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Use of Pose Estimation in Elderly People Using Machine Learning.

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ABSTRACT

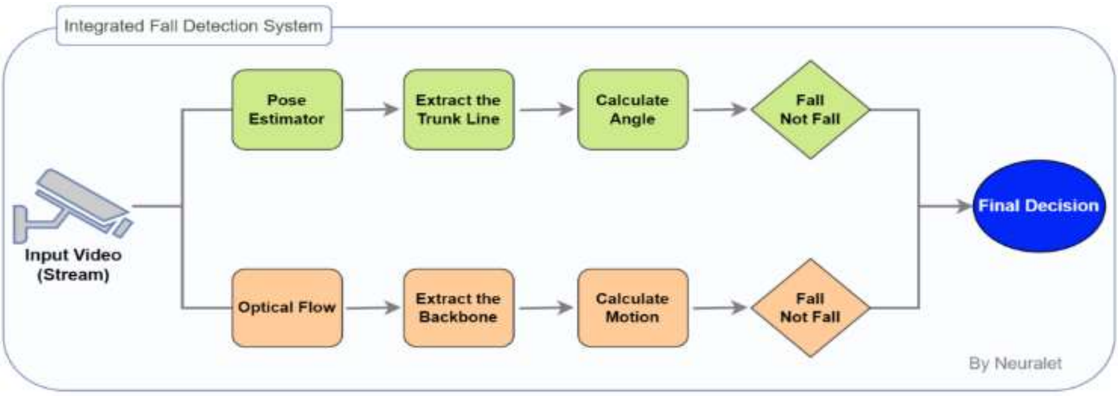
The use of pose detection in elderly people using machine learning techniques is to explore how machine learning can accurately detect and analyze the poses of elderly individuals. By leveraging advanced algorithms, we can track movements, assess balance, and detect potential fall risks. The application of pose detection in elderly care can greatly enhance their safety and well-being. Through this research, we aim to develop robust and reliable systems that can assist caregivers in monitoring and providing timely support to elderly individuals. For pose detection in elderly individuals, we are utilizing machine learning algorithms such as Convolutional Neural Networks (CNNs),Assistive technology. These algorithms are trained on large datasets of labeled pose data to learn the patterns and characteristics of different poses. Key words: Labelled pictures, CNN.

INTRODUCTION

Aging populations are a global concern, emphasizing the need for innovative solutions in elderly care. Our project focuses on leveraging machine learning techniques, specifically pose estimation, to enhance the well-being of elderly individuals. Pose estimation involves tracking the body's position and orientation, providing valuable insights into daily activities and health . The integration of machine learning aims to analyze and interpret these poses, offering a proactive approach to elderly care.

PROBLEM STATEMENT

The aging population presents a unique set of challenges in healthcare, including a higher risk of falls and related injuries. Addressing this issue requires an accurate and non-intrusive method for monitoring elderly individuals. The problem at hand is to develop a machine learning-based pose estimation system that can effectively track and analyze the body movements of elderly people. This system aims to enhance fall detection, assess mobility, and provide valuable insights into their overall well-being, contributing to proactive and personalized healthcare for the elderly.



FUTURE ENHANCEMENT

- Camera-based pose estimation utilizes computer vision and machine learning algorithms to analyze visual data captured by cameras.

- Machine learning models, such as CNNs or RNNs, can be trained on diverse datasets of elderly individuals performing various poses.

- Data augmentation techniques can help increase the diversity and size of the training dataset.

- Transfer learning allows leveraging pre-trained models on related tasks to improve pose estimation accuracy.

- Model optimization techniques, like pruning or quantization, can improve the efficiency of pose estimation algorithms.

- Real-time pose estimation using cameras can enable monitoring of elderly individuals' movements and assist in fall detection or healthcare applications.

DATA PRE-PROCESSING TECHNIQUES

- Federated Averaging(DATA PROFILING) : After local training, the weights of each client's model are averaged to create a new set of global model weights. This is the key step in federated learning, where knowledge from different clients is aggregated to improve the global model.
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- IMAGE RESIZING: The images in the dataset are resized to specified ‘image_size’=[244,244] and these images are feeding to neural networks.
- Batching: The data is batched to training .[batch_size :32] and federated approach is used.
- Shuffling: The function shuffles the data set to improve the randomness of images.This helps in preventing the model from memorizing the order of the data.

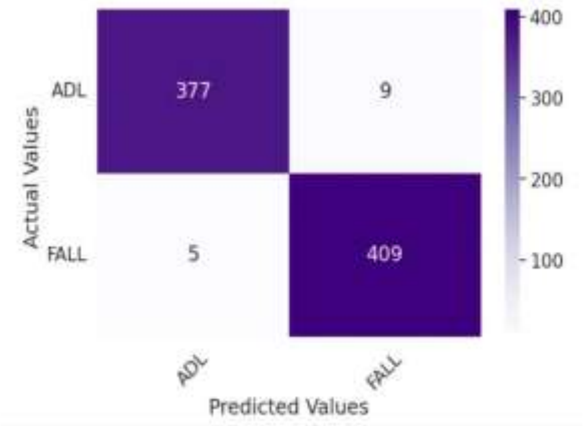
MODEL EVALUATION METRICS

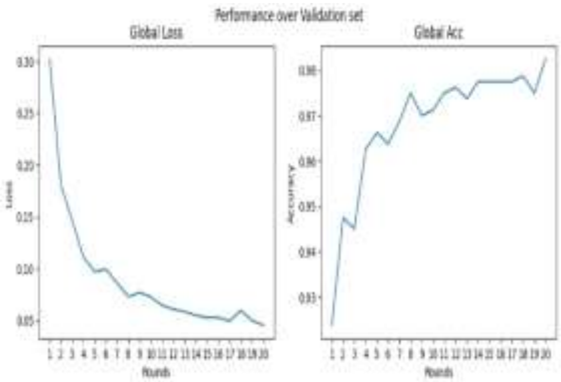
Accuracy is an assessment metric that counts the number of correct predictions a model makes overall.

Precision measures a model's accuracy in foreseeing positive labels. The proportion of your results that are relevant is known as precision.

Recall is calculated by dividing the total number of real positive cases by the number of true positive forecasts.

The F1-score, which is the harmonic mean of recall and precision, offers a balance between the two.





CONCLUSION

We presented an embedded system for accurate fall detection with very few false alarms in this study. The utilisation of depth maps and accelerometric data is the basis for fall detection. A tri-axial accelerometer is used to show whether the person is moving and to signal the possibility of a fall. The programme extracts the subject, computes the features, and then runs the SVM-based classifier to validate the fall alarm if the measured acceleration is greater than a presumptive threshold value. We show that the distance between the subject's centre of gravity and the floor, in addition to the person's surrounding features, contribute to accurate fall detection. The floor equation's parameters are automatically determined.

The individual is only extracted if the accelerometer detects movement on the part of the subject. By comparing the current depth map with the online-updated depth reference map, the individual is extracted. The system protects the user's privacy and enables inconspicuous fall detection. The suggested fall detection method is best suited for indoor use, though, because sunlight interferes with the pattern-projecting laser, which is a drawback of the Kinect sensor.

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