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Domestic Child Physical Abuse Detection using Machine Learning

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Abstract: Child physical abuse is a distressing social issue that requires timely intervention to protect vulnerable children. In this work, the main detection for child physical abuse is focused on slapping action. Slapping is still a common form of physical violence in a variety of contexts, including domestic violence, child abuse, and bullying. The ability to detect and recognise slapping incidents automatically can help prevent and address such harmful behaviours. Moreover, this work aims to develop an effective and automated system for detecting domestic child physical abuse using machine learning techniques. This work focusing on child physical abuse which on slapping detection using machine learning utilizes several libraries, including MediaPipe, OpenCV, NumPy, matplotlib, and math. Furthermore, the uses of OpenCV as a computer vision library, to pre-process the collected data. This may involve tasks such as video frame extraction, resizing, and noise reduction to enhance the quality of the input data. Furthermore, the MediaPipe library uses, which provides a collection of pre-trained machine learning models for a variety of computer vision tasks, including pose estimation and hand tracking. Moreover, uses of the libraries NumPy, matplotlib, and math to assist with data manipulation, visualization, and calculations within the application. In addition, the dataset is used to train a deep learning model, such as a convolutional neural network (CNN), to learn the visual patterns associated with slapping gestures and then a separate set of videos is used for testing to evaluate the performance of the proposed slapping detection system. Based on the experiment, the testing process has yielded a result indicating an accuracy rate of 90% which it has been classified as a slapping incident with a high level of certainty. Besides, there is a limitation in the system wherein if there are multiple individuals in the video and only one is not facing the camera, it may cause confusion and ambiguity in determining which person is performing the slapping action. The experimental results indicate that the suggested technique is effective at detecting slapping gestures.

Keywords: Child Physical Abuse, Slapping Action, Machine Learning Techniques

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1. Introduction

Children are vital human capital for the nation. This human capital can be optimally developed by providing a safe and conducive environment. Moreover, protecting children from neglect, abuse, violence, and exploitation is crucial and should be prioritised. Detecting and reacting to instances of child physical abuse as soon as possible is critical for ensuring the safety and protection of vulnerable children. However, detecting and reporting cases of domestic child physical abuse can be difficult due to a variety of factors, including the complexity of the abuse, apprehension to report, and limited resources for manual monitoring.

Machine learning, a subset of artificial intelligence, has shown immense potential in a variety of fields, including image and pattern recognition. Machine learning models can learn patterns and features that can be used to identify specific characteristics associated with child physical abuse by training algorithms on large datasets. In this context, the use of machine learning techniques has the potential to improve the accuracy and efficiency of abuse detection, allowing for timely intervention and protection of vulnerable children.

Cases of child abuse should be taken seriously and there is no compromise for perpetrators who involve ordinary children as well as special children. Childhood abuse can result in internal and external behavioural issues that can have long-term negative consequences [1]. Abuse has different effects on two children depending on their physical, psychological, and emotional health. The following are some of the issues that children and youth face:

(i) Depression
(ii) Anxiety Disorder
(iii) Mental Health Disorder
(iv) Learning and Eating Disorder
(v) May cause Sleep Disruptions

Next, below is the physical abuse that commonly happened to child:

(i) Slapping
(ii) Hitting which any objects
(iii) Kicking

Social Welfare Department (JKM) recorded 1,055 cases of child abuse nationwide from January to June of 2022. Physical abuse was the most common, according to Deputy Women, Family, and Community Development Minister Datuk Siti Zailah Mohd Yusof, with 578 cases (54.8 per cent). She stated in the news that these infractions are criminal under the Child Act 2001, and that three parties, such as medical practitioners, guardians, and babysitters, must assist in the case. They are required to report any cases of abuse [2]. Until September 2020, a total of 3,875 cases of child abuse, mistreatment, and neglect were recorded in this country. The following year's total was 6,061 cases, a decrease from 2019. Physical abuse cases totalled 1,571 in 2019, while 1,1,20 cases were recorded in 2020 until September [3].

2. Summary of Literature Review

In this work, machine learning method is used to detect acts of abuse. Machine learning models can continuously learn and adapt based on new data. Regular updates and retraining can improve the model's performance over time. In addition, machine learning models can be trained on large datasets, allowing them to learn from a diverse set of abuse and non-abuse examples. Moreover, this work can analyze patterns and indicators of child physical abuse more objectively and quickly than human observation alone. Comparing with [4], [5], and [6], this work focuses on the detection of slapping incidents involving children. It aims to develop a system that can identify slapping gestures or actions and classify them as instances of child abuse. Furthermore, analyzing visual or sensor data to identify specific patterns or gestures associated with slapping is one of the detection techniques. It could entail training a model on labelled data with examples of slapping and non-slapping actions. Other works may use motion detection, authentication, crowdsourced reporting, or streamlined reporting processes without focusing on slapping detection specifically. In [4], it utilizes motion sensors and authentication mechanisms with Raspberry Pi for child monitoring which focuses on technical aspects of child monitoring using motion detection and authentication. In [5], it leverages a mobile application for crowdsourced reporting which emphasizes crowdsourced reporting and community involvement in reporting child abuse cases. Next, comparing proposed work with [6], the work employs an online system for streamlined reporting by mandated reporters which designed centered around an online system specifically designed for mandated reporters to submit child abuse reports.

3. Materials and Methods

In this section, there are three stages that lead to the work's success by acknowledging software function.

3.1 Block Diagram

A block diagram is illustrated to aid in the most basic understanding of the system's software implementation. The relationship between input, process, and output is represented by the block and arrow. In other words, a block diagram of the system is created to provide a quick overview of the system's building blocks and their interactions. Figure 1 depicts the block diagram of domestic child physical abuse detection using machine learning.

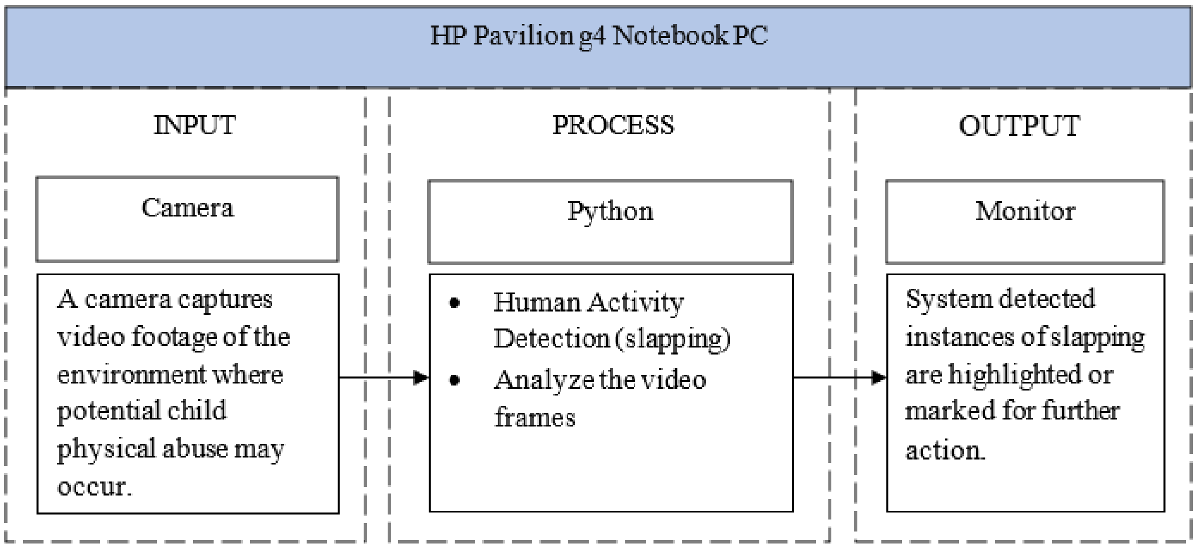

Figure 1: Block diagram of domestic child physical abuse detection using machine learning

Figure 1 shows the block diagram for domestic child physical abuse detection using machine learning. This work was developed using HP Pavilion g4 Notebook PC. The camera captures real-time or recorded video footage, which serves as the primary input for the system. The video footage is processed offline on a laptop or similar computing device. Machine learning algorithms are employed to analyze the video frames and identify slapping actions. The algorithms are trained using labeled data that includes examples of both slapping actions classified as child abuse and non-abusive actions. The system provides an output in the form of monitoring. This could include a visual display or an alert mechanism that indicates instances of slapping gestures associated with child physical abuse. The monitoring output serves as a means to detect and potentially intervene in cases of child abuse.

3.2 System's Operation

Figure 2 shows the flowchart of the domestic child physical abuse classification using machine learning. The flowchart explained the techniques of how the system worked.

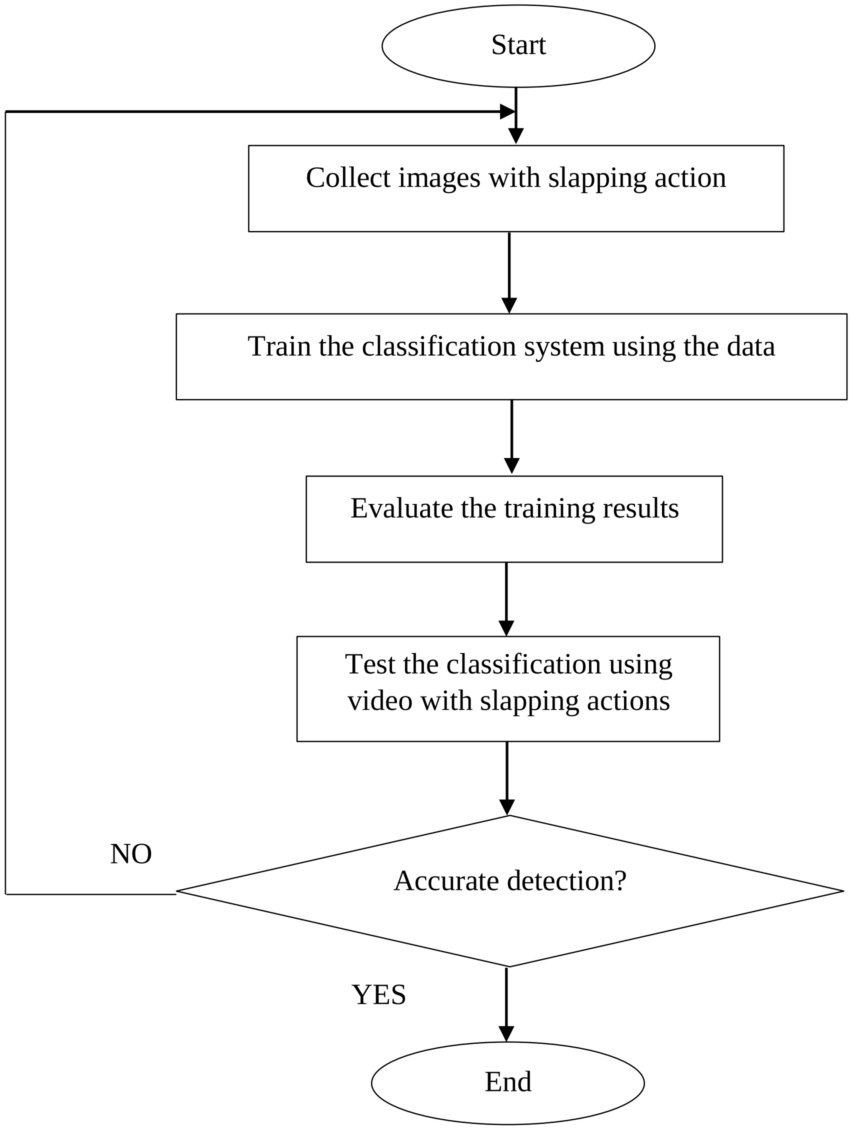

Figure 2: Flowchart of domestic child physical abuse detection using machine learning

Based on Figure 2, the work starts by loading the acquired images, which contain instances of slapping, as the initial dataset. Identify potential sources for collecting the images. In this work, manually search for images that meet the defined criteria has been used as collecting data. By using search engines, social media platforms, or online archives to find images that depict slapping actions involving children. These may include publicly available datasets, online platforms, research institutions, or collaborations with relevant organizations working in child protection or abuse prevention. Moreover, in this step diversity and variations needed which seek diversity in the collected images, considering variations in lighting conditions, backgrounds, child ages, gender, ethnicity, and other relevant factors. This helps improve the model's generalization ability. Python is utilized as the programming language and relies on various libraries such as OpenCV, MediaPipe, Matplotlib, and NumPy. These libraries provide essential functionalities for image processing, pose estimation, visualization, and numerical operations. Preprocess the collected data to ensure its suitability for training. This involves tasks such as resizing images, normalizing pixel values, and converting the data into a consistent format.

Next, train the selected classification model using the labeled training data that learns to differentiate between slapping actions and non-slapping actions involving children. This involves optimizing the model's parameters based on the extracted features and corresponding labels. The training process aims to find the best model that can accurately distinguish between slapping and non-slapping actions. Then, evaluate the trained model's performance using the validation set. Assess metrics such as accuracy, precision, recall, and F1 score to determine how well the model generalizes to new data and compare the system's predictions with the ground truth labels of the test videos. This evaluation helps in understanding the strengths and weaknesses of the model and guides further improvements or refinements to enhance its effectiveness in identifying child physical abuse through slapping actions.

In addition, testing the classification system using videos with known instances of slapping actions, we can assess its ability to accurately detect and classify such actions in real-world scenarios. This step helps validate the system's performance and provides insights for further improvement or optimization if necessary. Additionally, it will analyze the results and identify areas where the classification system may have made errors or shown limitations More, the term "accurate detection" refers to the classification system's ability to correctly identify instances of slapping actions involving children. Achieving accurate detection means that the system can effectively differentiate between slapping actions and non-slapping actions.

3.3 Detection system using pose landmark

In this work, initialize the pose detection model is by using MediaPipe and OpenCV. The reason of uses MediaPipe compared to other deep learning software such as YOLO is because YOLO is a specialized object detection framework that is known for its speed and real-time detection capabilities, whereas MediaPipe is a multi-purpose framework with pose estimation and gesture recognition modules that can be used for slapping detection [3]. The decision between the two is influenced by factors such as the slapping detection specific requirements, available resources, and the desired trade-off between accuracy and speed.

In addition, in MediaPipe library have Pose Landmark which lets to detect landmarks of human bodies in an image or video. The body pose landmark allows to identify key body locations, analyze posture, and categorize movements. It uses machine learning (ML) models that work with single images or video. First, some mandatory model parameters must be provided, and this case will aid in model testing later in the process. Initialize the media pipe pose main class in example "*solutions.pose"* with a variable that will hold the instance of that media pipe pose detection model and then, stored the instance of pose detection class in "*mp_pose"* variable that use this variable to call the Pose method. The pose landmark creates a pose detection function that assists in performing the detection in a modular manner, making the entire pipeline more efficient.

In [7], the pose landmark model tracks 33 body landmark locations which indicating the approximate position of the following body parts. The MediaPipe library's Pose Landmark model is a pre-trained machine learning model that can detect and track 33 key landmarks on the human body [7]. These landmarks indicate particular anatomical points and can be used in a variety of applications, involving pose estimation, motion analysis, gesture recognition, and virtual reality. The trained models were tested using various elbow angles to determine their accuracy in detecting slapping on child physical abuse. This Pose Landmark model is trained on large-scale datasets through deep learning techniques along with is intended to work well in real-time scenarios. It enables developers to create applications that analyse and interpret human poses from images, videos, or live camera feeds by providing a reliable and accurate estimation of body landmarks.

4. Results and Discussion

4.1 Analysis: Testing Slapping between Adult-to-adult and Adult-to-child

The experiment on slapping between adult-to-adult and adult-to-child is carried out by testing on video dataset. The trained models were tested using various elbow angles to determine their accuracy in detecting slapping on child physical abuse. The testing and the output results are shown in Figure 3.

(a) (b)

Figure 3: Condition result when slapping by (a) adult-to-adult and (b) adult-to-child

Referring to Table 1, there are two parameters that have been set in this experiment which are the adult-to-adult and adult-to-child. Based on the results of the experiments, adult-to-child parameter achieved 90% accuracy. Meanwhile, the adult-to-adult parameter achieved 80% accuracy. In experiment 1, the video is not detected as slapping because does not adequately capture the complexity of slapping motions or fails to consider relevant features. While, the experiment 2 not detected because angle or performed by individual make the detection is not accurate. This result indicates that slapping between adult-to-adult and adult-to-child performance considering that it is capable of performing perfectly.

Table 1: Slapping Test on Adult and Child (/ - detected and x - not detected)

Slapping Testing	Experiment										Accuracy (%)
	1	2	3	4	5	6	7	8	9	10	
Adult-to-Adult	x	x	/	/	/	/	/	/	/	/	80
Adult-to-Child	x	/	/	/	/	/	/	/	/	/	90

4.2 Analysis**:** Testing Slapping vs non-slapping

The slap detection experiment below performs two hand movement conditions. The output results are shown in Figure 4. In this experiment, the first-hand movement was a slapping. The second-hand movement is touching the shoulder. Both of these conditions are determined by the training the model with angle of elbow. This is so because, movement of touching the shoulder have a bit similar with slapping. This case can be categorized based on several factors. Firstly, slapping usually involves a larger and more dramatic movement of the hand and arm. The motion is often fast and abrupt. Touching the shoulder, in comparison, is typically a smaller and more controlled movement. It can be a gentle tap or a brief placement of the hand on the shoulder. Second factor, the intensity of movement. slapping involves a more forceful contact with the shoulder, resulting in a louder sound and a stronger physical impact. Touching, on the other hand, is a gentler, lighter contact with the shoulder.

(a) (b)

Figure 4: Condition result when (a) slapping is detected and (b) other motion is detected

Figures 4 illustrate the successful detection of slapping and other motion results in various hand movements. Table 2 shows the accuracy results for two conditions which is slapping and other motion study the effectiveness of the hand movement if one of the conditions be performed. Based on the experiment of other motion above, there are a few reasons why the model not detecting non-slapping. Firstly, because the model's architecture or training method fails to adequately capture the complexity of non-slapping actions, making it difficult to detect them accurately. Second, because the model's features do not effectively capture the distinctive characteristics of non-slapping actions, which leads to lower detection accuracy. Lastly, because the model was trained on a dataset that was heavily skewed towards slapping actions and had a limited representation of other motion actions, it had difficulty to detect and classify non-slapping actions accurately.

Table 2: Slapping vs non-slapping (/ - detected and x - not detected)

Conditions	Experiment										Accuracy (%)
	1	2	3	4	5	6	7	8	9	10	
Slapping	x	x	/	/	/	/	/	/	/	/	80
Other Motion	/	x	x	/	x	x	/	/	/	/	60

*Other motion in the experiment referring to holding shoulder, pinching ear and pushing shoulder

4.3 Summary of testing analysis and design limitations

Based on the results of Table 1 and 2, it is possible to conclude that the performance of slapping detection with various parameters and conditions. The difference in accuracy between parameters of adult-to-adult and adult-to-child is 10%, where adult-to-adult parameter achieves 80% accuracy and adult-to child achieves 90% accuracy. In other hand, for difference in accuracy of condition parameters which is slapping and non-slapping. Slapping parameter achieves 80% accuracy while non-slapping parameter achieves 60% accuracy. Moreover, there have limitation in the system which if there are multiple individuals in the video, and only one person is not facing the camera, it can introduce confusion and ambiguity in identifying which person is performing the slapping action. In fine, pose landmark detection of various dataset is applicable for test on adult-to-adult and adult-to-child.

5. Conclusion

According to the results testing, the overall work has successfully achieved goal of developed an effective and automated system for detecting domestic child physical abuse (slapping) using machine learning. This work's goal was to develop an automated system that can detect instances of slapping in videos or real-time streams. In this study, a comprehensive dataset of domestic child physical abuse in slapping cases was collected, which was annotated and utilized for model training and evaluation. The dataset includes image and video recordings, as well as non-slapping samples for comparison. The trained models were tested using various elbow angles to determine their accuracy in detecting slapping on child physical abuse. This work used the MediaPipe library, which contains powerful tools for real-time hand and gesture recognition. As a result, the system is capable of tracking and analyzing hand movements in video frames or live camera feeds. In addition, through the application of machine learning techniques, such as image or video classification, this work seeks to identify and address cases of child physical abuse. It proved to be robust and reliable, consistently detecting slapping actions with few false positives or false negatives. However, there is a limitation in the system that if there are multiple people in the video and only one of them is not facing the camera, it can cause confusion and ambiguity in determining who is performing the slapping action.

For future work, recommended to expand the labelled dataset of slapping and non-slapping hand to include examples of multi-person scenarios where slapping actions occur and incorporating new features or techniques. Use multi-person pose estimation techniques to accurately identify and track multiple individuals' poses and body landmarks in video footage. This will provide useful information about the spatial relationships and interactions between people during slapping actions, allowing for more precise detection. Additionally, annotate the dataset of multi-person hand tracking to identify the individuals involved in the slapping actions for training and evaluation purposes. Moreover, recommended to expand the scope of the work to include other forms of physical abuse beyond slapping which incorporating additional abusive actions, such as punching or kicking, can enhance the system's effectiveness in detecting a broader range of child physical abuse. Overall, the system performed well in detecting slapping actions and demonstrates the potential for machine learning to contribute to societal well-being by helping detect and prevent child physical abuse, ultimately ensuring a safer environment for children, achieving a high level of accuracy which it able to distinguish between slapping actions and other hand gestures.

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References

[1] Gupta, V. (2022, October 18). YOLOv7 Pose vs MediaPipe in Human Pose Estimation. LearnOpenCV. https://learnopencv.com/yolov7-pose-vs-mediapipe-in-human-pose-estimation/

[2] A. Srinivasan, S. Abirami, N. Divya, R. Akshya and B. S. Sreeja, "Intelligent Child Safety System using Machine Learning in IoT Devices," 2020 5th International Conference on Computing, Communication and Security (ICCCS), 2020, pp. 1-6, doi: 10.1109/ICCCS49678.2020.9277136

[3] Malaymail, "Child abuse: 1,055 cases recorded nationwide from Jan- June this year, says deputy minister" Bernama (Pertubuhan Berita Nasional Malaysia), Sept. 6, 2022. [Online], Available: https://www.malaymail.com/news/malaysia/2022/09/06/child-abuse-1055-cases-recorded-nationwide-from-jan-june-this-year-says-deputy-minister/26818. [Accessed Sept. 6, 2022].

[4] O. Permatasari, S. U. Masruroh and Arini, "A prototype of child monitoring system using motion and authentication with Raspberry Pi," 2016 4th International Conference on Cyber and

IT Service Management, Bandung, Indonesia, 2016, pp. 1-6, doi: 10.1109/CITSM.2016.7577516.

[5] Dhruv Chand M, S. Sankaranarayanan and C. Sharma, "Project Jagriti: Crowdsourced child abuse reporting," IEEE Global Humanitarian Technology Conference (GHTC 2014), San Jose, CA, USA, 2014, pp. 609-613, doi: 10.1109/GHTC.2014.6970346.

[6] Knodell, R. J. (2020, May 27). Online System for Child Abuse & Neglect Reporting (OSCR). Missouri Department of Social Services. https://apps.dss.mo.gov/OnlineCanReporting/default.aspx

[7] K. (2022, March 8). Building a Poor Body Posture Detection & Alert System Using MediaPipe Body Tracking. LearnOpenCV. https://learnopencv.com/building-a-body-posture-analysis-system-using-mediapipe/