Towards maximizing the potential of wearable sensors and machine learning for health monitoring in elderly: Using demographics and gait to predict falls and quality of life

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Summary

This study predicted quality of life accurately from a few personalized and gait features that were calculated from wearable sensor signals. A digital platform for fall risk communications and fall risk models have been previously developed. The results demonstrated the feasibility of predicting both quality of life and fall risk using the same set of features, highlighting strong potential for remote/home monitoring and enhancing efficiency in clinical settings.

Introduction

Frailty among the elderly is becoming an increasing concern in Singapore. Accurate fall risk and functional abilities predictions are essential for frailty management. Fall indicators have been extensively studied in recent years and identified using wearable sensor signals, mostly inertial measurement units (IMU), and questionnaires [1]. Quality of life is recognized as one of the important fall indicators in fall risk predictions. Quality of life is generally accessed via EQ-5D test by clinicians and each round could take up to 5 minutes to complete [2]. Our project aims to implement a digital tool for fall risk communication that can be used in both clinical and community settings. To maximize the potential of wearable sensors and machine learning for monitoring health in older adults, if quality of life can be predicted from the same set of features as our fall risk predictions, our models will be both time-efficient and cost-effective.

Methods

The PIONNER dataset was used in this study in which over 2500 participants above 60 years old were recruited for data collection, completing a comprehensive clinical examination (systemic, ocular, and non-ocular) in SERI clinic and a 6-minute walk test wearing 3 IMU sensors [3]. Linear logistic regression model was first used to train the quality of life predictive model with data from **1283** participants (80% were for training and the rest were for testing). For each participant, **eight personalized**: (1) gender; (2) age; (3) hearing_loss; (4)visual_loss; (5) fear of falling; (6) cognitivite; (7) fallcutact; (8) fall history; and **seven gait features**: (1) Var_stride time; (2) Var_stance time; (3) Var_swing time; (4) Cadence; (5)Asymmetry; (6) Var_stride length_right (7) Var_stride length_left; were extracted and used as inputs of predictive models. Quality of life (EQ-5D test) was used as the outputs of models. Mean squared error was used as the metrics. The model was regulated by using ElasticNet (α=0.01, L1=0.5). The importance of each feature was visualized via SHAP plots.

Results and Discussion

Four gait features: (4)-(7) and **four** personalized features: (1), (2), (7), (8) were selected via ElasticNet for quality of life predictions (Figure 1). Lower mean squared error of 0.008 has been achieved with both personalized features and gait features than that of 0.009 with only using the four gait features.

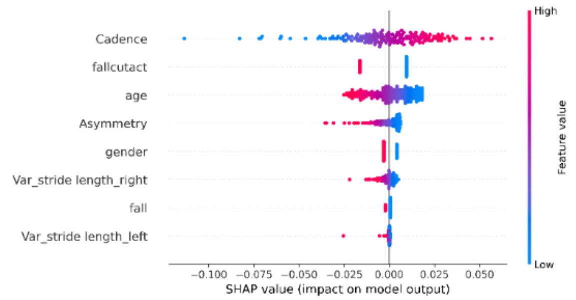

Figure 1: SHAP values of the selected eight features for quality of life predictions; Var: Variability; fallcutact: cut activities due to falls; fall: retrospective falls.

The presented results showed the feasibility of predicting quality of life accurately from gait features fused with or without personalized features. Cadence was with the highest impact among gait features. Variabilities in gait features were more informative than means and deviations, which aligns with the findings in our fall risk models. Similarly, demographics: gender and age, and fall history were also important factors in fall risk predictions.

Predicting quality of life directly from raw wearable sensor signals using **LSTM-CNN** model is under training to make the predictions compatible to real-time uses. The trained model will be embedded into a **fall risk communication tool** and evaluated in real environments.

Conclusions

Our results presented high accuracy in life quality predictions from the selected 8 features. These results presented potential for embedding functional ability predictions into the fall-risk communication platform.

References

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