Fall Risk Prediction Using Machine Learning and Computer Vision: Development of a Clinical Decision Support System in Nursing

NCT07000981

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1. MATERIALS AND METHODS

1.1. Type of Research

This research is planned as a design and development research since an innovative system will be developed.

1.2. Place and Time of the Research

The study was conducted in Turgut Özal Medical Center Physical Medicine and Rehabilitation service between December 2024 and May 2025.

1.3. Population and Sample of the Study

The population of the study consisted of all patients treated in Turgut Özal Medical Center Physical Medicine and Rehabilitation service. The sample size of the study was determined as 161 people with an effect size of 0.30 at a confidence interval of 0.95, a bias level of 0.05, and an effect size of 0.30 with a population representativeness of 0.95 by power analysis.

Foreseeing that possible data losses, missing or erroneous data, and situations that should be excluded from the evaluation may occur during the research process; the number of individuals included in the sample was increased above the minimum sample size determined and a total of 177 participants were reached by non-probability sampling method.

Inclusion Criteria

18 years of age or older

Be able to read and write Turkish

Being able to walk with or without support

Exclusion Criteria

Not being able to speak or understand Turkish

adequately To be detected

Being immobile

Cognitively inadequate for the study

1.4. General Framework

The methodology shown in Figure 3.1 was followed in the development of the fall risk assessment application to be used in this study. A descriptive information sheet was created for each participant, including basic information such as age, height, weight and other data.

This information was combined with the application of the Morse Falls Scale to assess fall risks. Patients included in the sample were first administered the Morse Falls Scale and then a gait assessment using a computer vision system consisting of a digital camera monitoring walking at a comfortable pace in the clinic corridor. In addition, accelerations in the X, Y and Z axes during walking were assessed with an accelerometer carried in the patients' pockets.

The data obtained from this system was analyzed in real time using machine learning methods to predict the biomechanics of the lower and upper limbs and infer the main features of gait such as stride length, cadence, period and range of motion. It was then used to train and validate an artificial neural network (ANN) looking for correlations between the extracted features and the Morse Fall Scale score. As a result, the final system was able to predict the fall risk of new cases in real time through gait analysis. The artificial intelligence-based system developed within the scope of the study was introduced to the literature under the name "GuArDrop".

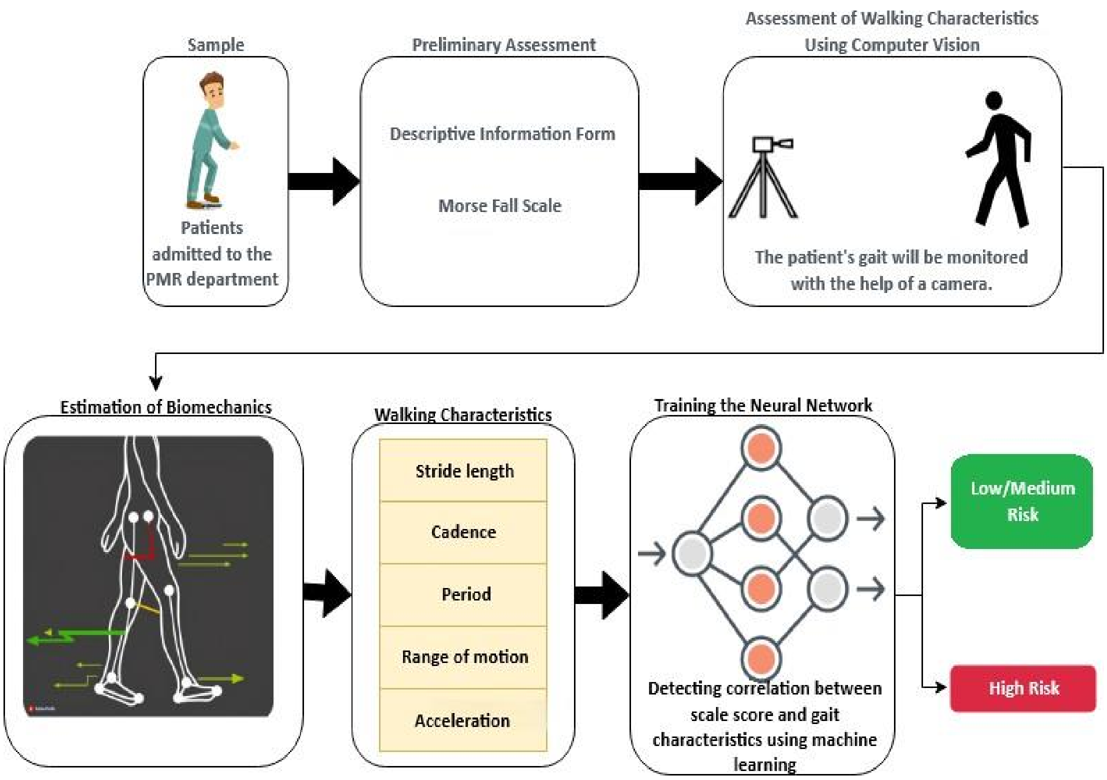

Figure 3.1. Flow diagram of the research

1.4.1. Computer Vision System

The computer vision system was created with one camera connected to a computer and configured to record at 20 frames per second (FPS). The camera was mounted on a tripod for stable imaging of all extremities. The system was illuminated with artificial lighting from infrared reflectors with a wavelength of 850 nm so that the study area could be properly illuminated without disturbing the participants.

1.4.2. Gait Evaluation

A biomechanical gait study was performed using computer vision to determine kinematic parameters. The methodology used to obtain this information required participants to move through the clinic corridor at their own comfort pace. Patients were also allowed to walk with the assistance of a companion or nurse. The walk lasted 2 minutes for each patient. They were informed about this process in advance to ensure that it did not pose any risk to their health or safety. Each test was interrupted as soon as the participant needed assistance due to fatigue, discomfort or dizziness.

1.4.3. Biomechanics Estimation

For image analysis, we used "You Only Look Once version 8" (YOLOv8), a high-speed, high- precision model used in computer vision (Manssor et al., 2021). The YOLOv8 algorithm is reported to support tasks such as object detection, segmentation, pose estimation, tracking and classification. It is stated that it can be trained with specially created databases in order to recognize specific objects, especially complex structures such as the human body, and track key points. Development work was carried out based on the placement of key points to identify different segments of the left and right extremities. During the training and implementation of the algorithm, it was preferred to use the open source Python-based Keras library, which is designed to work with deep learning models (Yunas & Ozanyan, 2021).

These models can be used both for the development of neural networks for the analysis of statistical databases and for the training of models in combination with the analysis of images performing tasks such as the detection of objects, people, faces and body orientation. Therefore, using the database obtained from Keras, the training of personalized models was carried out, in which information and images were divided for training and validation. The resulting model was then used to analyze the walking test videos from. In this analysis process, each video frame was processed so that limb segments could be identified through key points.

1.4.4. Machine Learning Based Classifiers

In this study, seven classifiers were used to classify the gait data, including Logistic Regression, Support Vector Machine (SVM), K-nearest neighbor (KNN), Boosting, Random Forest, Naive Bayes and Decision Tree classifier. KSA with two 2D convolutional layers was used as a reference. KSA is a type of deep neural network classifier used in image classification and recognition (Krizhevsky et al., 2017; Santos et al., 2019). Without the need for manual extraction of features, they can be recognized directly from the data by the system (Zhao et al., 2020). In the KSA structure in this study, the data was passed through several layers with different tasks. The input, in the form of a weight window, was passed to the convolution layer where a spatial filter was applied to the input. This approach has been used in medical applications where datasets are small in size and successful results have been obtained in medical image recognition (Akhtaruzzaman et al., 2016).

1.5. Data Collection

Data were collected between December 2024 and May 2025 in the Physical Medicine and Rehabilitation service of Turgut Özal Medical Center. The data were collected through questionnaires and measurements made by the researcher through face-to-face interviews.

1.5.1. Data Collection Tools

Descriptive Information Form (Appendix-4), Morse Fall Risk Scale (Appendix-5), a video camera and an accelerometer were used to collect the data.

Descriptive Information Form

This form was prepared to collect information about the basic socio-demographic characteristics of the participants (such as age, gender, marital status, marital status, educational status, income status and family type) and information about the risk of falls (such as BMI, genetic factor, duration of the disease, history of falls in the last year, information about where they fell if they fell, what measures they take to prevent falls at home, the risk of the patient falling according to the patient's relatives and the risk of the patient falling according to the nurse (Fitzgerald et al., 2016; Lin et al., 2020).

Morse Fall Scale

Developed in 1985 by Janice M. Morse, the scale was adapted into Turkish by Demir and Intepeler in 2012 (Demir & İntepeler, 2012). The Morse Falls Scale, which is frequently used in hospitals in Turkey, is accepted as an effective and simple measurement tool for diagnosing potential patient fall risks in nursing practices. This scale is structured to assess the risk of falls based on a total of six criteria: secondary diagnosis, presence of a history of falls, mobilization support, presence of intravenous access or heparin use, gait/transfer and mental status. According to the score obtained from the scale, it is stated that individuals with a score of 50 points and below are in the low/medium risk group, while individuals with a score of 51 points and above are in the high-risk group. A minimum score of 0 and a maximum score of 125 can be obtained from the scale. Due to the short duration of use of the scale, it was found to be practical by the nurses; in fact, 82.9% of the nurses evaluated the use of the scale as easy and fast. In addition, 54% of the nurses stated that they were able to identify the risk of falls by spending less than three minutes with the patient when using this scale. Although the Cronbach's Alpha coefficient of the original scale was reported as 0.16, this value was calculated as 0.55 in the Turkish validity and reliability study (Demir & İntepeler, 2012; Morse et al., 1985).

Video Recording

For recording, a video recording device was used to record the patients' spontaneous gait for 2 minutes to create a database for computer vision and machine learning methods. Video and sensor data were stored only with coded IDs, and patient identifiers were kept inaccessible. All digital data were stored on an encrypted external disk, and analysis was performed on the researcher's computer.

Accelerometer

This device, which has a very simple structure, is designed in compact sizes that can be carried in a pocket. In this way, it was possible to measure linear acceleration changes in the three-dimensional plane (X, Y, Z axes) during spontaneous walking of individuals. The measurements were performed with a high-precision sensor, and the accelerations in the X (front-back), Y (up-down) and Z (right-left) axes were digitally recorded at millisecond intervals. During the data collection process, the individuals were allowed to walk for approximately two minutes, during which the accelerometer data and video recording data were recorded simultaneously. The collected data was structured to be processed with deep learning algorithms in order to analyze micro-level movement parameters such as gait patterns, step length, step duration, acceleration variability and direction change behaviors. Through this structure, a database was created to be used in fall risk prediction and it became possible to extract risk profiles of individuals based on their mobility patterns.

1.6. Data Evaluation

The data obtained within the scope of the study were analyzed using a combination of classical statistical methods and machine learning-based modeling techniques. RStudio and Python programming environments were used for all analyses. The analysis process includes the stages listed below:

1.6.1. Preprocessing and Cleaning

At this stage, the collected data were checked for gaps, missing observations, outliers and inconsistencies. If missing data were less than 10 percent, they were replaced with appropriate values using multiple imputation methods. Outliers were checked using the winsorization technique. Continuous variables including age, BMI and sensor data were standardized with z-scores. Categorical variables were included in the model through dummy coding. The significance level for the whole study was set at 0.05.

1.6.2. Descriptive Statistics

Sociodemographic and clinical data of the study sample were presented as mean ($\bar{x} \pm SD$) with frequency count and percentage (n, %) and standard deviation. The assumption of normality was tested by skewness and kurtosis analysis. Morse Fall Scale scores were correlated with video and sensor-based features and these relationships were analyzed using Pearson or Spearman correlation coefficients.

1.6.3. Machine learning based analysis

Data splitting and feature selection

Each participant was randomly assigned to a training (70%), validation (15%) and test (15%) set. Correlation matrix, analysis of variance and iterative feature elimination methods were used for feature selection; variables that made a significant contribution to the model were removed.

Model building and performance measurement

The machine learning classifier algorithms (Boosting, k-Nearest Neighbors, Long Short-Term Memory network, Support Vector Machine, Convolutional Neural Network, Decision Tree classifier, and Naïve Bayes) were trained using multidimensional features extracted from gait and accelerometer data and Morse Fall Scale scores. For each algorithm, baseline parameters were determined using a validation set with grid search for model tuning.

Comparison and evaluation of the models

The evaluation of the model performance was performed on the test set according to the defined metrics. The differences between the algorithms were compared using McNemar and ROC curves, while Friedman's test was used for multiple classifier comparisons. The importance of features was calculated with Gini importance in Boosting, Decision Tree and Random Forest algorithm.

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