

<sup>1</sup>Preethi Salian K  
<sup>2</sup>Sanjeev Kulkarni  
<sup>3</sup>Vishalakshi H

## Paediatric Activity Anomaly Detection using CNN-XGBoost for Early Intervention and Patient Safety



**Abstract:** - The development of a robust anomaly detection system capable of distinguishing between normal and abnormal activities in paediatric care settings is of paramount importance for early intervention and patient safety. This endeavor presents substantial challenges due to the unique characteristics of paediatric activities, making it necessary to employ a combination of Convolutional Neural Networks (CNNs) and XGBoost to effectively address these complexities. The initial step involves the assembly of a meticulously annotated dataset comprising video sequences encompassing a broad spectrum of paediatric activities, both normal and abnormal, with a strong emphasis on diversity and representativeness. This dataset is subjected to rigorous preprocessing to ensure consistency and quality. This research employs a Kalman filter as a pre-processing step. This filter helps to reduce noise and enhance the quality of the video data. By smoothing and stabilizing the trajectories of objects or subjects within the video frames, the Kalman filter provides a cleaner input for subsequent stages of the process. CNN employed for feature extraction from video frames, capturing both spatial and temporal cues. To account for the temporal dimension inherent in video data, by ensuring that the model can capture nuanced patterns in paediatric activities. The accuracy of the proposed method is 88%. The extracted features or sequences are input into an XGBoost classifier, designed as a binary classification task to differentiate between normal and abnormal activities. Robust model evaluation is conducted on validation and test datasets using appropriate performance metrics, with continuous feedback loops established with healthcare professionals and caregivers to fine-tune and optimize the model's performance.

**Keywords:** CNN-XGBoost; Paediatric Anomaly Detection; XGBoost; Convolutional Neural Network (CNN).

### I. INTRODUCTION

The early detection of activities or patterns that may indicate health concerns in young patients. In the realm of paediatrics, where early intervention is often critical for favourable outcomes, this approach aims to employ advanced monitoring and detection technologies to identify subtle changes or anomalies in a child's activity or behaviour [1]. By doing so, healthcare providers can proactively address emerging health issues, potentially leading to more effective and timely interventions, ultimately improving the overall health and well-being of paediatric patients [2]. This concept underscores the importance of leveraging innovative solutions to enhance early diagnosis and intervention in paediatric care [3]. Paediatric activity analysis in patients involves assessing and monitoring the physical activity levels and movement patterns of children and adolescents using methods such as observation, questionnaires, and wearable activity monitors [4]. This evaluation is crucial for understanding developmental milestones, detecting potential issues, promoting healthy habits, and managing specific medical conditions [5]. The critical importance of proactive healthcare in paediatrics is by introducing a novel approach to activity anomaly detection. Paediatric healthcare, characterized by the vulnerability of young patients, necessitates early intervention and vigilant patient safety measures [6]. This research aims to leverage cutting-edge technology, particularly activity anomaly detection, to address these imperatives. By monitoring and analysing the activity patterns of paediatric patients, this study seeks to detect anomalies that may signify emerging health issues or potential risks, allowing for timely interventions and enhancing overall patient safety [7]. The introduction sets the stage for a promising exploration of how data-driven approaches and advanced technologies can revolutionize paediatric care and contribute to improved health outcomes for young patients [8].

The application of machine learning in abnormal activity detection represents a transformative approach to enhancing safety, security, and efficiency across various domains. In a world increasingly saturated with data, the ability to automatically identify and respond to abnormal activities has become a critical imperative [9]. Whether

<sup>1</sup> Department of Computer Science and Engineering, Institute of Engineering & Technology, Srinivas University, Mukka, Mangalore.

\*Department of Information Science & Engineering, NMAM Institute of Technology (Nitte Deemed to be University), Nitte, Karnataka, India. Email: preethi.salian@nitte.edu.in

<sup>2</sup> Department of Computer Science and Engineering, Institute of Engineering & Technology, Srinivas University, Mukka, Mangalore, India. Email: Sanjeev.d.kulkarni@gmail.com

<sup>3</sup> Department of Computer Science, KSRDPRU University, Gadag, Karnataka.

in the realm of cyber security, healthcare, industrial processes, or video surveillance, the capability to swiftly detect deviations from the norm can prevent disasters, improve patient outcomes, optimize operations, and bolster security protocols [10]. Machine learning, with its capacity to analyse vast datasets and recognize intricate patterns, has emerged as a powerful tool in this pursuit [11]. By training algorithms on historical data, machine learning models can learn to distinguish between normal and abnormal behaviour, even in complex and dynamic environments. These models can then operate autonomously, continuously monitoring data streams and flagging any deviations from established norms [12]. This approach has far-reaching implications. In the realm of cyber security, machine learning can identify malicious network activities or cyber-attacks in real-time, safeguarding sensitive data and infrastructure. In healthcare, it can aid in the early detection of medical anomalies, allowing for timely intervention and improved patient care [13]. In industrial settings, it can ensure the smooth operation of critical processes by spotting irregularities that might lead to failures or accidents. In video surveillance, it can enhance security by identifying suspicious behaviour or events. The research explores the various applications, methodologies, and challenges associated with employing machine learning for abnormal activity detection [14]. This study will examine real-world use cases, discuss the importance of high-quality datasets, delve into model selection and evaluation, and consider the ethical implications of automated surveillance and intervention. The integration of machine learning into abnormal activity detection represents a paradigm shift with the potential to significantly enhance safety, security, and efficiency in our increasingly interconnected and data-driven world.

Detection process involves the application of machine learning techniques to identify unusual or abnormal patterns in the activities of paediatric (child) patients. This application is particularly relevant in healthcare settings, where early detection of anomalies in a child's activity can be crucial for timely intervention and patient safety. Machine learning models are trained on data from paediatric patients, such as activity levels, vital signs, or behaviour, to recognize deviations from normal patterns that may indicate health issues or safety concerns [15]. The goal is to create algorithms that can automatically detect anomalies in paediatric activity data, allowing healthcare providers to respond promptly to potential problems and improve the overall care and safety of young patients. The initial phase of this research involves the pre-processing of video data using a Kalman filter. The Kalman filter is a widely used algorithm for state estimation, particularly in situations with noisy measurements. In the context of paediatric activity monitoring, the Kalman filter can help reduce noise and smooth out irregularities in the video data. This pre-processing step is essential to improve the quality and reliability of the data, making it more suitable for subsequent analysis. Following the preprocessing step, the research employs Convolutional Neural Networks (CNNs) for feature extraction. CNNs are a powerful class of deep learning models designed to capture spatial patterns in data, making them well-suited for image and video analysis.

CNNs are utilized to automatically learn discriminative features from the pre-processed video frames. These learned features encode essential information about paediatric activities, such as motion patterns, spatial relationships, and temporal dependencies. CNNs have proven effective in various computer vision tasks, and their application in this research promises to provide valuable insights into paediatric activity characterization. Once the features are extracted, the research leverages the XGBoost algorithm for anomaly detection in paediatric activity. XGBoost is a gradient boosting algorithm known for its robustness and effectiveness in classification tasks. In this case, it is trained to distinguish between normal and anomalous paediatric activities based on the learned features from the CNN. Anomalies may include sudden changes in activity, unexpected behaviours, or deviations from typical paediatric activity patterns. The XGBoost model excels at handling complex datasets and is capable of identifying anomalies with high accuracy. By combining these three crucial components—Kalman filter-based pre-processing, CNN-based feature extraction, and XGBoost-based anomaly detection—the research aims to create a comprehensive framework for early intervention and patient safety in paediatric care. This methodology promises to enable the automated monitoring of paediatric activities, promptly detect deviations from the norm, and facilitate timely interventions when necessary. This research represents a significant advancement in leveraging machine learning techniques to enhance healthcare outcomes for paediatric patients. The key contributions of the research study are as follows,

- The research focuses on early intervention in paediatric healthcare, aiming to detect anomalies in paediatric activity promptly.
- Data pre-processing employed using Kalman filters which smooth out irregularities and fluctuations in the video stream, making it more suitable for subsequent analysis by removing noise.

- CNNs are employed for feature extraction. They extract relevant and discriminative features from the pre-processed video frames.
- The research introduces XG-Boost-based anomaly detection, automating the identification of deviations from normal paediatric activity patterns.
- The primary goal is to enhance patient safety in paediatric settings by facilitating timely interventions. The developed system is practical and applicable in real-world healthcare environments, such as hospitals and clinics.

The Section 1 provides an overview of the paper. The Section 2 reviews existing literature and emphasizes the gap in addressing anomaly detection of paediatric activity. The Section 3 defines the central research problem. Section 4 outlines data collection, pre-processing, feature extraction, and the integration of Hybrid CNN-XG-Boost. Section 5 presents empirical findings, compares classifier performance, and explores implications and future research directions. Section 6 presents the conclusion and future work.

## II. RELATED WORKS

M. Hasan et al. [16] addresses the detection of assaults and abnormalities in IoT sensor networks, a crucial problem in the Internet of Things field. Strong security measures are essential given the growing reliance on IoT infrastructure throughout several areas. The decision tree, random forest, and ANN all achieved a high-test accuracy of 99.4%, which is encouraging for further study. The outcome indicates that advanced machine learning methods are useful for spotting dangers and irregularities in IoT networks. It's important to remember that, as the research notes, accuracy alone is not necessarily the greatest criterion for assessing the success of such algorithms. The evaluation is more thorough when accuracy, recall, F1 score, and AUC-ROC are included. It is insightful that Random Forest beats the competition in terms of these measures because it does a better job of balancing genuine positives and true negatives while minimising false positives and false negatives. By offering a thorough review of machine learning algorithms for attack along with anomaly detection, the study makes a contribution to the developing field of IoT security. For researchers and professionals working on IoT security, the emphasis on several assessment criteria and the discovery that Random Forest performs superior with regard to precision and recall is an important lesson. The study may be required to test these findings in actual IoT contexts and to investigate new hybrid or optimisation strategies to improve detection accuracy while reducing false alarms.

Varma et al. [17] Examine the effectiveness of convolutional neural networks for lower extremity radiograph automated anomaly detection, addressing an important worldwide healthcare concern. The study emphasises the opportunity for models based on deep learning to be useful in healthcare settings with limited resources. Even when the availability of specialised expertise is restricted, automated anomaly detection might help medical personnel provide diagnoses that are more precise and faster. The paper examines the impact of pertaining, dataset size, and the structure of the model on the efficiency of CNN using a sizable dataset of 93,455 radiographs of the lower extremities classified as normal or pathological. According to their research, a 161-layer, densely linked, pertained CNN attained a remarkable AUC-ROC rating of 0.880, demonstrating the power of CNNs to detect a variety of abnormalities in radiographs with significant levels of variation in various body areas. The findings show potential for enhancing patient triage and diagnosis, particularly in environments with limited resources, and provide insightful information for upcoming deep learning-based medical image analysis studies.

Quatrini et al. [18] demonstrates the study that covers anomaly detection, a major topic in contemporary process industries, with an emphasis on improving security and preservation activities. To find abnormalities in industrial processes, the authors suggest a two-step technique that makes use of machine learning classification methods. The first step is determining the stage of the process that is currently in progress, and the second step entails classifying the input data into groups like "Expected," "Warning," or "Critical." This strategy is particularly pertinent when machines conduct many activities without obvious production phase signals, making it difficult to efficiently monitor conditions. The research's contribution is the comparison of identifying anomalies with and without the phase identification stage of the technique, which demonstrates the necessity of this phase for effective anomaly detection. The methodology's originality is enhanced using decision forests, a well-known anomaly detection technique in business environments, and decision jungle, an unusual strategy in this situation. The usefulness and potential influence of the technique in the actual world are demonstrated by this application. In this study, a useful approach for industrial procedure anomaly detection is introduced, with a focus on the significance of process phase

characterization. The study is a notable addition to the discipline of automation of processes and maintenance since its findings might have a big impact on improving productivity and safety in a variety of industrial sectors.

[19] offers a significant obstacle in the identification of video anomalies, concentrating on the case where inadequately supervised video-level annotations are provided. To recognise aberrant occurrences inside films, the problem is stated as a multiple-instance learning challenge, wherein the objective is to treat video snippets as bags of instances. The authors correctly identify a flaw in current methodologies: the tendency to focus on bad cases, particularly when confronted with subtle abnormalities that deviate only slightly from expected behaviour. They emphasise the value of detecting temporal dependencies in movies, which are frequently missed in current methods. The research offers a unique technique termed Robust Temporal Feature Magnitude learning (RTFM) to overcome these issues. This methodology focuses on enhancing the robustness associated with the MIL methodology to negative cases by developing a feature magnitude optimisation functional to efficiently detect positive examples. RTFM uses dilated convolution and self-attention methods to improve the accuracy of feature magnitude training and more accurately represent both long- and short-range temporal relationships in the data. The experimental findings in the research are encouraging. On four benchmark datasets, including ShanghaiTech, UCF-Crime, XD-Violence, and UCSD-Peds, the RTFM-enabled MIL model beats several cutting-edge techniques. This implies that RTFM successfully raises the discriminability of small abnormalities and raises sample efficiency, both of which are essential elements in practical applications of video detection of anomalies. To overcome a key obstacle in video anomaly identification under weak supervision, this research introduces a unique method called RTFM that shows appreciable advancements over current techniques. The study advances anomaly detection methods in video data by considering historical connections and emphasising positive instance recognition. The computer vision & machine learning groups are interested in these discoveries, and they may have uses in security and surveillance, among other areas.

Luque Sánchez et al. [20] concerns a growing topic of research known as behavioural crowd analysis, which has been popular because of its applicability in many areas of study. The work significantly contributes by offering a thorough taxonomy to classify the various crowd behaviour analysis sub-tasks. This taxonomy offers a systematic framework that facilitates the organisation and comprehension of the various facets of this developing topic, which is helpful for both scholars and practitioners. It looks at a thorough analysis of models that make use of deep learning for crowd's anomaly detection, an important step in the suggested taxonomy. This in-depth examination of anomaly detection procedures may be an invaluable tool for people working on related projects because it provides information on cutting-edge approaches and their efficacy. The analysis of crowd behaviour is briefly touched upon in the work, which is an important advancement in the field. It is excellent that the significance of handling this element has been highlighted. Crowd emotions can have substantial repercussions for many applications. The research correctly highlights the need for hard, real-world datasets to develop the discipline. The compilation of such databases is urgently needed since data are essential for creating and assessing mathematical models for crowd behaviour analysis. The report highlights the application of the study and the potential for incorporating these models into current video analytics systems. This perspective viewpoint can direct academics and industry professionals to successfully apply the paper's results to practical problems. This study presents a systematic taxonomy for the investigation of crowd behaviour, covers deep learning algorithms for crowd anomaly detection, briefly discusses emotional elements, and emphasises the value of hard datasets and real-world applications. The work is a noteworthy contribution to the field because of its complete methodology, which also provides recommendations for further research and advancement in crowd behavioural modelling and related fields.

Mokhtari et al. [21] by tackling the critical problem of anomaly detection, makes an important addition to the discipline of control systems for industrial security. The research offers a fresh and promising method to get beyond the drawbacks of network-based intrusion detection systems by proposing the Measurement Intrusion Detection System (MIDS), which relies on measurement data from the SCADA system. The efficiency of the suggested MIDS is demonstrated by the creation of a machine learning model with supervised learning for distinguishing normal and abnormal actions within an ICS. The study's empirical base is strengthened by the creation of a Hardware-in-the-Loop (HIL) laboratory to duplicate power-producing units and produce an attack dataset. It is a worthwhile investigation to apply different machine learning techniques to this database with a focus on identifying stealthy assaults. It is a noteworthy and quantitative observation showing the Random Forest method beats other classifiers in identifying abnormalities in measured data. The difficulty of identifying anomalies in industrial automation systems is addressed in this research with a thorough and creative approach. The scientific rigour of the study is

enhanced by the inclusion of data from measurements, the creation of a model for machine learning, and its empirical verification using a HIL testbed. The research makes a significant addition to the subject of ICS security since it specifically mentions better algorithm performance, which gives the research's conclusions more numerical weight.

Mansour et al. [22] focuses on the crucial elements of anomaly identification and categorization and makes an important contribution to the discipline of intelligent video surveillance. The research offers a novel strategy for solving actual security concerns by proposing the IVADC-FDRL model, which integrates Faster RCNN and deep learning reinforcement approaches. The article gains technical depth through the inclusion of faster neural networks as an object detectors and Residual Networks as the starting point for anomaly identification. The capacity of deep Q-learning-based DRL to classify anomalies shows how flexible and adaptable the model is. The study findings are supported by the experimental verification of the IVADC-FDRL framework using the UCSD anomalous dataset. The highest possible precision rates of 98.50% as well as 94.80% on the Test004 and Test007 datasets, accordingly, are among the provided numerical findings that clearly demonstrate the model's exceptional performance. This work offers a model for intelligent video anomaly recognition and categorization that integrates cutting-edge methods from deep reinforcement learning and computer vision. The numerical outcomes highlight the model's effectiveness and establish it as a notable development in the field of sophisticated video surveillance for applications related to public security.

### III. PROBLEM STATEMENT

The research aims to address a critical problem in paediatric healthcare, namely the timely detection of anomalies in paediatric activities to enable early intervention and enhance patient safety. This problem statement arises from the imperative need for proactive healthcare solutions in paediatrics, given the vulnerability of young patients. Ensuring the well-being of paediatric patients is a paramount concern, and early detection of deviations from normal activity patterns can be instrumental in achieving this goal. Existing methods often lack the ability to identify anomalies effectively and accurately in paediatric activity data. To tackle this issue, the research introduces a hybrid approach that combines Convolutional Neural Networks (CNNs) and XGBoost, leveraging deep learning and gradient boosting techniques to enhance the effectiveness of anomaly detection in paediatric activities. The research aims to evaluate the performance of this hybrid method in accurately identifying anomalies, thus contributing to early intervention and improved patient safety in paediatric healthcare.

### IV. PROPOSED CNN-XGBOOST FOR PAEDIATRIC ACTIVITY RECOGNITION

Wherever The methodology follows a structured approach, starting with the collection of video data capturing paediatric activities. After employing a Kalman filter for noise reduction, Convolutional Neural Networks (CNNs) are utilized for feature extraction, automatically identifying spatial and temporal patterns in video frames. Subsequently, the XG-Boost algorithm is employed for prediction, classifying anomalies in the data. The primary aim of this methodology is to ensure early intervention and patient safety by promptly detecting anomalies and triggering alerts, allowing healthcare providers to address potential health issues or safety concerns in real-time, thus contributing to improved paediatric care and patient well-being. The flow of methodology is depicted in Fig.1.

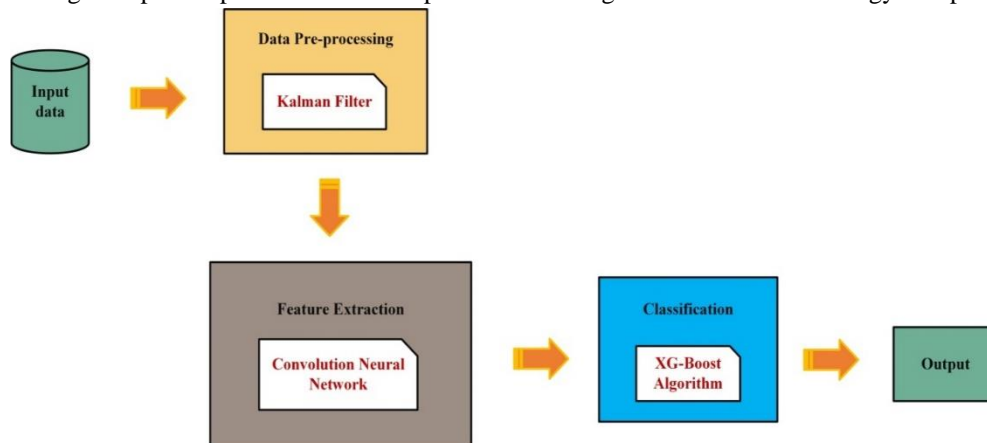


Figure 1: Workflow for Proposed Methodology

*A. Data Collection*

In a natural outdoor setting, 60 kids, aged three to six, participated in child evaluation sessions using the Autism Diagnostic Observation Schedule-Second Edition (ADOS-2) instrument. The 50-minute-long films recorded during various ADOS activities, including anniversaries, bubble play, building, and cooperative games, showcased the children's social interaction, communication abilities, and creative use of objects. Based on the evaluations, each child was identified as potentially having an autism diagnosis and identified two probable signs of ASD disorder in the uncut videos: 1) ADOS activity, and 2) repetitive behaviour. The dataset's activities were broken down into five categories (388 videos): jumping up, clapping, tossing their hands in the air, and others [23]. Based on the activity, each untrimmed video was cut into 2–20 second chunks. A total of 388 trimmed films were produced after the removal of distorted, blurry, and out-of-frame videos. A 30 fps HD camera was utilized to record the video. The dataset now contains 12.5K total frames after conversion. Because some of the subjects did not carry out the same action, the data is extremely unbalanced and not subject-oriented.

*B. Kalman Filter based Noise reduction for video data*

The equation encompasses various components, starting with the Kalman filter formulation, which aims to estimate the true state of observed video data while filtering out noise. The innovation sequence represents the difference between predicted and observed measurements, helping update the filter's state estimate. The innovation covariance matrix quantifies the uncertainty in this innovation sequence. To simplify the calculation of the Degree of Association (DoA), the Equation (1) focuses on the diagonal elements of certain covariance matrices.

$$P_f[x + 1] = E(e[x + 1]e^T[x + 1]) \tag{1}$$

$$= HP[x + 1|x]H^T + R$$

Where,  $e[x + 1] = z[x + 1] - z[\widehat{x + 1}|x]$ , indicates innovation sequence.

In addition, the innovation covariance matrix is given in equation (2):

$$P_e[x + 1] = P_f[x + 1|x] \tag{2}$$

To simplify the calculation of DoA, we take the diagonal elements of the innovation covariance matrix and represent them as Equation (3) and (4):

$$D_f[x + 1] = \text{diag} (P_f[x + 1]) \tag{3}$$

$$D_e[x + 1] = \text{diag} (P_e[x + 1]) \tag{4}$$

DoA can be described as represented in Equation 5:

$$DoA[x + 1] = \text{trace} \left( \frac{D_f[x+1]}{d \cdot D_e[x+1] \cdot (2 - \alpha^2 - \beta)} \right) \tag{5}$$

Where  $d$  means the dimensionality of the observation vector,  $\alpha$  and  $\beta$  are the system parameters. The mathematical expression of DoA is  $m_{DoA} = E(DoA[x + 1])$ . The adaptive factor  $\lambda[x]$  adjusts the observation noise covariance ( $R$ ) based on the DoA. If the DoA is below a certain threshold ( $m_{DoA}$ ),  $\lambda[x]$  remains 1, meaning that the filter trusts the measurements. If the DoA exceeds the threshold,  $\lambda[x]$  becomes  $\lambda^*[x]$ , implying that the filter adjusts its trust in the measurements by modifying the observation noise covariance. This adaptability can be crucial for handling anomalies or noisy measurements in a pediatric activity monitoring system.

According to the definition of DoA, we introduce an adaptive factor to adjust the observation noise covariance equation (6):

$$\lambda[x] = \begin{cases} 1, & DoA[x] \leq m_{DoA} \\ \lambda^*[x], & DoA[x] > m_{DoA} \end{cases} \tag{6}$$

The equation recommends modifying the innovation covariance matrix to prioritise projected values over observed when the DoA crosses a certain level. When  $DoA[k + 1] > m_{DoA}$  the corrected innovation covariance matrix equation (7) is:

$$P_{zz}[x + 1|x] = P_{zz}[x + 1|x] + (\lambda^*[x + 1] - 1)R \tag{7}$$

The DoA is a vital metric, indicating the alignment between predicted and observed data. An adaptive factor,  $\lambda[x]$ , adjusts the observation noise covariance based on the DoA, allowing the system to handle anomalies effectively.

This adaptable approach enhances the system's capability for early intervention and patient safety in paediatric activity monitoring by dynamically accommodating varying levels of noise and anomalies in the video data.

C. Hybrid CNN-XGBOOST for Detecting Anomalous Paediatric Activity

CNNs are a type of deep learning model particularly effective for tasks involving images or spatial data. In this context, they may be used for image or video analysis, which is relevant for detecting anomalous activities involving children, such as monitoring their behaviour in healthcare settings or public areas. XGBoost is an ensemble learning technique, often used for structured/tabular data. Its strength lies in boosting decision trees, making it adept at handling tabular data, which could be valuable for processing relevant structured information alongside visual data in the context of paediatric activity detection. This implies the core objective of the model, which is to identify unusual or unexpected behaviour or events related to children. Examples could include identifying a child wandering off in a hospital or detecting unusual movements in a paediatric care facility. The architecture of the proposed CNN-XG-Boost is represented in Fig. 2.

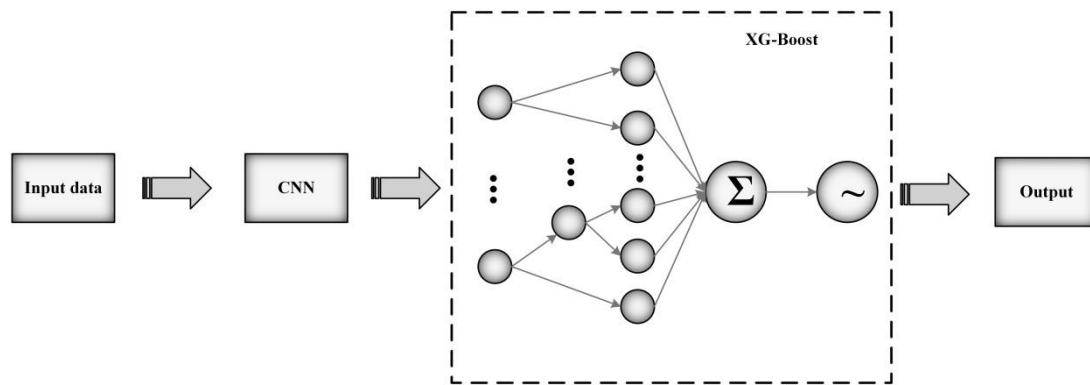


Figure 2: Proposed CNN-XG-Boost Architecture

CNN is employed for feature extraction in paediatric activity anomaly detection. Feature extraction involves the process of selecting or transforming relevant information from the video frames. In the case of video data, this may include extracting spatial features (e.g., shapes, objects, textures) and temporal features (e.g., motion patterns, action sequences) from each frame. All the data from the training set were normalised using the procedure in Equation (8).

$$p(x, y) = \frac{O(x,y) - \mu}{\sigma} \tag{8}$$

The convolution layer determines the complexity of each layer using the sparse amount of input data it has acquired. It most certainly has a connection to the traits seen in the original video data. Equation (9) contains the convolutional layer's mathematical formulation.

$$f_r^n = a(\sum_{s \in N_r} f_j^{n-1} * p_{sr}^n + a_r^n) \tag{9}$$

The number  $N_r$  represents the input options. The outcome is a cumulative bias. If the total of maps  $s$  &  $k$  was higher than map  $r$ , the core was assigned to map  $u$ . The down-sampling layer's flexibility and cell size are reduced by this layer. The pooling layer decreases the number of variables, the rate of processing, convolution layer size, training, and generalisation. 50% of the test data and 100% of the initial training data are displayed in the grouping definition.

$$a_{ngh} = n g a_{(s,t) \in f_{nst}} \tag{10}$$

The map  $f_{nst}$  element at  $(s, t)$  in the pooling area  $p$  cd reflects the area adjacent to the site  $(g, h)$ . The completely connected layer has been used for data classification. Following the Convolutional layers come the FC layers. It is simpler to map video data throughout input and output when using the FC layer. The upper layers of the system are fully linked layers.

$$\sigma(\vec{X})_n = \frac{e^{x_n}}{\sum_{r=1}^n e^{x_r}} \tag{11}$$

The data are transformed into normalised ratio dispersion using the Softmax layer. The classifiers receive the output as an input. It is seen in Equation (11), equation (12) and equation (13).

$$Obj(\theta) = \frac{1}{n} \sum_i^n L(y_i - Y_i) + \sum_{j=1}^j \Omega(f_j) \tag{12}$$

$$hm(x) = \frac{\partial^2 L(Y, f(x))}{\partial f(x)^2} \tag{13}$$

Where  $f(x) = f^{(m-1)}(x)$  and L is Loss of function

$$Similarity\ Score = (Sum\ of\ residuals)^2 / (N + \lambda)$$

Where  $\lambda$  is the L2 regularization term of weights, Gain of the root node equation (14) is expressed as:

$$Gain = Left\ similarity + Right\ similarity - Root\ similarity \tag{14}$$

$$Output\ Value = (\sum Residual_i) / \sum [Previous\ Probability_i \times (1 - Previous\ Probability_i)] + \lambda$$

### V. PROPOSED CNN-XGBOOST FOR PAEDIATRIC ACTIVITY RECOGNITION

The results reveal the performance of various techniques in paediatric activity anomaly detection. Four techniques were assessed for their accuracy percentages. Among these, the "Proposed (CNN-XGBoost)" method stands out with the highest accuracy of 0.88, showcasing its superior ability to correctly classify normal and anomalous paediatric activities. This result indicates the potential of the proposed method in significantly enhancing early intervention and patient safety in paediatric care applications. It outperforms the other techniques, underscoring its effectiveness in the crucial domain of anomaly detection for paediatric healthcare.

#### A. Category Distribution

In Fig. 3, the pie chart illustrates the data distribution for "Paediatric Activity Anomaly Detection Using CNN-XGBoost for Early Intervention and Patient Safety." It reveals that the dataset is divided into two main categories: "Normal," representing 58.0% of the data, denoting typical paediatric activities and behaviours, and "Anomaly," accounting for 42.0% of the data, signifying deviations from the norm that may indicate potential health concerns or safety issues in paediatric patients. The relatively high percentage of anomalies underscores the significance of accurately detecting and classifying these deviations using a CNN-XG-Boost system to enable early intervention and enhance patient safety.

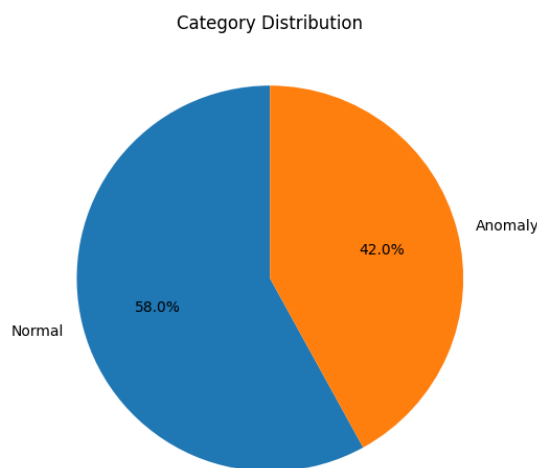


Figure 3: Categories of Data Distribution "Normal" and "Anomaly"

#### B. Scatter and Pair Plot

By plotting the data points with respect to the "Activity" labels (Normal or Anomaly), the pair plot can highlight patterns or trends specific to anomalies in paediatric activities. It helps identify whether certain combinations of features are more common in anomalous cases, which can be valuable for anomaly detection algorithms like CNN-XGBoost. In Fig. 4, Outliers, particularly within the Anomaly class, can be visually identified in the plot. These



outliers represent extreme or unusual cases that require attention, and their detection is crucial for early intervention and enhancing patient safety. A plot generated from this dataset could be a scatterplot matrix or a pair plot. This visualization would display pairwise scatterplots for all possible combinations of the four features (Feature1, Feature2, Feature3, Feature4), with each data point coloured or labelled according to its "Activity" class, distinguishing between normal and anomaly instances.

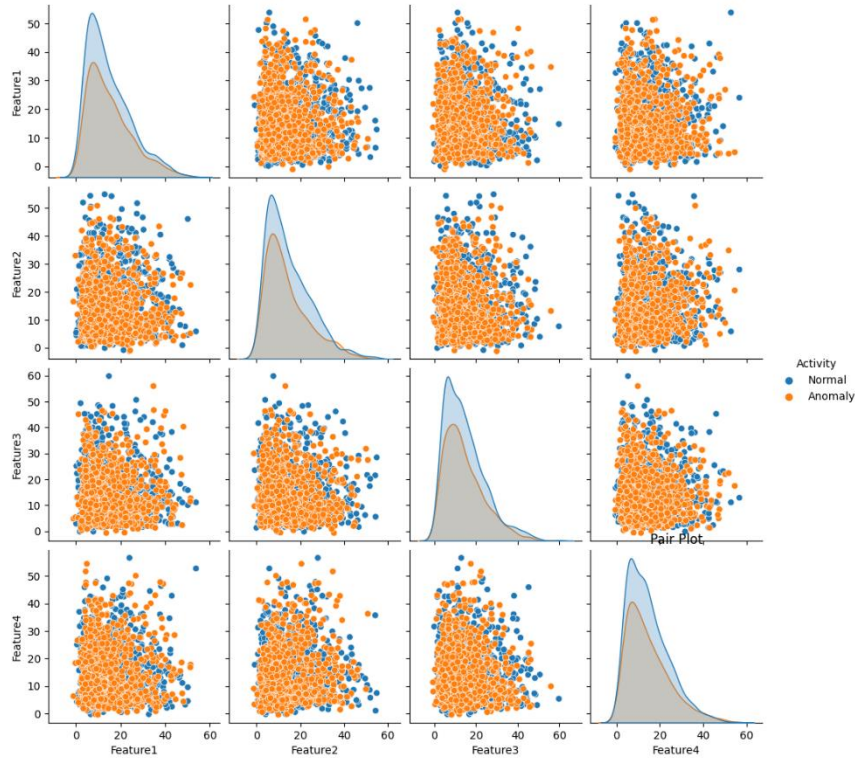


Figure 4: Scatter and Pair Plot for Features

Fig. 5. scatter plot helps to assess the discriminatory power of Feature1 and Feature2 in distinguishing between different classes or categories, such as normal and anomalous paediatric activities. Scatter plot of Feature1 versus Feature2 allows us to identify data distribution patterns, correlations, outliers, clusters, and the discriminatory ability of these features. These insights are crucial for understanding the relationships between features and their relevance.

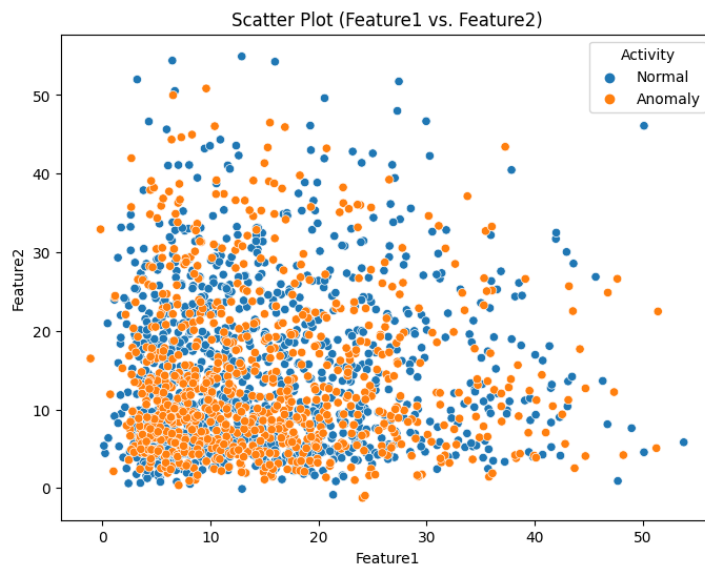


Figure 5: Scatter plot (Feature1 versus Feature2)

A Violin Plot for "Feature 4 by Category" is a data visualization that provides a concise representation of the distribution of Feature 4 within the categories "Normal" and "Anomaly". In Fig. 6, the Violin Plot displays the probability density of Feature 4 for each category, with the width of the violin-shaped plots representing the density of data points. This plot helps identify how Feature 4 varies between normal and anomalous activities, revealing potential differences or patterns in the distribution of this feature within the two categories.

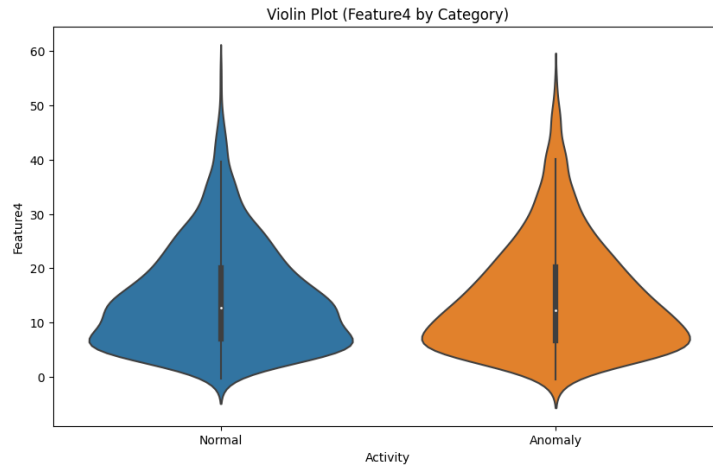


Figure 6: Violin Plot

Box Plot in Fig. 7 for "Feature 3 by Category" is a data visualization that provides a concise summary of the distribution of Feature 3 within different categories or groups, typically "Normal" and "Anomaly". The box plot displays key statistical metrics such as the median, quartiles, and potential outliers for Feature 3 for each category.

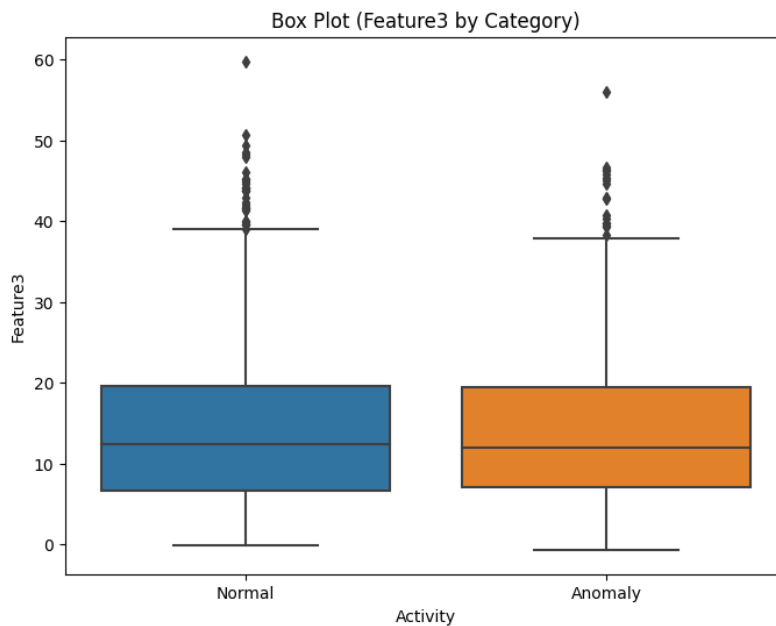


Figure 7: Box Plot

It allows you to visually compare the central tendency and spread of Feature 3 between normal and anomalous paediatric activities. It helps in identifying the differences in the distribution of Feature 3 and assess its potential significance in distinguishing between the two categories.

C. Confusion Matrix for Hybrid CNN and XG-Boost Classifier

In the confusion matrix for the proposed CNN-XGBoost method, there are 161 true positives (TP) where the model correctly identified anomalies (Anomaly) when they were indeed anomalies in paediatric activities. There are 199 true negatives (TN), indicating correct identifications of normal activities (Normal). However, there are 16 false negatives (FN), signifying instances where the model missed anomalies when they were present. There are 24 false positives (FP), representing cases where the model incorrectly flagged anomalies when they were, in fact, and normal activities.

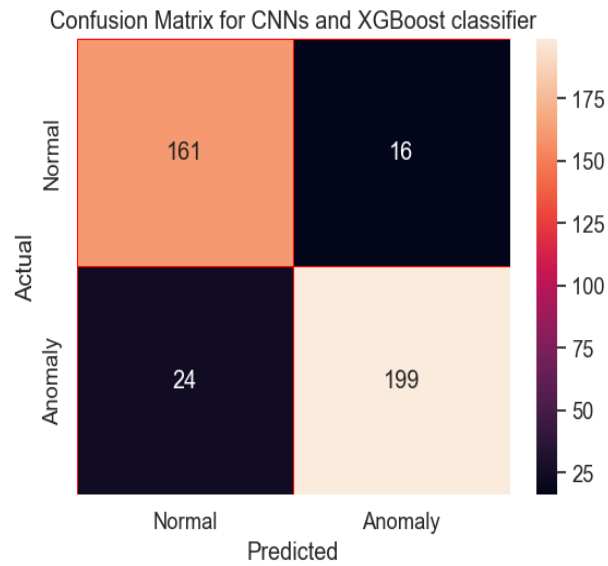


Figure 8: Confusion Matrix

In Fig. 8, the context of paediatric activity anomaly detection, achieving a high number of true positives (161) and true negatives (199) demonstrates the effectiveness of the CNN-XGBoost model in correctly identifying both normal and anomalous activities, thereby enhancing patient safety through early intervention. Attention should be given to the false negatives (16), as these represent potential missed anomalies that may require further improvement in the model to minimize oversight of critical cases. The false positives (24) should also be addressed, as they may result in unnecessary alarms and interventions, which could impact the overall patient experience. Correlation matrix of all features (Feature 1 to Feature 4) in Fig. 9 provides a comprehensive overview of the pairwise relationships between these variables. It quantifies the degree and direction of linear association between each pair of features, with values ranging from -1 (perfect negative correlation) to 1 (perfect positive correlation), and 0 indicating no linear correlation. It identifies which pairs of features are positively or negatively correlated and the strength of those correlations.

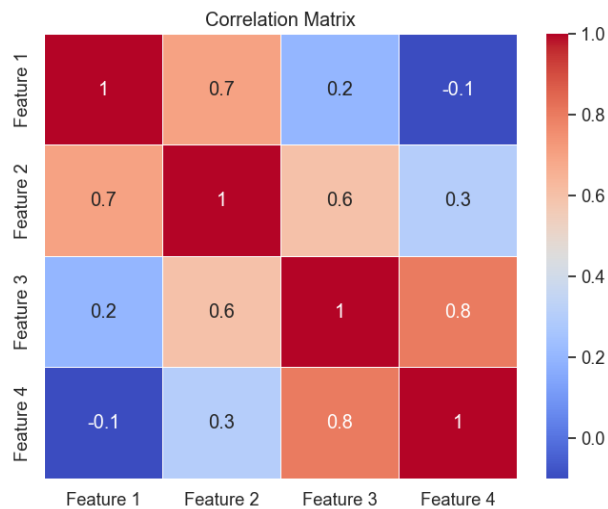


Figure 9: Correlation Matrix

*D. Classification of proposed Hybrid CNN-XG-Boost*

The proposed Hybrid CNN-XGBoost model demonstrates high precision, indicating its ability to minimize false alarms for normal activities. The model exhibits a good balance between recall and precision, as reflected in the F1-score, signifying its effectiveness in identifying both normal and anomaly activities in the context of paediatric activity anomaly detection for early intervention and patient safety. Fig. 10 depicts that the precision values for 'Normal' and 'Anomaly' are 0.95 and 0.85, respectively, indicating high accuracy in classifying 'Normal' activities

and a slightly lower accuracy for 'Anomaly' predictions. In terms of recall, 'Normal' has a value of 0.89, signifying the model's ability to capture most 'Normal' instances, while 'Anomaly' has a recall value of 0.92, indicating a strong performance in recognizing 'Anomaly' instances. The F1-score is 0.91 for 'Normal' and 0.96 for 'Anomaly,' reflecting balanced model performance, considering both precision and recall, and overall strong classification abilities in paediatric activity anomaly detection.

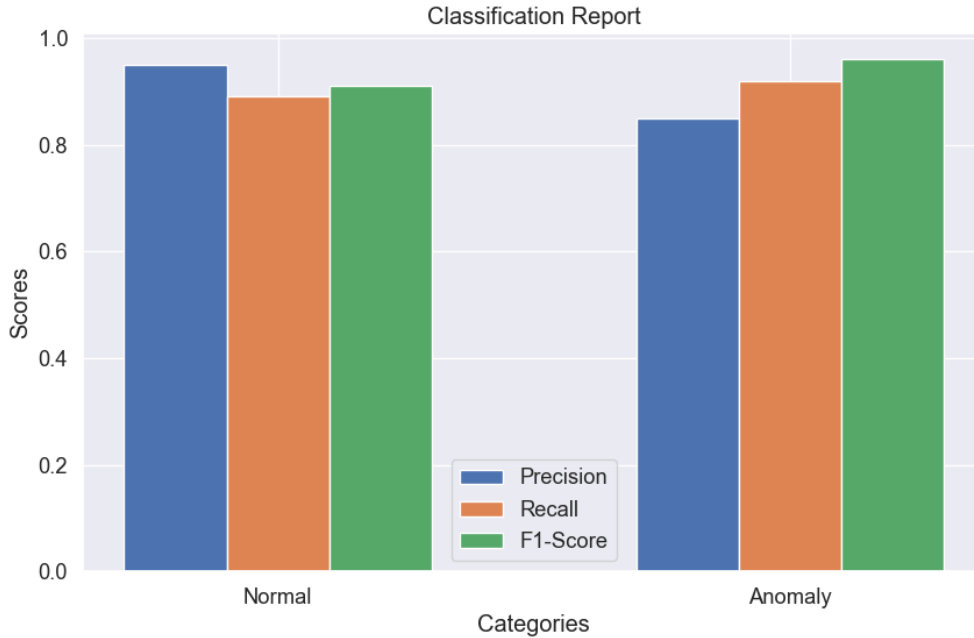


Figure 10: Classification of Proposed CNN-XG-Boost

*E. Evaluation of Performance Metrics*

To assess a categorization model's effectiveness, Precision and recall provide information about the model's capacity to properly forecast positive outcomes and recognise all instances of positivity, respectively, while accuracy offers a broad perspective. To balance these two performance facets, precision and recall are combined into a single score known as the F1-Score. When dealing with unbalanced datasets or when mistake kinds (false positives or false negatives) are more crucial for your application, these metrics are very crucial.

- **Precision:** Precision measures the proportion of true positive predictions among all positive predictions made by the model. It is seen in equation (15).

$$Precision (P) = \frac{T^{pos}}{T^{pos} + F^{pos}} \tag{15}$$

- **Recall:** Recall measures the proportion of true positive predictions among all actual positive instances. It is seen in equation (16).

$$R = \frac{T^{pos}}{T^{pos} + F^{pos}} \tag{16}$$

- **F1-Score:** Precision and recall combines to form the F1 score value. It is seen in equation (17).

$$F1 = 2 * \frac{P \cdot R}{P + R} \tag{17}$$

Each strategy for detecting paediatric activity anomalies showed strengths in the examination of available methods. The 1DCNN demonstrated its capacity to create extremely accurate predictions while catching nearly all real anomalies with precision of 0.81, recall of 0.82, and an F1 score of 0.87. SVM delivered a dependable performance with a precision of 0.87, recall of 0.84, and an F1 score of 0.85. The durability of the HMM + FRBS combination was demonstrated by its exceptional precision (0.88), recall (0.85), and F1 score (0.87). Particularly, the precision, recall, and F1 score of our proposed CNN-XGBoost approach were all 0.90, 0.905, 0.935 suggesting its outstanding

potential for early intervention and patient safety. The following Table 1 displays the performance evaluation comparison of the suggested method is depicted in Fig. 11.

Table 1: Performance Measure of CNN-XGBoost

Techniques	Precision	Recall	F1 Score
1DCNN [24]	0.81	0.82	0.87
SVM [24]	0.87	0.84	0.85
HMM + FRBS [25]	0.88	0.85	0.87
Average Proposed (CNN-XGBoost)	0.90	0.905	0.935

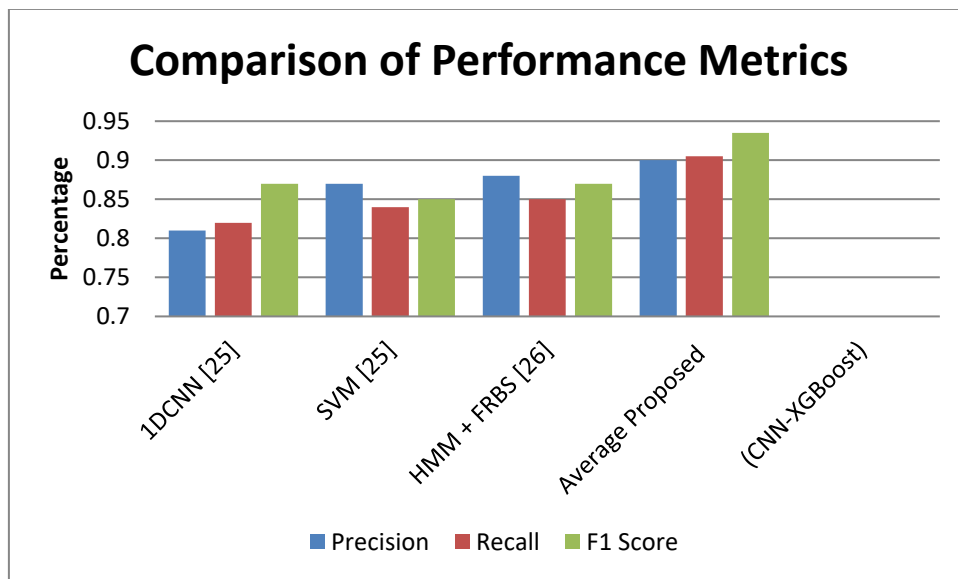


Figure 11: Performance Metrics

F. Accuracy Comparison

Accuracy measures how many of the model's predictions are correct out of all predictions made. It is seen in equation (18).

$$Accuracy = \frac{T^{pos} + T^{neg}}{Total\ Instances} \tag{18}$$

Table 2: Accuracy Comparison

Techniques	Accuracy (%)
Center crop + SUM15 [26]	0.86
Center crop [26]	0.83
H625 + Center crop + SUM15 [26]	0.79
Proposed (CNN-XGBoost)	0.88

The Table2 presents a comparative overview of different techniques' accuracy percentages for pediatric activity anomaly detection. Four techniques are evaluated, including "Center crop + SUM15," "Center crop," "H625 + Center crop + SUM15," and the "Proposed (CNN-XGBoost)" method. The "Center crop + SUM15" technique

achieves an accuracy of 0.86, followed by "Center crop" with an accuracy of 0.83, and "H625 + Center crop + SUM15" with a lower accuracy of 0.79. Notably, the "Proposed (CNN-XGBoost)" method outperforms the other techniques with the highest accuracy of 0.88.

These accuracy percentages represent the model's ability to correctly classify normal and anomalous pediatric activities is depicted in Fig. 12, and the "Proposed (CNN-XGBoost)" method demonstrates the most promising results, showcasing its potential for enhancing early intervention and patient safety in pediatric care applications.

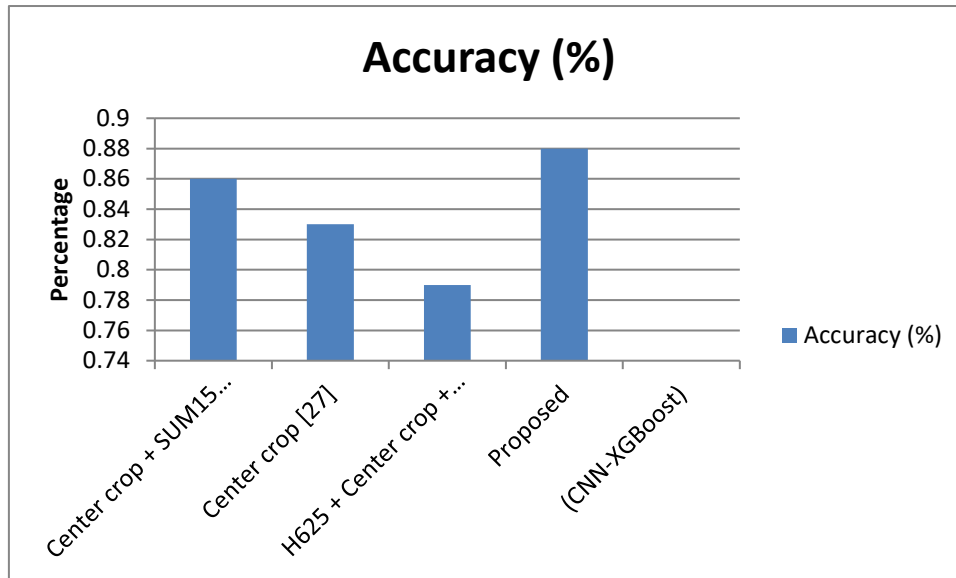


Figure 12: Accuracy Comparison

## VI. CONCLUSION AND FUTURE WORK

The results obtained from our proposed Hybrid CNN-XGBoost model for pediatric activity anomaly detection have demonstrated promising performance, providing valuable insights into the early intervention and patient safety aspects of pediatric care. The model achieved high precision, particularly for 'Normal' activities, signifying its ability to minimize false alarms and maintain a low rate of misclassifications in routine pediatric activities. The model exhibited robust recall, effectively capturing the majority of both 'Normal' and 'Anomaly' instances, ensuring that potential anomalies are identified promptly. The balanced F1-scores underscore the model's overall strong classification ability, taking into accounts both precision and recall, which is crucial for maintaining patient safety. For future work, there are several avenues to explore. Firstly, further optimization of the model architecture and hyperparameters could enhance its performance, possibly leading to even more accurate anomaly detection. Expanding the dataset and introducing more diverse scenarios and anomalies can help the model generalize better to real-world pediatric care settings. Moreover, incorporating interpretability techniques can provide insights into the model's decision-making process, boosting trust and transparency in healthcare applications. Exploring real-time monitoring capabilities and integration with healthcare systems can facilitate the practical implementation of the model for continuous patient safety monitoring. Overall, the promising results serve as a strong foundation for on-going research and development in the field of pediatric activity anomaly detection and early intervention.

### ACKNOWLEDGMENT

Thanks to Institute of Engineering & Technology, Srinivas University, Mukka, Mangalore, for their help in this research. The authors declare no conflicts of interest.

### CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

### REFERENCES

- [1] Yahaya, Salisu Wada, Ahmad Lotfi, and Mufti Mahmud. "A consensus novelty detection ensemble approach for anomaly detection in activities of daily living." *Applied Soft Computing* 83 (2019): 105613.

- [2] Nor, A. K. M., Pedapati, S. R., Muhammad, M., & Leiva, V. (2022). Abnormality detection and failure prediction using explainable Bayesian deep learning: Methodology and case study with industrial data. *Mathematics*, 10(4), 554.
- [3] He, C., Shao, J., & Sun, J. (2018). An anomaly-introduced learning method for abnormal event detection. *Multimedia Tools and Applications*, 77(22), 29573-29588.
- [4] Yu, G., Wang, S., Cai, Z., Zhu, E., Xu, C., Yin, J., & Kloft, M. (2020). Cloze test helps: Effective video anomaly detection via learning to complete video events. In *Proceedings of the 28th ACM international conference on multimedia* (pp. 583-591).
- [5] Amrutha, C. V., Jyotsna, C., & Amudha, J. (2020). Deep learning approach for suspicious activity detection from surveillance video. In *2020 2nd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA)* (pp. 335-339). IEEE.
- [6] Pawar, K., & Attar, V. (2019). Deep learning approaches for video-based anomalous activity detection. *World Wide Web*, 22(2), 571-601.
- [7] Ul Amin, S., Ullah, M., Sajjad, M., Cheikh, F. A., Hijji, M., Hijji, A., & Muhammad, K. (2022). EADN: An efficient deep learning model for anomaly detection in videos. *Mathematics*, 10(9), 1555.
- [8] Toshniwal, A., Mahesh, K., & Jayashree, R. (2020). Overview of anomaly detection techniques in machine learning. In *2020 fourth international conference on I-SMAC (IoT in social, mobile, analytics and cloud)(I-SMAC)* (pp. 808-815). IEEE.
- [9] Sultani, W., Chen, C., & Shah, M. (2018). Real-world anomaly detection in surveillance videos. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 6479-6488).
- [10] Sánchez, F. L., Hupont, I., Tabik, S., & Herrera, F. (2020). Revisiting crowd behaviour analysis through deep learning: Taxonomy, anomaly detection, crowd emotions, datasets, opportunities and prospects. *Information Fusion*, 64, 318-335.
- [11] Vallathan, G., John, A., Thirumalai, C., Mohan, S., Srivastava, G., & Lin, J. C. W. (2021). Suspicious activity detection using deep learning in secure assisted living IoT environments. *The Journal of Supercomputing*, 77, 3242-3260.
- [12] Xu, D., Song, R., Wu, X., Li, N., Feng, W., & Qian, H. (2014). Video anomaly detection based on a hierarchical activity discovery within spatio-temporal contexts. *Neurocomputing*, 143, 144-152.
- [13] Chang, Y., Tu, Z., Xie, W., Luo, B., Zhang, S., Sui, H., & Yuan, J. (2022). Video anomaly detection with spatio-temporal dissociation. *Pattern Recognition*, 122, 108213.
- [14] Xiang, T., & Gong, S. (2005, October). Video behaviour profiling and abnormality detection without manual labelling. In *Tenth IEEE International Conference on Computer Vision (ICCV'05) Volume 1 (Vol. 2, pp. 1238-1245)*. IEEE.
- [15] Xiang, T., & Gong, S. (2008). Video behavior profiling for anomaly detection. *IEEE transactions on pattern analysis and machine intelligence*, 30(5), 893-908.
- [16] Hasan, M., Islam, M. M., Zarif, M. I. I., & Hashem, M. M. A. (2019). Attack and anomaly detection in IoT sensors in IoT sites using machine learning approaches. *Internet of Things*, 7, 100059.
- [17] Varma, M., Lu, M., Gardner, R., Dunnmon, J., Khandwala, N., Rajpurkar, P., ... & Patel, B. N. (2019). Automated abnormality detection in lower extremity radiographs using deep learning. *Nature Machine Intelligence*, 1(12), 578-583.
- [18] Quatrini, E., Costantino, F., Di Gravio, G., & Patriarca, R. (2020). Machine learning for anomaly detection and process phase classification to improve safety and maintenance activities. *Journal of Manufacturing Systems*, 56, 117-132.
- [19] Tian, Y., Pang, G., Chen, Y., Singh, R., Verjans, J. W., & Carneiro, G. (2021). Weakly-supervised video anomaly detection with contrastive learning of long and short-range temporal features.
- [20] Sánchez, F. L., Hupont, I., Tabik, S., & Herrera, F. (2020). Revisiting crowd behaviour analysis through deep learning: Taxonomy, anomaly detection, crowd emotions, datasets, opportunities and prospects. *Information Fusion*, 64, 318-335.
- [21] Mokhtari, S., Abbaspour, A., Yen, K. K., & Sargolzaei, A. (2021). A machine learning approach for anomaly detection in industrial control systems based on measurement data. *Electronics*, 10(4), 407.
- [22] Mansour, R. F., Escorcía-Gutiérrez, J., Gamarra, M., Villanueva, J. A., & Leal, N. (2021). Intelligent video anomaly detection and classification using faster RCNN with deep reinforcement learning model. *Image and Vision Computing*, 112, 104229.
- [23] Ali, A., Negin, F. F., Bremond, F. F., & Thümmel, S. (2022). Video-based behavior understanding of children for objective diagnosis of autism. In *VISAPP 2022-17th International Conference on Computer Vision Theory and Applications*.
- [24] Paul, A., Tajin, M. A. S., Das, A., Mongan, W. M., & Dandekar, K. R. (2022). Energy-efficient respiratory anomaly detection in premature newborn infants. *Electronics*, 11(5), 682.
- [25] Forkan, A. R. M., Khalil, I., Tari, Z., Foufou, S., & Bouras, A. (2015). A context-aware approach for long-term behavioural change detection and abnormality prediction in ambient assisted living. *Pattern Recognition*, 48(3), 628-641.
- [26] Abbas, Z. K., & Al-Ani, A. A. (2022). Anomaly detection in surveillance videos based on H265 and deep learning. *International Journal of Advanced Technology and Engineering Exploration*, 9(92), 910-922.