HARMFUL CHILD ACTIVITY DETECTION AND PREVENTION ASSISTANCE SYSTEM

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Declaration

We declare that this is our work, and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or institute of higher learning, and to the best of our knowledge and belief, it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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The above candidates are carrying out research for the undergraduate Dissertation under my supervision.

..…………………………… …………………..

Signature of the supervisor: Date

Acknowledgement

This project themes were a dream at the beginning when it accidentally planted on my mind. And how this tiny seed has been grown until a plant is a great work of the dedicated and acknowledgeable team.

I would like to express my great appreciation to my research supervisor, Mr. Prasanna Sumathipala. He gave me solid guidance by showing me the way to narrow down the research area to make it a more compelling thesis project.

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Finally, I would greatly appreciate the assistance given by my team members as and when it was needed.

Thank You.

Abstract

Preventing serious falls is a major problem for a working mother and a caregiver as and when they are keeping a watchful eye to look after their young kids all the time at home. Generally, young children like to climb on everything, including consumer commodities, like tables, highchairs, and cupboards, etc., that are not designed to be climbed on. As a result, children are at risk of severe injuries. Some falls can lead to death or permanent disability. Because of that, Child accidents have become a significant concern in the contemporary world due to the high rate of severe injuries and deaths caused. And the same can be proven by both research results and evidence such as CCTV footage collected from various locations. The implemented research consists of three main features that could provide a solution to the explained problem. It helps to both detect and prevent incidents that could negatively affect child safety, such as Detecting child safety zone breachers and climb detection and child action of falling on video surveillance footage. We present an approach that can detect child safety zone exiting and climb detection in the real-time video feed and deep learning and computer vision pipeline that detects child fall action to identify potential domestic fall-related child accidents in surveillance footage.

Keywords:

Surveillance footage, Computer vision, Deep learning, Door Detection, Safety exiting, fall detection, Climb detection.

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List of Abbreviations

CDC - Centers for Disease Control

SVM - Support Vector Machine

GMM - Gaussian mixture model

DTL - Direct linear transformation

RRT - Rapidly-exploring random tree

CNN - convolutional neural network

VGG - Visual Geometry Group

R-CNN - Region-Based Convolutional Neural Network

R-FCN - Region-based Fully Convolutional Network

HOG - Histogram of Oriented Gradients

SSD - Single-Shot Multibox Detector

YOLO - you only live once

CCTV - Closed-circuit television

NMS - Non-Maxima Suppression

COCO - Common Objects in Context

VOC - Volatile organic compounds

CPU - Central processing unit

GPU - Graphics processing unit

1 INTRODUCTION

1.1 Background

It is highly encouraging for working parents globally to be aware that new technical assistance is readily available with Novel to invent to undertake all the fall-related issues of their child. And it is fully capable of detecting when the child is about to exit (breaching) safety zone and susceptible behavior leading to fall as well alerting parents to prevent fall-related injuries.

The number of dual-income families has been increased dramatically in recent years. As mothers are working, the movements of Toddlers and the young children are confined to a specific area to spend time or play with babysitters until them returning home. Why did this cut off freedom for underage children in their own homes where they were born? The answer is quite obvious that parents are concerned more about their Household safety: Preventing injuries from exiting the safety zone, Falling and Climbing. It seems that the parents need their children to live in a safe environment where there are no accidents come across to disturb their lives.

Why falls prevention?

Children's injuries are most commonly caused by falls. In fact, the Centers for Disease Control and Prevention (CDC) reports that around 8,000 children are treated in emergency departments in the United States each day for fall-related injuries [1]. It is reported that the principal causes of falls are as babies reach, grasp, roll, sit, and eventually crawl, pull up, and toddlers will try to climb but may not have the coordination to react to certain dangers.

Children should be able to study and grow in a safe environment at home. However, most injuries caused by falls in children under the age of 5-10 occur at home. Kids are exposed to the home environment as usual, but in their rooms- settings are apparently designed to have adults' comfort and to address fine outlook leaving the safety of children in second place. As a part of the growing stages of a child will express his or her curiosity in different ways. The world of a young child is full of new foods to taste, new people to meet, new games to play, words to understand, places to visit, whereas the toddler and young child will touch, taste, smell, climb over, poke at, take apart, watch, listen, and learn more than at any other time in life. In short, especially kids are using their natural sense of discovering their surroundings by using Aid supporters as walkers for infants or toddlers, highchairs, sofas, and changing tables etc.[2].

Why is a real solution so much delay?

Preventing serious falls is a major problem for a working mother as well as for a caregiver. It is reported that the most common type of fall happened by falling from high tables, windows, chairs, and stairs. Although there are much more wearable accelerometry and gyroscope-based fall detection devices available on the market, the unacceptable false-positive rates of those devices have become a considerable problem. [3]. The rate of false positives is climbed up to a higher number, especially in devices of Visual fall detections. As a result, that what seems to be a fall is not a fall. In other words, most present methods [4] cannot distinguish between a natural fall movement and an event in which a person sits or lies abruptly. Also, fall detection systems are widely used to protect adults, and very few are for child activity based. Those systems consist of sensor-based detection techniques implementing from the environment to monitoring seniors' motion. And does not require wearing special devices or gadgets is one of the advantages of this system. However, their operation is limited to those places where the sensors have been previously deployed. Among all the possible types of sensors, the most common are cameras, floor sensors, infrared sensors, microphones, and pressure sensors. Video-based systems can be considered as a subcategory in this group as they use computer vision techniques that differ from the rest of the detection methods.

In such an environment, it is badly needed for child fall and detection system as A "harmful, unsafe child activity detection and prevention assistance, and quick reporting surveillance system is introduced "to manipulate the hardest role that is the role of a mom by taking care of her toddler or pre-school kid. Features of communicating the monitored behavior modified to capture even a single move that is performed and reported in real-time would make the system outperform and provide promising results structuring a secure environment for end-users and their minors

1.2 Literature Review

The problem mentioned in the introduction is addressed in this approach, including novel features as Child safety zone exiting detection, fall detection, and climb detection. Those features are discussed separately in the literature survey below.

<u>Child safety zone exiting detection</u>

Considering past research, no research studies have been implemented to detect the action of a child exiting the safe zone nor leaving through the door. However, there have been few instances that door detection has been subjected to implementation. In [5], by utilizing edges and corners, image-based door detection is performed. But no neural network approach is capable of detecting doors with adequate accuracy in new environments. Hensler et al. [6] use an AdaBoost algorithm to combine multiple features such as the color of the door, the door Handel, the gap of the door, the frame of the door, and the concavity. The door Handel model is defined and fixed in their approach. This model is focused on a single environment. In [7], By utilizing the shape features of the door and color, two neural network-based door classifiers are trained to detect the doors of the authors' office. Their algorithm is trained with door images that have a similar color. It would fail to detect doors with different color doors. Much of the prior work depends on 3d facts, such as distance and visual data from sonar, laser, and stereo-vision sensors [8],[9]. These techniques are accurate but considering power, complexity, cost-wise, they are not effective.

In recent years, several human and object tracking, and trespassing detections have been developed using computer vision. But none of the studies have been implemented by aiming children. In [10], moving object detection is performed by utilizing time-differential images. A previously taken background image is saved and compared to a new one in one of these approaches. And in [11] also introduced an approach to detect trespass using images, which calculates the difference of time-sequential images to produce a region of a moving object. All of these approaches identify a moving object on an image. When impediments in front of the moving target object, such as a pole, a sign, etc., it becomes difficult to detect the target. To address the issue, detection techniques employing several cameras are being developed (A distributed surveillance system) as shown in *figure 1.1* [12],[13]. These approaches, however, need a huge investment to set up the system.

To detect moving objects, Shah et al. [14] used color-based background subtraction. Color, motion, and size-based characteristics are used to monitor those objects. Then Tracked objects are categorized as people or vehicles.

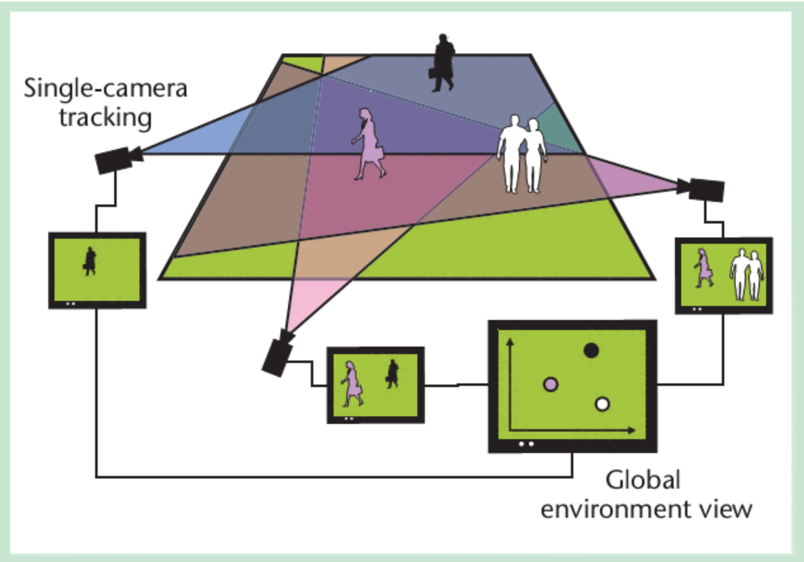

Figure 1.1 : A distributed surveillance system [14]

Fall detection and climb on furniture detection.

The problem of fall detection has been extensively studied in the past. Many systems have been implemented in climb and fall detection due to the high demand, high commercial value, and social importance of climb and fall detection systems and technologies. In recent years, several technologies have been developed. They are classified into three approaches based on how they detected and tracked the action

[15]: wearable sensor-based (*Figure 1.2*), Ambient Sensor Systems (*Figure 1.3*) and vision-based approaches (*Figure* 1.4).

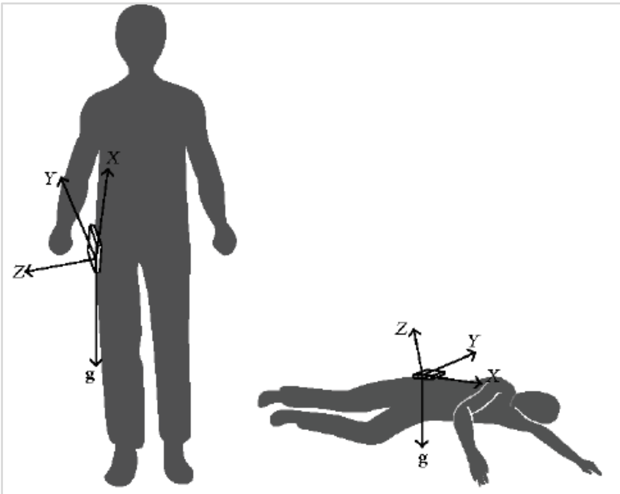

Figure 1.2 : Wearable sensor based approach [16]

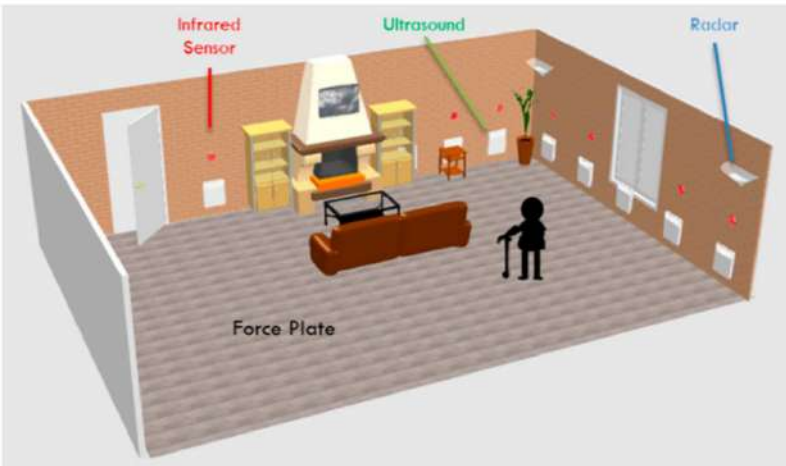

Figure 1.3 : Ambient Sensing Fall Detection [17]

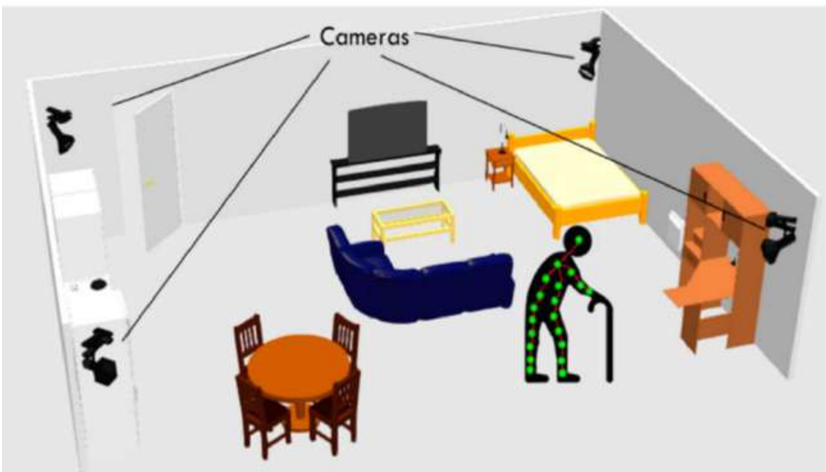

Figure 1.4 : Computer Vision Approach [17]

There were many methods and approaches to detect the action of falling. The existing fall detection systems and devices have a similar architecture, as shown in *figure 1.5*

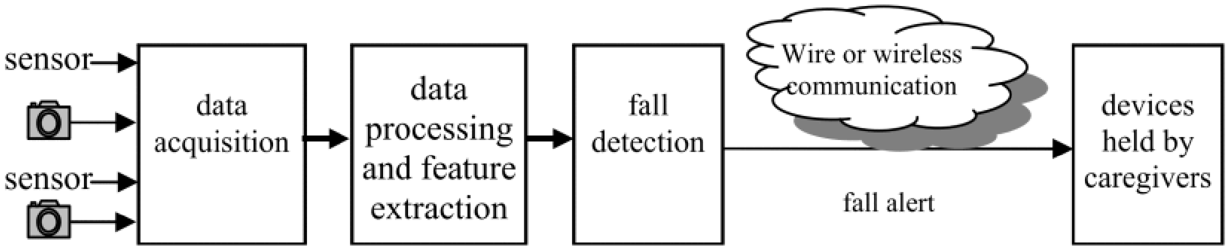

Figure 1.5 : General architecture of fall detection system [18]

- Wearable Device Approach

The wearable device approach entails holding specific devices or wearing a certain garment with an integrated sensor to monitor the wearer's behavior and movements of the human body and using classifiers to recognize suspicious, dangerous activity such as climb and fall.

In the last few years, increased attention to climb and fall detection has led to the development of many approaches to climb and fall detection. Some techniques are commonly based on details collected by sensors such as vibration and acceleration sensors. Motion sensors are used in the wearable type of fall detection techniques [19],[20]. The motion sensor is capable of detecting acceleration, gravity acceleration, and acceleration direction, among other things. Based on these values, motion sensors detect falls. The motion sensors are housed in a wearable device that looks like a belt. Furthermore, instead of a motion sensor, there are fall detection techniques that use an acceleration sensor or a smartphone's voice function [21],[22].The fall detection pattern was the common technique in all of the developed systems. The main weakness of present systems is that they only detect the fall after it has occurred [23],[24]. It does not take any precautions to avoid or prevent it.Many studies have utilized threshold-based algorithms for fall detection. In [25], Bourke, O'Brien, and Lyons presented a two-phase threshold method for distinguishing falls from day-to-day activities.

Petelenz et al. [26] invented a system and device for detecting elderly falls. This device, like the previous one, collects motion data using accelerators. The difference is that this system often helps to differentiate between threatening falls and threats to one's life. In recent years, various accelerometer-based fall detection performance has been examined, utilizing sensitivity, complexity, specificity, accuracy, and false alarm rate [27].

Doukas et al. [28] designed a wearable sensor to track patient falls, collecting data from multiple accelerometers and using an SVM and GMM to differentiate between falls and non-falls.

Hasen et al. [29] introduced a method for detecting falls in the elderly. Three accelerators (sensors) and a processor make up the system. Three sensors gather motion data, which the processor analyzes to detect falls by discriminating between fall and non-fall patterns of motion data.

Montanini et al. [30] presented a footwear-based method by incorporating an accelerometer and a force sensor into a pair of shoes that can detect falls in both indoor and outdoor contexts as illustrated in *figure 1.6* , whereas ambient or camera-based systems can only detect falls in a restricted zone.

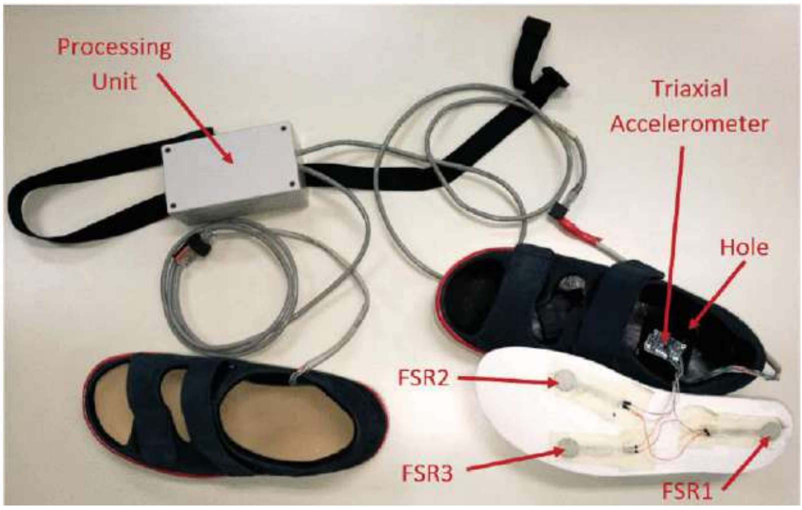

Figure 1.6 : Acquisition system prototype [24]

Saleh and Jeannès [31] have suggested a low-cost, high-accuracy method for machine learning-based fall detection utilizing wearable sensors. They proposed a new approach for online feature extraction based on the temporal features of falls.

Patrick Boissy [32] introduces a technique to detect falls and drops by utilizing fuzzy logic. Their experiment results in a high success rate for fall and drops detection, but the false detection rate of non-fall activity needs to be decreased. Xiuxin Yang [33] discover Naive Bayes as the best algorithm in terms of efficiency and accuracy.

So, the theory of fall detection in the above devices or systems is that falls have a different pattern of motion data from other activities. The approach to wearable devices has its benefits. For starters, apart from wearable garments, most wearable sensors, devices for fall are inexpensive. Second, wearable climb and fall monitoring systems are simple to set up and use and have several drawbacks. For instance, those method suggests that the worn device retains a fixed relative relation with the wearer and this condition can easily be broken. As a consequence, this method is prone to generating a high number of false alarms. Another major drawback of the wearable system is its intrusiveness.

- Ambient systems approach

In addition to wearable devices, ambient and vision-based systems can track human posture and detect falls. Ambient systems give a solution by gathering user data as well as examining the environment. These systems employ external sensors positioned around the user's daily activity area to monitor the posture of the person during a fall, as well as certain parameters such as the time spent falling.

Ultrasonic array sensors and IR array sensors are ideal choices for low-cost sensors. The ultrasonic array sensor detects falls by employing a particular frequency rather than the depth sensor's infrared ray [34],[35]. However, the ultrasonic array sensor has a smaller detection range than the IR array sensor. Hence, this study offers a fall detection technique based on IR array sensors.

In [36], by using a Kinect sensor, a Real-time fall detection system is developed. The method constructs a 3D bounding box of human posture to estimate the subject's width, height, and depth. One of the challenges is that this approach needs a large amount of computational power.

An Acoustic fall detection system is implemented in [37] by using acoustic signals captured by arrays of microphones. This method is ineffective because false alarms are caused by big equipment, and items that are dropped on the ground are recognized as falls.

In [38], an ambient system is created by combining a floor pressure sensor with an infrared sensor. There are several limitations, such as an infrared sensor cannot differentiate between the monitored person and other people or pets, and slowly falls are difficult to detect with the floor pressure sensor.

- Vision-based approach

Surveillance Cameras are gradually being used in in-home assistance systems due to their various benefits over wearable sensor-based approaches, and the price of CCTV cameras decreases rapidly [39]. As a non-wearable form of fall and climb detection technology, detection techniques involve a camera mounted on a room's wall. Based on the image captured by the camera, these algorithms identify a fall and climb action. One of the most common and widely used fall detection approaches is to examine the bounding box representing the human [40] in the frame. But this approach is only effective when the camera is positioned sideways, and it may fail due to occluding objects. To avoid the occlusion of obstacles and provide more realistic situations, the camera should be in the higher position of the room.

Visual fall detection has a high rate of false positives and what seems to be a fall is not a fall. In other words, most existing approaches [41] [42] cannot differentiate between a real fall action and an incident in which a person suddenly sits down or lies.
In [43][44] by utilizing bound box orientation as demonstrated in *figure 1.7*, fall detection is performed. If a person falls immediately in the camera's line of sight, their approach fails to detect the fall.

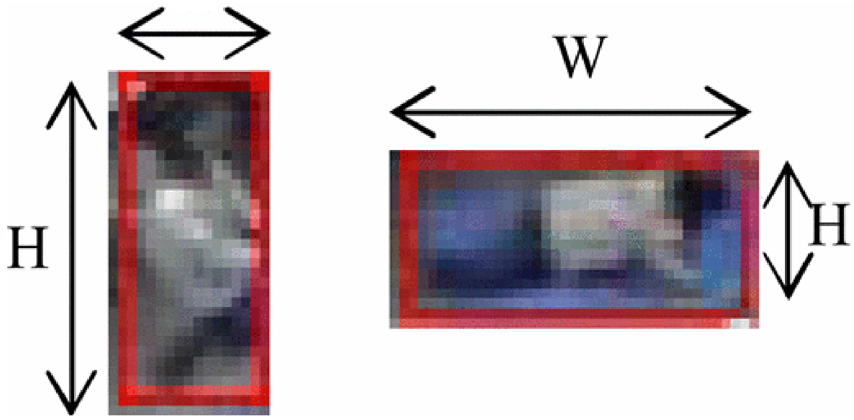

Figure 1.7 : Bound box orientation based fall detection.[44]

In [45], threshold-based fall detection is performed as shown in *figure 1.8*. In this approach, also persons lying on the floor are incorrectly identified as fall action in this technique.


Figure 1.8 : The red line shows the threshold [45]

In [46], a data-driven kid behaviour prediction system was introduced based on a posture database to prevent falls in the home. This approach consists of a children's climbing behaviour database produced using a posture recognition system (OpenPose), RGB-D cameras (Microsoft's Kinect), and the DLT technique *figure 1.9*. This simulation approach uses the RRT algorithm to predict which object a kid can climb based on climbing behaviour data and a motion planning method.

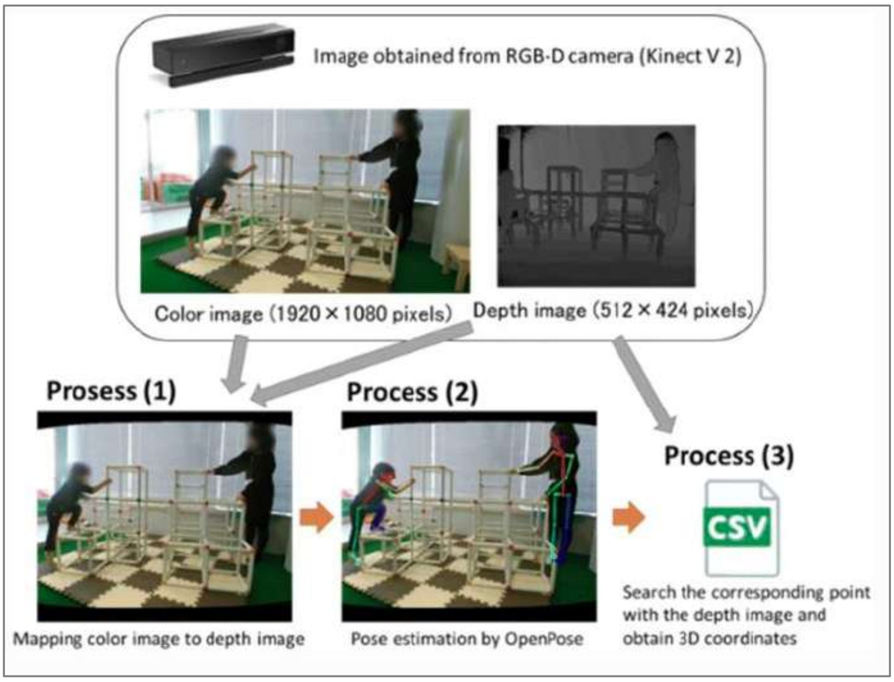

Figure 1.9 : Overview of the system used to gather 3D posture data [46]

Compared to previous studies, an extremely limited number of research studies for child climb on furniture object detection have been implemented. However, there have been few cases when furniture object detection has been implemented.

End-to-end furniture object detection is carried out in [47] by utilizing a deep learning technique. In addition, given an image collection and video frames, this object detector can identify, classify, and segment multiple furniture items.

In [48], the Classification of Images on Furniture and Household Goods is performed by utilizing Transfer learning and Fine-Tuning techniques. They used a data collection of household and furniture pictures from Kaggle for their approach. The pre-trained deep CNN models called VGG-16 and Inception V3, which were trained on ImageNet.

An Image Recognition system has been developed in [49] to find furniture and appliances in kitchen photos. In [50], chair detection is performed by utilizing YOLO models, which is one of the best models, providing excellent real-time performance.

Object Detection techniques

Object detection methods include Fast R-CNN, R-FCN, HOG, Retina-Net, and Single-Shot Multibox Detector (SSD). While these methods have solved data limitation and modelling problems in object detection, they are not capable of identifying objects in a single algorithm run [51].To overcome the problem, because of that, YOLO algorithms were introduced. The YOLO algorithm comes in a variety of flavors. Among the most prevalent are “YOLOv3”, “tinyYOLO”, “YOLOv4”, and “YOLOv5”.

The YOLO method is popular for many reasons:

- Speed: YOLO is capable of real-time item prediction. This method increases the speed of detection.
- Capacity for learning: YOLO has an exceptional capacity for learning.
- High precision: YOLO can produce precise findings while reducing background mistakes.

In our situation, we are focusing on YOLO models such as the tiny YOLO, the YOLOv4, and the YOLOv5, which are all very distinguishable, as seen below.

[a] YoloV4

YOLOv4 is an extension of the YOLOv3 model for object detection [52]. The Yolov4 network architecture is shown in *figure 1.10*. It consists of four different blocks.

- Backbone.
- Neck
- Dense prediction
- Sparse prediction

Each object detector starts with an image and compresses its information using a convolutional neural network backbone. Additionally, it is referred to as the architecture for feature extraction that serves as the backbone. The neck contributes to the layering of the backbone and thick prediction block (head). Additionally, it is beneficial to categorize object detectors into two groups: one-stage detectors and two-stage detectors. Detection occurs in the head.

Detectors with two stages decouple the tasks of object localization and classification for each bounding box. One-stage detectors simultaneously generate predictions for object localization and categorization.

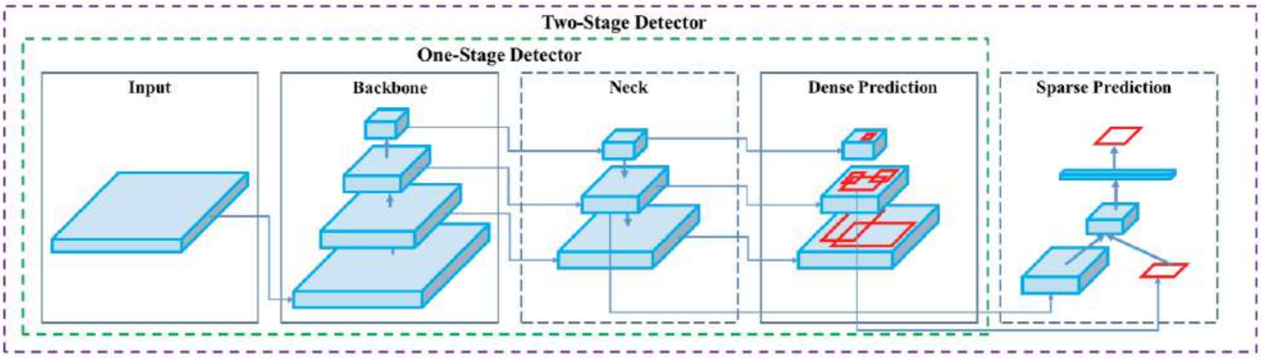

Figure 1.10 : YOLOv4 architecture [52]

[b] Tiny-YoloV4

Tiny-YOLOv4 is a simplified version of YOLOv4 designed for training on machines with low computing capabilities [53]. tiny-YOLOv4 may be utilized for faster detection and training. The tiny-YOLOv4 network architecture is shown in f*igure 1.11*.

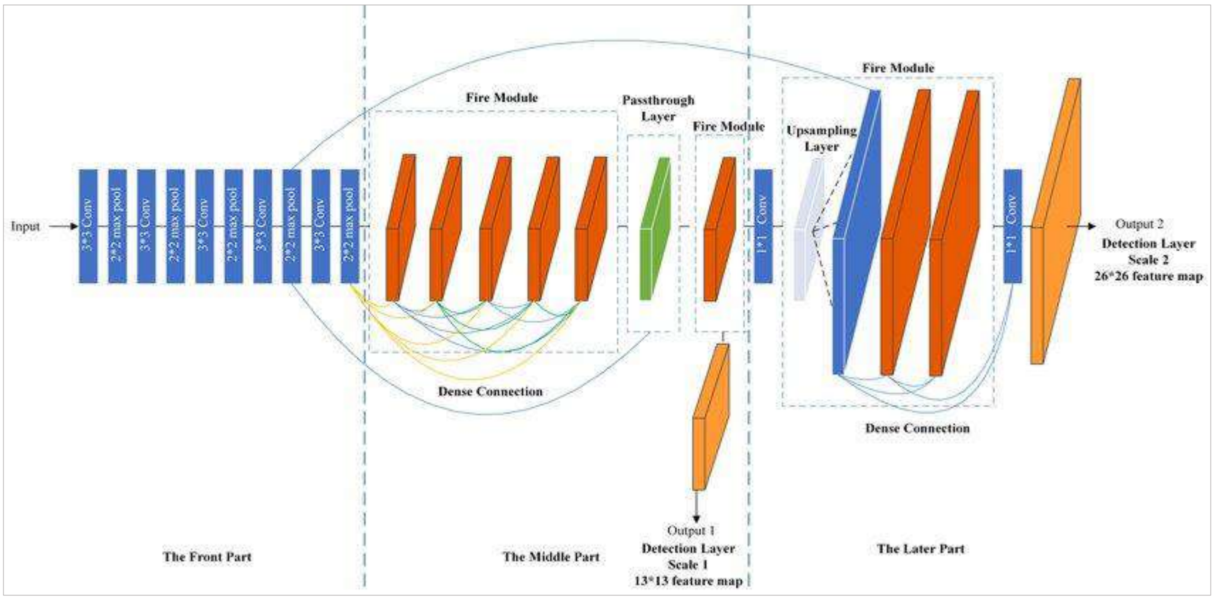

Figure 1.11 : Tiny-YOLOv4 network architecture [53]

When comparing the network architecture of tiny-YOLOv4 to that of YOLOv4, it has two YOLO heads rather than three. Tiny-YOLOv4 was trained using 29 pre-trained convolutional layers, while YOLOv4 was trained using 137 pre-trained convolutional layers.

[c] YOLO v5

YOLO v5 is about 90% lighter than YOLO v4. As a result, YOLO v5 is reported to be faster and smaller than YOLO v4. Another main difference over earlier models in the YOLO series is that it is written entirely in PyTorch, and it became faster than all prior versions of YOLO [54].

Figure 1.12 depicts the Yolov5 network architecture. It is divided into three sections:

- Backbone: CSPDarknet
- Neck: PANet
- Head: Yolo Layer

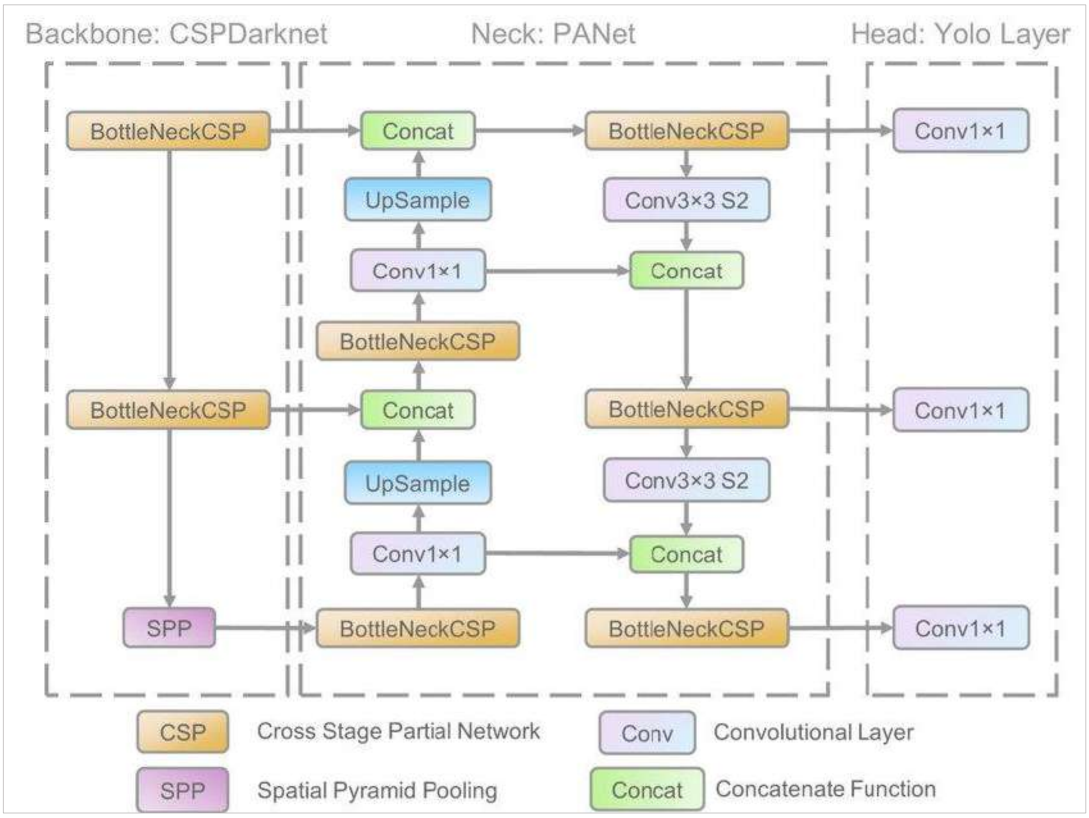

Figure 1.12 :Yolo v5 network architecture [55]

The data is initially sent to CSPDarknet for feature extraction and then processed to PANet for feature fusion [56]. Then PANet enhances the utilization of accurate localization signals in lower layers and improves the position accuracy of the object. Finally, the YOLO layer, known as the head of Yolov5, creates three distinct sizes (18x18, 36x36, 72x72) of feature maps to perform multi-scale prediction [57], and allowing the model to handle tiny, medium, and large objects and produces detection results (class, location, score, size).

1.3 Research Gap

Leaving the safe zone boundary of the room, climbing to a dangerous position, and falling are the leading causes of accidental injury to young children. Some falls can result in death or long-term disability.

To deal with those problems, various types of approaches have been taken. One option is to wear a sensor that detects the acceleration of the falls, and these Wearable fall detectors are the most affordable and widely used form of fall detectors. These Wearable devices are selected for their low cost and higher efficiency. However, if the parent forgot to wear the sensor to the child, no falls can be detected even when the incident happened. So, this approach fails to address users' acceptability issues [29],[30],[32].

Apart from wearable devices, various ambient-based and systems can monitor human posture to identify falls. These systems give a more comprehensive study of users' posture by considering surrounding factors (environmental factors) than sensor-based wearable devices [34], [35], [36], [37]. However, there are certain limitations, such as this approach is not suitable for outdoor environments. Furthermore, most systems can only handle one individual in the monitored area, which means no pets or other people.

To address these challenges, computer-based vision approaches can be used so that they do not require the child to wear anything. Another reason for using a computer-based vision approach is that a Surveillance camera can grant more data and accuracy than the accelerometer in the motion of a child's actions. Over the past years, some developments have been carried out on computer vision-based fall detection. Those systems are unable to differentiate between a real fall action and an incident in which a person suddenly sitting down or lying [41], [42], [43], [44].

Based on the literature review performed, A very limited number of real-time fall detection solutions specifically implemented targeting children even though there are some solutions to detect the action of falling for adults. Also, when considering climb detection, it is very rare to find systems encapsulating features like flagging falls caused due to furniture, identifying safety zone, and capturing breaching of the specified boundary.

The details regarding to the research gap is mentioned given below *Table 1*. As the purpose of this research the necessity of overcome this gap by introducing a new approach.

Table 1 : Compare Existing systems

	[5][6][7][8][9]	[47][48][49][50]	[34][35][28][29][30]	[40][45]	[43][44]	[46]	Our selection (AI care)
Door detection	✓	✗	✗	✗	✗	✗	✓
Furniture object detection	✗	✓	✗	✗	✗	✗	✓
Build for child	✗	✗	✗	✗	✗	✓	✓

Fall detection approach	✗	✗	✓	✓	✓	✓	✓
Non senser based	✗	✗	✗	✓	✓	✓	✓
Furniture object-based climb detection	✗	✗	✗	✗	✗	✗	✓
Child safety zone existing feature	✗	✗	✗	✗	✗	✗	✓
Orientation or threshold based fall detection	✗	✗	✗	✓	✓	✗	✓
Combine approach of orientation, speed, and angle for all detection	✗	✗	✗	✗	✗	✗	✓
Taking prompt, responsive action/alert	✗	✗	✓	✗	✓	✗	✓

The research aims to develop a system to detect child exiting the safety zone and spot unsafe heights from the current position based on furniture objects and detect the action of falling effectively and accurately and taking prompt, responsive actions to avoid danger by utilizing computer vision-based and deep learning approach. Such as Child detection, climb detection, fall detection and this system is planned to exceed all existing climb/ fall detection and prevention systems.

1.4 Research Problem

Nowadays, human lives accelerate at an unbelievable speed forcing everyone living in this generation to live with the pressure of engaging in numerous activities within a time frame of 24 hours, narrowing down one's leisure time to a negligible figure. The role of a working mom is no brainer, but an obvious victim of the explained situation as her life is sandwiched between the two roles: the role of a mom and a wife's role. Due to the pandemic situation, most of the corporates changed their rosters and working plans to work from home. It is given that with the current situation, safety plays a huge role, but due to the current working arrangement followed by most offices, mothers are forced to balance office work along with balancing the two roles mentioned earlier, which can be hectic.

Generally, young children like to climb on everything, including consumer commodities, like tables, highchairs, and sofas, etc. that is not designed to be climbed on. As a result, children are at risk of severe injuries. Some falls can lead to death or permanent disability. Given the scenario is such, a babysitter sounds like a good idea but then again leaves us with a question mark on how safe it is. As a solution to the issue explained above, it is proposed to implement remedial action as "harmful, unsafe child activity detection and prevention assistance, and quick alerting surveillance system "to manipulate the hardest role that is the role of a mom by taking care of her toddler or pre-school kid.

It has been known the fact that working parents are pursuing various kinds of technological sound surveillance systems such as Door and Window Sensors, Motion sensors, High-decibel alarms, Wearable Sensor Systems, surveillance cameras along with computers, smartphones, apple watches to get information about the unsafe activity of their child. Even though they already installed Dutch doors, child safety gates, safety locks, child safety door alarms, they are looking for an updated version of them to obtain a reliable information system to assure their child safety further. The prime reason searching is they can't wait any longer until completing trial and error testing to check any device performance as it is entirely related to matters of their child safety.

However, it is reported that most of the currently available child monitoring systems may contain one or more unacceptable features and those negative aspects troubling, worrisome mothers losing their faith in the device those they are willing to embrace. And Some of them are based on the high cost of installation, very complex working networks, battery replacements, working on a limited area, specific for adults with much more generalized form of detection, using more number cameras for recognition of human postures so and so forth, in short, there is very few only focusing child domestic accident detection obtaining a high percentage of sensitivity and selectivity for the target of interest.

Vertical and horizontal behavior has been heavily used for analyzing purposes in order to design security systems was a prominent factor realized through background literature. First, it has been assessed the frequency of a child requiring exiting the defined safety zone specified by parents. Based on data collected on this matter, it is not advised by experts to lock a child inside the room. It is not a practical scenario to place CCTV cameras covering the entire house to track where the child is heading using pre-assumption theories. The trial and error approach cannot be attempted as breaching the safety zone could cause fall accidents that cause child injuries. It is a noticeable factor that a child safety application should be capable of keeping track of child motions and notify respective parties in an emergency as a preventive measure reducing the risk of unsafe situations caused due to breaching safety zones. Also, it is important that the solution efficiently communicates the message as having a surveillance system in place will not add any value if it does not involve in the process of damage control. Based on the literature review, the existing computer vision-based systems, human trespassing detection solutions, sensor-based approaches, solutions with thermal cameras for identify moving images do not show a considerable amount of effectiveness. Also, all the available solutions have been designed mainly focusing on outsiders entering the safe zone, and a very limited number of projects were identified that detects the action of the child leaving the safety zone through defined doors.

Next in line when considering causes for child injuries is injuries caused due to falling. There are various types of fall-related accidents such as fainting, stubbing, slipping, falling from objects, etc. [2]. Even though there are many solutions available to detect the action of falling designed for adult fall prevention, there were limited number of child fall detection solutions to be identified. There were some sensor-based approaches that prevented such accidents through a sensor placed in wearable accessories such as bracelets, pendants. The main drawbacks of such solutions are that the fragility of wearable accessories, and also, if the child forgets to wear, the solution is unable to perform any detections. Based on the literature review performed, vision-based concepts have been applied for implementing fall detection systems, and the main drawback is that the inability to differentiate laying and sitting from the action of actually falling. With the disadvantages in the currently available systems, it is questionable how child security is ensured by detecting and how preventive measures will be taken by notifying parents are accurately in order to take necessary actions so that the damage caused to the child is mitigated.

Climbing to furniture objects could result in falling from unsafe heights. Therefore, if the action is identified at an early stage, it could be prevented. Parents could take necessary actions to remove any furniture objects that could create unwanted risks but falls take place even due to objects such as tables, chairs and sofas. There were few research solutions implemented to detect the action of child climbing but in outdoor surroundings such as in playgrounds. For computer vision, it is a challenge to detect the action of climbing and to detect children reaching unsafe heights.

Considering breaching a specified boundary, there are few solutions available that detect the same, but the identified solutions have not been specifically designed to capture the action of a child exiting a safe zone. The research problem addressed in this research is that the absence of a solution that detects all three mentioned actions of leaving the safe zone, falling, and reaching unsafe heights.

1.5 Research Objectives

To prove the concept that it is realistically possible to create a surveillance-based methodology using computer vision to prevent falls, leaving the safe zone (room), cuts and burns, kidnap, and electric shock related to children in an identified domestic space.

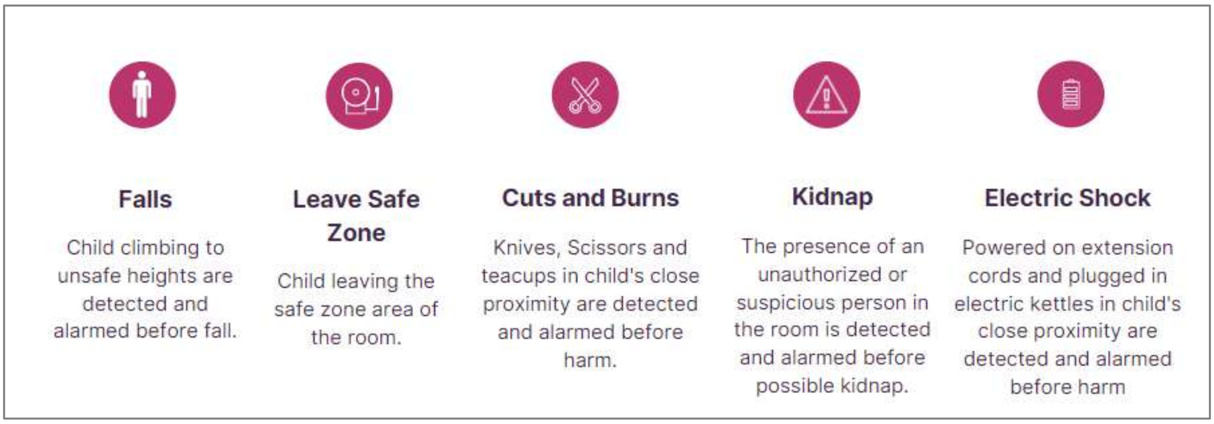

Figure 1.13 : Overall Objective

1.5.1 Main objective

The main objective of the system is to ensure that when a child is out of a parent's or a guardian's sight, to detect and prevent or mitigate the damage resulted by domestic injuries caused due to breaching an identified safe zone boundary or accidents caused due to falling or even reaching unsafe heights by climbing certain furniture objects. The aforementioned causes to be identified and relevant parties to be notified as a preventive measure to ensure child safety in the mentioned scenarios is assured is the main objective.

In order to achieve the objectives, certain prerequisites are required to be implemented. They are child mid-point calculation, object mid-point calculation, overlapping calculation, motion speed calculation and child angle calculation. Once the pre-requirements are satisfied, the main objective can be achieved by attaining success in the sub-objectives mentioned below:

1.5.2 Specific objectives

Specific objective 1

A specific objective to ensure that the main objective is fulfilled is to capture and detect child safety zone exiting. The action of the child leaving the safety zone is detected first, and the mentioned action is checked by interpreting the room as the safety zone and action of leaving the room through the door as breaching the safety zone boundary. Therefore, first, a model with higher accuracy of detecting the door was implemented as a sub-objective of this specific objective. Then a mechanism to identify the action of leaving the room through the door is required to be identified as another sub-objective under the explained specific objective.

Specific objective 2

Detect child fall-related accidents such as tripping, fainting, slipping and various other types of falls. Using a novel approach to ensure detection is performed with higher accuracy is another specific objective.

Specific objective 3

The next specific objective is to detect and prevent accidents triggered as a result of climbing to furniture objects. In a domestic environment as climbing to furniture, objects were identified as the main reason for accidents caused due to falling. This objective was given priority, the same as the other specific objectives mentioned. The action of a child reaching a higher level from the ground level is identified in order to attain the completion of this specific objective.

Specific objective 4

The aforementioned detected actions to be communicated to guardians and parents to either prevent the accident or mitigate the damage caused by ensuring that the notified parties immediately take necessary actions is the last and most important specific objective.

2 METHODOLOGIES

2.1 Methodology

This study's main objective is to detect child unsafe actions; safety zone boundary breach detection, climb detection, fall detection. The overall framework of the proposed system is shown in f*igure 2.14.*

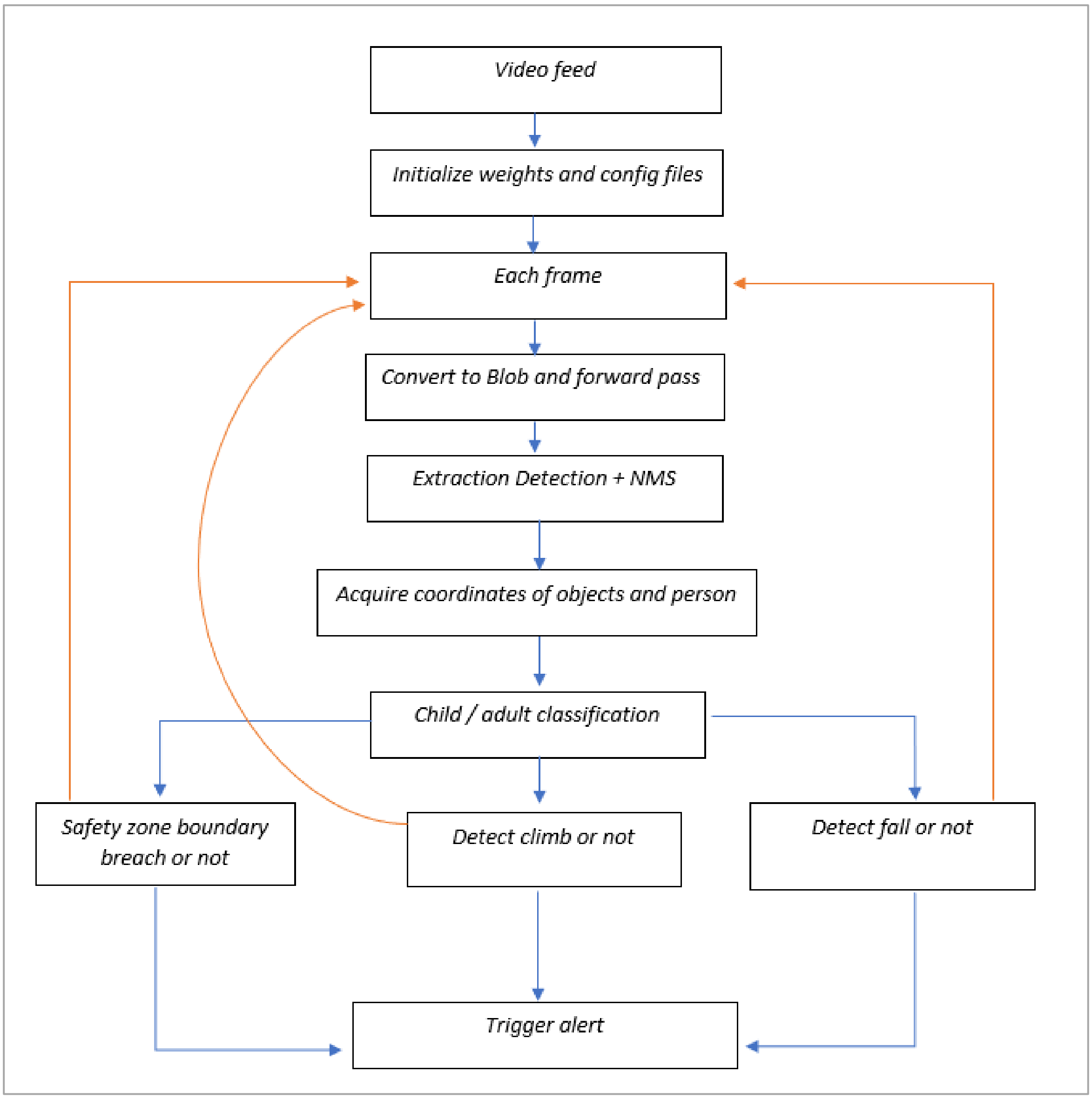

Figure 2.14 : Overview of the proposal method

The above representation shows the overview of the proposed method. Input for the system is a continuous video stream, and output is a detection: whether the child leaving the room (safety zone boundary breach), whether the child reached an unsafe height and whether the child fell or not, as well as an alert. A video stream is an input, and for each frame, the following procedure follows.

First, the model's weights and configuration files are initialized. Realtime video streams or video clips can be used as input, and the following steps are taken for each frame. The captured frames are then converted into a Blob and pass through the classifier to update the weights of each output node. Then, in the output layer of each output, check each detection in the current output node and get the bound boxes, confidences, and class lists for the corresponding detections.

Then apply NMS (Non-Maxima Suppression) technique [58] to filter object detector predictions and select the Right Bounding Box. It is a class of algorithms to select one entity (e.g., bounding boxes) out of many overlapping entities. We can choose the selection criteria to arrive at the desired results. In our research, we Only consider the human and the objects and use them for further processing. The adult child classification mentioned in the above diagram is handled by another component of this research, and is obtained through that.

2.1.1 Prerequisites

<u>Midpoint Calculations</u>

Bounding box of the person was used to calculate the center point of the child. After detecting the child, calculate width and height by extracting the coordinates of the bounding box. This logic is implemented by using a calculation, and the calculation is demonstrated in the image below f*igure* 2.15.

Top1 : Top Left coordinate of object person box.
Bottom1 : Bottom Right coordinate of object person box.
Right1 : Top Right coordinate of object person box.
Left1 : Bottom Right coordinate of object person box.

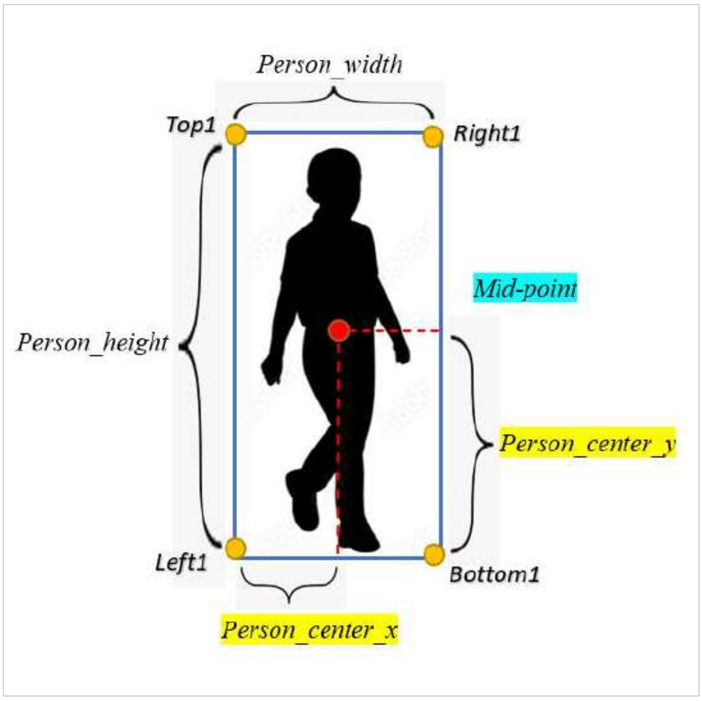

Figure 2.15 : Calculating the child mid-point

Mid-Point Calculation

Person_height = Top1 - Bottom1

Person_width = Right1 - Left1

Person_center_y = Bottom1 + (Person_height / 2)

Person_center_x = left1 + (Person_width / 2)

Overlapping

Bounding boxes of the person and the object were used to identify whether the checked whether the two bounding boxes were on top of the other. When the bounding boxes overlap, it is considered as the person, and the object is in the same place. This logic is implemented by using a calculation to measure the width and height of the intersection area of the bounding boxes. Resulting in zero width and height means there is no intersection between the bounding boxes of the person and the object. The calculation for the overlapping is demonstrated in *figure 2.16*

Top1 : Top Left coordinate of object bound box.

Bottom1 : Bottom Right coordinate of object bound box.

Right1 : Top Right coordinate of object bound box.

Left1 : Bottom Right coordinate of object bound box.

Top2 : Top Left coordinate of person bound box.

Bottom2 : Bottom Right coordinate of person bound box.

Right2 : Top Right coordinate of person bound box.

Left2 : Bottom Right coordinate of person bound box.

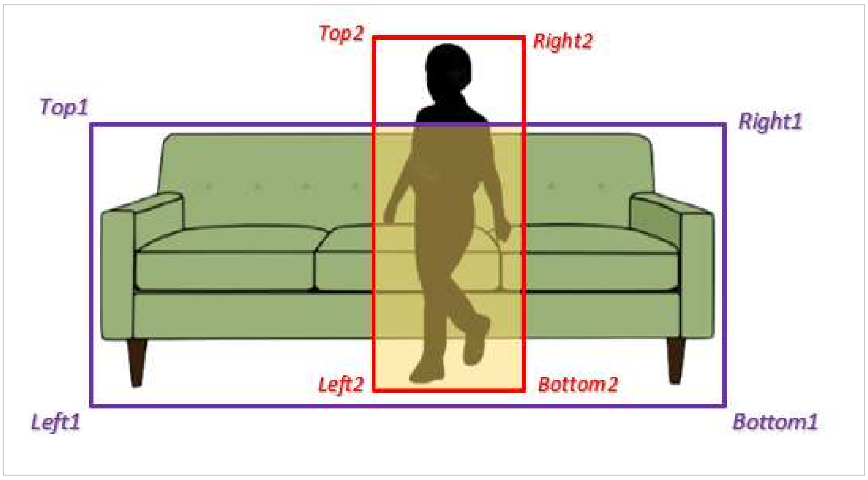

Figure 2.16 : Calculating the intersection area of the child and object

Overlapping Calculation

$x = \max(Left1, Left2)$

$y = \max(Top1, Top2)$

$width = \min(Left1 + right1, Left2 + Right2) - x$

$height = \min(Top1 + Bottom1, Top2 + Bottom2) - y$

2.1.2 Child boundary breach detection

Considering the safety zone breaching factor, it has been reported that the majority of the child injuries have taken place as a result of breaching a given safe zone, and a solution to the cause, child boundary breach functionality, was implemented. First exit points of the specified safe zone are identified, and in other words, this functionality first checks whether the child is leaving the room through the door.

Dataset and Pre-Processing

This section implies the dataset and how it has been adjusted for the model training phase. Since we were used the transfer learning method for the model training phase, pre-trained algorithms model weights were obtained for YOLOv4 and YOLOv5 models. All the pre-trained weights have been implemented by using the COCO dataset. The obtained weights were then used to train the custom model for the custom dataset, which were corporate to build a child safety zone existing detection approach.

The dataset was prepared to detect the mentioned action of the child leaving the room through the door by collecting images of various doors from multiple sources: door image datasets available on the internet, images captured by us, and Google images contributed to the image obtaining process, resulting in 2400 images, and segregating the collected dataset into four: a normal door, cabinet door and refrigerator door, *figures 2.17* show representative samples of the dataset.

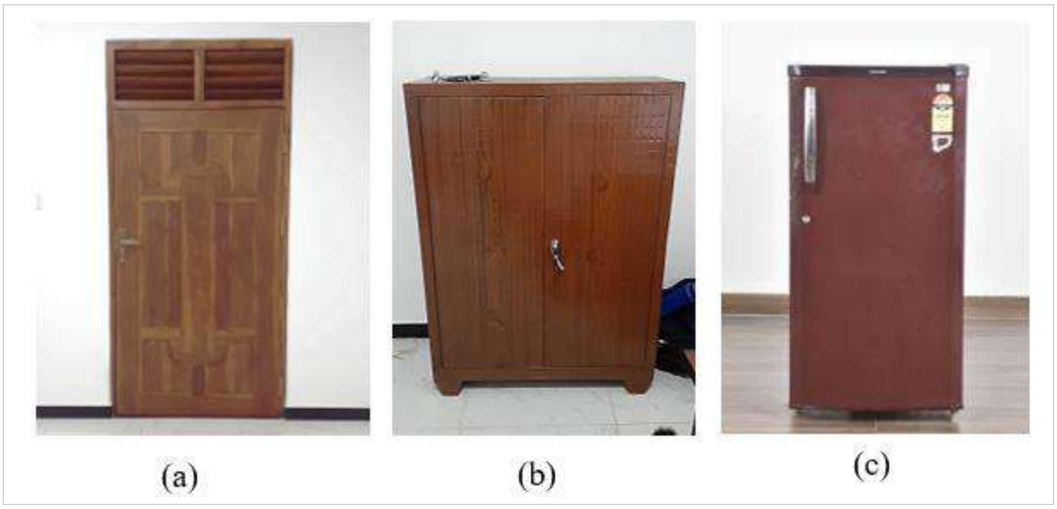

Figure 2.17 : Representative table images of our door dataset, including (a) normal door, (b) cabinet door, (c) refrigerator door

Then images are resized in to 1200pixels x 1200pixels.To resize images, utilize the "BULK RESIZE PHOTOS" tool [59]. The reason for choosing this tool is that it is free, fast, and can resize many images at once.

After that, all the images are labelled into above mentioned three classes and annotated into PASCAL VOC format. The image annotation was done using a graphical image annotation tool called "LabelImg" and generated an annotation file per one annotated image[60], As shown in *figure 2.18.*

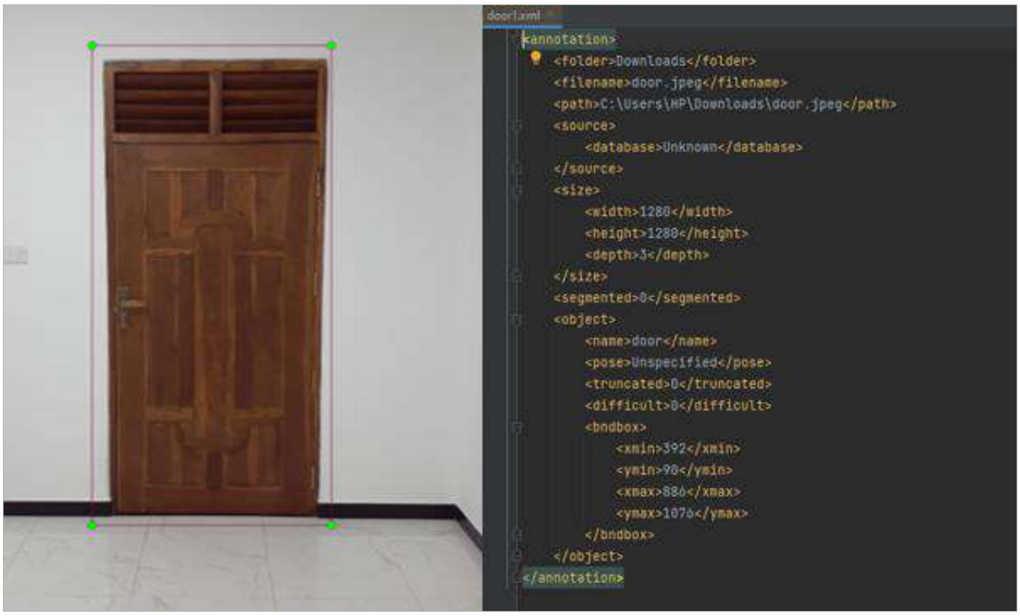

Figure 2.18 : Annotated image an annotation file

The annotation files contain information on the objects in the images, such as the image name and label name, the object class name, and the bounding box coordinates. These annotated images and files are utilized for training the model.

The data was separated into training and testing sets to minimize overfitting or underfitting. The data set was divided into 0.8/0.2 ratios. To verify the dataset, 0.2 splits of data are preserved, while the remainder is used for model training.

Model selection and training

Next, the YOLOv4 and YOLOv5 models have been trained for door detection under the three classes: a normal door, cabinet door and refrigerator door. To create an accurate and optimal model, we used the sigmoid function as the activation function and Adam as the optimizer. To improve accuracy, we varied the number of epochs and training/testing batch sizes.

YOLO5 was selected as the model as it is a proven factor that processes real-time data resulting most favourable outcomes in an optimum way. With the obtained results, YOLOv5 was chosen to be used as the detector for the door.

Solution Implementation

After capturing each frame, the following procedure follows, detect the child and the door, then after it will proceed to NMS filter to filter out the best-bound box. Next, the coordinates of the frame and their bounding boxes are extracted, the action of the child exiting the safe zone (room) is detected following two main steps. First, determine if the child bounding box and door bound box overlapping.

As the next step to the child midpoint and the midpoint of the door is calculated, as shown in *figure2.20*. And the distance between the two midpoints mentioned is calculated in pixels using the Pythagorean distance formula [61], as shown in *figure2.19.*

Suppose the child and door bounding boxes overlap, and the calculated Pythagorean distance is less than the defined threshold pixel distance. In that case, it is detected as a child exiting the safety zone (room), and end-users will be notified using an alert message.

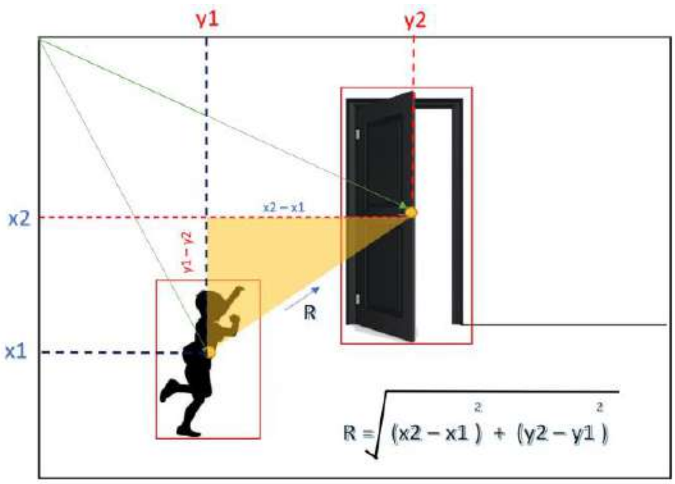

Figure 2.19 : Distance calculation using Pythagorean distance formula

2.1.3 Child fall detection

There have been many child injuries caused as a result of falling due to many reasons such as fainting, slipping, stumbling and various types of other falls. Based on the literature review performed, it is very rare to find any fall detection solutions specifically implemented targeting children even though there were solutions to detect the action of falling for adults utilizing computer vision and orientation-based techniques. The aforementioned solutions showcase certain drawbacks that affect performance and accuracy levels. In this research, fall detection is performed using a novel approach that is based on a combination of 3 main steps, such as orientation, falling angle, and falling speed in order to detect child fall accidents precisely and the overall framework of the proposed system is shown in *figure 2.20*.

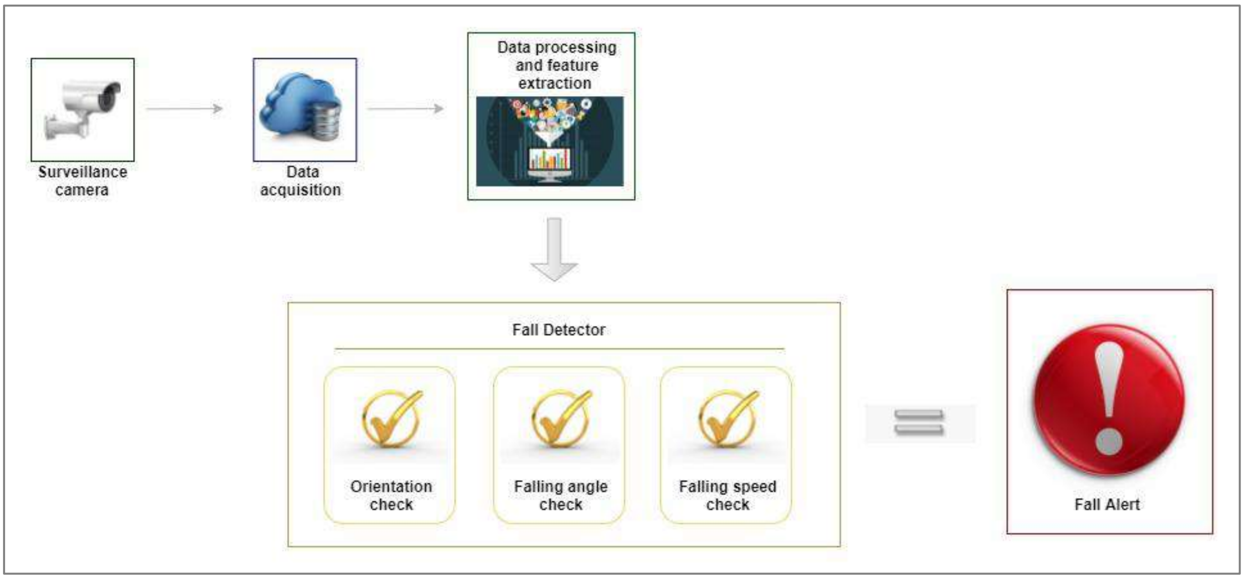

Figure 2.20 : Overall framework of the proposed system

The above-mentioned 3 steps are sequential since they are dependent on one another, and the computations are quick enough that it not required to execute parallel. After every x second (which is our time threshold), it checks the orientation and angle first. If the angle is greater than a certain number of frames and orientation is also in such a way that the width is greater than the height, then the speed can be calculated.

As the first step, the child is detected. The next coordinates of the bounding box are extracted to calculate the height and width of the box. Based on that, change of orientation is assessed, and if a child's bound box width is greater than the child's bound box height (figure 2.21) by a significant number of frames, it is taken into consideration as passing the first condition

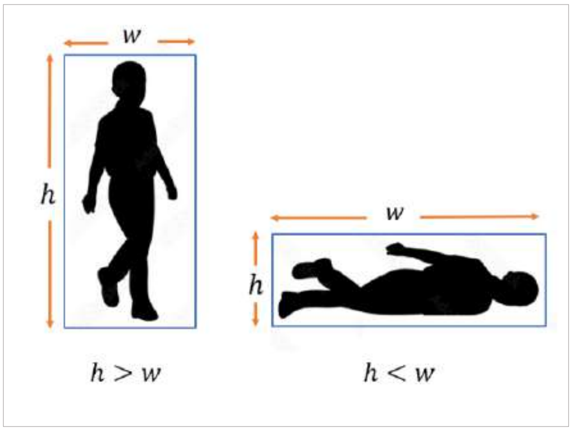

Figure 2.21 : Bound box orientation

Secondly, the child's variation of angle when falling is evaluated. When a child is standing, the angle with the ground is 90 degrees, and in a situation where the child is falling, the angle decreases (*figure 2.22*). This angle logic is implemented by using a Trigonometric function (goniometric functions), and the calculation is demonstrated below. If the calculated degrees are less than threshold degrees, it is considered as passing the second condition.

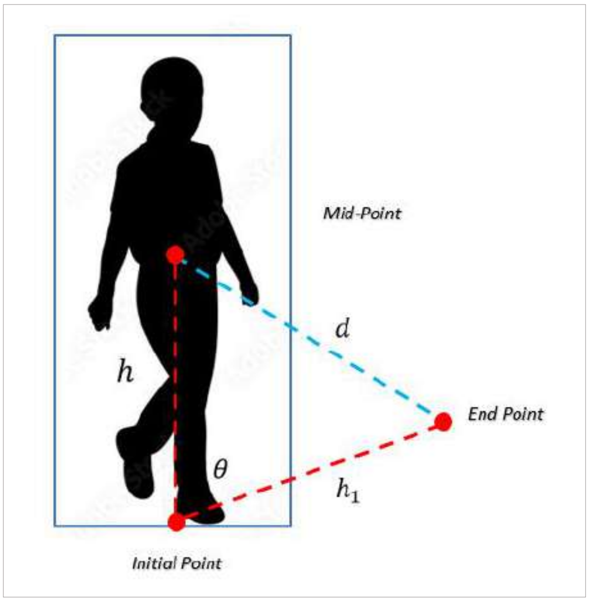

Figure 2.22 : Calculating the falling angle

h = Mid-point – Initial Point

h_1 = End Point – Initial Point

t = threshold

$$d^2 = h^2 + {h_1}^2 - 2hh_1 \; cos\,\theta$$

$$2hh_1 \, cos\,\theta = h^2 + h_1^2 - d^2$$

$$cos\,\theta = \frac{h^2 + h_1^2 - d^2}{2\,h\,h_1}$$

$$\theta = cos^{-1}\left(\frac{h^2 + h_1^2 - d}{2\,h\,h_1}\right)$$

$$if\ \theta < t$$

In order to different actions such as sitting, laying down, crawling from the action of literally falling, speed detection is performed, taking into consideration the change of orientation and angle. Speed is calculated from pixels per second, and initially, a threshold value is set to segregate and identify the action of falling. And the speed calculation is mentioned in the below *fig*ure 2.23. If the resulted pixels per second value is less than the defined time threshold value, it is concluded as passing the third condition.

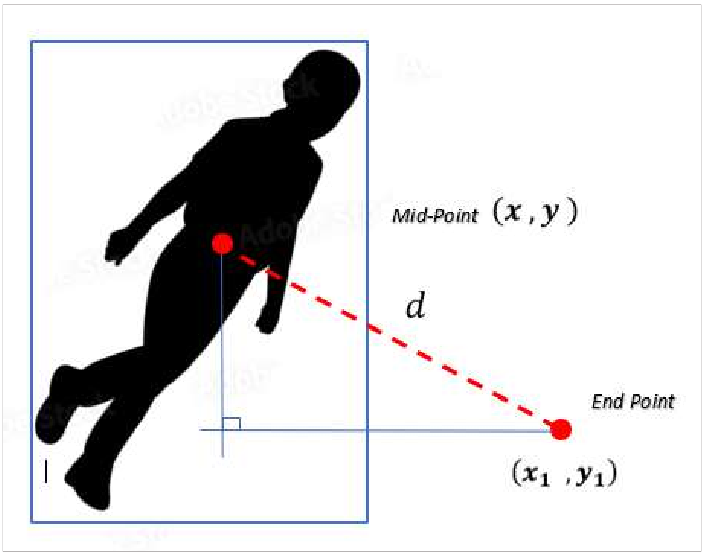

Figure 2.23 : Calculating the falling speed

$$Mid\ Point\ = (x\ ,\ y)$$

$$End\ Point\ = (x_1\ ,\ y_1)$$

$$t = adjustable\ time\ threshold$$

$$distance\ = \sqrt{(x_1 - x)^2 + (y_1\ - y)^2}$$

$$speed = \frac{distance}{t}$$

$$speed = \frac{\sqrt{(x_1 - x)^2 + (y_1\ - y)^2}}{t}$$

If above mention three conditions (bound box width is greater than height, the calculated degree is less than the threshold degree and falling speed is greater than a threshold speed) are satisfied, it is detected as an actual fall, and end-users will be notified using an alert.

2.1.4 Child climb detection

Apart from the child exiting the safety zone factor and fall accidents, children reaching dangerous heights is also a predominant cause when assessing reasons for domestic childhood injuries and climbing furniture objects such as chairs, tables, sofas have been the cause for a large percentage of it.

<u>Dataset and Pre-Processing</u>

The dataset was prepared to detect the mentioned action of the child climb on furniture objects by collecting images of various furniture objects from collected images from multiple public furniture object datasets: Bonn Furniture Style Dataset [62], Open Images Dataset V6 [63] and images captured by ourselves. After manual filtration, we produced a single integrated furniture object dataset with 2700 images, including 1000 table images, 700 sofa images, and 1000 chair image as shown in *Figure2.24, figure 2.25* And *figure2.26* shows representative samples of the furniture object dataset.

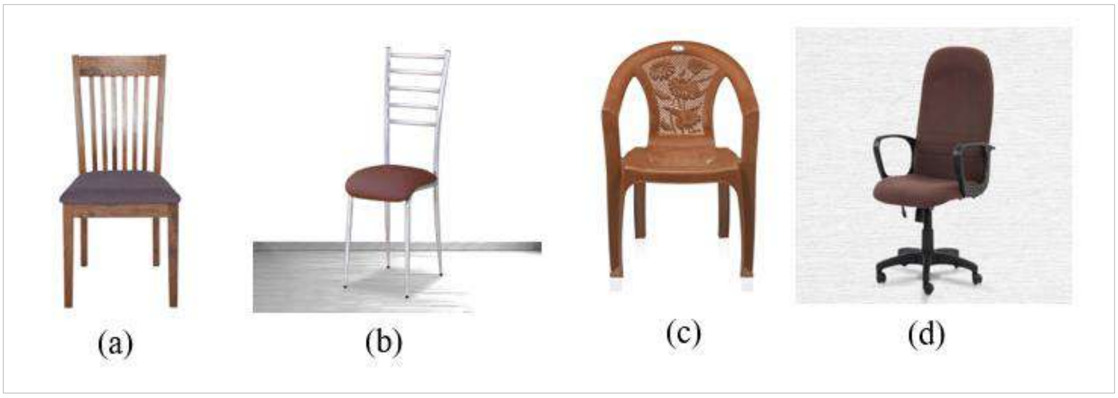

Figure 2.24 : Representative chair images of our dataset, including (a) wooden chairs, (b) metal chairs, (c) plastic chairs, and (d) Swivel chairs.

Figure 2.25 : Representative sofa images of our dataset, including (a) classic sofas, (b) modern sofas, (c) transitional sofas.

Figure 2.26 : Representative table images of our dataset, including (a) worktables, (b) computer desks, (c) dining tables, and (d) round table

Then images are resized (1200pixels x 1200pixels) and followed the same annotation process that we used for the child boundary breach component. The annotation was done using the LabelImg tool for furniture objects, as illustrated in *figure 2.27*.

Figure 2.27 : Dataset Annotation and Labelling, including (a) table annotation, (b) sofa annotation, (c) chair annotation

Then data were separated into training and testing sets. The data set was divided into 0.8/0.2 ratios. 0.2 splits of data are saved for validated datasets, while the rest of the data is used for a model train.

<u>Model selection and training</u>

To answer the mentioned concern, tiny-YOLOv4 and YOLOv4 models were trained using three classes as chairs, tables, and sofas. We utilized the sigmoid function as the activation function and Adam as the optimizer, which is a default optimizer. We adjusted the number of epochs and training/testing batch sizes to improve accuracy.

YOLOv4 was selected as the model as it is a proven factor that processes real-time data resulting most favourable outcomes in an optimum way. With the obtained results, YOLOv4 was chosen to be used as the detector for the door.

<u>Solution Implementation</u>

The action of reaching unsafe heights is detected following two main steps. First, detect the child and the furniture object, and it is checked whether the two bounding boxes are on top of the other or, in other words overlapping.

As the next step to calculate and determine the safe height threshold value, two scenarios are being used.

1. In the first scenario, the midpoint of the child is used provided that both object and the child reside at ground level.
2. Similarly, in the following scenario, the child's midpoint value is again used provided that the child has climbed the object.

Based on the assumptions and height calculations of the two scenarios, the safe height for the child will be found. Suppose the child and objects bounding boxes overlap, and the child's mid-point go above the threshold safe height. In that case, it is detected as an unsafe action of climbing the detected furniture and end-users are notified to prevent injuries.

2.2 Commercialization Aspects of the Product

In a society where families with both parents working have become a common norm, children have left to grow up by themselves. Children between the age 1 year and 5 year is the most crucial period where a child need a lot of parental attention. Thereby, AICare has the potential to be the latest trend in childcare in the coming decade. Being able to give real time protection assistance to a child when parents are attending to work increase the average working time of an employee. Being able to work from home reduces the number of leaves an employee might take. We anticipate that AICare is going to be a top solution companies will invest on providing for their employees because of the high return of investment AICare provides.

2.2.1 Market potential

The global child safety products market size is anticipated to reach USD 132.2 billion by 2025, according to a new report by Grand View Research, Inc., expanding at a

CAGR of 5.0% over the forecast period. Rise in government initiatives regarding infant safety has been driving the global market.

From 2019 to 2025, Asia Pacific is anticipated to witness at the fastest CAGR of 5.8 percent. The market in this region has been primarily driven by an increase in the birth rate and the number of working mothers in countries such as China and India. The female labor participation rate has increased by 4.1 percent over the last three decades, according to EPRA International Journal of Economic and Business Review.

The rise in the number of new births in this region, and also the large population, are the factors driving the growth of the child safety products market in this region. According to the National Health and Family Planning Commission (NHFPC), the average number of new births in China each year from 2016 to 2020 is estimated to be 17 million to 20 million.

2.2.2 Target Market

Working parents with children in the age group of 5 - 12 years old are priority target group of this product. With the current working from home context, parents find it difficult to provide fulltime constant attention to their children even at home. Situations such as when parent is having office meetings while the child is playing in his room are evident proof to the uncomfortable arrangement’s parents have to face while working from home. The curve of working mothers has rapidly increased during the past century. The high cost of living has made it tough for one parent to support the entire family. With this constraint many mothers have been obligated to engage with an employment in order to co-support the family. At this situation it is foreseeable that AICare will have high demand within working parents.

Figure 2.28 : User persona of working from home parent

Companies such as Facebook and Twitter have started to embrace the permanent work from home culture. Thinking of the on-premises cost cutting benefit the companies get, it is expected for more and more companies to embrace forever-work-from-home. Some companies return real-estate savings to staff by offering home office set-up reimbursements or monthly stipends. We anticipate that AICare is going to be one of the top products companies will invest to support work from home parents in the next five years.

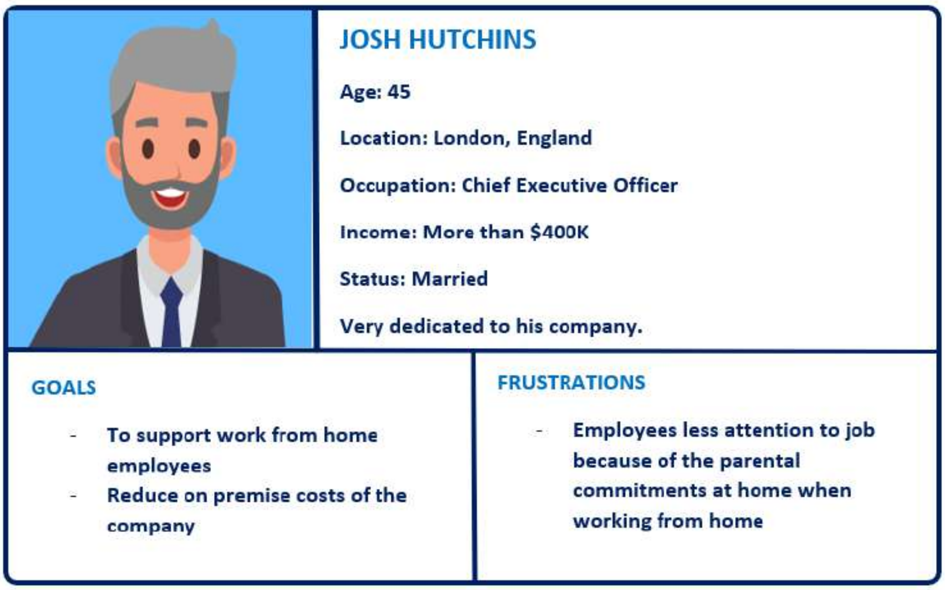

Figure 2. 29 : User persona of a chief executive officer of a company supporting working from home

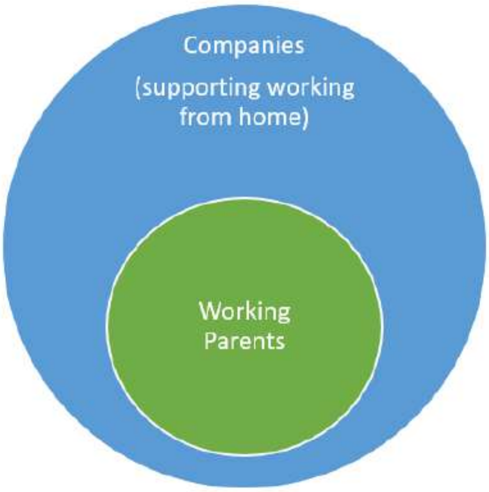

Figure 2. 30 : Target market for AICare

2.2.3 Competitive Analysis

In this section, the currently available child safety products in the market will be compared and understood to get a clear picture of the competition and the advantage of demand and supply that exists.

	Mommy I'm Here, Child Locator	Amber Alert GPS V3	Child Angel	Drop Cam HD Video Monitoring System
Product Specific	Includes a transmitter and a receiver. Transmitter is with mother and receiver can be attached to the baby's shoe or belt. If the baby gets lost, mother can press the button in the transmitter, and it will set an alarm attached to the receiver. Price - $49	A tracker that includes voice recognition and command. Provides the child's location. Allow two-way communication between parent and child with one press of button. Safety zones can be set up and can receive alerts when child leave safety zone. Price - $135	Location monitoring child tracking device. Measure child's daily fitness level. Allows moving geo fence to create safe zone radius around the child. Provide an alarm when the strap is removed. Price - $119	Allow parents to remotely monitor and supervise what is going at home through video monitoring. Price - $177
Target Customer/Message	Parents with toddler kids.	Parents with schoolings children.	Parents with schooling children.	Working parents who leave their child with sitters at home.
Positioning	Only able to locate the child if the parent and child is within 30m. Not a one-time solution, should replace the product time to time. Does not protect the child from injuries or provide preventive measures.	Power lasts only upto 40 hours. Does not protect the child from injuries or provide preventive measures.	Power lasts only upto 48 hours. Does not protect the child from injuries or provide preventive measures.	Does not provide safety measures. Does not protect the child from injuries or provide preventive measures.

Figure 2.31 : Competitor analysis

2.2.4 Business Model

This product has market potential in the areas of Child Safety and Protection. Adhering to the requirements of the working parents in providing in house protection for their children, we have introduced a unique business model to attract potential clients. Initially, a free plan would be provided to get acquainted with the system. If the customer (Parents/Companies) becomes interested in the product, they can switch for the paid version where the required equipment (Cameras and Speakers) will be installed by charging for the cost of the installation. Interestingly, this is a one-time payment for the user to utilize this product for their needs. A brief summary of the business model is provided in the figure below.

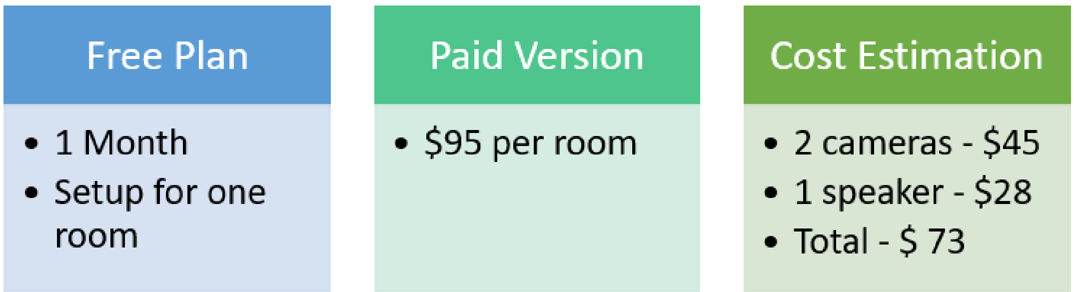

Figure 2.32 : . Business model of AICare

2.3 Testing and Implementation

2.3.1 Testing

Table 2 :Test cases for the child-safe zone border exiting component.

Test ID	Test Case	# Of clips	Sub test case	Expected Result	Actual Result	Status
1	provide video chips where the child actually leaves the room by changing the angle and location of the camera and the motion of a child heading towards the door	15	*Case 1*	Triggering alarm	Alarm successfully triggered	Pass
			Case 2	Triggering alarm	Alarm successfully triggered	Pass
			Case 3	Triggering alarm	Alarm successfully triggered	Pass
			Case 4	Triggering alarm	Alarm successfully triggered	Pass
			Case 5	Triggering alarm	Alarm successfully triggered	Pass
			Case 6	Triggering alarm	Alarm successfully triggered	Pass
			Case 7	Triggering alarm	Alarm not triggered	Fail
			Case 8	Triggering alarm	Alarm successfully triggered	Pass
			Case 9	Triggering alarm	Alarm not triggered	Fail
			Case 10	Triggering alarm	Alarm successfully triggered	Pass
			Case 11	Triggering alarm	Alarm successfully triggered	Pass
			Case 12	Triggering alarm	Alarm not triggered	Fail
			Case 13	Triggering alarm	Alarm successfully triggered	Pass
			Case 14	Triggering alarm	Alarm successfully triggered	Pass
			Case 15	Triggering alarm	Alarm successfully triggered	Fail
2	provide video clips that captured actions where the child heads towards the door by	10	*Case 16*	Not to trigger the alarm	Alarm not triggered	Pass
			Case 17	Not to trigger the alarm	Alarm not triggered	Pass
			Case 18	Not to trigger the alarm	Alarm not triggered	Pass

	changing the angle of the camera and the motion of a child that does not actually leave the room		*Case 19*	Not to trigger the alarm	Alarm not triggered	Pass
			Case 20	Not to trigger the alarm	Alarm triggered	Fail
			Case 21	Not to trigger the alarm	Alarm not triggered	Pass
			Case 22	Not to trigger the alarm	Alarm not triggered	Pass
			Case 23	Not to trigger the alarm	Alarm triggered	Fail
			Case 24	Not to trigger the alarm	Alarm triggered	Fail
			Case 25	Not to trigger the alarm	Alarm not triggered	Pass

Table 3 : Test cases for the child-fall detection component.

Test ID	**Test Case**	**# Of clips**	**Subtest case**	**Expected Result**	**Actual Result**	**Status**
3	Provide real fall accident video clips captured by changing the camera angle and location and check whether the fall action is accurately detected.	12	*Case 26*	Detect the fall	successfully detected	Pass
			Case 27	Detect the fall	successfully detected	Pass
			Case 28	Detect the fall	successfully detected	Pass
			Case 29	Detect the fall	successfully detected	Pass
			Case 30	Detect the fall	successfully detected	Pass
			Case 31	Detect the fall	successfully detected	Pass
			Case 32	Detect the fall	Not detected	Fail
			Case 33	Detect the fall	successfully detected	Pass
			Case 34	Detect the fall	Not detected	Fail
			Case 35	Detect the fall	successfully detected	Pass
			Case 36	Detect the fall	successfully detected	Pass
			Case 37	Detect the fall	successfully detected	Fail

4	Provide non-fall behaviors including such sitting and lying down by changing the camera angle and the location and check whether it is detected as a fall or not.	8	*Case 38*	Not to detect as a fall	Not detected	Pass
			Case 39	Not to detect as a fall	Not detected	Pass
			Case 40	Not to detect as a fall	Not detected	Pass
			Case 41	Not to detect as a fall	Not detected	Pass
			Case 42	Not to detect as a fall	Detected as a fall	Fail
			Case 43	Not to detect as a fall	Not detected	Pass
			Case 44	Not to detect as a fall	Not detected	Pass
			Case 45	Not to detect as a fall	Not detected	Pass

Table 4 : Test cases for the child climb detection component

Test ID	**Test Case**	**# Of clips**	**Subtest case**	**Expected Result**	**Actual Result**	**Status**
5	Provide video clips of a child climbing on a chair that was captured in a fixed camera angle and position and evaluate if the climbing action is correctly detected.	10	*Case 46*	Detect the action of the climb (Warning message)	successfully detected and display (warning message)	Pass
			Case 47	Detect the action of the climb (Warning message)	successfully detected and display (warning message)	Pass
			Case 48	Detect the action of the climb (Warning message)	successfully detected and display (warning message)	Pass
			Case 49	Detect the action of the climb (Warning message)	successfully detected and display (warning message)	Pass
			Case 50	Detect the action of the climb (Warning message)	successfully detected and display (warning message)	Pass
6	Provide video clips of a child climbing on a sofa recorded in a fixed camera angle and a location and check whether the climbing	5	*Case 51*	Detect the action of the climb (Warning message)	successfully detected and display (warning message)	Pass
			Case 52	Detect the action of the climb (Warning message)	successfully detected and display (warning message)	Pass
			Case 53	Detect the action of the climb (Warning message)	successfully detected and display (warning message)	Pass

	movement is accurately detected.		*Case 54*	Detect the action of the climb (Warning message)	successfully detected and display (warning message)	Pass
			Case 55	Detect the action of the climb (Warning message)	successfully detected and display (warning message)	Pass
7	Provide video clips of a child climbing on a table that was pre-recorded in a fixed camera angle and position and evaluate if the climbing action is correctly detected.	5	*Case 56*	Detect the action of the climb (Warning message)	successfully detected and display (warning message)	Pass
			Case 57	Detect the action of the climb (Warning message)	successfully detected and display (warning message)	Pass
			Case 58	Detect the action of the climb (Warning message)	successfully detected and display (warning message)	Pass
			Case 59	Detect the action of the climb (Warning message)	successfully detected and display (warning message)	Pass
			Case 60	Detect the action of the climb (Warning message)	successfully detected and display (warning message)	Pass

The results of above Table 2, Table 3 and Table 4 will be discussed separately under the results and discussion section.

2.3.2 Implementation

The main objective is to ensure the safety of children in the early development stages by tracking their movements and prevent them from exiting the safety zone, falls and reaching cautious heights using furniture object that could result in injuries, and communicate the incident efficiently to the parent or caregiver.

Hardware specifications mainly used are listed in Table 5.

Table 5 : Hardware Specification

Model	Dell Inspiron 5567
Operating System	Windows 10 Pro
Processor	Intel(R) Core (TM) i7-7500U CPU @ 2.70GHz 2.90 GHz
RAM	8.00 GB
System type	64-bit operating system, x64-based processor

Tools and Technologies

- **Google colab** was mainly used for model training. It is a free jupyter book that entirely runs in the cloud platform. It does not consist of complex setup prerequisites and also smoothens collaborative work.
- T**wo ways of storage methods** were used, and they are storing in google drive and storing in the local machine. Google drive space was used to store images, annotation files, datasets and local machine storage was used to store results, files
- **Python** was mainly used as the programming language as it is an easy to learn high-level language that is compatible for any deep learning and machine learning developments.
- **Darknet framework** was used as it is easy to set up, fast, supports CPU and GPU computations. It is an open-source neural network. As this framework supports both CPU and GPU computations it is capable of processing the video feed faster than a usual machine.

- **Keras and tensorflow** was also used implementation. Tensorflow is an opensource library that consists of various machine learning tasks. Keras is a neural network library which is user friendly, helps fastens the development process, supports GPU computations. In addition to that, keras provides pretrained weights that could be used for feature extractions and predictions. VGG16, VGG19, XceptionV3 are few examples of such weights. Tensorflow was used as it visualizes result in a graphical manner and is also compatible with many languages.
- **OpenCV** is a library that is mainly used for real time computer vision. It consists of many real time libraries and bases on that factor OpenCV was used for implementation purposes as this approach is designed to be amalgamated with CCTV footages that requires real time processing.

Model training Process

After completing all the preceding phases and making the necessary changes to the configuration file, the training procedure is started. The model training was carried out in the Google Colab environment. The training procedure has been divided into several steps.

- GPU environment configuration.
- Set up the Darknet YOLO training environment.
- Set up the folders after downloading the custom dataset specified in the 'Dataset' section for YOLO.
- Configure a custom YOLO training config file for Darknet.
- Train our YOLO object detection model.
- Reload YOLO trained weights and make inference on test images.

Functional Requirements

- Integration should be allowed between subsystems.
- There should be a way to identify child separately.

Non-Functional Requirements

- Response time and net processing time.
- Efficiency
- Availability

Personal Requirements

- Parent/Guardian should be available.
- Child should listen to the warnings.
- Parent/Guardian should react to the alerts.

Hardware Requirements

- There should be a way to configure the speaker to the system
- There should be a way to configure the camera to the system

3 RESULTS AND DISCUSSION

3.1 Results and Findings

Child boundary breach detection

This section mainly focuses on the results and discussion of the child existing safety zone detection component. This section provides a summary of model training results and figures and outcomes gathered throughout the testing phase.

Model training Results

Model training results are as follows:

Door detection was performed by training YOLOv4 and YOLO5 models. A comparison of the results is reflected in Table 6. After comparing and comprehensive analysis, YOLOv5 was selected as the best model.

Table 6 : Door detection model training results

Matrices	YOLOv4	YOLOv5
Mean Average Precision (MAP)	**93.07%**	**97.23%**
Precision	0.78	0.92
Recall	0.97	0.96
F1 Score	0.86	0.93

Child boundary breach detection approach Evaluation

The explained approach was tested using 25 video clips with the MP4 format, consisting of 15 videos where the child actually leaves the room by changing the angle of the camera and the motion of a child heading towards the door and 10 videos that captured actions where the child heads towards the door but does not actually leave, to ensure the detection approach outputs acceptable results as expected. The results are shown in Table 7.

Table 7 : Evaluation of Results of child safety zone exiting component

N = 20	*Actual: leave*	*Actual: not leave*
detected: leave	13 (TP)	3 (FP)
detected: not leave	2 (FN)	7 (TN)

To evaluate this technique, we utilize a set of criteria that include accuracy, sensitivity, and specificity [11]. Figure 3.33 shows equations of these criteria:

$$\text{accuracy(A)} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{sensitivity} = \frac{TP}{TP + FN}$$

$$\text{specificity} = \frac{TN}{TN + FP}$$

Figure 3.33 : Equations of evaluation criteria:[11]

The final child safety zone exiting approach performance is shown in Table 8. according to the evaluation criteria followed.

Table 8 : Performance results of child safety zone exiting component

criteria	**score**
Accuracy	0.80
sensitivity	0.86
specificity	0.70

And the below section provides a summary of the results and findings obtained during the testing phase of child boundary exiting component.

Child exiting the boundary breach scenario has tested as correctly detected or not by using the output of the triggering alarm

- Figure 3.34 shows an instance where the child moving towards the door was successfully detected when the camera was positioned angled towards the right *(case 1).*

Figure 3.34 : test case ID 1 – case 1

- Figure 3.35 shows an instance where the child moving towards the door was successfully detected when the camera was positioned angled towards the right more than the above case (*case3*)

Figure 3.35 : test case ID 1 – case 3

- *Figure 3.36* shows an instance where the camera is angled in the opposite direction *as* before. This instance also successfully detected that the child left the room *(Case 6).*

Figure 3.36 : test case ID 1 – case 6

The approach was tested in multiple angles, and the expected results were obtained at the end of each test. Out of the 15 video clips that consisted of child actually leave the room, 13 were detected accurately, while the system failed to detect 2. And the reasons for the failures are identified as follows.

- *Figure 3.37* shows an instance where the incident was taken in a dark environment (case 7). At instances like this, the action of the child leaving the room could not be detected.

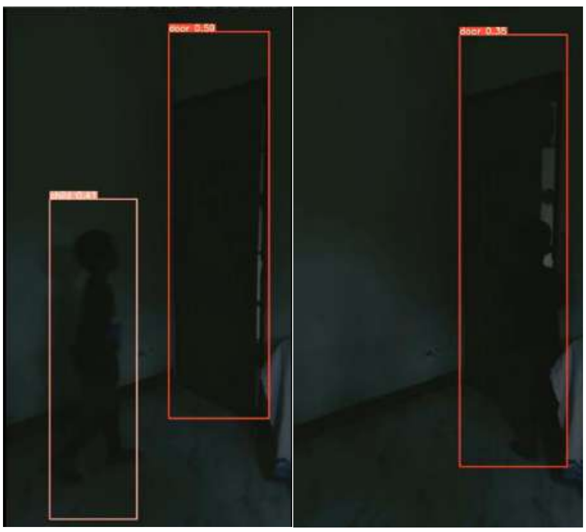

Figure 3.37 : test case ID 1 – case 7

- Figure 3.38 shows an instance where the color of the door and the outfit of the child is similar (Case 9). the instance is not detected

Figure 3.38 : test case ID 1 – case 9

Next, out of the 10 video clips that consisted of child heads towards the door but did not actually leave the room, 7 were detected accurately, while the system failed 3 times. In other words, it was expected for the system to detect this action as not exiting, and 7 out of the 10 test cases passed as it detected accurately, while on 3 occasions, the system captured the action as leaving the room through the door and resulted in notifying the end-users even though the child did not actually leave the room.

For the below mention scenarios, not detecting the action as a child exiting the room is the correct result.

- Figure 3.39 shows an instance where the distance between the camera and the door (35 feet) is long (case 20). The instance is detected as a child exiting.

Figure 3.39 : test case ID 2 – case 20

- Figure 3.40 shows an instance where the video captured in low lighted environment and if there are any objects similar to the door, this can be mislead the door detection. (case 23). The instance is detected as a child exiting.

Figure 3.40 : test case ID 2 – case 23

- Figure 3.41 shows an instance where the video frame captures the door partially or if the frame only covers some portion of the door (case 24). The instance is detected as a child exiting. (in this case child was not leave the room)

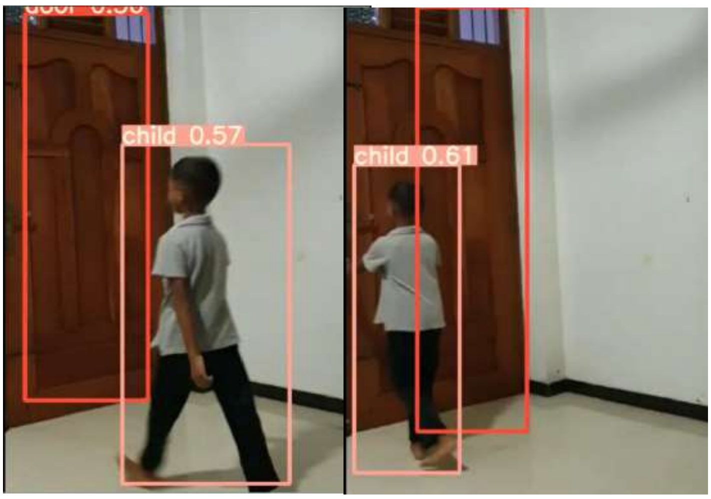

Figure 3.41 : test case ID 2 – case 24

To mitigate the above issues, the camera needs to be in a fixed position, angled on the left or right side to the door. The height of the camera should be unreachable to a child, but not too high. The distance between the door and the camera should be a considerable distance, so that the camera is not very far from the door.

When all of the above conditions are maintained, the issues that arise can be mitigated.

Child fall detection

This section mainly focuses on the discussion and findings of the child fall detection component. This section also provides a summary of conclusions and figures gathered throughout the testing phase.

The described method was evaluated using 20 video clips consisting of 12 actual falls and 8 videos that captured actions such as sitting and lying down. To ensure the detection approach outputs acceptable results as expected. Table 9 displays the results of the fall detection method.

Table 9 : Evaluation of Results of child fall detection component

N = 20	*Actual: fall*	*Actual: not a fall*
detected: fall	10 (TP)	1 (FP)
detected: not a fall	2 (FN)	7 (TN)

To evaluate this method, we utilized the same set of criteria used for child safety zone exiting one, and the performance of the child fall detection component is given in Table 10.

Table 10 : Performance results of child fall detection

criteria	score
Accuracy	0.850
sensitivity	0.833
specificity	0.875

The following section summarizes the outcomes and findings obtained during the testing phase of the child fall detection component.

Out of the 12 video clips of child actual fall incidents captured by different camera angles and locations, 10 were detected accurately. *Figure 3.42* and *figure 3.43* shows the few results of the scenario mentioned above that the child actually fell, and our system detected it as a fall accident.

Figure 3.42 : test case ID 3 – case 26

Figure 3.43 : test case ID 3 – case 30

The introduced fall detection approach is detecting the incident clearly in both indoor and outdoor environments. The given below figure 3.44 shows the testing phase for an outdoor scenario.

Figure 3.44 : test case ID 3 – case 33

The method was tested from several viewpoints. Out of the 12 video clips of child actual fall accidents (Test ID = 3), our method failed to detect 2. And the reasons for the failures are identified as follows.

- Figure 3.45 shows an instance where the incident was taken in a dark environment (case 32). In instances like this, the action of the child falling could not be detected.

Figure 3.45 : test case ID 3 – case 32

Figure 3.46 shows an instance where the child falls down too close, in a direct line to the camera, and the camera position is also high (case 34). The instance is not detected as a fall.

Figure 3.46 : test case ID 3 – case 34

Next, out of the 8 video clips that consisted of child normal behavior: sitting, laying and sleeping but not actual falls, 7 were detected accurately as not a fall accident, while the system failed 1 time.

For the abovementioned scenario, not detecting the action as fall is the correct result.

- Figure 3.47 shows an instance where the child sits down too close to the camera. So, in instances like this, the action of the child can be detected as fall. The issue is that 2D velocity is high when the child is close to the camera, so it is hard to differentiate falls and non-fall activities that

Figure 3.47 : test case ID 4 – case 42

The camera needs to be in a fixed position to mitigate the above issues in the fall detection approach. The height of the camera should be unreachable to a child, but not too high. The distance between the door and the camera should be a considerable distance.

Child Climb on furniture object detection

This section mainly focuses on the results and discussion of the child climb detection component.

Model training Results for furniture object detect detection

furniture object detection was performed by training YOLOv4 and tiny-YOLOv4 models. The following are the results for the models built for the Furniture Object Detection Model. According to literature review, tiny-YOLOv4 is faster and smaller than YOLO v4. But in general, YoloV4 tends to perform better than Tiny-YOLOv4 because of the complexity. The added complexity allows it to understand features better (more layers in the network). But this reduces the speed compared to a less complex model (less layers).

Table 11 : furniture Object detection model training results

Matrices	YOLOv4	tiny-YOLOv4
Mean Average Precision (mAP)	**98.81%**	**98.88%**
Precision	0.99	0.96
Recall	1.00	0.99
F1 Score	0.99	0.98
Overall - Average IoU (Intersection Over Union)	88.89 %	81.46 %

YOLOv4 was chosen as the best model after thorough comparison and evaluation.

Child Climb detection approach Evaluation

The described climb detection approach was tested using 15 video clips in MP4 format, including 5 videos in which the child climbs on a chair, 5 videos in which the child climbs on a sofa, and 5 videos in which the child climbs on a table, to ensure that the detection approach produces acceptable results as expected.

These test cases for Child Climb detection have been personalized according to a static location and with the same height. The system is implemented to function similar to this as well. Therefore, the test cases were done accordingly. As a result, all the test cases passed.

Due to this, if the location of the camera is changed, the result of the child climbing the furniture may not be obtained correctly. Considering this, the solution was implemented assuming the camera is in a fixed location.

3.2 Discussion

Mainly 3 approaches were used for this research. Climb detection, fall detection and exiting the safety zone features were implemented using various techniques unique that differs from one technique to another, ensuring novelty not only as a product but also between the components. When focusing on child safety zone exiting detection, door detection and object detection were given priority. The model is capable of distinguishing doors from other objects and in order to ensure that doors are detected accurately with the minimum level of confusion, a model was trained using a dataset that consisted 3 classes in order to make sure a higher level of classification. YOLO model can be identified as a fast model that is capable of performing real-time analysis and there are various types of YOLO models. For this approach, the best and most suitable YOLOv4 model was selected by attempting and comparing the results of 3 YOLO models. For the techniques used, mathematical functions were blended accordingly to obtain the best results. **Pythagoras theorem** has been used in the child boundary breach detection model to identify the proximity distance between the door and the child.

Detecting the angle has been given importance in the child fall detection approach and the angle was calculated using **trigonometry** concepts. When developing an approach to detect the action of climbing, it was identified that the task of implementing a generalized approach that fits any scenario is a tedious task as the height of a child cannot be predefined because it varies from one child to another and the same applies to furniture objects as the height factor often defers. Therefore, as a solution, it was decided to build a personalized model that is capable of behaving in a customizable manner depending on the child and furniture object.

There were limitations in the three approaches that we have implemented. The approaches were discussed under research and research findings. The camera should be positioned in a place where the child cannot take and cannot go near. The result will be more effective if the requirements addressed were highly considered and if the camera is positioned in a fixed location.

However, approaches such as depth concept, camera calibration, projection can be used to overcome these limitations. Future implementation will provide the users with truly useful product.

4 CONCLUSIONS

The main aim of the research was to detect and prevent child injuries because of reaching unsafe heights due to climbing furniture objects, breaching the safety zone and as a result of falling. The action of breaching the safety zone was detected by identifying the action of the child leaving the room through the door. Also, the model is capable of detecting various types of falls in order to prevent or even in a tragic situation that the injury takes place, to reduce the damage. As another feature system is encapsulated with an approach that detects climbing to certain furniture objects by training a YOLO model passing one image dataset and testing using another unseen set of images. A novel computer vision-based approach was implemented, combining, and attempting various innovative mechanisms to calculate mid-point, motion speed, deviation of angle, variation of orientation in order to accomplish success in completing the specific objectives and delivering promising results. Models were trained, optimized, tested for various video frames, and evaluated accordingly to finally implement a system that is capable of preventing and mitigating the damage activated due to such actions.

5 FUTURE WORKS

The system consists of mainly three functionalities that detects and prevents breaching an identified safe zone boundary, falling, reaching dangerous heights by climbing certain furniture objects and under future work, the main focus would be to mitigate certain drawbacks identified. Models implemented for door detection and furniture object detection to be improved in a way that it is capable of detecting any door and any furniture object with higher accuracy by utilizing a larger dataset covering a broader scope is planned to be completed under future work. To mitigate the Nighttime issue, it is planned to use dim lights on at night to avoid disturbing the child's sleep and aimed to refine the fall detection and other approaches in low-light conditions as it was identified as a drawback to be addressed.

The current system is a combination of three main functions that are integrated and tested for a child placed inside a domestic environment or a room in other words, and it is aimed to be further developed as a solution that is capable of detecting the currently perceptible factors related to 2-3 children. Also, to apply vision-based depth concepts in order to strengthen the commercialization and usability aspects is to be achieved in the forthcoming. Finally, to implement the system as a commercialized profit-oriented solution that could be promoted to be used in child supervision centers is the final aim to be accomplished under future work.

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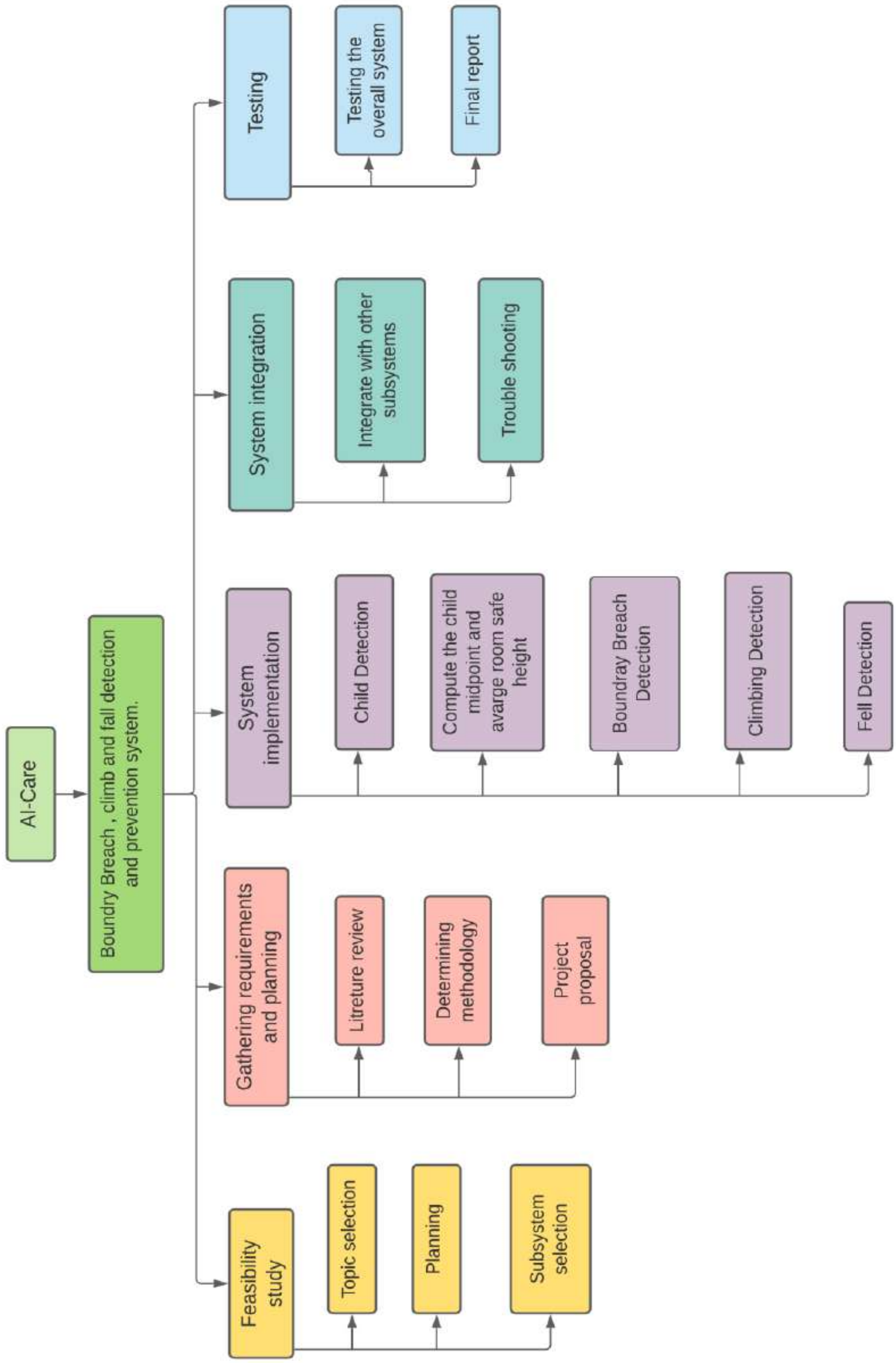
Appendices

[I] Work Break Down Structure



[II] Turnitin Report

Assignment Inbox: Research Project (20/21 Regular Intake)

Assignment Title	Info	Dates	Similarity	Actions
Project Proposal Report	ⓘ	Start 06-Oct-2021 10:25AM Due 09-Oct-2021 11:59PM Post 07-Oct-2021 12:00AM		Submit / View
Research Project Final Report	ⓘ	Start 05-Oct-2021 10:48AM Due 31-Dec-2021 11:59PM Post 13-Oct-2021 12:00AM	12%	Resubmit / View

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