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Research Article

Recognition of Sensory-based Motion Information using Virtual Reality based Rehabilitation Exercises for COVID19 Recovered Patients

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Abstract: Exercise therapy is observed as one of the major treatments for rehabilitation of patients, those attacked by any injury, mental disorder, and even Covid-19. Virtual reality in healthcare rehabilitation demands accurate classification of gestures or movements. This study aims to recognize the prescribed rehabilitation exercises of computer-assisted sensory systems using machine learning (ML) and deep learning (DL) approaches for automated assessment of the quality of physical rehabilitation exercises for COVID19 recovered patients. The Kinect and Vicon sensory systems were used in this study for motion capture of 10 movements of the rehabilitation program. Patients perform these 10 movements in their physical therapy and rehabilitation program. The ML models such as K-Nearest Neighbour (KNN), Decision Tree (DT), and DL based Multi-Layer Perceptron (MLP) were used to classify Kinect and Vicon. The binary Classification performance is measured with standard methods and metrics. This study utilized 10 movements of the 10 subjects of two sensory systems and mean accuracy in training and testing part of KNN, DT, and MLP was 88.3%, 89.4%, and 78.95% respectively. DT misclassified 102 training and 104 testing values, MLP misclassified 333 training and 152 testing values, and KNN misclassified 153 training and 94 testing values. Overall mean accuracy of DT was greater than the other two models. The DT method showed better performance than other methods with best-learned features for any rehabilitation exercise. The DT revealed that the most important rehabilitation exercises were deep squats and sit-to-stands to recognize the Kinect and Vicon sensory system information. This study achieved an overall 89.4% accuracy rate to recognize the prescribed rehabilitation exercises of computer-assisted sensory systems. Therefore, our findings are helpful in clinical gait analysis, medical applications and related computer-assisted sensory systems for the recognition process.

Keywords: Virtual reality; COVID19; Machine learning; Rehabilitation; Healthcare

1. Introduction

Exercise therapy is observed as one of the major treatments for rehabilitation of patients, those attacked by any injury, mental disorder, and even Covid-19. The movements during the exercise were recorded to observe the accuracy and perfection by Kinect and Vicon motion. Rehabilitation is a precaution that helps people improve or get back abilities that they need in their daily lives. These abilities can be mental, physical, and cognitive (encompassing thinking and learning) that can be lost due to injury, disease, the COVID-19 pandemic, or any other side effect from medical treatment [1]. The rehabilitation also helps the patients with neurological conditions like multiple sclerosis, stroke, motor neuron disease, and Musculoskeletal disorders such as fractures, hip and knee arthroplasty, and sub-acute or chronic back pain. Patients who also have other conditions, such as Pulmonary and respiratory, Cardiac conditions [2], are also common during the COVID-19 pandemic. It was also recommended that the exercises have a positive impact on COVID-19 [3-4]. The rehabilitation also covered different areas such as grooming, bathing, dressing, toileting, sexual function, medication, skincare, walking, and transfers. It also helps adapt to lifestyle changes, financial concerns, discharge planning, identifying problems and solutions with thinking, behavioral, and emotional issues. It helps people interact with others at home and within the community, concentration, judgment, problem-solving, and organizational skills [5, 69]. The best option and recommendation to stop the rapid spread of infections is to require a radical change in lifestyle and adopt physical activities and exercise to maintain adequate health status [7,8], to counteract the negative consequences of certain diseases such as COVID-19. As the psychological impact of Covid-19 has been recently reviewed [9]. Therefore, basic principles should be considered to design a proper exercise program at home.

Self-management programs and exercise are recommended as first-line treatments for osteoarthritis, according to current guidelines. Osteoarthritis is becoming more common, yet cost and resource restrictions prevent patients from receiving treatment in person. For patients with musculoskeletal pain problems such as osteoarthritis and back pain, digital treatments have emerged as a viable tool for providing exercise therapy and interdisciplinary rehabilitation [10,11]. A variety of digital solutions have been offered to increase access to therapeutic workouts by correcting and optimizing body position during exercise execution. Many mobile health apps for musculoskeletal rehabilitation, on the other hand, rely solely on video instructions and lack the ability to detect and correct posture during exercise [12].

Hardware devices for digital treatments include the Kinect and Vicon. The Kinect is a non-invasive, low-cost sensor that may be used for human motion analysis under various settings. It is largely employed in the video gaming industry. Multiple high-definition cameras are used in Vicon 3D Motion Capture systems, which are accurate yet costly and impractical to utilize in many situations. The Vicon system requires retro-reflective markers, which distinguishes it from Kinect. Markers in the area of vision reflect light from the Vicon cameras [13]. For the evaluation of rehabilitative exercise, researchers employed the Hidden semi-Markov Model (HSMM), deep learning-based framework (DBLF), Multi-path Conventional neural network (MP-CNN), and Sensor-based activity recognition (SBAR) [14].

The purpose of this study is to design the Smart Sensor-based Rehabilitation Exercise Recognition System (SSRER) approach using the ML approach and DL approach, to compare the performance of ML and DL classifiers, which play an important role in discrimination. To detect the most important exercises that play an important role in the discrimination process of Kinect and Vicon. The ML models such as KNN, DT, and DL based MLP, were used to classify the Kinect and Vicon using 10 movements of the rehabilitation program. The KNN is an ML algorithm that is known as a non-parametric technique. It can be used for regression and classification purposes. The prediction in KNN is based on the data values of neighbors, where "K" represents the number of nearest neighbors in the data set. The "K" also helps in classification decisions in the KNN classifier. The prediction or classification is based on a similar instance, and instances make by searching 'K' neighbor instances in the training set, class's highest instance uses for classification [16]. The DT is a widely useful technique for classification in data mining. It is also useful to make the decision and classify knowledge based on the training set. The DT have different types like Iterative Dichotomies 3 (ID3), Successor of ID3 (C4.5), Classification and Regression Tree (CART), CHi-squared Automatic Interaction Detector (CHAID), and many more. Decision trees are powerful methods commonly used in various fields, such as machine learning, image processing, and identifying patterns [17]. The MLP processes the information based on the biological nervous system. Nowadays ANN is used for solving a large number of real-world problems. There are many types of ANN but in this study, MLP was adopted. It is an example of a feedforward neural network. It has three layers: input, hidden layers, and output layers. Each one layer connects to the next layer. The MLP maps the input data on output categories appropriate way [18]. In short, these three models were utilized because, KNN also has a useful application on motion-based feature representations by presenting a pipeline that extracts deep spatial motion features from video. The precise and clinically relevant results demonstrated DT's interpretability in motion contexts. Strong performance from MLPs demonstrates how well MLPs work with clinical motion data [19], [20]. The proposed approach will more accurately classify or recognize the Kinect and Vicon using 10 movements of the rehabilitation program and reveal which exercise plays the most important role in classifying the Kinect and Vicon for COVID-19 recovered patients. This study will identify rehabilitation activities for COVID-19 patients, filling a gap in practical post-COVID rehabilitation tracking.

The structure of this paper is as follows: Section 2 provides the methodology to achieve our objectives. Section 3 is about the data description in detail. Section 4 presents results and the points that were found regarding ML and DL approaches. The study's findings are presented in Section 5. Finally, the study is concluded in the last section.

2. Methodology

The study was developed to recognize the rehabilitation exercise from two sensory systems for motion capturing, such as Kinect and Vicon, with 10 movements. Also, develop a classifier for the prediction that can classify the Kinect and Vicon two sensory systems for motion captures using the 10 movements patients perform in their physical therapy and rehabilitation program. The objective of classification will be achieved using the ML and DL techniques to classify the physical therapy and rehabilitation programs of Kinect and Vicon using 10 movements. Deep squat, hurdle step, inline lunge, side lunge, sit to stand, standing active straight leg raise, standing shoulder abduction, standing shoulder extension, standing shoulder internal- external rotation, and standing shoulder caption were the ten motions employed as independent variables. It is a challenging topic to recognize human activity during the ML [15]. Therefore, the ML models such as KNN, DT, and MLP as a DL model were used to classify the Kinect and Vicon using 10 movements of the rehabilitation program. All the study analysis were performed using the Python language. The (Numpy, Pandas, matplotlib, seaborn, and Scikit-learn) libraires were used to perform the models and estimate evaluation reports. The 10 features were utilized in the input layer, 100 by default neurons were utilized in the hidden layer, and 1 was used in the output layer with the sigmoid function. The architecture of the MLP is presented in Figure 1, which explains the structure used to classify the Kinect and Vicon data. Similarly, the default parameters, such as 5 for the number of neighbors, 30 for the number of features affecting tree-based algorithms, etc., of KNN and entropy: Gini, splitter: best, etc., of DT were utilised to classify the Kinect and Vicon using 10 movements from the rehabilitation program.

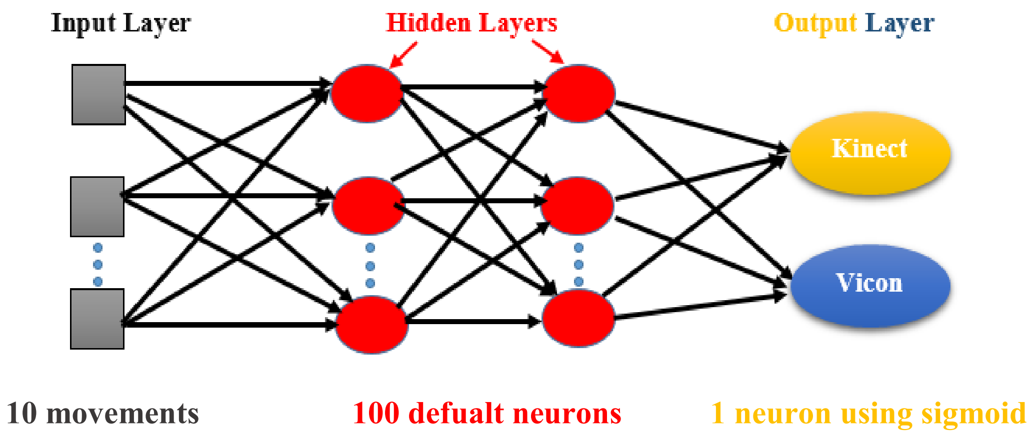

Figure 1: Architecture of Multilayer perceptron for the classification of Kinect and Vicon.

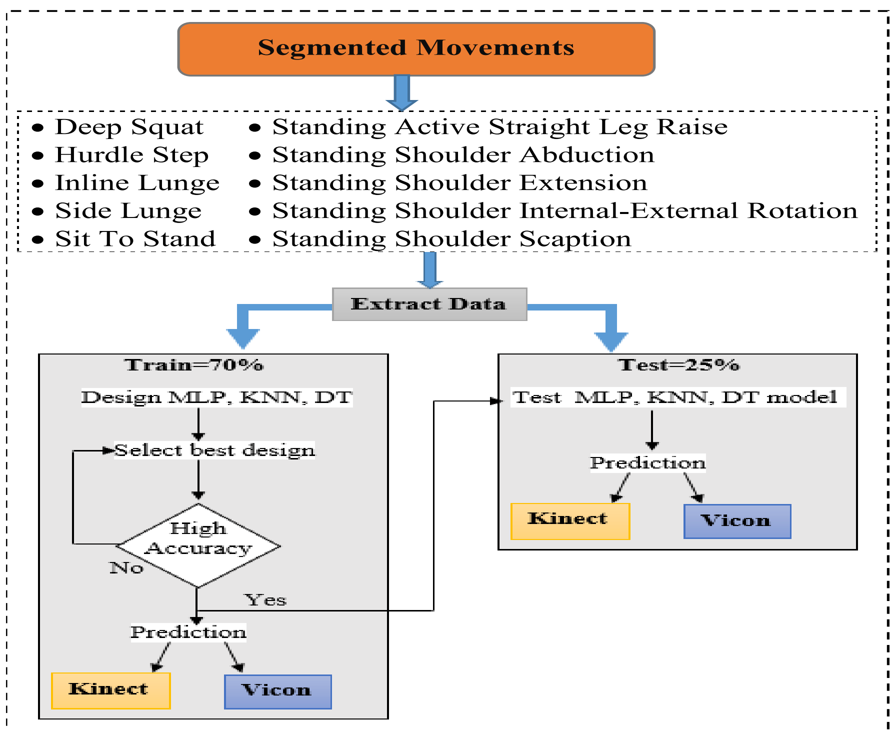

Figure 2: The work architecture of MLP, KNN, and DT with training and testing data.

2.1 Dataset description

We utilized the segmented movement data from https://webpages.uidaho.edu/ui-prmd/ to achieve our goal. The data of 10 movements were collected from two sensory systems for motion captures such as Kinect and Vicon. The 10 movements include the deep squat, hurdle step, inline lunge, side lunge, sit-to-stand, standing active straight-leg raise, standing shoulder abduction, standing shoulder extension, standing shoulder internal-external rotation, and standing shoulder caption. Kinect and Vicon are two sensory systems for motion captures used to capture the 10 movements performed by patients in their physical therapy and rehabilitation program. This dataset of movements was created and collected by Vakanski, et al. [21]. The demographic of the 10 subjects is given in Table 1. A participant who had a BMI of 43.2 at presentation was considered severely obese. Despite being significantly higher than the group average, this value was included in the analysis because it represents variability in the real world.

Table 1. Demographics of the selected subjects for exercise.

Gender	Weight(kg)	Height(cm)	BMI
Female	69.4	169.0	24.3
Male	83.0	180.0	25.6
Male	64.8	169.5	22.6
Female	79.4	178.5	24.9
Male	148.	185.5	43.2
Female	53.6	164.6	19.8
Female	53.1	166.1	19.2
Male	77.3	170.5	26.6
Female	56.0	164.0	20.8
Male	94.7	174.2	31.2

2.2 Preprocessing and partition

The imported data in python language was used further for preprocessing and partition process. The standard preprocessing approaches were utilized on the raw data, including checking for missing values and removing duplicate values. After the cleaning the data, the training-testing split approach was used for data partition. The 70% data was split into a training part and 30% data was split into a testing part to train the ML and DL models. The algorithms were trained on training samples and test on testing sample to estimate the prediction error and validity of the ML and DL algorithms for classification in between Kinect and Vicon.

2.3 Feature importance

After applying all ML and DL classifiers, the best model among both approaches will be applied to extract the feature importance plots. The feature importance is the most common way of explanation of classification model [22]. The bars will explain the importance of the input features while classification process. The top bar will showing the more importance and top lower bars will showing the lower importance in classification process.

2.4 Evaluation metrics

The accuracy rate, sensitivity rate, specificity rate, ROC, Area under the curve (AUC), false-positive rate (FPR) rate, and false-negative rate (FNR) rate were measured for the performance of the ML and DL algorithms. These measures were estimated for the both training and testing datasets for both ML and DL models. The detailed pseudocodes of the methodology are given in algorithm 1.

Algorithm 1: Algorithm for Recognition of Sensory-Based Motion Data in Rehabilitation Exercises for COVID-19 Recovered Patients.

1. **Input:**
2. **Motion feature from 10 movements:**
$$m = \{m_1, m_2, \dots m_{10}\}$$
3. **Dataset:**
$$D = \{(x_i, y_i)\};\ i = 1..N, \quad x_i \in \mathbb{R}^{10}, \quad y_i \in \{0,1\}$$
$$y_i = \begin{Bmatrix} 0 \ \ Kinect\ (System\ 1) \\ 1\ \ Vicon\ (\ System\ 2) \end{Bmatrix}$$
4. **Data Split:**
$$D_{train} = 0.7\, D, \ D_{test} = 0.3\, D$$
5. **Models:**
$$MLP{:}\ y_i^{\wedge} = Softmax(W_2\, \sigma(W_1\, x_i + b_1) + b_2)$$
$$KNN{:}\ y_i^{\wedge} = mode\{\, y_j \mid j \in K, NN(x_i)\,\}, \quad d(x_i, x_j) = \|x_i - x_j\|2$$
$$DT{:}\ IG(S, A) = H(S) - \sum_{v} \frac{S_v}{S}\ H(S_v), \ H(S_v) = - \sum_{c \in \{0,1\}} (c)\ log\ p(c)$$
6. **Evaluation:**
$$Accuracy, sensitivity, specificity, ROC - (AUC), FPR, FNR$$
7. **Output:**
$$y_i^{\wedge} \in \{0,1\} = \begin{Bmatrix} 0\ \ Predicted\ as\ Kinect \\ 1\ \ Predicted\ as\ Vicon \end{Bmatrix}$$

3. Results

This study developed prediction classifiers that can classify the two sensory systems for motion captures such as Kinect and Vicon using 10 movements performed by patients in their physical therapy and rehabilitation program. We applied KNN, DT, and MLP classifiers to data, with the methodology given in Figure 2. Out of the extracted data, 70% was used as the training sample set and 30% as the testing sample set for the ML and DL algorithms. The best design model achieves the classification accuracy until it reaches at highest accuracy. The prediction performance of ML and DL models is shown in Table 2. Table 2 includes the Accuracy, Sensitivity, specificity, FPR, FNR, and mean value of all training and testing data criteria. The accuracy of the KNN model was 90.06% and 86.6% of training and testing data respectively. Similarly, the accuracies of the DT model were 93.7% and 85.1% of training and testing data respectively. The accuracies of the MLP model were 79.6% and 78.3% of training and testing data respectively. The mean accuracy of KNN, DT, and MLP was 88.3%, 89.4%, and 78.95% respectively. Thus, overall mean accuracy of DT was greater than the other two models.

Table 2: Accuracy, Sensitivity, specificity, FPR, and FNR of training and testing data.

Model	Sample	Accuracy	Sensitivity	Specificity	FPR[1]	FNR[1]
KNN	Training	90.06%	0.888	0.926	0.111	0.073
	Testing	86.60%	0.861	0.871	0.138	0.128
	Mean[1]	88.30%	0.874	0.898	0.124	0.1
DT	Training	93.70%	0.925	0.95	0.074	0.05
	Testing	85.10%	0.841	0.863	0.158	0.136
	Mean	89.40%	0.883	0.906	0.116	0.093
MLP	Training	79.60%	0.766	0.833	0.233	0.166
	Testing	78.30%	0.758	0.814	0.241	0.185
	Mean	78.95%	0.762	0.823	0.237	0.175

1. Average results of the training and testing sample
2. False-positive rate
3. False-negative rate

The classification detail related to all classifiers in the form of a confusion matrix is presented in Figure 3. In Figure 3 the KNN correctly classified the 757 and 727 values of Kinect and Vicon respectively and a total of 153 values are misclassified in the training data. Similarly, the KNN correctly classified the 310 and 298 values of Kinect and Vicon, respectively, and a total of 94 values are misclassified in the testing data.

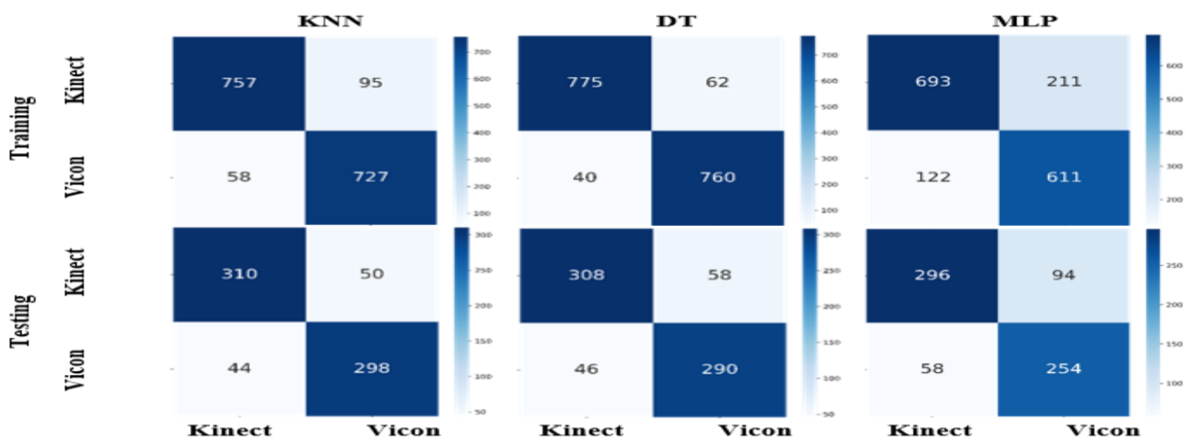

Figure 3: Confusion matrix of KNN, DT, and MLP of training and testing data.

The DT correctly classified the 775 and 760 values of Kinect and Vicon, respectively, and a total of 102 values are misclassified in the training data. Similarly, the DT correctly classified the 308 and 290 values of Kinect and Vicon, respectively, and a total of 104 values were misclassified in the testing data. The MLP correctly classified the 693 and 611 values of Kinect and Vicon, respectively, and a total of 333 values are misclassified in the training data. Similarly, the MLP correctly classified the 296 and 254 values of Kinect and Vicon, respectively, and a total of 152 values were misclassified in the testing data. Thus, overall, the DT model got a higher accuracy than other models.

4.1. Feature importance

In this case, DT achieved a higher accuracy rate than other models, so we generated the feature importance of DT. The generated feature importance was given in Figure 4 of 10 movements. Figure 4 features importance explore which movement performs an important role in discriminating Kinect and Vicon two sensory systems for motion capture. For example, the deep squat, sit-to-stand, standing shoulder press, inline lunge, and side lunge had importance scores of 0.31, 0.25, 0.07, 0.068, and 0.063, respectively. Similarly, standing shoulder abduction, standing active straight leg raise, standing shoulder internal-external rotation, standing shoulder extension, and hurdle step had feature importance of 0.059, 0.057, 0.043, 0.033, and 0.029, respectively. In other words, we can say that, standing shoulder internal-external rotation, standing shoulder extension, and hurdle step movements were the most frequently confused movements. Because they do not play much important role in detecting the Kinect and Vicon two sensory systems by model, as we can observe with a confusion matrix approach. Deep squat and sit-to-stand were found to be the most discriminative movements for classification processes. This is probably because both Kinect and Vicon sensors can easily record these actions, which include significant posture changes, wide ranges of motion across several joints, and distinct temporal phases. Additionally, these movements' intricacy and biomechanical requirements produce unique kinematic patterns that help the models differentiate them from other, subtler movements.

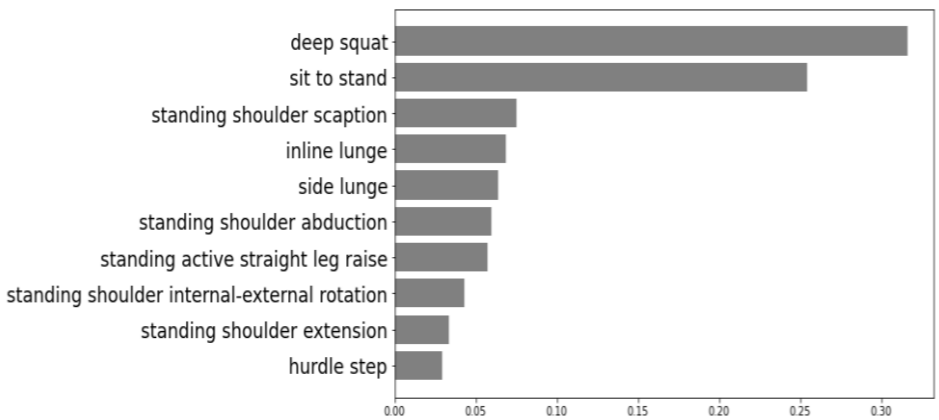

Figure 4: Feature importance of DT

4.2. Sensitivity analysis

We also assessed sensitivity, specificity, ROC, AUC, FPR, and FNR to measure the performance of the ML and DL algorithms. The sensitivity rate presents the rate or ability of all classifiers to correctly classify the Kinect with the help of 10 movements if it is an actual Kinect. The specificity rate represents the ability of all classifiers to correctly classify the Vicon with the help of 10 movements, assuming it is in actual Vicon. The FPR is the probability that a classifier declares Kinect but in actual it is Vicon. The FNR is the probability that a classifier declares Vicon but actually Kinect [23]. The sensitivity, specificity, FPR, and FNR of training and testing data was given in Table 2. The ROC curves with AUC for KNN, DT, and MLP are given in Figure 5. The ROC Curve is a representation of the statistical information discovered in binary classification problems [24]. Figure 5 explained the ROC with AUC of all purposed models where orange, blue, and green color solid lines present the ROC with AUC of KNN, DT, and MLP of training and testing data. The AUC values achieved in training data were 0.91, 0.94, and 0.80 of KNN, DT, and MLP models respectively. Similarly, the AUC values achieved in the testing data were 0.87, 0.85, and 0.78 for the KNN, DT, and MLP models, respectively. The ROC curve AUC values fall into one of three categories: acceptable (between 0.70 and 0.80), excellent (above 0.80), and infrequently (above 0.90) [23].

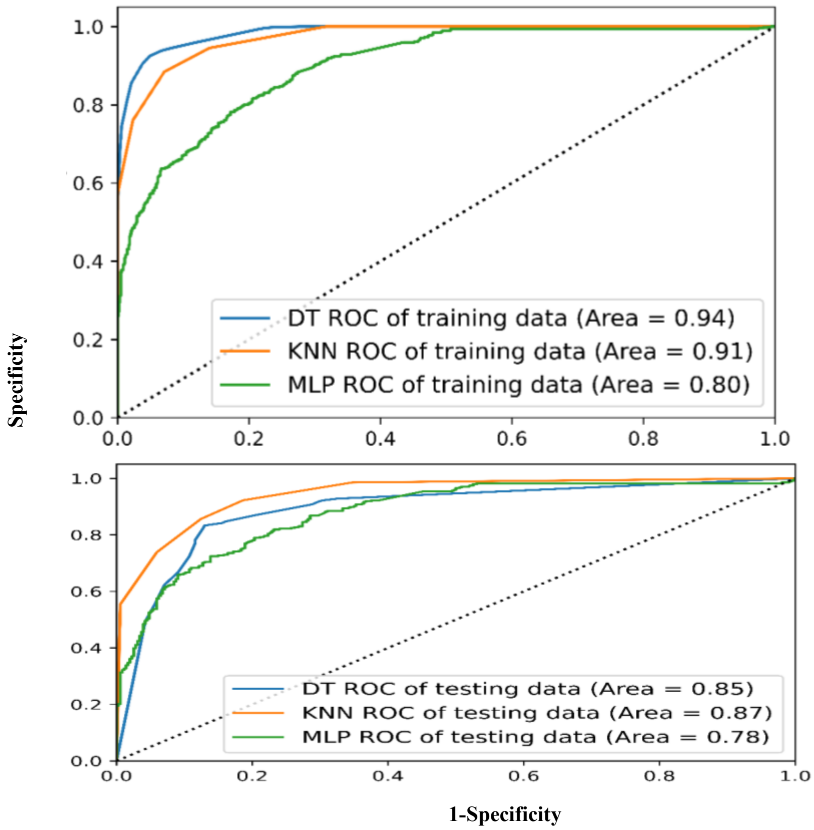

Figure 5: Sensitivity Analysis of the KNN, DT, and MLP analysis

4. Analysis and discussion

The researchers want to detect the efficient way to recognize the Kinect and Vicon two sensory motion capture efficiency. Here we developed the ML and DL models to recognize the Kinect and Vicon two sensory motion capture with the help of 10 movements. The ML models such as KNN, DT, and DL models such as MLP were used to classify the Kinect and Vicon using 10 movements of the rehabilitation program. The training-testing approach was used to split the data into two parts. Out of 100%, 70% of data was trained and 30% of data was tested by ML and DL algorithms. The algorithms were trained on training samples and test on testing samples to estimate the prediction error and validity of the ML and DL algorithms for classification in between Kinect and Vicon. The accuracy, sensitivity, specificity, ROC, AUC, FPR, and FNR were measured to performance of the ML and DL algorithms. The accuracies of the KNN model were 90.06% and 86.6% for the training and testing data, respectively. Similarly, the accuracies of the DT model were 93.7% and 85.1% of training and testing data respectively.

The accuracies of the MLP model were 79.6% and 78.3% of training and testing data respectively. The mean accuracy of KNN, DT, and MLP was 88.3%, 89.4%, and 78.95% respectively. Overall mean accuracy of DT was greater than the other two models. The literature revealed that DT achieves the best results for image processing and identification of patterns. The AUC values achieved in training data were 0.91, 0.94, and 0.80 of KNN, DT, and MLP models respectively. Similarly, the AUC values achieved in testing data were 0.87, 0.85, and 0.78 of KNN, DT, and MLP models respectively. Overall, the DT model got a high accuracy than other models. In our case, DT got a higher accuracy rate than other models, so we generated the DT's feature importance. The generated feature importance was given in Figure 4 of 10 movements.

Figure 4 features importance explore which movement performs an important role in discriminating Kinect and Vicon two sensory systems for motion capture. The deep squat, sit to stand, standing shoulder caption, inline lunge, side lunge had 0.31, 0.25, 0.07, 0.068, and 0.063 feature importance respectively. Similarly, standing shoulder abduction, standing active straight leg raise, standing shoulder internal-external rotation, standing shoulder extension, and hurdle step had feature importance of 0.059, 0.057, 0.043, 0.033, and 0.029, respectively.

Overall, the mean performance of DT and KNN was good, but DT had a higher performance than KNN and MLP. The deep squat and sit-to-stand movement play an important role in recognizing the Kinect and Vicon two sensory motion capture. Therefore, the results suggest that the DT model is the most suitable model for recognizing the Kinect sensory motion capture over Vicon. Also, focus on deep squat and sit-to-stand movement because they had an important role to discriminate the Kinect to Vicon or Vicon to Kinect.

5. Conclusion

The researcher wants to find an easy way to recognize the Kinect and Vicon two sensory motion capture systems. This study aims to recognize the prescribed rehabilitation exercises of computer-assisted sensory systems using ML and DL approaches. ML models, such as KNN and DT, and DL models, including MLP, were used to classify the Kinect and Vicon data using 10 movements from the rehabilitation program. The accuracy, sensitivity, specificity, ROC, AUC, FPR, and FNR were measured to performance of the ML and DL algorithms. The mean accuracy of KNN, DT, and MLP was 88.3%, 89.4%, and 78.95% respectively. Overall mean accuracy of DT was greater than the other two models. The AUC values achieved in training data were 0.91, 0.94, and 0.80 of KNN, DT, and MLP models respectively. Similarly, the AUC values achieved in the testing data were 0.87, 0.85, and 0.78 for the KNN, DT, and MLP models, respectively. In our case, DT got a high accuracy rate of recognition than other models so we generate the feature importance from the DT. The deep squat and sit to-stand had 0.31, 0.25 feature importance respectively. The deep squat and sit to stand movement play an important role to recognize between the Kinect and Vicon two sensory motion capture. The results suggest that the DT model is the most suitable model for recognizing the Kinect sensory motion capture than Vicon. Also, focus on deep squat and sit to stand movement because they had an important role to discriminate the Kinect to Vicon or Vicon to Kinect. Therefore, our findings are helpful in clinical gait analysis, medical applications, and related computer-assisted sensory systems for the recognition process. DT model can also be used for real-time movement classification and clinicians can use DT to monitor progress, identify deficiencies, and customize rehabilitation programs.

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Data Availability: The data that support the findings of this study is reported in the article section 2.1

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Authors contributions. Conceptualization: MNS, MH; methodology: MNS, MH, validation: MNS, MH; writing—original draft preparation, MNS, MH; writing—review and editing: MNS, MH; visualization: MH; supervision: MNS; project administration: MH; The author had approved the final version.

AI Usage Disclosure: Artificial intelligence tool Grammarly was used only for language polishing and grammatical correction. All scientific and technical contents were created and validated by the authors.

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