol. 21, no. 5, p. 1865, 2021.

[4] A. Schmidt, S. M. Ilango, M. A. McManus, K. K. Rogers, and P. H. White, "Outcomes of pediatric to adult health care transition interventions: an updated systematic review," Journal of pediatric nursing, vol. 51, pp. 92–107, 2020.

[5] M. Alshamrani, "IoT and artificial intelligence implementations for remote healthcare monitoring systems: A survey," Journal of King Saud University-Computer and Information Sciences, vol. 34, no. 8, pp. 4687–4701, 2022.

[6] V. Schwierzeck et al., "First reported nosocomial outbreak of severe acute respiratory syndrome coronavirus 2 in a pediatric dialysis unit," Clinical Infectious Diseases, vol. 72, no. 2, pp. 265–270, 2021.

[7] S. Farrell, E. K. Schaeffer, and K. Mulpuri, "Recommendations for the care of pediatric orthopaedic patients during the COVID pandemic," The Journal of the American Academy of Orthopaedic Surgeons, 2020.

[8] D. Chowdhury et al., "Telehealth for pediatric cardiology practitioners in the time of COVID-19," Pediatric Cardiology, vol. 41, no. 6, pp. 1081–1091, 2020.

[9] A. C. Shah and S. M. Badawy, "Telemedicine in pediatrics: systematic review of randomized controlled trials," JMIR pediatrics and parenting, vol. 4, no. 1, p. e22696, 2021.

[10] A. Curfman *et al.*, "Pediatric telehealth in the COVID-19 pandemic era and beyond," *Pediatrics*, vol. 148, no. 3, 2021.

[11] P. Bourgoin et al., "The prognostic value of early amplitude-integrated electroencephalography monitoring after pediatric cardiac arrest," Pediatric Critical Care Medicine, vol. 21, no. 3, pp. 248–255, 2020.

[12] P. N. Huu and H. N. T. Thu, "Proposal gesture recognition algorithm combining cnn for health monitoring," in 2019 6th NAFOSTED Conference on Information and Computer Science (NICS), IEEE, 2019, pp. 209–213.

[13] X. Zhou, Y. Li, and W. Liang, "CNN-RNN based intelligent recommendation for online medical pre-diagnosis support," IEEE/ACM Transactions on Computational Biology and Bioinformatics, vol. 18, no. 3, pp. 912–921, 2020.

[14] G. A. Oguntala et al., "SmartWall: Novel RFID-Enabled Ambient Human Activity Recognition Using Machine Learning for Unobtrusive Health Monitoring," IEEE Access, vol. 7, pp. 68022–68033, 2019, doi: 10.1109/ACCESS.2019.2917125.

[15] X. Zhou, W. Liang, K. I.-K. Wang, H. Wang, L. T. Yang, and Q. Jin, "Deep-Learning-Enhanced Human Activity Recognition for Internet of Healthcare Things," IEEE Internet of Things Journal, vol. 7, no. 7, pp. 6429–6438, Jul. 2020, doi: 10.1109/JIOT.2020.2985082.

[16] N. Tufek, M. Yalcin, M. Altintas, F. Kalaoglu, Y. Li, and S. K. Bahadir, "Human Action Recognition Using Deep Learning Methods on Limited Sensory Data," IEEE Sensors Journal, vol. 20, no. 6, pp. 3101–3112, Mar. 2020, doi: 10.1109/JSEN.2019.2956901.

[17] N. Tziolas, N. Tsakiridis, E. Ben-Dor, J. Theocharis, and G. Zalidis, "Employing a Multi-Input Deep Convolutional Neural Network to Derive Soil Clay Content from a Synergy of Multi-Temporal Optical and Radar Imagery Data," Remote Sensing, vol. 12, no. 9, Art. no. 9, Jan. 2020, doi: 10.3390/rs12091389.

[18] M. Chen et al., "Iterative integration of deep learning in hybrid Earth surface system modelling," Nat Rev Earth Environ, vol. 4, no. 8, Art. no. 8, Aug. 2023, doi: 10.1038/s43017-023-00452-7.

[19] J. N. et Al, "Innovative AI-driven Automation System Leveraging Advanced Perceptive Technologies to Establish an Ideal Self-Regulating Video Surveillance Model," Tuijin Jishu/Journal of Propulsion Technology, vol. 44, no. 2, Art. no. 2, Sep. 2023, doi: 10.52783/tjjpt.v44.i2.220.

[20] A. Ali et al., "Blockchain-Powered Healthcare Systems: Enhancing Scalability and Security with Hybrid Deep Learning," Sensors, vol. 23, no. 18, Art. no. 18, Jan. 2023, doi: 10.3390/s23187740.

[21] S. Mekruksavanich and A. Jitpattanakul, "LSTM Networks Using Smartphone Data for Sensor-Based Human Activity Recognition in Smart Homes," Sensors, vol. 21, no. 5, Art. no. 5, Jan. 2021, doi: 10.3390/s21051636.

[22] I. Priyadarshini, R. Sharma, D. Bhatt, and M. Al-Numay, "Human activity recognition in cyber-physical systems using optimized machine learning techniques," Cluster Computing, vol. 26, no. 4, pp. 2199–2215, 2023.