

Advanced Child Safety and Monitoring System

Venkata Naga Rani Bandaru^{1*}, Jnana Prasuna Posina^{2*}, V. K. Ramarao^{3*}, Y. Rahul^{4*}, S. Tejaswi^{5*}, U. Durga Prasad^{6*}

Department of Information Technology, Vishnu Institute of Technology, Bhimavaram, Andhra Pradesh, India-534202
prasunaposina513@gmail.com

Abstract— In today's world, many families experience a common scenario where parents are engaged in demanding work schedules that stretch round the clock. This trend has led to an increasing concern regarding the safety of children left home without adequate oversight. To perform this problem, the aim is to establish a 'Human Action recognition-based Monitoring System'. The operational process involves extracting frames from the video stream generated by a webcam. These frames undergo analysis by a human action recognition model, which then produces outputs observing the various activities of the children.

Keywords— Children Monitoring application; Children Action Recognizing; Machine Learning; Image Processing.

I. INTRODUCTION

Parents plays an indispensable in the trajectory of their children's lives. The modern lifestyle characterized by a dual-income family structure has presented challenges in raising children. Leave working parents with limited care options. Videos are often unused in absence of these reports. The proposed system aims to address this gap by employing algorithms to detect human movement allowing for real-time monitoring of a child's activities at home. This innovative approach seeks to move beyond traditional surveillance methods. Instead of solely relying on manual monitoring the system uses algorithms to provide parents with timely updates on their children's activities making the process more proactive. This shift towards real-time processing improves the effectiveness of the child supervision of the nuclear family offering a dynamic and responsive solution for working parents. The proposed child surveillance system goes beyond conventional surveillance by introducing automation and real-time processing through human action detection algorithms.

II. METHODOLOGY

Data Collection and Data Preprocessing:

Data Collection: Gathering the dataset for this project was an extensive process, involving the collection of images from various sources such as the Stanford40 dataset and online outlets. Additionally, we captured real-time images of children on campus to incorporate a diverse range of data and enhance its representativeness. Labelling the dataset was a pivotal and labour-intensive stage. To streamline this task, we utilized specialized software known as 'labelling'. This advanced software enables the precise identification and marking of specific objects in the images through the use of bounding boxes. Each image in the dataset was accompanied by a corresponding .xml file, providing in-depth information about the bounding boxes and their associated labels. This meticulous labelling process is pivotal for the training and optimization of the human activity recognition model, ensuring that it can effectively distinguish and understand various activities within the images.

Training set and Testing set:

Here 80% of the images are training data and another 20% on images are for testing set. This division, known as a 4:1 ratio.

To generate training data for the TensorFlow model, the labelled images go through a multi-step process. The information stored, which essentially serve as a structured format for organizing the data. These .csv files contain details about the images, including the file paths, bounding box coordinates, and associated labels.

Training:

The training process of Faster RCNN consists of two main parts: training the Region Bidding network and training the search network. Initially, the input image is processed by a convolutional layer to extract the map. This convolution process uses filters to create a unique map that represents the features of the input image. Then RPA is trained. The image feature map is the input to RPA, and the network produces a set of product offerings and their associated scores as output. RPA adopts the sliding window method for low-level maps and passes the results to and from the regression layer. After this, the RCNN model is used to create the ROI pool. This step involves mapping a specific area and activating it. The flat map is then converted to RELU to generate predictions. ROI pooling helps reduce the next level of the network. Anchors help simplify defined areas.



Fig 1: Testing Data

III. EXPERIMENTAL RESULTS

The dataset was systematically splitted, providing 80% of images are used for training data and remaining 20% are test data. This segmentation is crucial to ensure that the machine learning model is exposed to a comprehensive range of scenarios during training, allowing it to generalize effectively to new, unseen instances.

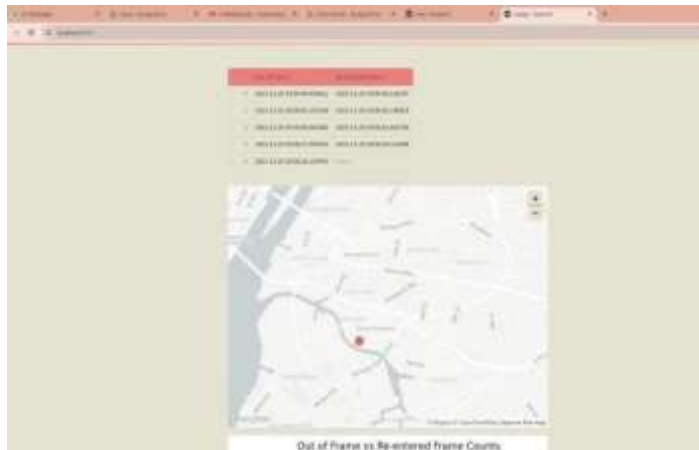


Fig. 2: Date and Time

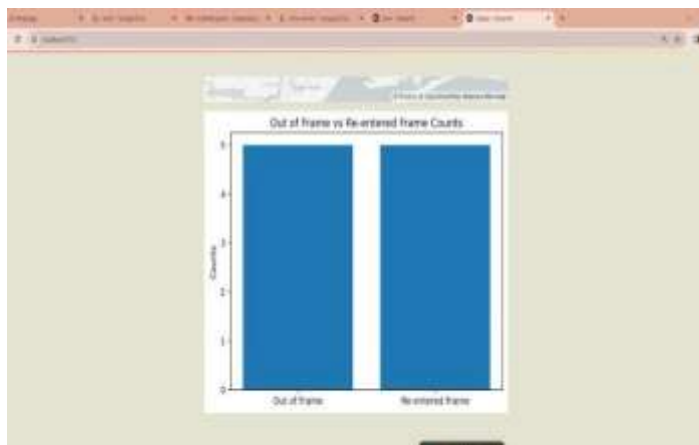


Fig. 3: Frame rate

IV. CONCLUSION

The child's monitoring system, employing through machine learning, demonstrates notable efficiency in recognizing movements performed by a child. However, it encounters challenges in accurately recognizing activities that involve multiple individuals, such as fighting, leading to a decrease in accuracy.

To enhance the system's accuracy and overall robustness, a well-curated and extensive dataset of actions becomes essential. A more diverse and comprehensive to accurately identify and differentiate activities involving multiple individuals. This approach ensures that the system becomes more adapt at handling various real-world situations, ultimately elevating its performance and reliability in child monitoring.

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