Enhancing Elderly Population Health Supervision Through Posture Detection Using Deep Learning

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Abstract: In light of the growing aging population and limited healthcare resources, there's a need for technology that supports the independence of the elderly through remote monitoring, particularly in maintaining proper posture, which is crucial for health. Posture recognition, the assessment of how one holds their body, is challenging due to scarce data and the need for real-time analysis. To tackle this, a dataset with over 7600 images of yoga poses was compiled. Dance poses add complexity to posture recognition due to their dynamic and multimodal nature. While most studies have used traditional machine learning (ML) classifiers for posture detection, they fall short in accuracy. This study introduces a novel hybrid approach that combines ML techniques—K-Nearest Neighbor (K-NN), Support Vector Machine (SVM), Naive Bayes, Random Forest, Logistic Regression, Decision Tree, Linear Discriminant Analysis (LDA), and Quadratic Discriminant Analysis—with deep learning (DL) models like 1D and 2D Convolutional Neural Networks (CNNs), LSTM, and bidirectional LSTM. This hybrid method leverages the strengths of both ML and DL to improve prediction accuracy, achieving over 98% on a recognized benchmark dataset.

Keywords: Posture detection system, 1D-CNN, 2D-CNN, LSTM, posture recognition

1. INTRODUCTION

Applications for posture detection include healthcare, indoor and outdoor monitoring, surveillance, virtual environments, and virtual reality for entertainment and animation. Moreover, the home-human interface framework can incorporate the posture detecting system. With the increasing elderly population and severe shortage of healthcare resources, it is imperative to develop technology that allows old and vulnerable people to live more independently with the help of remote monitoring. Upholding proper posture is essential for living a healthy lifestyle. The way a person holds their body and positions their limbs is known as their posture. The advancement of technology has led to a fall in movement and physical exercise as individuals choose to live sedentary lives [1]–[5]. Sitting for extended periods while working or studying causes muscle strength to decline. Human bodies suffer from sedentary lifestyles, and bad posture can lead to neck, back, and shoulder pain. Thus, it is critical to maintain proper posture when working or studying to protect people's health and safety.

2. LITERATURE SURVEY

2.1 DL approach for automated squat posture classification with inertial sensors

Refrain from seeking professional guidance, inexperienced exercisers such as performing core exercises, which include squats, possess higher chance of suffering knee or spinal injuries. Wearable sensors and algorithms have the potential to analyze the kinematics of body segments and identify exercise modes, yet, existing implementations lack sufficient accuracy. This study examined the effectiveness between deep learning and conventional machine learning for classifying squat postures. Beyond that, the ideal site for the positioning of sensors was identified. 39 healthy individuals had their gyroscope and accelerometer data recorded with the use of five inertial measurement units (IMUs) that were affixed to their lumbar region, right calf, right thigh, left calf and left thigh. Every participant carried out six proper squat repetitions and five inadequate squat repetitions, which are usually seen in inexperienced exercisers. We examined the classification accuracy of squat postures using deep learning and traditional machine learning techniques. Each result was achieved with one IMU or a combination of two to five IMUs. Conventional machine learning provided an accuracy of 75.4% when classifying squat position using five

IMUs; deep learning achieved an accuracy of 91.7%. DL for a combination of IMUs on the right thigh and right calf produced the best accuracy (88.7%) when two IMUs were used together. The single IMU produced the best results on the right thigh, with an accuracy of 58.7% for conventional machine learning and 80.9% for deep learning. Overall, deep learning produced better results than the traditional machine learning, for both single and multiple IMUs. The approach that was most feasible in terms of ease of use for self-fitness was to use one IMU on the right thigh.

2.2. Islamic prayer (salat) posture activity tracking using DL

Muslims are obligated to practice prayer, also known as salat, or the second pillar of Islam, five times a day. They view it as the most significant and essential act of devotion. When it comes to gestures, there are certain conventional human postures that must be accurately performed. Unfortunately, a number of people don't execute these postures correctly because they are unfamiliar with Salat or may have learnt prayers incorrectly. Moreover, a balanced amount of time must be spent in each posture. Our proposal is to create an artificial intelligence assistive framework that helps worshippers assess if their prayer postures are correct in order to overcome such issues. The current research uses convolutional neural networks (CNN) to solve the challenge of recognizing the fundamental movements of Islamic prayer, marking the first step towards achieving this objective. The creation of a dataset encompassing the fundamental Salat positions and the training of a YOLOv3 neural network to recognize the gestures constitute the contribution of this paper. Experimental results show that a training dataset of 764 pictures representing different postures can reach a mean average precision of 85%. This is among the very first study that uses deep learning to identify human activity using Salat, to the best of our knowledge.

2.3. Human posture detection using LoRa-based smart IoT application for smart cities

Even after hundreds of years of studying the human body, researchers are continuously finding new connections between behavior and health. Human posture detection, artificial intelligence, and data mining have made it much easier to understand the way, how people's movements and behaviors affect their health and lives, as well as how to better balance work and rest—a vital resource for modern people struggling with a fast-paced lifestyle. One of the main components of a smart city is the monitoring or prediction of people's health using smart technologies and everyday behavior. These applications require frequent and large-scale use in a smart city, therefore the system needs to be portable, low-cost, and low energy-consuming for long-term detection. This study offers a multimodal posture identification approach that uses LoRa technology for creating a long-term posture detection system in order to achieve these objectives.

2.4. Relationships in an augmented reality study between collaborative learning states and postures of the body

In this study, we explore the use of Kinect body posture sensors in dyad pairings with augmented reality systems to detect group collaboration and learning. We utilize information collected from a study (N = 60 dyads) where participant pairs researched on electromagnetism. Using Kinect body posture sensor data and unsupervised machine learning techniques, we provide a collection of dyad states linked to learning gains, attitudes toward physics, and collaboration quality.

2.5. Using machine learning techniques to identify yoga poses

In recent years, yoga has become a regular part of the lives of many individuals all around the world. Therefore, a scientific study of y postures is necessary. It has been noticed that pose detection algorithms can be used to both help people execute yoga more accurately and to identify the postures. Because there are few datasets available, it can be difficult to recognize posture and to do so in real time. In order to solve this issue, an ample data set comprising at least 5500 pictures of 10 distinct yoga poses was assembled. An algorithm called tf-pose estimation was used subsequently to construct a real-time skeleton representation of a human body. Joint angles are extracted using the tf-pose skeleton and then implemented as features in multiple machine learning models. Around 80% of the dataset was put to use for training, while the remaining 20% was used for testing. Several ML classification models are used to assess this dataset, and a Random Forest Classifier achieves an accuracy of 99.04%.

3. Algorithms

The following algorithms were used and results were compared such as K-NN, Random forest algorithm, AdaBoost Algorithm , Support Vector Machine (SVM), XGBoost, Decision Tree, LSTM and Convolution Neural Network (CNN), In neural networks, CNN is one of the primary classification and recognition categories used for images. Object identification, face recognition, scene labeling, and other applications are among the fields in which convolutional neural networks find extensive application.

System Architecture

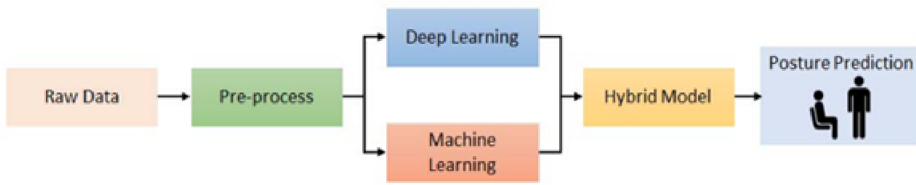

Fig.1: Architecture of our model

4. RESULTS AND DISCUSSION

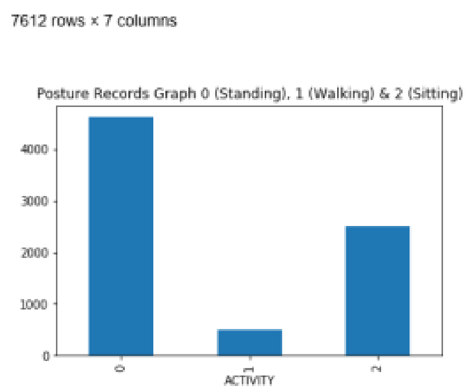

Fig.2: Posture Records Graph or standing, walking and sitting position classes

The dataset is loaded and graph with different classes plotted in X-axis and number of records in that class in Y-axis. Preprocessing dataset was done to remove the missing values and then the dataset was split into training and testing parts, where application using 80% of the dataset for training and the remaining 20% for testing purposes.

```
In [4]: #dataset preprocessing & splitting data into train and test
dataset = dataset.values #converting entire dataset into values and assign to X
Y = dataset[:,0]
X = dataset[:,1:dataset.shape[1]]
Y1 = dataset[:,0]
scaler = MinMaxScaler()
scaler.fit(X) #applying MIX-MAX function on dataset to preprocess dataset
X = scaler.transform(X)
X1 = X
X1 = X1.reshape((X1.shape[0], X1.shape[1], 1))
Y1 = to_categorical(Y1)
X2 = X1.reshape((X1.shape[0], X1.shape[1], X1.shape[2], 1))
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2)
X_train1, X_test1, y_train1, y_test1 = train_test_split(X1, Y1, test_size=0.2)
X_train2, X_test2, y_train2, y_test2 = train_test_split(X2, Y1, test_size=0.2)
print()
print("Dataset size : "+str(X.shape[0]))
print()
print("Dataset train & test split into 80% and 20%")
print("Training Dataset Size : "+str(X_train.shape[0]))
print("Testing Dataset Size : "+str(X_test.shape[0]))
print()

Dataset size : 7612

Dataset train & test split into 80% and 20%
Training Dataset Size : 6089
Testing Dataset Size : 1523
```

Fig.3: Total records with train and test size.

```
Support Vector Machine Accuracy  :  70.19041365725542
Support Vector Machine Precision : 44.4256659087535
Support Vector Machine Recall    : 45.178689358753665
Support Vector Machine FScore    : 44.13406562143809
```

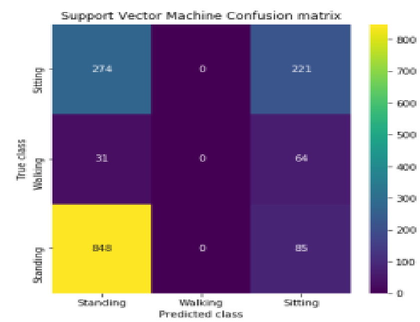

Fig.4: Training SVM and Accuracy, Precision, Recall and F-Score

Test data is used for predicting and calculating accuracy and confusion matrix and with SVM we achieved 70% accuracy and in above confusion matrix, x-axis represents the predicted classes and y-axis represents the TRUE TEST classes and in confusion only those predictions are correct which has same class label in X and Y axis.

```
Logistic Regression Accuracy  :  67.69533814839134
Logistic Regression Precision : 42.08483827525328
Logistic Regression Recall    : 43.062349107365186
Logistic Regression FScore    : 41.87682983776506
```

Fig.5: Logistic regression achieved 67.7% accuracy

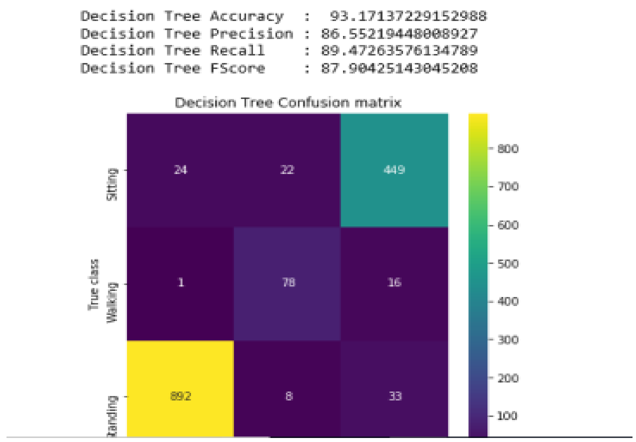

Fig.6:. Using Decision tree we achieved 93.1% accuracy.

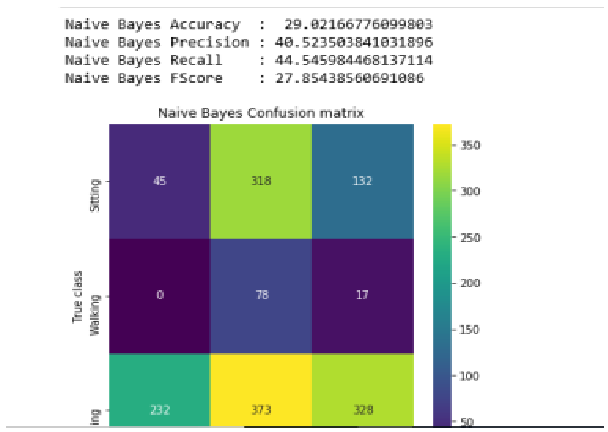

Fig.7: Using Naive Bayes we achieved 29% accuracy

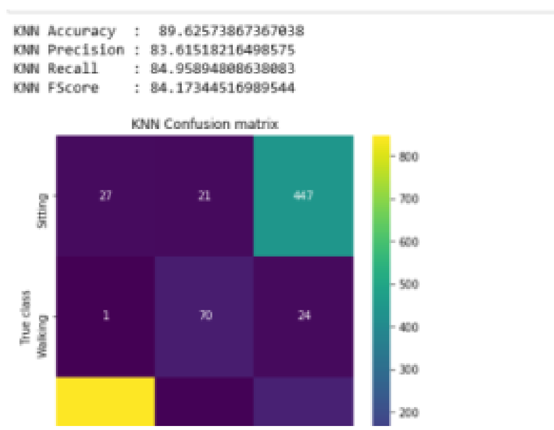

Fig.8: Using KNN we achieved 89.6% accuracy

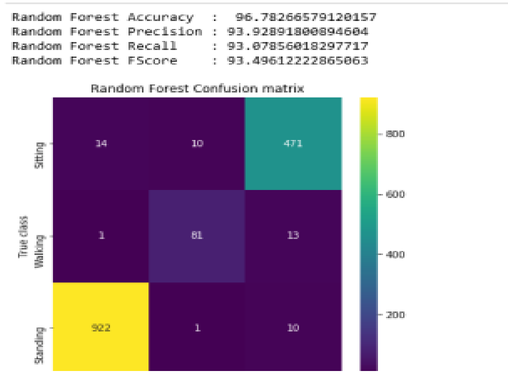

Fig.9: Using Random Forest we achieved 96.7% accuracy

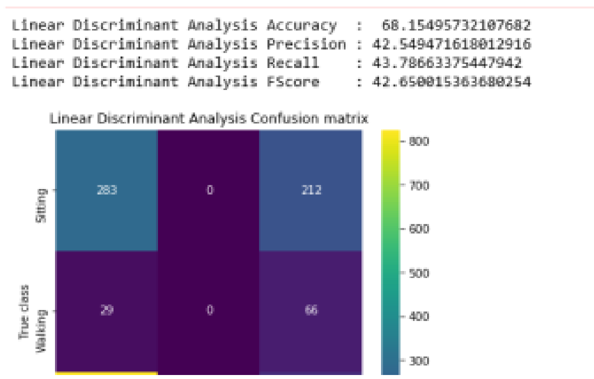

Fig.10: Using LDA we achieved 68.1% accuracy

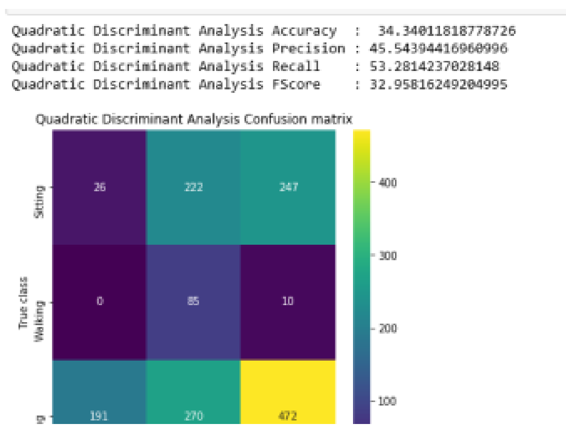

Fig.11: Using QDA we achieved 34.3% accuracy

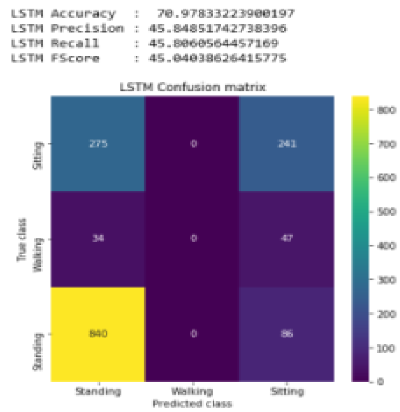

Fig.12: Output for LSTM and with LSTM we achieved 70.97% accuracy

Fig.13: Using BILSTM we achieved 75.83% accuracy

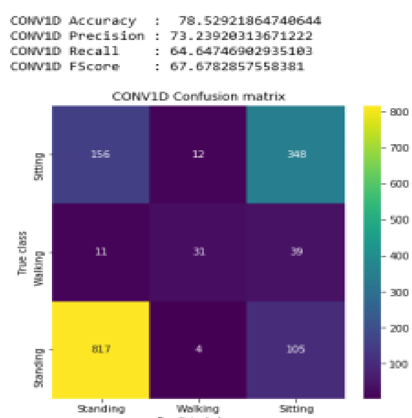

Fig.14: CNN 1D achieved 78.5% accuracy

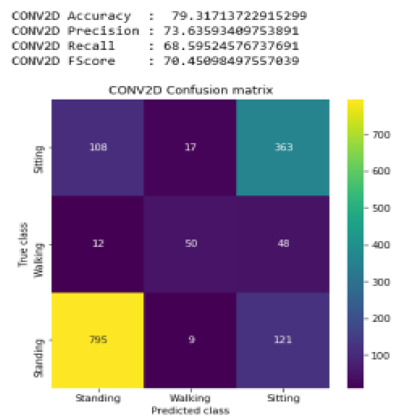

Fig.15: Using CNN 2D we achieved 79.3% accuracy

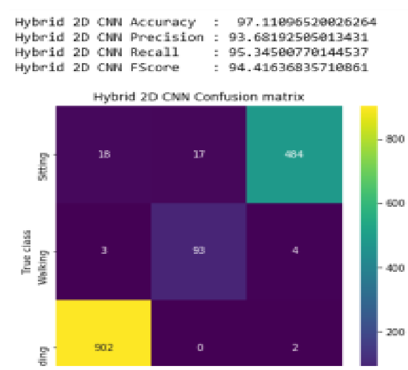

Fig.16: Using Hybrid CNN we achieved 97.1% accuracy

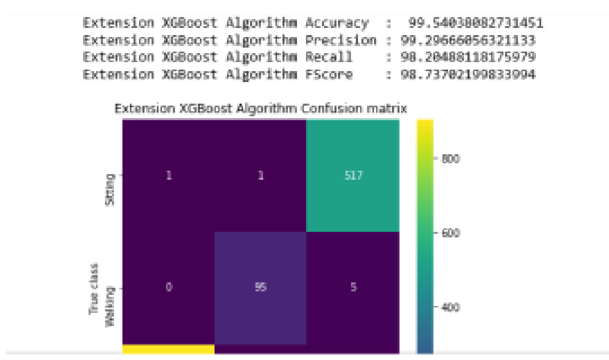

Fig.17: Extension XGBOOST achieved 99.54% accuracy

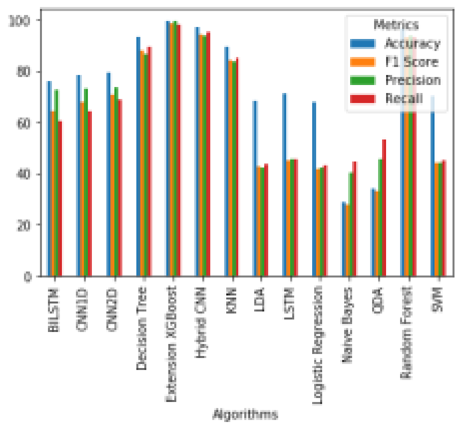

Fig.18: Accuracy, precision, recall and FSCORE values of various algorithms

In above graph x-axis represents algorithm names and y-axis represents accuracy, precision, recall and FSCORE values each with different color bar. In above graph extension XGBOOST has achieved high accuracy and other metrics values. The below figure (Fig.19) shows the comparison scores table of all algorithms.

	Algorithm Name	Accuracy	Precision	Recall	FSCORE
0	SVM	70.190414	44.425666	45.178689	44.134066
1	Logistic Regression	67.695338	42.084838	43.062349	41.876830
2	Decision Tree	93.171372	86.552194	89.472636	87.904251
3	Naive Bayes	29.021668	40.523504	44.545984	27.854386
4	KNN	89.625739	83.615182	84.958948	84.173445
5	Random Forest	96.782666	93.928918	93.078560	93.496122
6	LDA	68.154957	42.549472	43.786634	42.650015
7	QDA	34.340118	45.543944	53.281424	32.958162
8	LSTM	70.978332	45.848517	45.806056	45.040386
9	BILSTM	75.837163	72.708662	60.540170	64.203466
10	CNN 1D	78.529219	73.239203	64.647469	67.678286
11	CNN 2D	79.317137	73.635934	68.595246	70.450985
12	HYBRID CNN	97.110965	93.681925	95.345008	94.416368
13	Extension XGBOOST	99.540381	99.296661	98.204881	98.737022

Fig.19: The proposed HYBRID CNN 2D and Extension XGBOOST achieved high accuracy

CONCLUSION

Remote health monitoring is essential for enabling the elderly and fragile to live independently. As a result, we proposed a novel architecture in this paper that uses deep learning classifiers to determine posture, which includes sitting, standing, and walking. To determine the posture prediction, a new hybrid methodology based on DL methods is developed. To train the meta-learning, the hybrid approach combines various machine learning and deep learning predictions. The experimental findings of our work demonstrate that, in comparison to DL and ML approaches, the suggested hybrid strategy performed better.

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