ECE4094 Progress Report

Project Title:

Automated Video-based Epilepsy Detection and Classification using Deep Learning

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Objectives

The main intention/ objective of the project 'Automated Video-based Epilepsy Detection and Classification using Deep Learning' remains unchanged. As a revisit, this project is aiming to develop a deep-learning-based method to achieve classification and detection of epileptic seizures using video as input. For now, we are on track, so there is no need to change the original plan. A few months later, the project will move to the second stage, which is model training and testing. In terms of the budget, we have ordered more Nvidia Jetson Xavier as planed. There is no device damage or resource waste in the first stage of the project, the budget is totally in control.

Progress to date

Functions available:

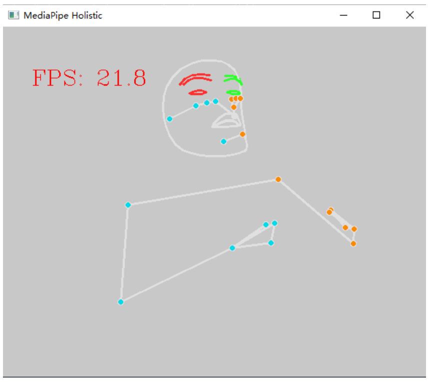
- Input video resize:
  Since the video size/resolution could vary for different video-recording devices, a video resizes section has been attached to the front of the software. The function of resizing could be enabled or disabled by control the argument of the command line.
- Video jump start command by user
  The jump start function can be used to jump over some useless video clip. (Usually, the video provided by Alfred hospital will have a section be recorded before epilepsy seizures happen). By doing so, the efficiency of dataset collection can be improved.
- Visualization display options control
  There are three settings for image display: on the original image, on a blank image or no display. When validating the performance of the pose estimation model, it can be set to display mode, and when processing a lot of videos, the display can be disabled.
- Data set automated saving and arrange
  All the data collected is saved automatically and placed in order (by video name). The joints information is saved in pickle files and the optical flow image will be saved as png files.
- Optical flow motion anaylsis
  Optical flow is a model used for motion analysis, it is one of the methods we used to generate the dataset. (The theory is discussed in the design specification.)
- Pose estimator
  There are two pose estimators currently available: the lightweight-human-pose estimator and the MediaPipe pose estimator. Both of them is used to extract the pose/ skeleton of a human body. Hence can be used as a tool to record body movement. (The theory is discussed in the design specification.)

<u>Details of each function and there purposes is discussed in the design specification document.</u>

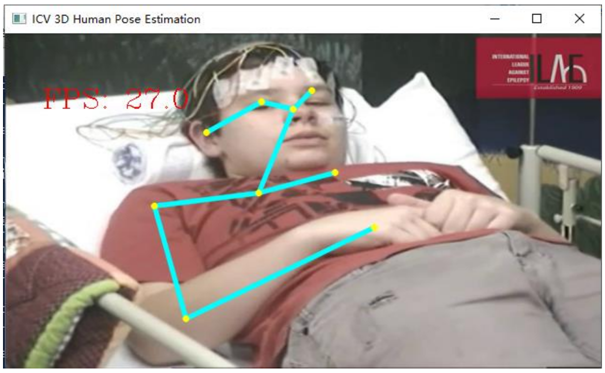
The following figure shows some aspect of the current status of the project.

MediaPipe pose estimation shown on original video:

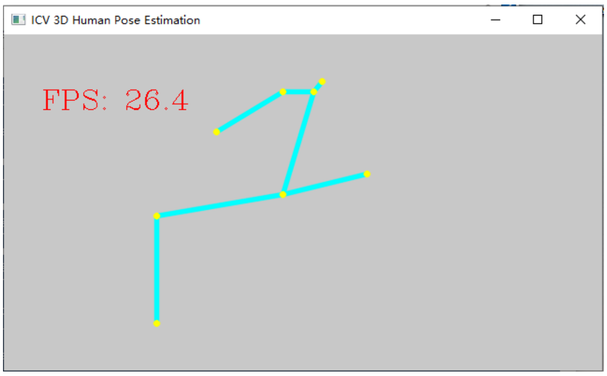
MediaPipe pose estimation shown on blank images:



Lightweight-human-pose-estimation with input data auto resize:

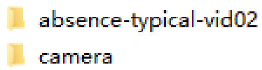


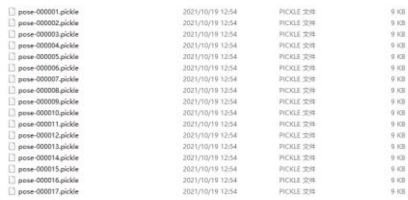
Lightweight-human-pose-estimation with input data auto resize displayed on blank image:



Optical flow motion anaylsis:

Dataset auto-saving:





Work to be completed

The remaining works for this project are about model refinement for the pose estimation software, as the current performance has not been perfected. It could be improved by the video resizing algorithm. Currently, we were directly resizing the video, which would have the possibility to make the video distorted. And Dr Deval and I both agree that the official start of the dataset collecting stage should be set after we have a robust pose estimation model. The data saving process is fully automated and we have Alfred hospital providing enourmous video data, hence there is no need to wory about the workload on collecting data. Once the process starts, the dataset should be fully collected within a week.

The main focus and the main task left is the model training. Train a deep learning model will always take time, and several aspects of the model will need experiments to see the performance. I consider this should be the most time-consuming work in the next semester. Learning the interface with Monarch would also take time.

Finally, I expect the workload for report writing and finalising will be heavy. The plan for writing the skeleton of the final report is to start in 2022-Feb, by doing this I can reduce the workload in later months and it will improve the quality of the final report without a doubt.

The Gantt chart below gives a visual illustration of the timeline structure.

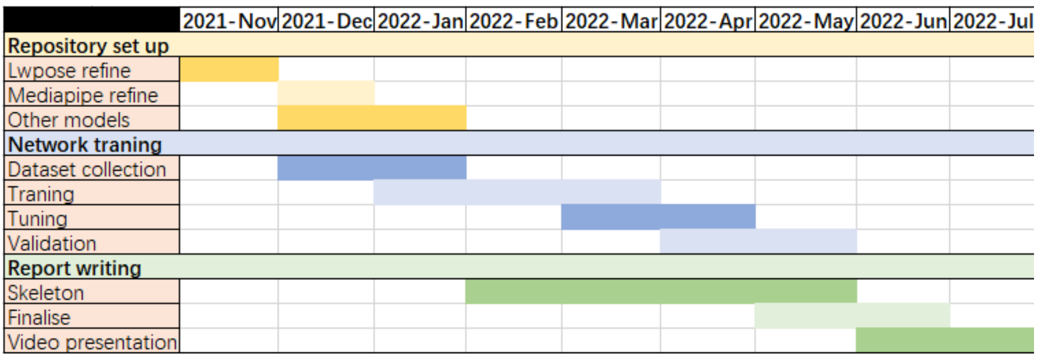


Fig 1. Timeline for the remaining project

Tasks and expected time allotment		
Task	**Expected hours**	**Start time**
Pose estimation model refinement	**15**	**2021-Nov**
Dataset collection	**20**	**2021-Dec**
Model traning and testing	**100**	**2022-Jan**
Final report	**60**	**2022-Feb**
Video presentation and poster	**10**	**2022-Jun**