

Configuration Manual

MSc Research Project
Data Analytics

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Project Submission Sheet
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Configuration Manual

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1 Abstract

The aim of this project is to design a fall prediction system with a hybrid GCN-LSTM model that can be integrated with real-time systems and has higher accuracy and reliability than existing methods using visual data. The biggest contribution of this research is to reduce false positives with a novel approach by weighting the relationship of certain joints of the human body and their distance from the ground.

2 System Requirements

- RAM: 8GB at least 16 or higher preferred.
- EFPDS datasets. -> <https://gram.web.uah.es/data/datasets/fpds/index.html>
- OpenPose
- CUDA Nvidia preferred

3 Software Requirements

- Python Version: Python 3.8 or higher.
- Visual Studio Code

4 Installation Guide

4.1 Environment Installation

- Install 3.7 or higher version of Python
- Install OpenPose and CUDA if your workstation has a compatible GPU

4.2 Install Required Packages

All necessary packages must be installed. Sample commands below:

```
pip install opencv-python
pip install sklearn
pip install matplotlib
```

4.3 Necessary Libraries:

```
import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.optim import Adam
from torch.utils.data import DataLoader
import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score
import os
import json
```

Figure 1: Import Commands

5 Data Preparation

5.1 Data Collection

In this project EFPDS dataset was used. There are three different zip folder train, validation, test. Since dataset includes thousands of images, downloading them by manually was a better solution. Official website is <https://gram.web.uah.es/data/datasets/fpds/index.html> . It is open dataset to public.

5.2 Data Preprocessing:

With this step all images will be prepared for OpenPose usage. With this class we are cleaning, resizing and sharpening images to get better keypoints of people on OpenPose. This class expects two input paths. It reads every image from input_folder and pre-processed images are saved on output_folder. Please give correct paths while using this class. In the dataset train has different folder under train as split1, split2 so I flattened all of them under train folder so every image was under same folder. Do not forget to run this step each folder train, validation and test.

```
class FallPredictionPipeline:
    def __init__(self):
        self.data_preparation = DataPreparation(
            input_folder="./openpose/examples/train",
            output_folder="./openpose/examples/train/pre=processed_images"
```

Figure 2: Data Preprocessing

5.3 Data Processing and Feature Extraction:

After having preprocessed images, we can use OpenPose to extract key points of people skeleton from images. To run OpenPose use this command:

```
bin\OpenPoseDemo.exe --image_dir train/preprocessed_images --
write_json train/output --write_images train/processed --
scale_number 4 --scale_gap 0.25 --model_pose BODY_25
```

This command creates key points and processed images on output and processed folders. When you have keypoint outputs then we are ready to complete Feature Extraction step.

FeatureExtraction class also expects two different input path. While the input folder is used to read the key points created with OpenPose, the output_folder is used as the path where the calculated data will be saved as labels.

```
self.feature_extractor = FeatureExtractor(  
    input_folder="./openpose/train/output",  
    output_folder="./data/json_output/featureExtraction/train"
```

Figure 3: Feature Extraction

6 Model Implementation:

GCN and LSTM models are created here. The data obtained with the Feature Extraction step is given as input to the GCN model. The calculated labels and keypoints are given to the GCN model to learn the decision according to the FallDecision label. The outputs obtained from the GCN model are given as input to the LSTM model and it is aimed to complete the temporal learning here.

```

303         t1jje_bacp = o2.bacp.j0iu(fojqae_bacp, t1jje_ysame)
305         t1 t1jje_ysame.oq2awp(„“)2eou);
307         fo1 t1jje_ysame ju o2.j0itju(fojqae_bacp):
309         b1b6j1ue_q9c9 = []
310
311         q6t b1b6b9c bcu suq j2caw q9c9(fojqae_bacp):
312             # b1b6b9c q9c9 fo1 ocm suq f21w
313
314             l6tluu 26it1c(μjqaeu[-1]) # n2e f1u j2c7 μjqaeu 2c9e
315             „ (μjqaeu) „ = 26it1j2caw(x)
316
317             q6t fo1uawuq(26it1, x):
318
319                 26it1c = uu.f1ueu(μjqaeu_2c9e, oqibnq_2c9e)
320                 26it1j2caw = uu.f1ueu(jubnq_2c9e, μjqaeu_2c9e, unu j9w6a,2, p9cju_t1j2caw_1ue6)
321                 2nb6c(f21wq6t, 26it1, j1u1c ())
322
323                 q6t j1u1c (26it1, jubnq_2c9e, μjqaeu_2c9e, unu j9w6a,2, oqibnq_2c9e):
324                     cj292 f21wq6t(uu.wq6tj):
325                         # f21w wq6tj
326
327                         l6tluu 26it1.oqibnq j9w6a(x*weou(q1w=0)) # o19bu-j9w6j awp9q1u6
328                         x = 26it1.j1ueu(q6B + x) # coμp1ue w1μ 26it1-j9w6j
329                         96B[1] = x(ue1bypoua,2)*weou(q1w=0) t1 j6u(ue1bypoua,2) > 0 6tj6 foucp„2eou2 j1k6(x[1])
330                         ue1bypoua,2 = (coj == j)„uou2eou(9e tnbj6_1ue6)[0]
331
332                         fo1 j ju b1u66(x*2c9e(0)):
333                             96B = foucp„2eou2 j1k6(x)
334                             uon1 coj = 6q6e j1uqex
335
336                             q6t fo1uawuq(26it1, x, 6q6e j1uqex):
337
338                                 26it1.oqibnq j9w6a = uu.f1ueu(μjqaeu_q1w, oqibnq_q1w)
339                                 26it1.j1ueu = uu.f1ueu(jubnq_q1w, μjqaeu_q1w)
340                                 2nb6c(o1wq6t, 26it1, j1u1c ())
341
342                                 q6t j1u1c (26it1, jubnq_q1w, μjqaeu_q1w, oqibnq_q1w):
343                                     cj292 o1wq6t(uu.wq6tj):
344                                         # ocm wq6tj

```

Figure 5: GCN & LSTM Model

7 Model Evaluation

There are couple of parameters to have better performance. The learning rate was initially set to 0.001. Training was performed with combinations of 32 and 64 dimensions and different numbers of epochs and different learning rates. Parameters can be changed on fallprediction.py file. Hyperparameter settings were made to find the most suitable values. Finally, among the evaluation criteria, F1 score, Accuracy, Precision and Recall metrics were considered. With these I was able to calculate False Positive rates as well.

Epoch	Dim	F1	Accuracy	Precision	Recall
10	64	80.92%	82.92%	79.82%	82.04%
10	32	83.45%	84.02%	76.82%	91.33%
25	64	84.06%	84.97%	79.02%	89.78%
25	32	84.15%	84.56%	76.92%	92.88%
50	64	82.76%	82.92%	74.63%	92.88%
50	32	80.58%	81.83%	76.24%	85.45%

Table 1: Results with different parameters

8 Execution of the Code

1. Download EFPDS Dataset from given URL
2. Unzip and flatten the subfolders into a folder
3. Open the folder in Visual studio Code
4. Run the Data Preparation step first with correct paths
5. Run OpenPose commands on your command window with correct paths
6. Run Feature Extraction with correct paths
7. Train & Evaluate Model with correct paths

9 Conclusion

According to the results obtained, it is possible to say that the study was completed successfully, and it was determined that it would make a great contribution to the literature for real-time fall detection applications with some improvements. When examined in detail, the important points contributing to the success of the model can be defined as the requirement of a powerful GPU and sufficient and well-detailed dataset. The layers and epoch numbers of the model are other factors affecting the success of the model. Thanks to the hybrid model, the strengths of both models were revealed in this study, and higher success was achieved compared to standalone models.