HARMFUL CHILD ACTIVITY DETECTION AND PREVENTION ASSISTANCE SYSTEM

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DECLARATION

I declare that this is my own work, and this dissertation 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 my 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. Also, I hereby grant to Sri Lanka Institute of Information Technology the non-exclusive right to reproduce and distribute my dissertation in whole or part in print, electronic or other medium. I retain the right to use this content in whole or part in future works (such as article or books).

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

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Signature of the Supervisor Date

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Abstract

The issue of Children's family mishaps, kidnapping, and getting harmed cause of unsafe child activities has raised huge worries of public interest in nowadays. The progression of surveillance system and Artificial Intelligence (AI) innovations, especially in image classification, computer vision and object detection, could be applied to defeat the current imperfections of the real time unsafe child activities recognition and prevention assistance system that regularly neglected to fill in as a triggering system to their guardians. This paper introduces a real time child injury detection and prevention system capable of detecting various dangers, particularly those related to unsafe electrical devices in the presence of children, while also attempting to overcome the limitations of current systems.

Most systems depend on human observation, which is time-consuming, unreliable, and costly. If this activity is automated, it may be implemented on a wide scale and would be ideal in terms of reducing or avoiding dangerous child domestic activities. In this paper, we investigate a pipeline for automated monitoring of home situations while addressing a variety of detection and performance issues. Because of the system's complexity, several analytical processes such as object detection, child detection, proximity-based warning techniques, and model validation are performed independently. We formalize and offer a detailed assessment of contemporary techniques for each phase in this study. We did an extensive evaluation by gathering a variety of datasets. Unlike present methods, such datasets allow for the evaluation of several and diverse scenarios.

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LIST OF ABBREVIATIONS

Abbreviation	**Description**
AAM	Active Appearance Model
AI	Artificial Intelligence
CCTV	Closed Circuit Television
CNN	Convolutional Neural Network
FN	Residual Neural Network
FP	False Negative
ResNet	Residual Neural Network
TN	True Negative
TR	True Positive
VGG	Visual Geometry Group
YOLO	You Only Looks Once

1. INTRODUCTION

The child unsafe electrical appliances-based injuries have been raised huge amount of impact to the society. According to the many researchers one of the most fatal child injuries/burnings happens due to unsafe electrical appliances [1], [2]. When it comes to the dangers of electrical burning, children lack the ability to discriminate between dangerous and safe devices. Even as adults sometimes they not able to distinguish unsafe electrical devices from safest ones. In the modern world parents have enormous pressure due to their office works. In case of that they are unable to always stay with their children.

Adults are more likely to get electrical injuries in the workplace, while children, who account for near 20% of all electrical injuries, are more likely to sustain them at home, with exposure to electrical outlets and cables being the most prevalent cause[2]. Burns are the most prevalent type of kid injury in many regions of the globe; however, they are at a higher risk in other situations due to their risk-taking behaviour. Burns are the world's ninth greatest cause of mortality among children aged 5 to 14 years old[1] [2]. Electrical burns can result in a wide range of ailments, ranging from minor tissue damage to severe multi-organ involvement. The fatality rate for major electrical injuries is 40%.

CCTV Because of active research fields in computer vision, artificial intelligence, and image processing applications, video surveillance has sparked a lot of interest. In this sense, automated video surveillance systems include or utilize real-time computer vision and intelligence technology. Automated video surveillance systems may therefore assist safety personnel by generating real-time alerts and object detection studies using modern video analysis techniques. Surveillance cameras are everywhere affordable and cost-effective, but the labour necessary to monitor and analyse cameras is costly. In case here we can bring automated real time object detection methodology for significant concerns.

Surveillance systems are frequently stored to be utilized in the event of an accident. Its often used to bring to an attention for the authorities after the accident happened.

Cameras may be a far more helpful tool if they can be utilized to track situations that demand attention as they occur and take action in real time rather than passively capturing. This is the goal of automated visual surveillance: to get a knowledge of what is going on in a controlled environment and then take necessary steps based on that Instructions. Using advanced techniques, real-time detection accuracy has substantially increased in recent years under a variety of circumstances.

1.1 Background and Literature Review

A video surveillance system uses electronic equipment to monitor the behaviour, activities, or other changing information of individuals from a distance. In the early days, surveillance was done manually by people, which was a laborious process because suspicious actions were infrequent in comparison to normal operations. With technology quickly advancing in recent years, there has been an increase in demand for video surveillance. With the introduction of intelligent Surveillance systems, as well as numerous techniques to surveillance, have been established. There are several methods were utilized, and some of them are listed here.

1. Object detection[3][4].
2. Object Tracking[5][6].
3. Fraud detection[7].
4. Object Classification[8]–[11].
5. Suspicious Activity detection[12][13].

Although various approaches were utilized, not all of them performed optimally in real-time. With the passage of time, more robust techniques that could resist real-time detection and prediction emerged. We investigated how deep learning and computer vision could be used to solve the problems we had found. These days' people are utilizing innovation to change their domestic community emphatically. Many of them were able to understand usefulness of the information technology and also now the technology has rapidly grown to the smart global environment. From this smart global concept child security has become major concern

Here our research problem consisted with three main points.

- Real time hazardous electrical devices detection.
- Real time child detection. (Adult child classification).
- Alerting based on the child proximity with detected electrical object.

Here onwards described what are the similar approaches have been found similar to our research solution. Following are the sum of research papers that I have found which related to our solution but it’s very hard to find out integrated system which are addressing all the objectives mentioned earlier. Let’s move to some existing approaches in much deeper.

Object detection in visual platforms has been studied for a long time. It can be used for human detection[14], gender classification[15][16], age prediction. Classification of child and adult is useful for the domestic security in that it makes it much easier to catch harmful child activities based on the detected physical traits. However, when it’s come to real time harmful child activity detection It is critical to watch children yet keeping eyes on them all the time is hard for guardians. A few guardians utilize general CCTV to screen infants, yet it cannot tell guardians of emergencies and it needed more human supervision. For classification, several studies of classification between child and adult have been introduced. For significant distance classification which is between 2 meters and 10 meters from the CCTV camera, biometric data is entirely relevant compared to other techniques.

Some of the existing paper authorities have proved the detection of child could implemented using ratio of the head and body height[17]. The main objective of this paper was to identify adult and child separately in digital images. According to the paper they detect some the face features of the dataset. A unique approach for recognizing children is given in this study. The suggested technique is divided into three major phases. First, the AAM was applied to the face picture to get the parameters for the facial appearance model. Second, the facial appearance model parameters were subjected to Linear Discriminant Analysis to extract more discriminative features. Finally, a minimum distance classifier was used to categorize face images as either children or adults. But according to this paper we were not being able to implement system to detect hazardous electrical objects in the environment and child injury prevention assistance system such as alerting system.

On the other hand several research papers have implemented child tracking system with the help of image processing and IOT[18]. In this paper[18], which is used for proper protection and tracking the operation of babies by their busy parents, a non-contact-based baby monitoring device using image processing is suggested. The Haar classifier is used to train the face detection algorithm for positive face images and negative non-face images and by using condender mic they captured babies abnormal crying. Once detected abnormal crying the email sends to the relevant authorities. This system would help minimize the chances that the baby will fall from the mattress. This approach is combination of computer vision and Internet of Things based strategy. When we compared with our solution this system [9] required additional hardware components and it will be more additional cost because of the Raspberry Pi along with the other components. And another huge difference is this approach is considered as combination of the IOT and computer vision, compared with our solution it required only computer vision-based strategies.

Some of the child monitoring systems have been implemented using IOT based strategies. The combination of artificial intelligence and smart devices can assist parents in monitoring their children. In this article, a smart vest is created for monitoring children's physical activities, allowing caregivers/parents to remotely monitor the children's activities using an inertial sensor integrated in the vest [19]. From this solution also they have tracked child activities using smart wearables. When compared with our solution this solution was not worked as injury prevention assistance system and it is not worked as real time hazardous electrical object detection system as well.

Another approach is an intelligent baby monitoring with automatic sleeping posture detection and notification system [20]. In here they have captured the baby different sleeping posture and using the algorithms the system classifies abnormal postures of the baby. If any abnormal posture occurred, it would trigger a notification via mobile application. In this system they mainly used multistage transpose convolutional networks in order to train the models. When compared to our solution since it is not classifying whether the sleeping person is child or adult, false notifications can be triggered. Since our system has done adult child classification part, we were able to track the child activities which related to our scenario.

1.2 Research Gap

The use of security cameras is increasing. It is essential in both the corporate and governmental sectors. Surveillance cameras are being deployed in many residential areas to monitor the activities of children. Incidents occur in household spaces on a regular basis, even when they are being monitored by a camera from a distance by guardians; CCTV cameras record massive volumes of footage. As a result, checking them all in real time is impossible. It is very costly to locate a human resource to monitor the footage. To address this, intelligent monitoring systems that identify and respond to events in real time are being created.

The identification of infant prenatal injuries caused by hazardous electrical items has been thoroughly investigated in recent years. In case of preventing child injuries from hazardous electrical appliances required to notify relevant authorities before happening the incident. When used, hazardous electrical item detection and child detection systems face a number of problems. In complex scenarios with changing circumstances and moving items as well as stationary objects, an efficient and reliable detection model is required. Many factors influence the performance of this system, including image noise, which shows in low-quality images, image resolution, brightness, and angles. Lighting variations, slow and unexpected moves, camera jitter, and camouflage between front and rear items are some of the problems in background removal techniques. Another important thing is Another major approach was dynamic backdrops, which included background movable items such as people in the domestic environment. Furthermore, as the relatively complex hazardous electrical item injury detection and prevention support systems must handle large amounts of data, challenges in real-time information processing occur.

The suggested system aims to build a surveillance system that requires less human supervision.

Table 1 Research gap

Specifications	[4], [5], [21],[3]	[19], [9], [20]	[14] [22]	[11], [23],[24]	Our solution (AI care)
Electrical object detection Vision based approach	✓	✗	✗	✗	✓
Person detection	✗	✗	✓	✓	✓
Image processing based Child detection (Adult child classification)	✗	✗	✗	✓	✓
Non sensor based	✗	✗	✗	✗	✓
Proximity detection	✗	✗	✗	✗	✓
Injury Prevention	✗	✓	✗	✗	✓
Proximity based, prompt responsive action /alert	✗	✓	✗	✗	✓

1.3 Research Problem

Nowadays, human lives are accelerating at an incredible rate, putting everyone in this generation under pressure to engage in various activities within a time frame of 24 hours, reducing one's free time to a tiny number. Because of the pandemic scenario, most corporations have altered their rosters and working schedules to allow employees to work from home. In many facets of life, human lives have diverged more from the present and past. In case of such situations parents also have more responsibility to keep their family safe and happy. Mothers are expected to manage office work as well as the two duties described before, which can be stressful. Specially it would have been complex if a working with their children. Children required more protection from their parents until they become younger. Children are always willing to accept risks without giving it much thought. The majority of mishaps occur as a result of children's curiosity and a lack of supervision. One solution is having a babysitter. A babysitter sounds like a wonderful idea, but it raises the question of how safe it is?

Domestic child accidents can be happening many ways such as burning injuries due to unsafe electrical appliances, child falling injuries from furniture’s, child kidnappings and due to some sharp objects as well. Burns are the most prevalent type of child injury in many regions of the globe; however, children are at greater risk in particular situations owing to their risk-taking behaviour. Electric shock Burns are the ninth leading cause of death among children age 5 to 14 years old in the world.

The main reason is for the above-mentioned accidents due to lack of attention. While parents are involving with their work, they don’t have time to give much attention to their children due to their work. As solution in early days parents attempt to incorporate CCTV surveillance and remove potential hazards from their children. By deployment of the CCTV surveillance system parents have been covered several aspects. However still have some risk behind that. By utilizing CCTV surveillance system, it cannot prevent a child accident before happening. It is only capable of keep recording footages and store it for the future use and moreover it needs more human supervision. Here major problem parents don’t have much time keep eye on their children as well as CCTV video recordings. We still facing lack of intelligence surveillance system.

Figure 1 Hazardous child activities

Deep learning models are currently in use in a variety of settings. Some prominent deep learning models are VGG16, Faster R-CNN, and YOLO. These models differ significantly in terms of design and performance owing to parameters such as Layer depth and Prediction time. The Fast R-CNN model is well-known for its ability to obtain the accuracy of deep layer models while also boosting their speed. YOLO, a 12-layer model, is recognized for its incredible prediction speed, with predictions up to 45 frames per second. As a result, many deep learning models differ from one another, and these models must be assessed in order to select the best deep learning model for the desired goal.

1.4 Research Objectives

Since we are approaching automated Realtime surveillance system for preventing unsafe electrical appliances-based injuries we have to experiment several approaches. Most importantly when implement such a system it should be fast, reliable and accurate. The goal of this thesis is to assess the classification and object detection performance of acceptable deep learning models for real-time object recognition and monitoring of dangerous electrical devices in the home, as well as a preventative assistance system.

- To find appropriate and highly efficient deep learning models for real-time object detection and tracking of household electrical appliances.
- Analyse the performance of the selected deep learning models in adult child categorization.
- Examine the classification performance of the chosen models and display the findings.

1.4.1 General objective

Our system's primary goal is to automate the security surveillance of a small surveillance space. The suggested system provides a reliable method of identifying and preventing electrical injuries from children. The system intended to work only for the children.

1.4.2 Specific objectives

Although our primary goal is to detect and prevent hazardous electrical accidents, we have more particular goals for our study. To implement this research the main objective, we have been broken down to few sub objectives as shown below.

- ➢ Person detection
- ➢ Child detection by validating the adult child classification model.
- ➢ Specific electrical object detection.
- ➢ Validate object detection model.
- ➢ Child and electrical object proximity detection.
- ➢ Alerting.

2 METHODOLOGY

The following figure shows high level system diagram

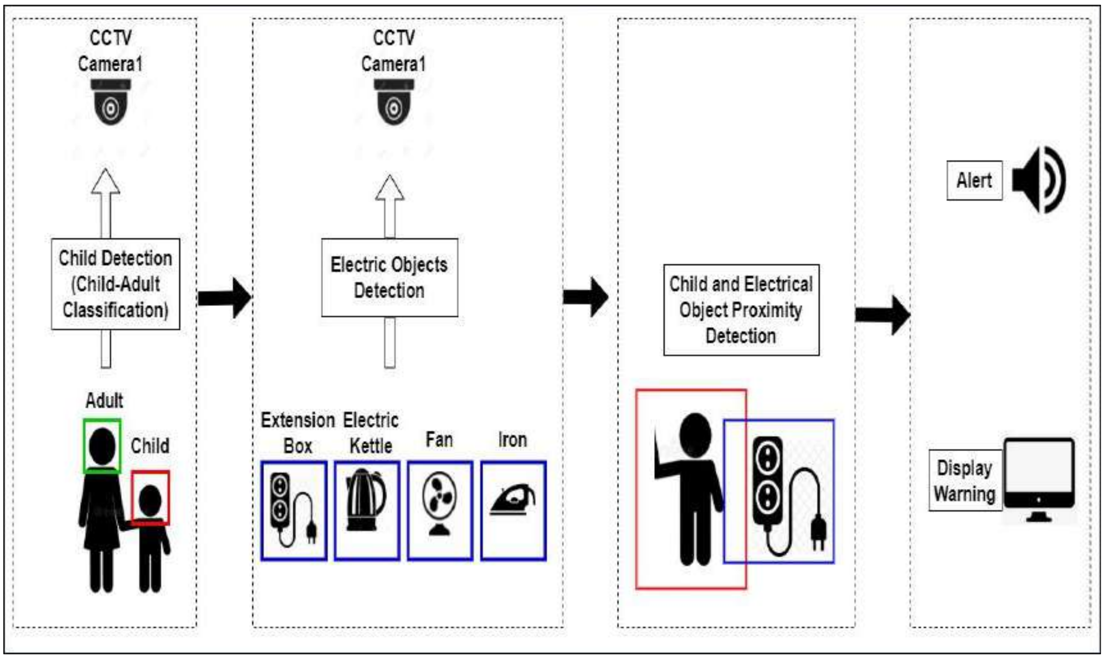

Figure 2 System Diagram

The major objective of this experiment is to assess deep learning models for object identification and adult child categorization in real-time, using the deep learning models chosen from a literature study.

This section contains with two main approaches.

1. Child detection (Child Adult classification)
2. Electrical object detection.

Before developing our solution for children's hazardous child activity detection and preventive assistance system, we made certain assumptions.

1. Good lightning conditions have in the environment.
2. Camera have been should setup in eye site.

Table 2 Hardware Specifications

System	HP Pro book
Operating System	Windows 10 64 bit
RAM	12 GB
GPU	Nvidia K80 / T4
Display Memory (VRAM)	12 GB

Hardware Environment: Hardware parameters of the machine on which the algorithm has been trained and implemented are provided in**.**

Software Environment: Python was chosen as the programming language since it is a high-level programming language that is simple to learn and use, making it a popular choice for creating machine learning and deep learning algorithms.

In order to commencement of this training process following steps have been taken and completed that are required for the training for the algorithms.

2.1 Child Detection

2.1.1 Dataset

Here we implement set of operations in order to implement real time adult child classification using image processing techniques. Kaggle dataset has been utilized when training and implementing real time adult child classification models. Totally dataset consisted with 4754 images. The dataset consisted with two classes which are child and non-child. The selected dataset consisted with combination of child and non-child images which are number of 2168 and 2586 images respectively. The Collected images consisted with different cultural child images. It has been making an impact to the model accuracy.

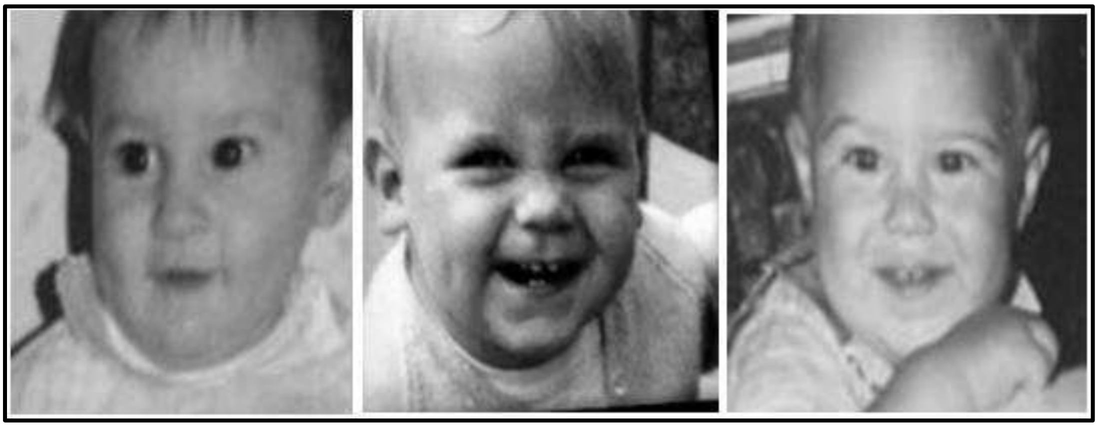

Figure 3 Child Sample Data

Figure 4 Adult Sample Data

2.1.2 Dataset pre-processing

The collected dataset set first we divided into three main categories which were useful when training process. From the dataset, 80% used to training, 20% used to testing and also 20% of data used from training dataset for the validation process. Before being sent into the network, all the images assured to be 150 x 150 in size. it is recommended that a fixed input size be maintained across the dataset as difficulties may arise later during the algorithm's implementation. The resized data then transfer to implement image normalization process. Normalization is the process of reducing pixel values to a range of 0-1. Initially the images were consisted with 0–255-pixel range and after executing normalization process each frame were scaled between 0–1-pixel range.

Normalized dataset then fed into several algorithms in training process in order to find best accurate model.

2.1.3 Framework

Here we used Keras API as training framework. The reason is to this selection Keras has a simple framework that allows for the creation of deep learning models based on TensorFlow and it is intended to be used to quickly define deep learning models. Keras, on the other hand, is an excellent choice for deep learning applications[25] .

2.1.4 Model selection and training

CNN and pre-trained CNN (transfer learning) were used to detect adult child classification phases. The transfer learning approach was utilized to overcome the data restriction. The following are three popular transfer learning models for image classification,

- VGG16 [26]
- ResNet50 [27]
- Incesptionv3 [28]

Because of their effectiveness, these models were frequently utilized for transfer learning. They also offered architectural improvements such as VGG16, Inceptionv3 module, and ResNet50.

Initially the training and testing data directories passed to the keras library generators and labelled the data as child and non-child. After labelling, these generators were utilized to create models in several transfer learning models such as VGG16, InceptionV3, and ResNet50. Rectified Linear Unit (ReLU) procedure was utilized to perform an accurate model. ‘Adam’ was assigned the role of optimizer. To improve accuracy, the number of epochs and training/testing batch sizes were changed. Batch size configured as 32 and 25 epochs has been execute in the training process. And here we have used learning reducer which reflects its monitors the loss during model training and reduces the loss when the loss has not reduced over a specific number of epochs. And the initial learning rate has given as 0.01 which will be later automatically tuned using a call back function.

In addition to that we have added three more dense layers for each 3 models. The added dense layers are consisted with two fully connected layers and one output layer. All fully connected layers have ''Relu' activation function, and the output layer has sigmoid function. First dense layer has 1024 units, second layer has 512 units and last layer has 1 unit because it is the output layer. The obtained results have been shown in table 3.

Table 3 Model Accuracy

Model	No of Epoch	Batch size	Added Layers	Accuracy
VGG16	25	32	Three dense	52.65%
ResNet50	25	32	Three dense	92.99%
Inceptionv3	25	32	Three dense	94.42%

Following figure shows InceptionV3 model architecture with modifications.

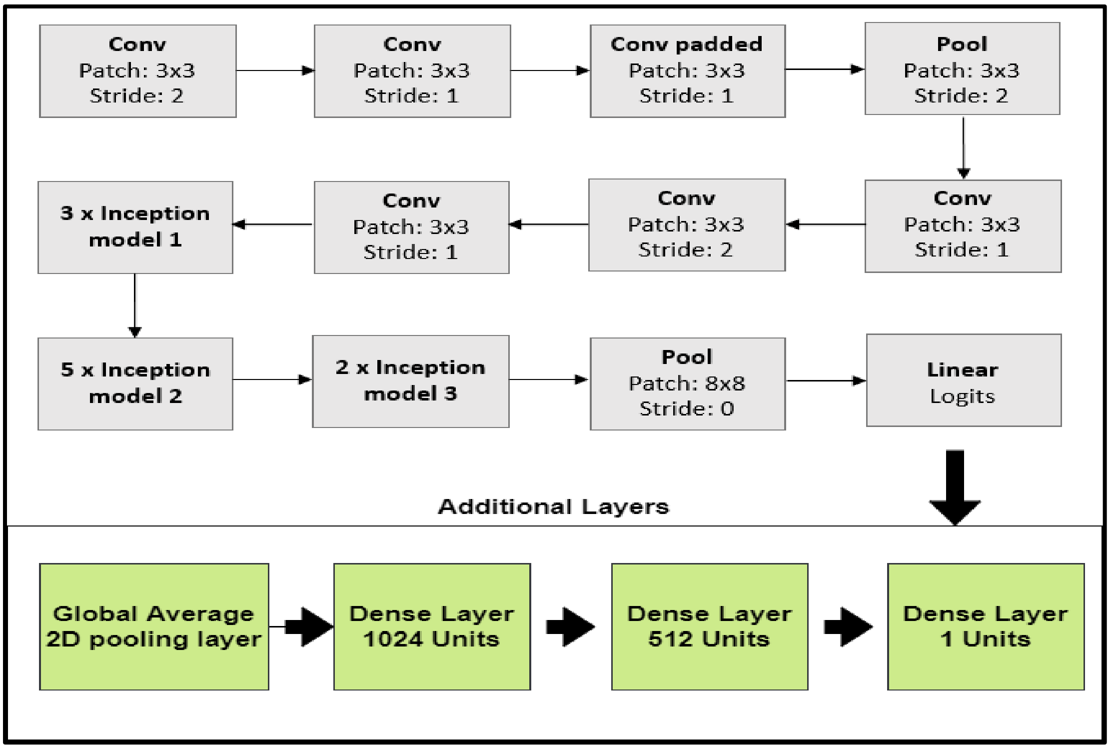

Figure 5 InceptionV3 Modified Architecture

After evaluating the training process the resulted wights stored in the separate weight file and then the stored weight files used to real-time adult child classification using Haar cascade object detection method [29]. The Haar cascade is an object detection algorithm that is used to recognize faces in images or real-time video.

Traditional object detection and tracking algorithms produce precise findings but are extremely sluggish. These techniques cannot be used by applications that demand a quick response. Paul Viola and Micheal Jones created haar cascade classifiers to address this issue. The concept is to introduce the items to the computer prior to activity recognition. During the detection phase, the computer uses an appropriate algorithm to try to locate the inserted object. In a face identification application, the Haar cascade classifier can identify eye, nose, head, mouth, hair, and other features.

Positive and negative images are introduced to the computer throughout the machine learning process. The computer will then recognize the target object by utilizing the features listed below. The picture that contains the desired item is referred to as a positive image and Negative object is an image that lacks the intended item.

- The first stage in this procedure is to scan the positive images with the modified feature frames.
- The step two is to separately calculate the pixels in the black and white areas.
- Finally, control the dark and bright portions and set some targets.

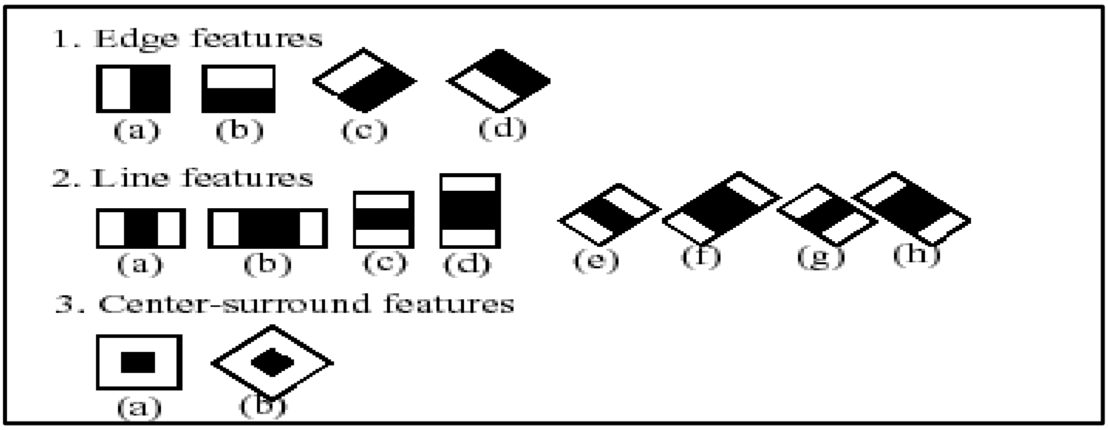

Figure 6 Haar features

As per the above-mentioned steps here we have been implemented the adult child classification in order to detect child hazardous activities as described in the introduction stage.

2.2 Electrical Object Detection

2.2.1 Dataset

In this section implies the about the dataset and how it has been adjusted for the model training phase. Since we were implemented the transfer learning method for the model training phase, pre trained algorithms model weights were obtained for YOLOv4 and Tiny-YOLOv4 models. All the pre trained weights have been implemented by using COCO dataset. The obtained weights then used to train the custom model for the custom dataset which were corporate to build child hazardous electrical accidents prevention and assistance system.

A dataset was constructed by gathering photos of four different types of dangerous electrical equipment – electrical extensions, table fans, electrical kettles, and irons – from varied angles, brightness, and contrasts. The images gathered included at least one of the four stated classifications, as well as additional items. A sum of 3000 images have been gathered, including 750 images each of table fans, electrical extensions, electric kettles, and irons. Data augmentation methods were used since the rule of thumb for deep learning is to have a minimum of 1000 pictures per class in the datasets. Among the various data augmentation techniques are image panning, zooming, flipping, rotating, and so on. The data set incorporates all the necessary conditions required for an image classification to do experiments. Images collected have all the attributes like brightness, sharpness, softness, noise, angles so that it appears to be as good as real.

2.2.2 Data pre-processing

Before being sent into the network, all pictures for the YOLOv4 and Tiny-YOLOv4 models have been assured to be 1200×1200 in size. The height and width of the input images are mostly determined by the backbone convolutional neural network into which the image is fed. These dimensions can be changed when changing the models. Even though YOLO is unaffected by the scale of the input images, it is recommended that a fixed input size be maintained across the dataset as difficulties may arise later during the algorithm's implementation. This was accomplished with the assistance of third-party software. The tool called BULK RESIZE PHOTOS is used to resize images. The reason is to select this tool its free, fast and bunch of images can resize at as whole. In all three situations, the images were fed into the network until the loss was reaches.

2.2.3 Dataset labelling

The images in the dataset were manually labelled with a tool called 'LabelImg'. As illustrated in Figure 6, each image is labelled by defining bounding boxes precisely enclosing the necessary items in the image and choosing their appropriate classes. The resulted files in XML format and also known as 'Annotation file. Each annotated image was then stored to a particular folder. The annotation files provide information about the object in the images, such as the image name and label name, class name of the objects, the image path and the coordinates of the bounding boxes that surround the objects in the image. These annotated images are then used to train the algorithm and enable it to recognize the appropriate class objects.

2.2.4 Framework

The Darknet Object Detection framework has been highlighted as a valuable tool since it allows us to quickly create and deploy picture recognition algorithms [30]. The image XML files generated by the annotation process were transformed to a darknet framework-compatible file format. The format contains a text file per image which contains the annotation, a numeric representation of the label and a label map which maps these numeric IDs to human readable strings. Reason for using Darknet instead of other libraries is that Darknet gives better performance compared to other libraries and it also has a GPU Version which is very fast. Darknet of CPU it would take 6 – 12 seconds per image/per frame in video feeds while if we use the GPU Version, it's a lot faster depending on the GPU.

2.2.5 Configurations

The default configuration files of the YOLO given by the TensorFlow Object Detection framework have been modified in several ways, including dataset, number of classes to be trained, label map and batch size. The dataset has been divided into two parts: the train dataset and the test dataset. The train dataset had 75% of the original dataset's pictures, while the test dataset contained 25% of the original dataset's images, which is the common rule of thumb used by many academics when dividing the dataset.

The parameter to be trained has also been modified to four, since the YOLOv4 and Tiny-YOLOv4 algorithms being trained are required to identify and recognize four classes of objects, including a table fan, electrical extension cord, electrical kettle, and an iron. A label map with class names and their matching class identifiers has been generated.

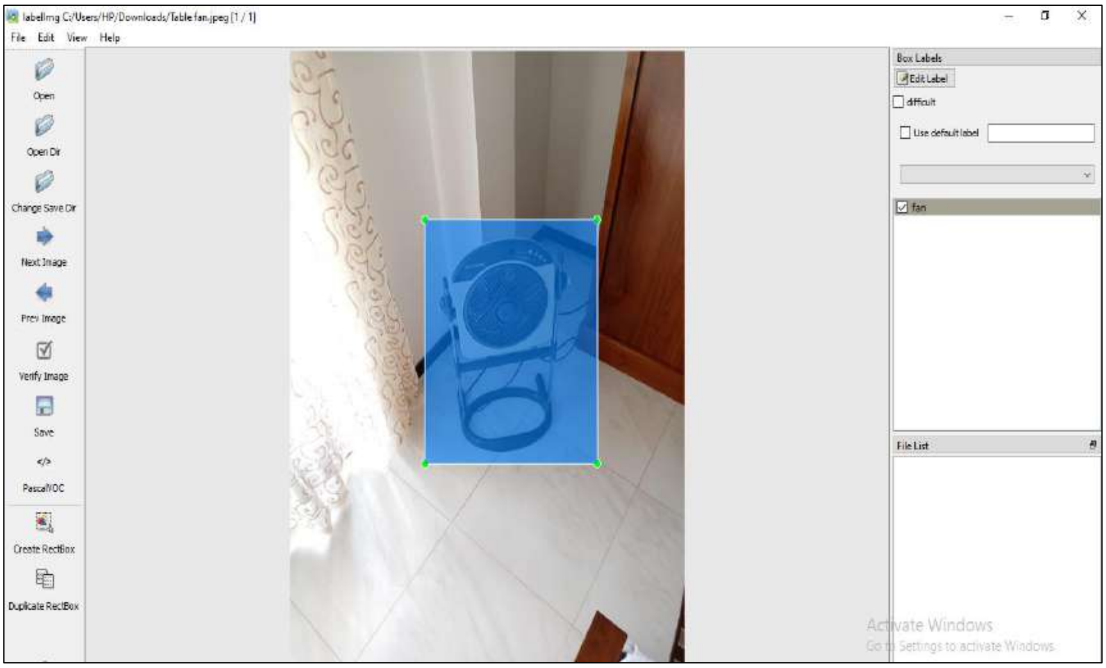

Figure 7 Dataset Annotation and Labelling

The batch size, which reflects the set of train images utilized by the algorithm in one iteration, is also altered since it influences VRAM usage. The larger the batch size, the more VRAM is consumed. As a result, a lower batch size has been chosen for the training procedure.

2.2.6 Model selection and training

The training procedure is initiated after completing all the preceding stages and making the required modifications to the configuration file. When the model initialization we have selected YOLOv4 and Tiny-YOLOv4 by referring existing research papers that was proven[3][31], [32].

The model training process has been done in google colab environment. Google colab is open-source product provided by Google. Colab allows anyone to create and run arbitrary Python code in the browser, and it is especially suited to machine learning and data analysis. Colab is a hosted Jupiter notebook service that requires no installation and provides free access to computational resources such as GPUs[33]. The Training process has been braked into few steps.

- Configuration of the GPU environment.
- Install Darknet YOLOv4 training environment.
- Download the custom dataset which mentioned in the ‘Dataset’ section for YOLOv4 and set up the directories.
- Configure a custom YOLOv4 training config file for Darknet.
- Train our custom YOLOv4 object detector.
- Reload YOLOv4 trained weights and make inference on test images

The following figure illustrate the YOLOv4 Model architecture.

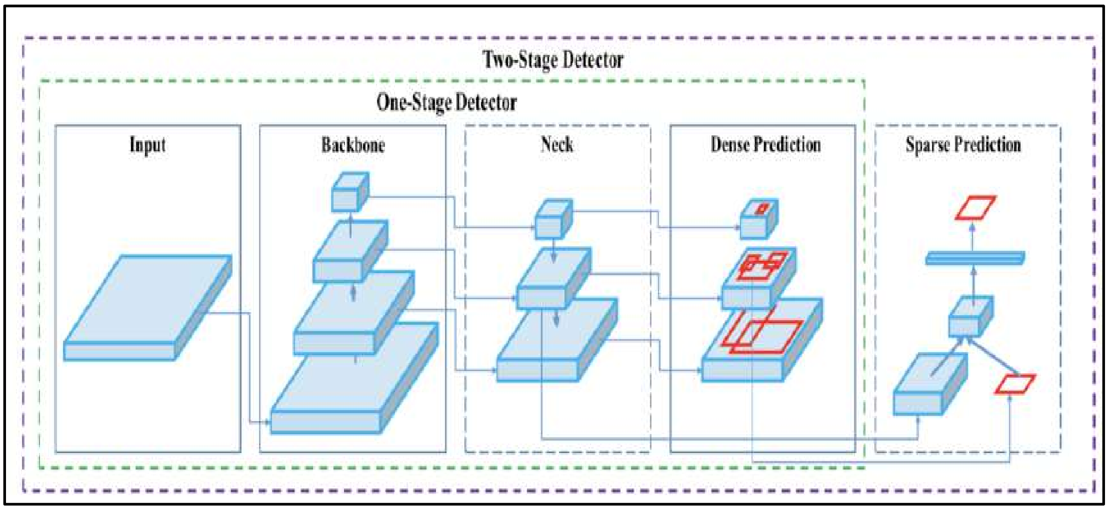

Figure 8 YOLOv4 Architecture

The figure 7 shows how the training process happened in the iteration phase.

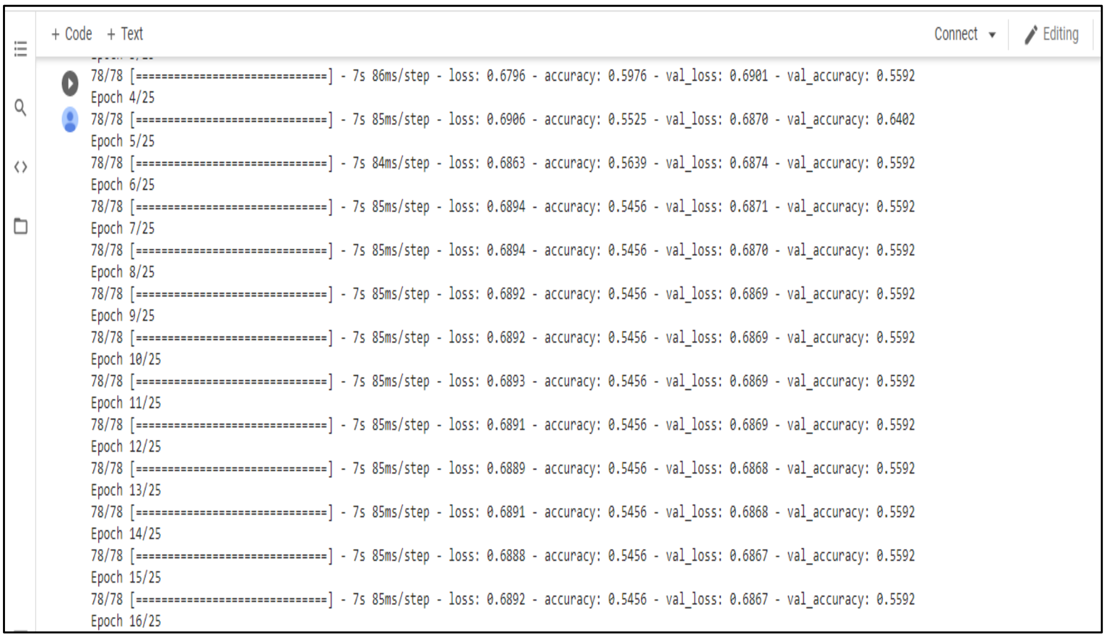

Figure 9 Model Training

2.3 Proximity Calculation

Once the child and electrical object detection were successfully executed the immediate next step is to detect proximity between electrical object and child. This section implies what are the calculations we have brought in order to trigger a warning message based on the child proximity to electrical devices.

Pre configurations

Before the proximity calculation we must ensure certain points.

- Electrical object must be detected and bounding box should create around the detected object.
- Child should be detected and bounding bonding box should appear around the child.

After ensuring above mentioned tasks work as intended, then we check whether the child come closer to the detected hazardous electrical device. If the child come more closer to the electrical device there must be a bounding box overlap between of child and electrical device. If the child bounding box overlap with electrical device bounding box, the alerting system will trigger to relevant authorities. Following figure will show you how this calculation works.

Proximity calculation

The figure 8 shows proximity calculation methodology as diagrammatical way.

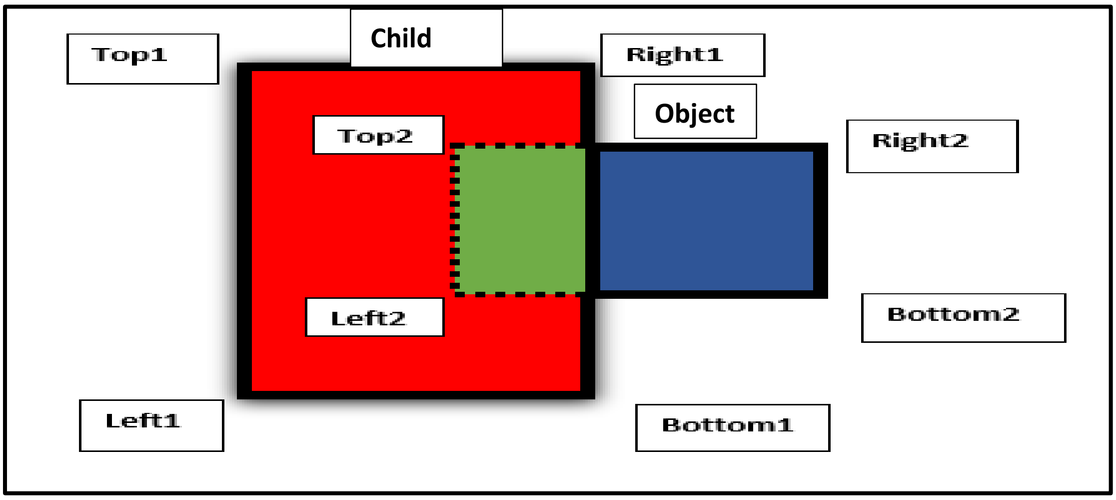

Figure 10 Defining Proximity

$$X = max\,(Left1, Left2)$$

$$Y = max\,(Top1, Top2)$$

$$Width = min\,(Left1 + Right1, Left2 + Right2) - X$$

$$Height = min\,(Top1 + Bottom1, Top2 + Bottom2) - Y$$

```
[ ]  # Calculate the intersection between two bounding boxes
     def intersection(a,b):
       x = max(a[0], b[0])
       y = max(a[1], b[1])
       w = min(a[0]+a[2], b[0]+b[2]) - x
       h = min(a[1]+a[3], b[1]+b[3]) - y
       if w<0 or h<0: return False # or (0,0,0,0) ?
       return True
```

Figure 11 Proximity Calculation

The overall framework of the proposed solution is shows in Figure 2.

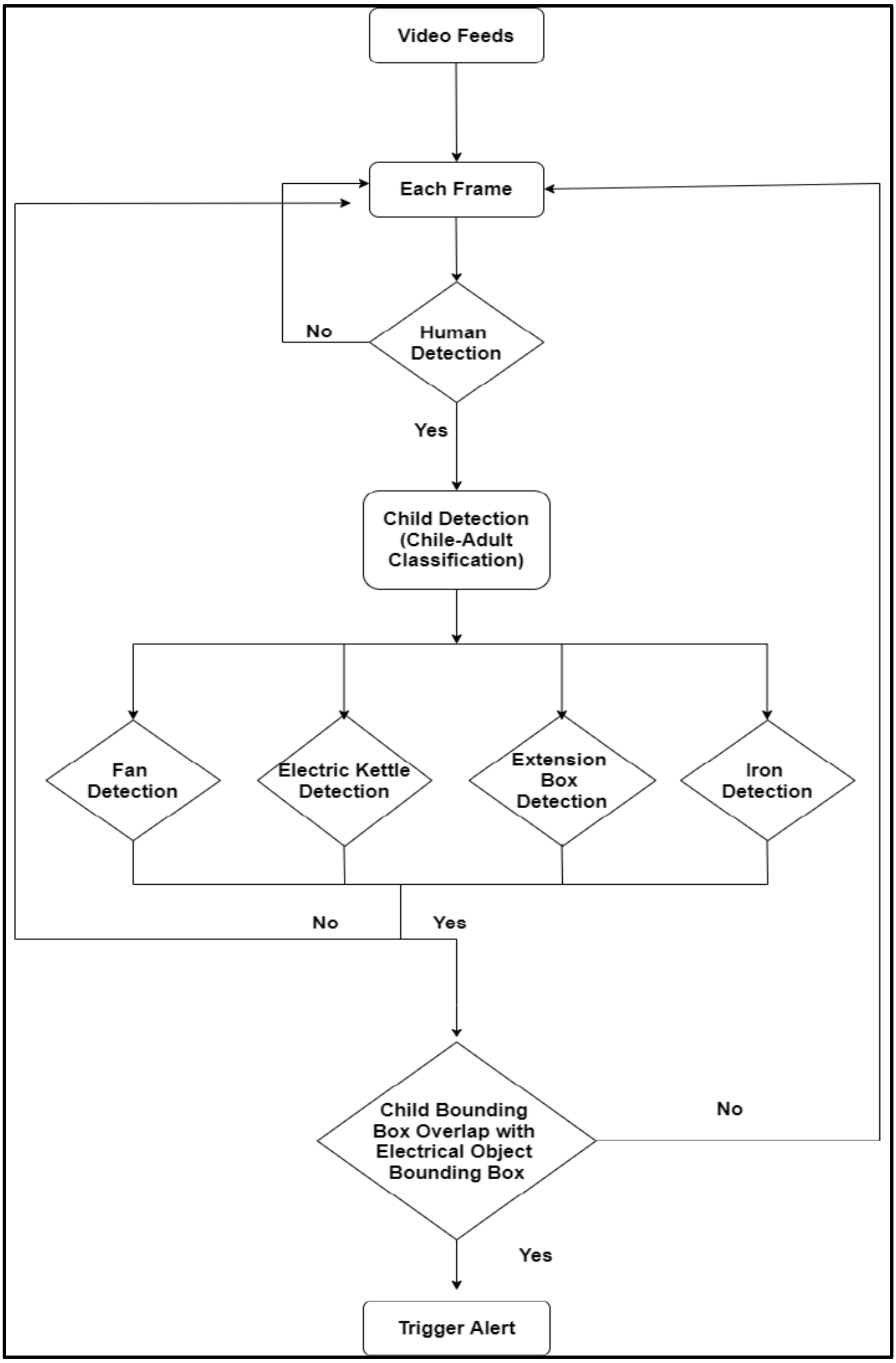

Figure 12 System Flow Diagram

2.4 Commercialization

In a society where families with both parents working has become a common norm, c hildren has 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 Metrics.

2.4.1 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 labour 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.

2.4.2 Target market

Working parents with children in the age group of 1 - 5 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.

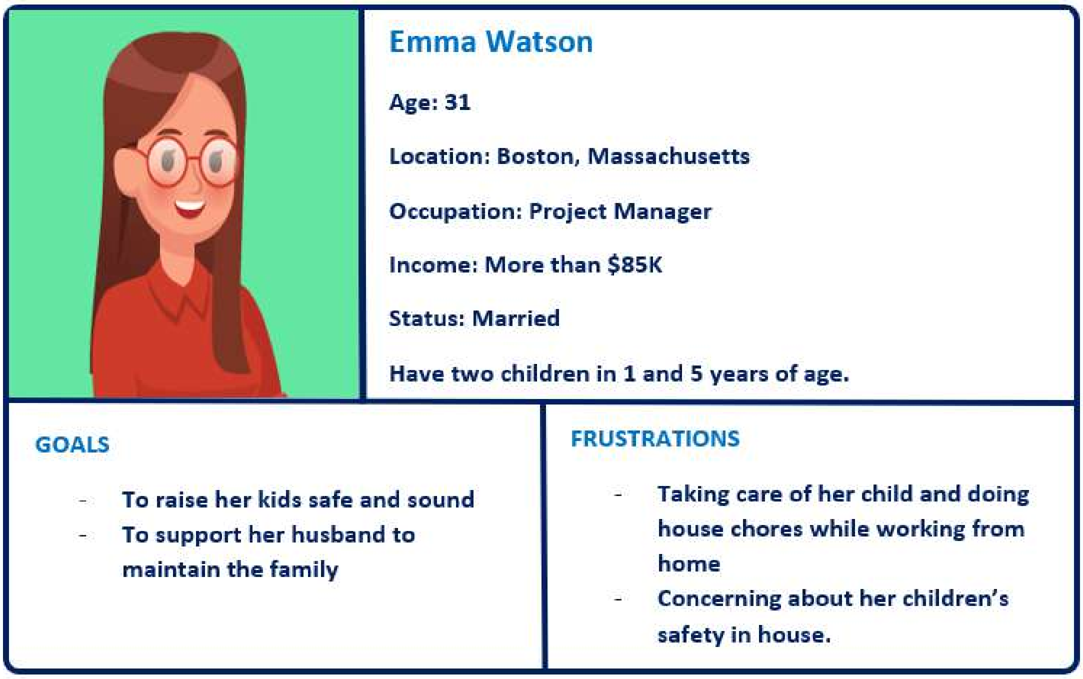

Figure 13 User persona of working from home parent

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.

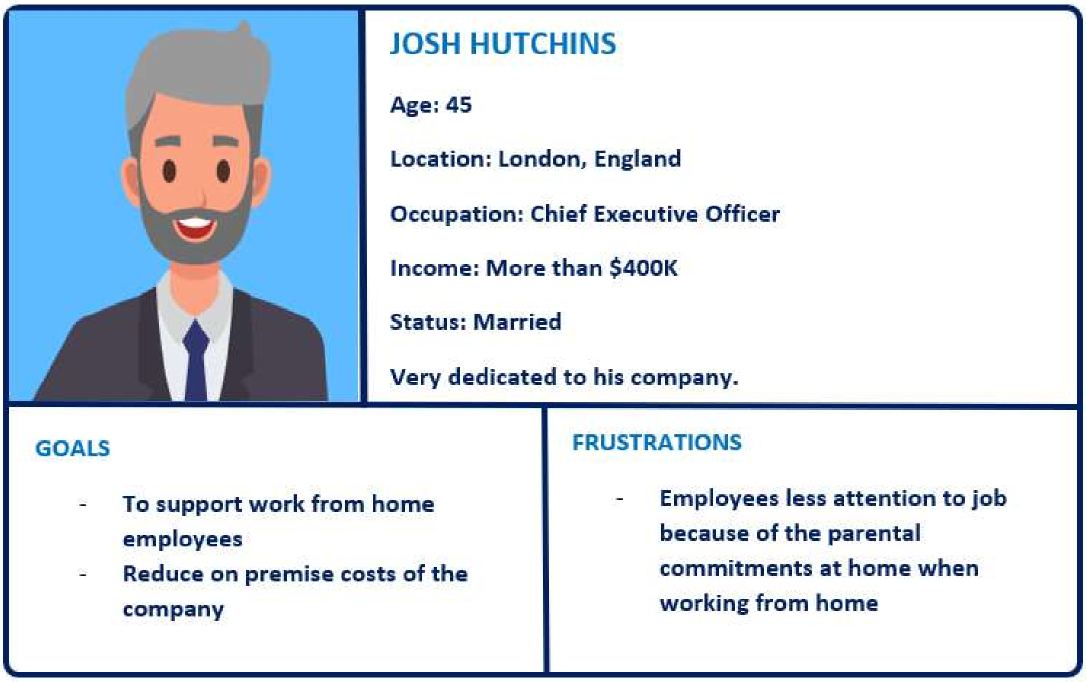

Figure 14 User persona of a chief executive officer of a company supporting working from home

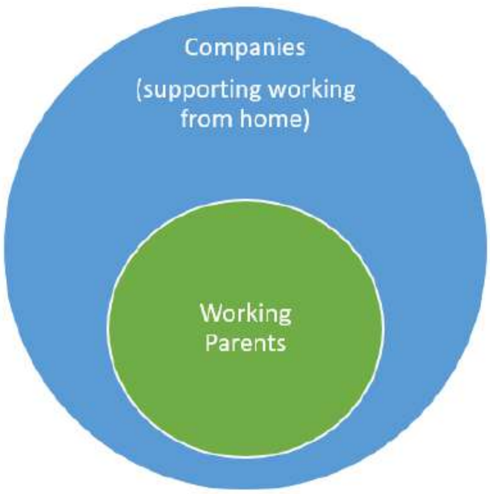

Figure 15 Target market for AICare

2.4.3 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 16 Competitor analysis

2.4.4 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.

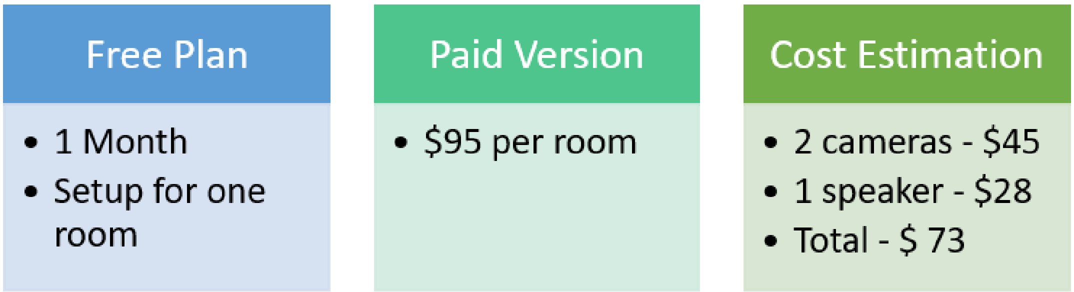

Figure 17 Business model of AICare

2.4.5 Accuracy

It is measured as the model's number of correct predictions divided by the total number of predictions.

$$TotalNo.of\ predictions\ (TP)\ =\ True\ Positives\ + True\ Negatives$$

$$+ False\ Positives\ +\ False\ Negatives$$

$$No.of\ correct\ predictions\ (CP)\ =\ True\ Positives\ +\ True\ Negatives$$

$$Accuracy\ =\ CP\ /\ T\ P$$

A True Positive is defined as a correct detection of the training object class. A True Negative is defined as a correct misdetection, which means that nothing is detected when there is no object to detect. A False Positive is defined as an incorrect detection, which means that there is a detection even if there is no item to be detected. A False Negative is considered as a ground truth that is not recognized, implying that the algorithm failed to recognize an item that should have been detected.

2.4.6 Precision

It is calculated by dividing the number of true positive outcomes by the total number of positive results predicted by the algorithm.

$$Precision\ =\ True\ Positives\ (True\ Positives\ +\ False\ Positives)$$

2.4.7 Recall

It is calculated by dividing the number of true positive results by the total of true positives and false negatives.

$$Recall = True\,positives\ (True\ Positives + False\ Negatives)$$

2.4.8 F1 Score

The F1 measure is used to assess the correctness of a test. If the total number of false positives and false negatives is minimal, the F1 score is considered good.

$$F1Score = 2 * Precision * Recall\ (Precision + Recall)$$

2.5 Testing & Implementation

In this section shown you the test cases we have followed in order to ensure the system works as expected.

2.5.1 Test cases for adult child classification

Table 4 Child Detection Test Cases

Test case No	Total number of test cases	Inputs	Expected Output	Actual Output	No. of positive Results	No. of Negative Results	Test Comments
1	5	Video feed of child	Child detection with rectangle bounding box	Child detection with rectangle bounding box	3	2	Successfully child detected most of test cases.
2	5	Video feed of adult	Adult detection with rectangle bounding boxes.	Adult detection with rectangle bounding box	4	1	Successfully adult detected most of test cases.
3	5	Video feed of both adult and child	Both adult and child detection with rectangle bounding boxes.	Both adult and child detection with rectangle bounding boxes.	3	2	Successfully both adult and child detected most of test cases.

2.5.2 Test cases electrical object detection

Table 5 Object Detection Test Cases

Test case No	Total number of test cases	Inputs	Expected Output	Actual Output	No. of positive Results	No. of Negative Results	Test Comments
4	3	Video feed of table fan along with the child or parent	Fan detection with rectangle bounding box	Fan detection with rectangle bounding box	3	0	Successfully fan detected most of test cases.
5	3	Video feed of iron along with the child or parent	Iron detection with rectangle bounding boxes.	Iron detection with rectangle bounding box	3	0	Successfully Iron detected most of test cases.
6	3	Video feed of electrical extension box along with the child or parent	Electric extension box detection with rectangle bounding boxes.	Electric extension box detection with rectangle bounding boxes.	2	1	Successfully electrical extension box detected most of test cases.
7	3	Video feed of electrical kettle along with the child or parent	Electric kettle detection with rectangle bounding boxes.	Electric kettle detection with rectangle bounding boxes.	1	2	Successfully electrical kettle detected most of test cases.
8	3	Video feed of electrical objects without any person in room	Electrical objects will not be detected.	Electrical objects were not detected.	3	0	Electrical objects should not detected if none of the person in the room

2.5.3 Test cases for overall system

Table 6 Overall System Test cases

Test case No	Total number of test cases	Inputs	Expected Output	Actual Output	No. of positive Results	No. of Negative Results	Test Comments
9	3	Video feed of table fan too close to the child	Alert and warning message must be trigger	Alert and warning message must be triggered	2	1	Successfull y displayed warning message and trigger audio alarm
10	3	Video feed of iron too close to the child	Alert and warning message must be trigger	Alert and warning message must be triggered	3	0	Successfull y displayed warning message and trigger audio alarm
11	3	Video feed of electrica l extensio n box too close to the child	Alert and warning message must be trigger	Alert and warning message must be triggered	2	1	Successfull y displayed warning message and trigger audio alarm
12	3	Video feed of electrica l kettle too close to the child	Alert and warning message must be trigger	Alert and warning message must be triggered	1	2	Successfull y displayed warning message and trigger audio alarm
13	3	Video feed of electrica l objects too close to adult.	Alert and warning message is not trigger	Alert and warning message must be triggered	2	1	Successfull y displayed warning message and trigger audio alarm

2.5.4 Tools and Technologies

The following is a list of the various tools, libraries, and technologies used in the proposed system module.

Google colab

Colab is a cloud based Jupyter notebook environment that is completely free. Most significantly, no setup is required, and the notebooks you create may be updated concurrently by your team members and another important factor is it allowed free cloud with free GPU.

Darknet

Darknet is a high-performance open-source framework for neural network implementation. Darknet may be used to do advanced deep neural network implementations with along with real time algorithms.

Python

Python is a high-level, interpreted general-purpose programming language. Here we have used Python as primary language and utilized for development end.

Keras

Keras is a Python-based deep learning API that runs on top of the TensorFlow machine learning framework. Keras is TensorFlow 2's high-level API: a user-friendly, highly productive interface for addressing machine learning issues, with an emphasis on contemporary deep learning.

NumPy

NumPy is a Python library that adds support for huge, multidimensional arrays and matrices, as well as a vast set of high-level arithmetic operations to work on these arrays

3 RESULTS & DISCUSSION

3.1 Child detection

3.1.1 Training Results

Child adult classification training have been done using three models. Following are the models that we have used in our training phase.

- VGG16
- ResNet50
- InceptionV3

All these three models have been trained with changes in model network architecture. Here we have added three more additional dense layers for all the three models. Following has shown you the results achieved by each model.

In the VGG16 model we were able to achieve 52.65% accuracy by using 25 epochs. Following confusion matrix have shown you obtained results from the VGG16 model.

```
Accuracy Score: 52.658884565499356
Precision Score: 52.658884565499356
Recall Scroe: 100.0
F1 Score: 68.98895497026338
Confusion Matrix
[[  0 365]
 [  0 406]]
Classification Report
              precision    recall  f1-score   support

       child       0.00      0.00      0.00       365
   non-child       0.53      1.00      0.69       406

    accuracy                           0.53       771
   macro avg       0.26      0.50      0.34       771
weighted avg       0.28      0.53      0.36       771
```

Figure 18 VGG16 Model Confusion Matrix

By training ResNet50 model we were able to be achieved 92.99% accuracy from 25 epochs implementation. Along with the accuracy following figure have shown you what are obtained results from the ResNet50 model.

```
Accuracy Score: 92.99610894941634
Precision Score: 91.9047619047619
Recall Scroe: 95.07389162561576
F1 Score: 93.46246973365618
Confusion Matrix
[[331  34]
 [ 20 386]]
Classification Report
              precision    recall  f1-score   support

       child       0.94      0.91      0.92       365
   non-child       0.92      0.95      0.93       406

    accuracy                           0.93       771
   macro avg       0.93      0.93      0.93       771
weighted avg       0.93      0.93      0.93       771
```

Figure 19 ResNet50 Model Confusion Matrix

As the final phase of training phase, we were able to achieve highest accuracy model by using InceptionV3 model. Following confusion matrix and graphs have shown you results obtained by InceptionV3 model.

```
Accuracy Score: 94.42282749675745
Precision Score: 95.03722084367246
Recall Scroe: 94.33497536945814
F1 Score: 94.6847960444994
Confusion Matrix
[[345  20]
 [ 23 383]]
Classification Report
              precision    recall  f1-score   support

       child       0.94      0.95      0.94       365
   non-child       0.95      0.94      0.95       406

    accuracy                           0.94       771
   macro avg       0.94      0.94      0.94       771
weighted avg       0.94      0.94      0.94       771
```

Figure 20 InceptionV3 Model Confusion Matrix

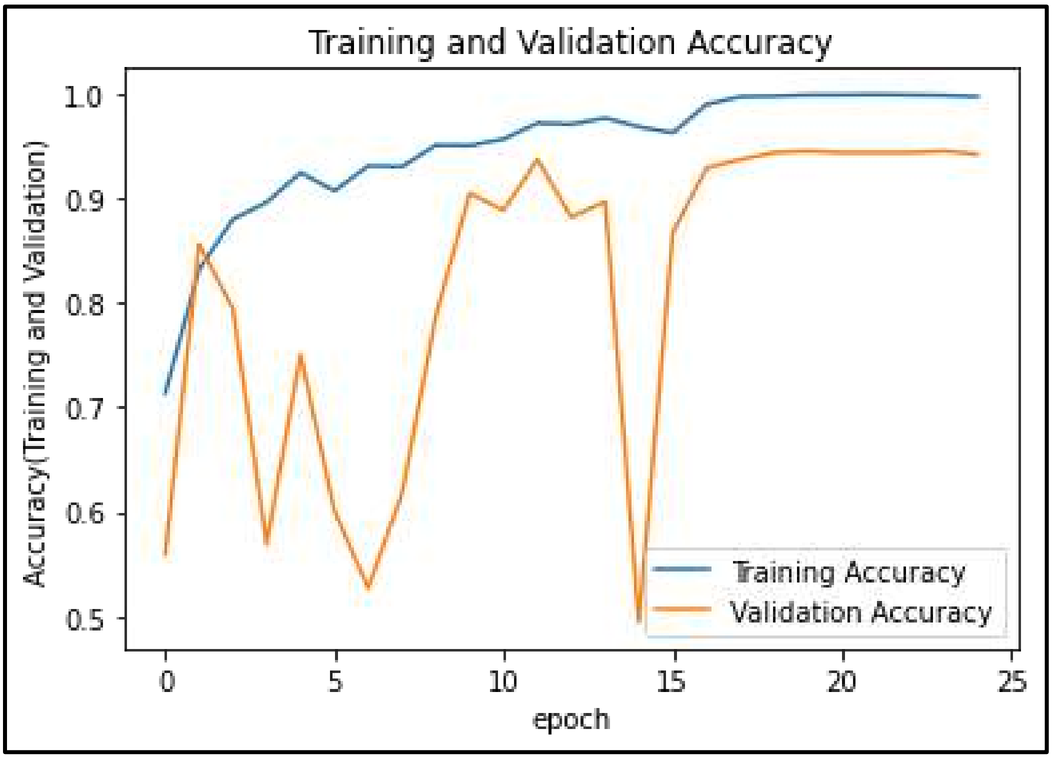

Figure 21 Training and validation accuracy of InceptionV3 model

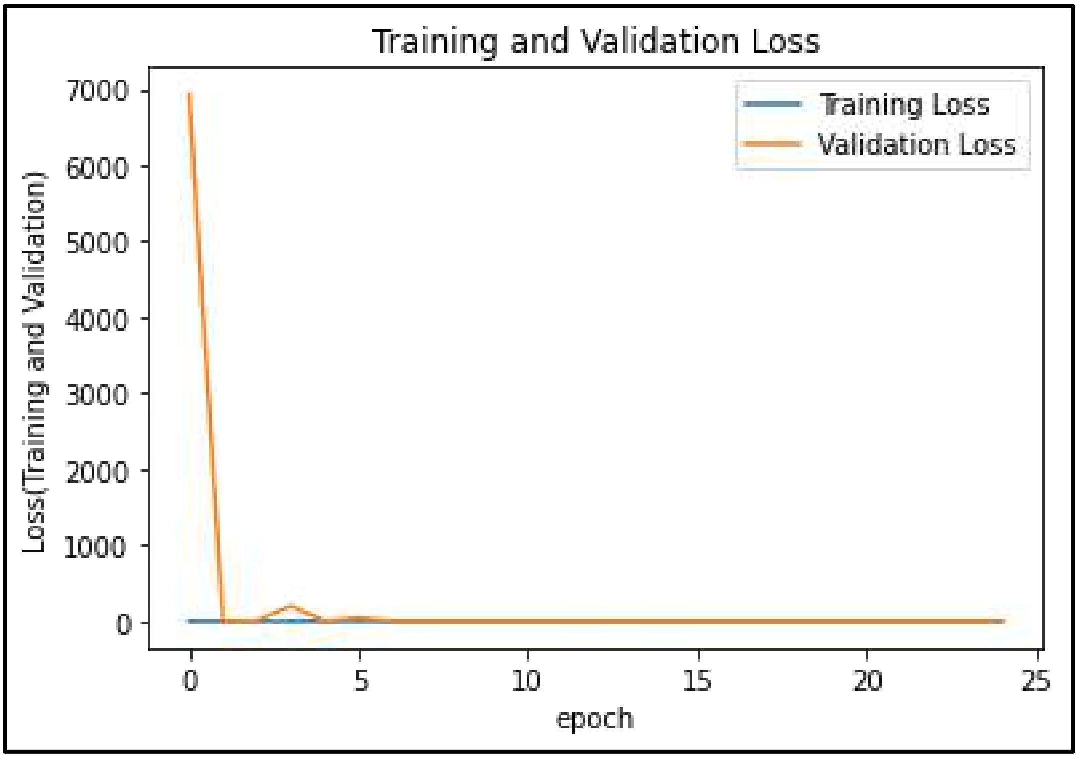

Figure 22 Training and Validation loss of InceptionV3 model

According to obtained results highest accuracy have bee obtained by InceptionV3 model. As shows in figure 12 from the inceptionV3 model we were able to optimize model accuracy by adding three more additional dense layers. These dense layers have been consisted following features,

1. First dense layer has 1024 units
2. Second layer has 512 units
3. Final layer has 1 unit because it is the output layer.

After configuration has done as shows in figure 13, we were able to take accuracy of the training and validation data. The graph shows the model training accuracy has increasing gradually up to 18 iterations but after it mostly behave as parallel line up to 25 iterations. Validation accuracy also consisted with ups and downs in the initial phase however from 18 iteration it mostly consisted as parallel line along with the training accuracy line. That has been reflected model achieved considerable accuracy for the object classification phase.

3.1.2 Child detection system testing results

In this chapter have shown you screenshots of the obtained results which were mentioned in the Testing phase related to adult child classification.

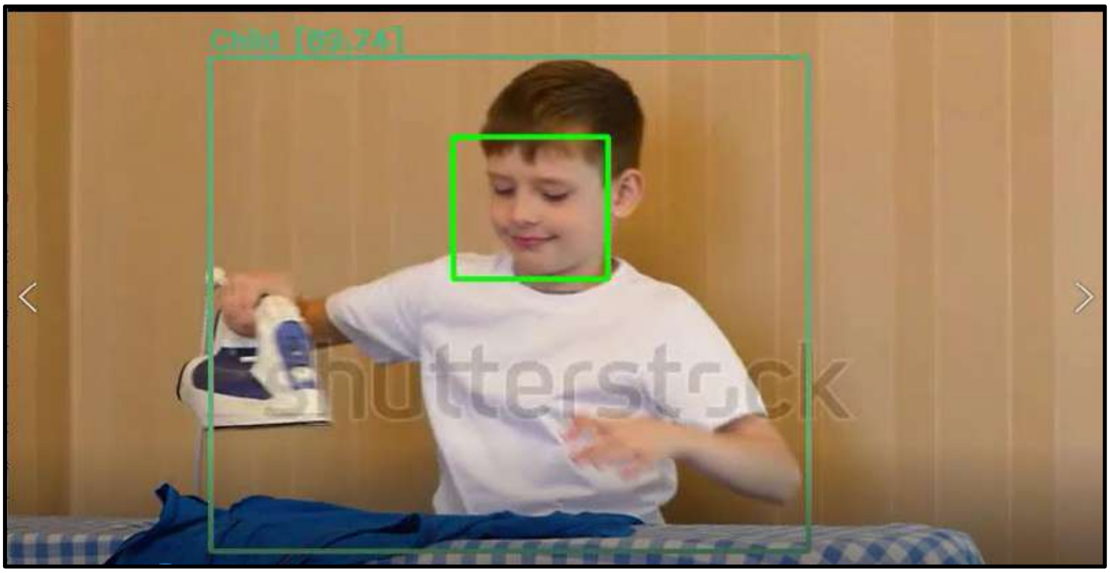

Figure 23 Child detection result

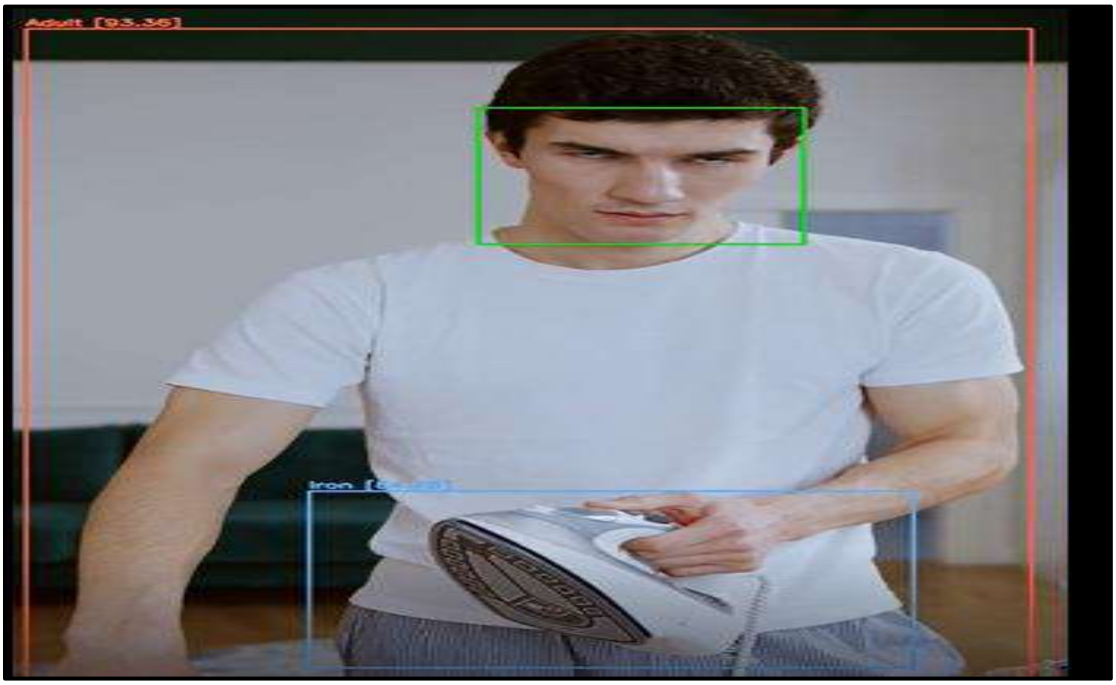

Figure 24 Adult detection result

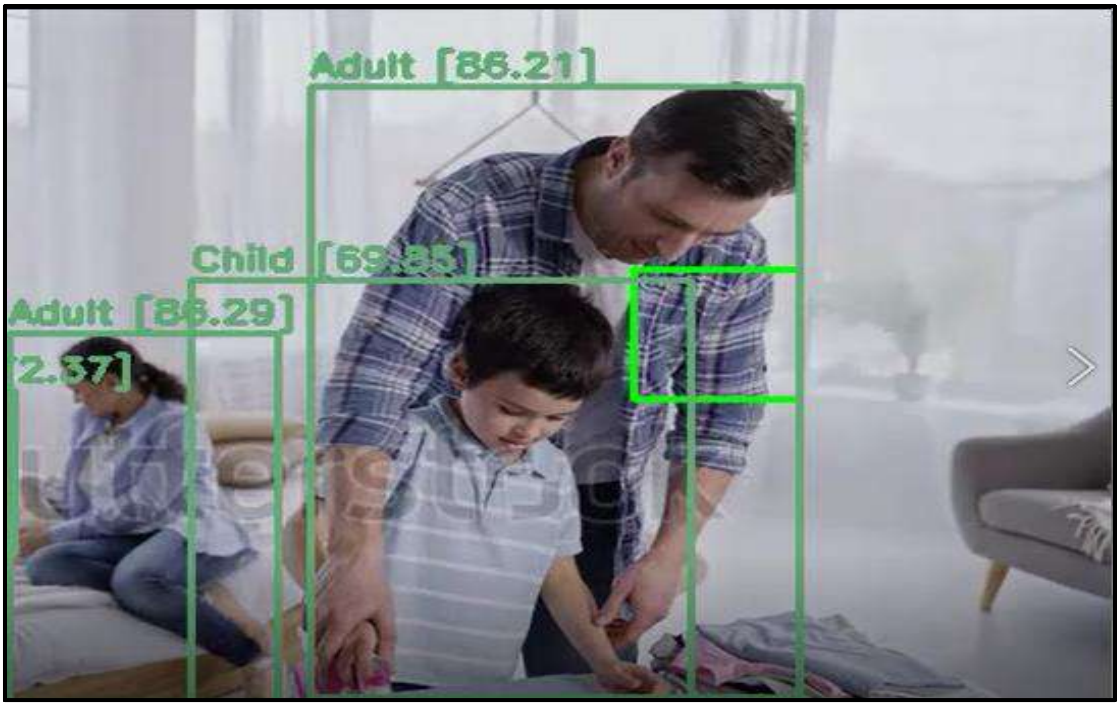

Figure 25 Adult child classification result

3.2 Electrical object detection

3.2.1 Training results

Following the conclusion of the algorithm’s training phase, a video consisting of four classes – fan, iron, electrical extension, and electrical kettle – was utilized as test data to assess the YOLO and Tiny-YOLOv4 algorithms. The results of the test cases are conducted as follows,

- Obtained results of object detection made by YOLOv4 and Tiny YOLOv4, as well as the probabilities for the detections.
- According to the figures, the models were successful in identifying and tracking the electrical devices from various angles and distances.
- The experiments were also repeated several times, utilizing a live feed from the webcam, real electrical equipment, and video footage as test data.

Based on the data in Table 7, the accuracy of the models has been determined to be 81.77 % for YOLOv4 and 81.00 % for tiny YOLOv4. The rationale for YOLOv4's better accuracy score is due to its design, which performs object detections at three distinct scales, making YOLOv4 more efficient in identifying small items or objects in challenging circumstances such as objects showing partially in a given frame. Since some object could be seen far from surveillance cameras then the objects will appear as small. As a result, Tiny-YOLOv4 failed to predict the objects more accurately in these circumstances. As a result, the YOLOv4 model is very accurate in the real-time identification and monitoring of hazardous electrical devices such as a table fan, an extension cord, an iron, and an electric kettle in a present household setting.

Precision

A model's precision is determined by the number of true positives and false positives. Models on the test video have determined the number of true positives and false positives. The mean average precision of the models has been calculated using the data in Table 7 as 0.8177 and 0.8000 for YOLOv4 and Tiny-YOLOv4, respectively.

Recall

A model's recall is determined by the number of true positives and false negatives. The models on the test video obtained the number of true positives and false negatives. Based on the values in Table 7, the recall of the models was determined to be 0.85 for YOLOv4 and 0.77 for Tiny-YOLOv4. Tiny-YOLOv4 had lower recall values than YOLOv4 due to erroneous detections in many video frames when the object is not identified, whereas YOLOv4 offered better results. As a result, it is possible to conclude that the recall of YOLOv4 in real-time identification and tracking of electrical devices is significantly higher than that of the other models considered.

F1 Score

Using the Precision and Recall values acquired in the preceding phases, the F1 score of the YOLOv4 and tiny YOLOv4 models was determined to be 0.83 and 0.81, respectively, as shown in Table 7**.** Because the model's performance is directly related to the F1 score, the YOLOv4 model outperforms the other models in this experiment in real-time identification and tracking of hazardous electrical appliances in a scaled residential setting.

Table 7 Object detection model training results

Matrices	YOLOv4	Tiny-YOLOv4
Accuracy	81.77%	80.00%
Precision	0.81	0.80
Recall	0.85	0.77
F1 Score	0.83	0.81

3.2.2 Electrical object detection system testing results

In this chapter have shown you screenshots of the obtained results which were mentioned in the Testing phase related to electrical object detection.

Figure 26 Electrical extension box detection

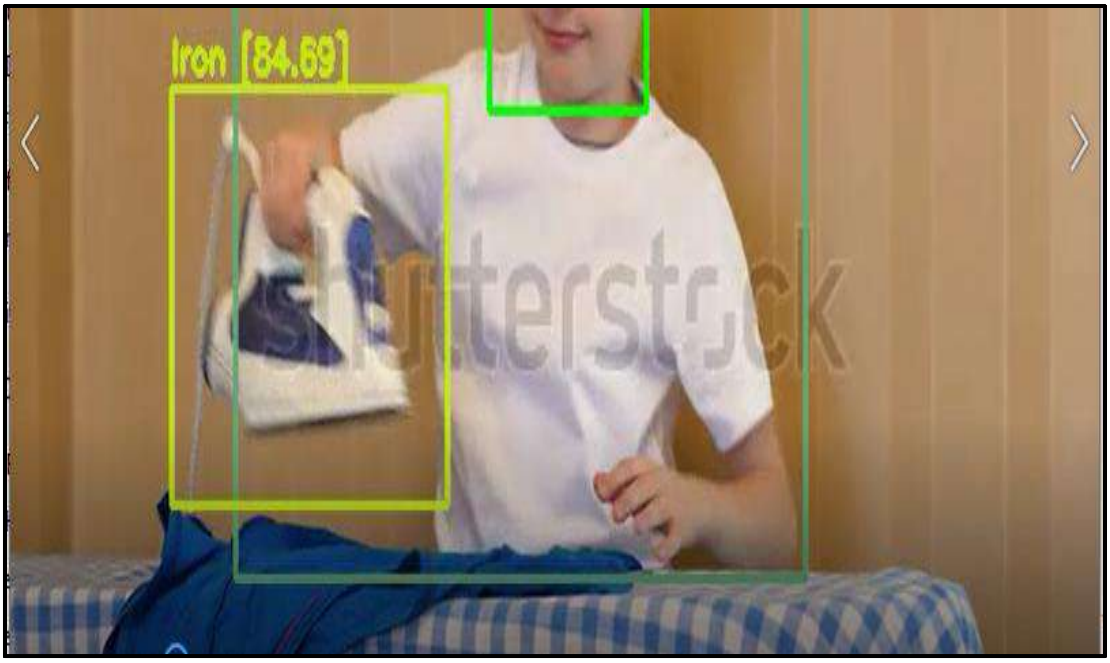

Figure 27 Iron detection

3.3 Overall system testing results

In this chapter have shown you screenshots overall system results which obtained from different use cases. As mentioned in the methodology section system should work only if the child is too closed to the electrical object. In the following screenshots have been shown you child is too proximate to the electrical device and it may cause to the injury. In order to prevention these types of dangers here we implemented to trigger an alarm to the parents. The alarm is trigger as a audio and also the danger displays as warning message on the screen.

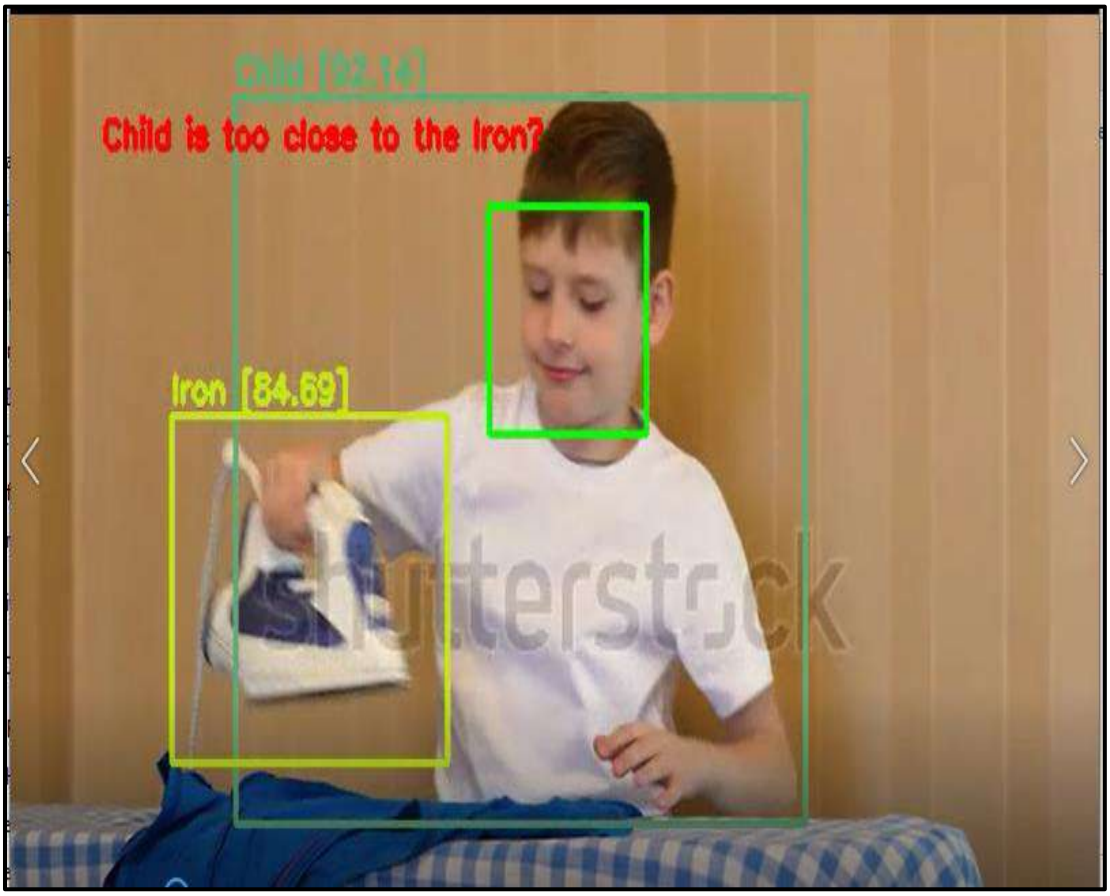

Figure 28 Child is too proximate to iron

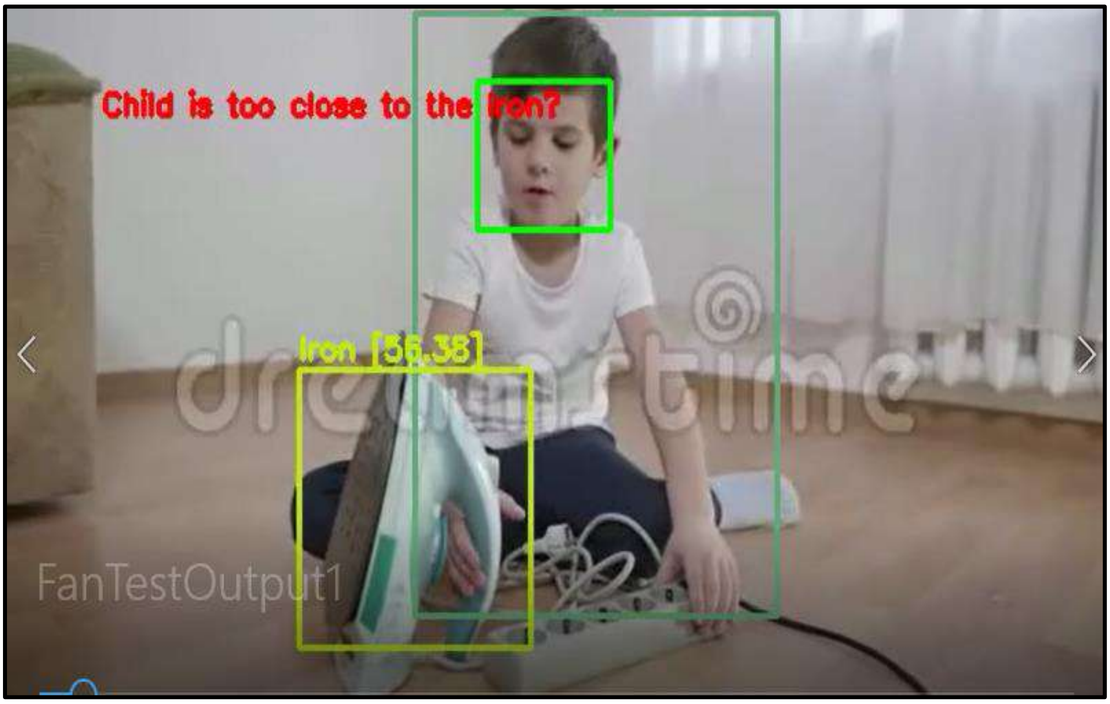

Figure 29 Child is too proximate to iron

Figure 30 Child is too proximate to extension box and iron

Figure 31 Child is too proximate to electrical extension box

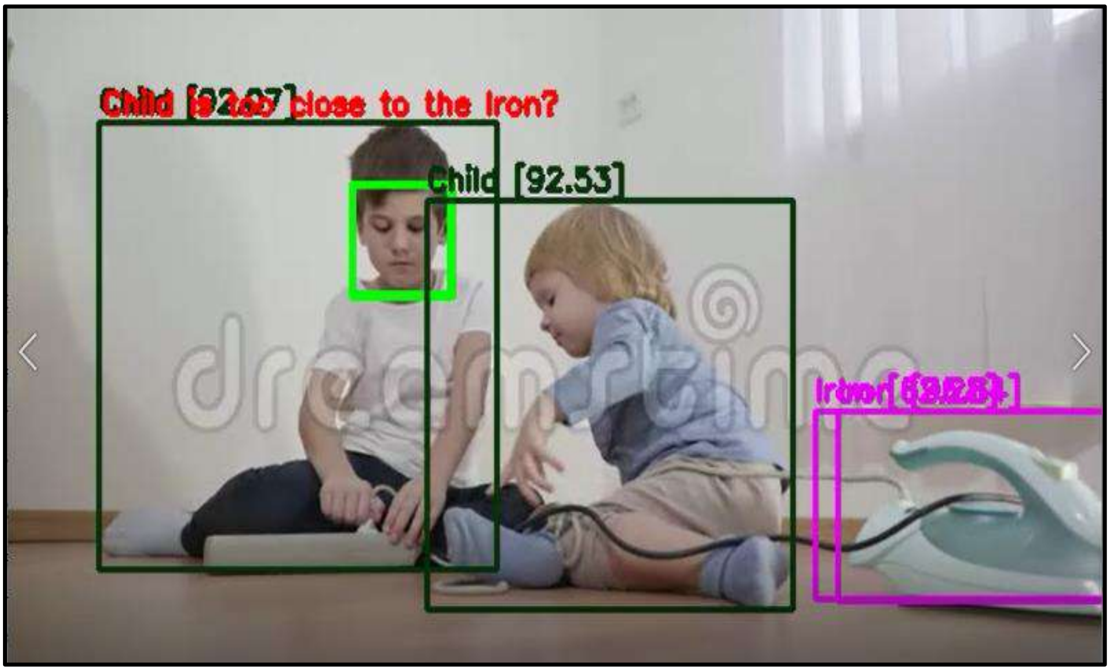

Figure 32 Child is too close to the iron

3.4 Research Findings

The main objective of the research is to be finding automate surveillance system prevention from unsafe electrical injuries in the domestic environment. Since the system capable of prompt an alert when child is proximate to hazardous electrical objects it also worked as injury prevention assistance system.

Several experiments have been conducted in order to calculate the accuracy of the novel approach pipeline. The proposed model is tested under a range of environmental situations.

This thesis report addresses the best deep-learning models for real-time object identification, recognition, and classification, as well as how to evaluate the performance of these algorithms in order to develop a novel computer vision-based strategy for preventing child electrical injuries. survey of the literature was conducted to get knowledge about several deep learning models capable of conducting real-time child detection and electrical object recognition. By analysing the performance of these algorithms on a standard dataset, the most suitable and efficient deep-learning models for this scenario were identified as YOLOv4, Tiny-YOLOv4 for real-time object detection [3], [31], [32], [34] and VGG16, Inceptionv3, and ResNet50 for real-time object classification [26]–[28]. It has been determined that Yolov4 and Inceptionv3 have the highest accuracy when compared to other models. As the obtained results from model training phases, we can illustrate YoloV4 and inceptionV3 models are more accurate and efficiently works for our solution compared to other models which were used in different training phases.

4 CONCLUSION

The study's major goal was to detect and prevent child injuries caused by electrical shocks and burns. This research consisting of several actions which helps to prevent child electrical shocking and burning injuries. The several algorithms have been performed for real time electrical object detection and real time child detection using object classification modals.

Following the creation of the dataset, the algorithms were trained on the train-dataset. The trained models were evaluated on test video taken at the location, and the number of true positives, true negatives, false positives, and false negatives for each frame of the detections produced by the two deep-learning models on the test video were detected. Using these findings, the models' Accuracy, Precision, Recall, and lastly the F1 score were computed, and the performance of the YOLOv4, Inceptionv3 models was assessed and compared. The experiment's results have been given, along with a comprehensive analysis of the findings.

The approach suggested in this work for detecting children utilizing real-time object classification algorithms and real-time hazardous electrical object detection is computationally efficient and has an exceptionally low false alert rate. It is capable of effectively classify child from adults in order to keep track child activities and also have more accurate and efficient in electrical objects detection as well. By utilizing these models, we were able to create real time alerting system in order to prevents from child injuries. Since this requires a small amount of processing time, this approach can be helpful for any real-time implementation.

5 FUTURE WORKS

The system primarily comprises of three functionalities: child identification using object classification algorithms, electrical object detection, and danger prevention assistance. The major emphasis of future development would be to eliminate some highlighted disadvantages.

Models implement for child detection function should be improved in a way that it capable of detecting child from different angles without detecting their faces.

To solve the Night-time issue, it is intended to utilize dim lighting at night to prevent disrupting the kid's sleep, as well as to enhance child recognition and electrical object detection techniques in low-light settings, which was recognized as a flaw to be corrected.

The current system is a combination of three main functions that are integrated and tested for a child safety inside a domestic environment or, in other words, a room, and it is intended to be further developed as a solution capable of detecting the currently perceptible factors related to 2-3 children. In addition, vision-based depth concepts will be used to enhance commercialization and usability elements in the near future. Finally, the system will be implemented as a marketed profit-oriented solution that may be pushed for usage in child monitoring facilities in the future.

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Appendices

Appendix A: Plagiarism Results