



Hybrid Posture Detection Framework: Connecting Deep Neural Networks And Machine Learning

.N Jeevana Jyothi^{1*}, K Lakshmi Devi², T Praneetha³, R Annapurna⁴, V Siva⁵, S Naveen⁶

^{1,2,3,4,5,6}Department of CSE, BVC Engineering College, Odalarevu, India

*njeevanjyothi@gmail.com, Lakshmik.bvce@bvcgroup.in, praneetha.bvce@bvcgroup.in,
Annapurna.bvce@bvcgroup.in, siva.bvce@bvcgroup.in, naveen.bvce@bvcgroup.in

Abstract: Many researchers in the fields of artificial intelligence and human sensing have been attempting to find a solution to the issue of posture detection. Posture recognition for the purpose of remote geriatric health monitoring, including standing, sitting, and walking. Most recent research has used conventional ML classifiers for posture recognition. When these algorithms are used for posture detection, the accuracy drops a bit. An innovative hybrid method for posture detection has been created by combining ML classifiers such as Support Vector Machine (SVM), Logistic Regression (KNN), Decision Tree, Naive Bayes, Random Forest, Linear Discrete Analysis, and Quadratic Discrete Analysis with DL classifiers such as Long Short-Term Memory (LSTM) and Bidirectional LSTM, 2D-convolutional Neural Networks (2D-CNN), and 1D-Convolutional Networks (1DNN). The goal of combining DL and ML algorithms in a hybrid fashion is to boost their prediction capabilities. With our experiments on a popular benchmark dataset, we achieved an accuracy of 98% or better.

Keywords: Artificial Intelligence, SVM, Logistic Regression, KNN, and 2D-convolutional Neural Network, 2D-CNN, ML and DL

1 Introduction

There are a plethora of possible applications for posture detection technologies. Healthcare, security, in-room monitoring, entertainment, animation, and countless more fields could benefit from virtual reality (VR). Additionally, posture detection can be utilised in a calming setting. The most vulnerable people of society must be empowered to live more freely through the provision of instruments that allow for remote monitoring, given the concomitant rise in the elderly population and the diminishing funding for home health care. Good posture is an important component of a healthy lifestyle since it lessens the chances of musculoskeletal deficits. Posture is the way a person holds their body and limbs together [2]. Because of its broader definition, "poses" may imply many things to different individuals. There are a wide variety of applications for posture detection, including security, healthcare, in-room monitoring, virtual environments, and virtual reality for animation and entertainment. It is also possible to implement posture detection in a comfortable environment. Because home health care budgets are shrinking and the population is getting older, it is more important than ever to put systems in place that enable vulnerable people to be monitored remotely so that they can live more independently [1]. A healthy lifestyle and a lower risk of musculoskeletal problems are both aided by maintaining proper posture. A person's upper and lower body alignment is known as their posture [2]. A more generic term, "poise," could have varying connotations depending on the speaker.

2. Literature Review

Consistently maintaining good posture is essential for building strong bones and muscles. Whether one is standing, sitting, or even asleep, their posture is the way their body is held. To avoid aches and pains in the back, neck, and shoulders, it is important to maintain good posture as part of a healthy lifestyle. It is important to keep an eye on one's posture, either manually or with the aid of technology, because modern living has become more sedentary due to people spending more time in front of computers. This can weaken muscles and alter one's posture. Posture detection and monitoring are particularly crucial for vulnerable and elderly folks when it comes to remote health monitoring and enabling them to live independently. Posture detection has many applications outside of geriatric healthcare, including health education, environmental awareness, surveillance, and human-computer interaction. Position is identified. Health prediction and monitoring in smart cities necessitates mobile systems and smart technology. This is why the present research looks at posture recognition with LoRa (long range) and multimodal approaches.

The LoRa WAN technology has a number of benefits, including long communication distances and low costs. The goal of developing multisensory and loRa technologies is to create clothing that may be worn comfortably in any position. Because of LoRa's tiny data transmission sizes and low transmit frequency, this study makes use of multiprocessing. The following are some of the jobs that utilise Random Forest: feature extraction, data processing, feature selection, and sliding window multiprocessing. Performance and accuracy are both enhanced by using a 500-group data set and three testers [20]. Body language and gestures are examples of non-verbal cues. We want to obtain the maximum feasible accuracy in remote posture detection using hybrid classifier selection, deep learning, and machine learning. The six metrics used for body language prediction are as follows: mean, kurtosis, standard deviation (SD), skewness, and square root (SR). Finding the best combination of features for anticipated posture is the next most important step after feature extraction. In this study, multiple machine learning models were used to assess six features and their combinations. This analysis made use of the following models: logistic regression, decision tree, Naïve Bayes, random forest, LDA, and QDA. The time-consuming nature of data integration made the use of deep learning algorithms for posture prediction inevitable. They don't require feature extraction and are generally more effective than ML models. deep learning techniques, such as 1D-CNN. This hybrid method for remote posture detection trains meta-learning with a number of predictions from deep learning and machine learning. The method enhances the performance of the system when used. Results from experiments show that the hybrid strategy achieves better posture recognition results than both deep learning and machine learning methods. The hybrid approach outperformed ML and DL on several assessment metrics, including f-measure, recall, accuracy, and precision. Sitting for long periods of time also causes another problem with human posture. Your physical and emotional well-being can take a hit if you sit for long periods of time or have poor posture. The fundamental objective of the posture training approach is to maintain a record

of one's sitting and stretching positions. The smart cushion can then utilize AI to detect your position from that point on.

3. Methodology

We provide a novel mixed-methods strategy that leverages ML and DL to get better results in posture prediction and detection than each method alone. The suggested work makes three important contributions: An innovative hybrid method for posture prediction involves a number of machine learning techniques, including support vector machines (SVMs), decision trees, Naive Bayes, K-nearest neighbours (KNNs), and random forests. New developments in LSTMs and convolutional neural networks (CNNs) have brought the possibility of automated posture identification closer.

The suggested approach is shown to be more precise and efficient when compared to current best practices. Its advantages are: Improved performance, Efficient accuracy.

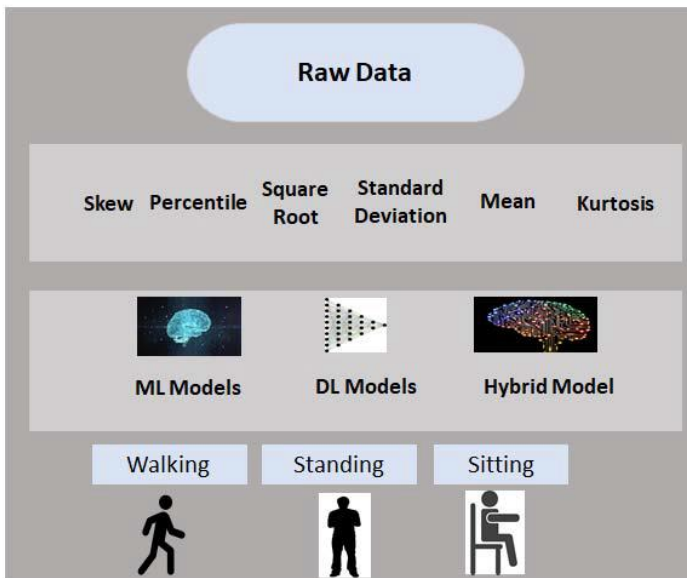
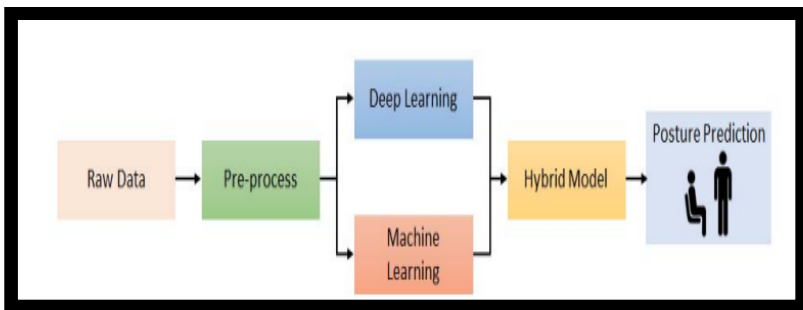


Fig.1. Architecture Diagram

This hybrid method for remote posture detection trains meta-learning with a number of predictions from deep learning and machine learning. The method enhances the performance of the system when used. Results from experiments show that the hybrid strategy achieves better posture recognition results than both deep learning and machine learning methods. The combined approach outperformed deep learning and ML when tested using f-measure, accuracy, precision, and recall. Machine learning

Algorithms

Random forest algorithm : In this model, there are three principles related to randomness: first, the random selection of training data for tree construction; second, the random selection of feature subsets for node splitting; and third, the random consideration of feature subsets for each node split in each simple decision tree. Each tree in a random forest learns from a randomly selected subset of the data points used for training.

Decision Tree

Though it is more commonly employed to solve classification difficulties, Decision Tree is a supervised learning technique that can handle regression issues as well. The classifier is constructed like a tree, with the features of the dataset at the root, the decision rules at the branches, and the results at the leaf nodes

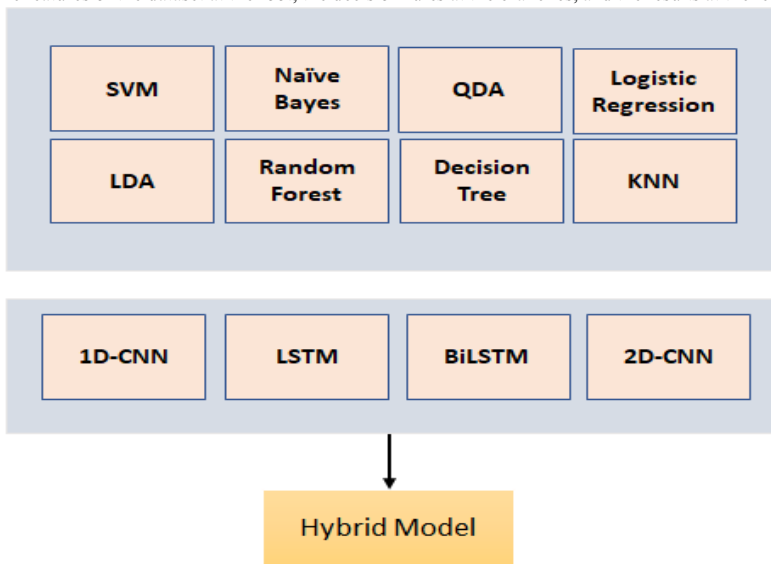


Fig. 2. Proposed Hybrid Classifier.

AdaBoost Algorithm

One ensemble method in machine learning is AdaBoost, which is also known as adaptive boosting. In AdaBoost, one-level decision trees, also known as decision trees with a single split, are the most used algorithm. Another name for these trees is Decision Stumps.

SVM

Among the many supervised machine learning algorithms, Support Vector Machine (SVM) stands out. This model performs worse in the long run than its shorter and medium-term alternatives. Algorithms differ in how they learn patterns and make predictions.

XGBoost

One ensemble ML method that relies on decision trees and a gradient boosting framework is XGBoost. When it comes to prediction issues involving unstructured data (pictures, text, etc.), artificial neural networks always outperform all other algorithms and frameworks. But these days, when it comes to tiny to medium structured/tabular data, decision tree-based algorithms are considered top-notch.

K-NN

One of the most basic ML algorithms, K-NN stands for "K-Nearest Neighbor" and is based on the supervised learning method.

When a new data point is compared to the existing data, the K-NN algorithm sorts it according to how similar it is. As a result, the K-NN algorithm makes short work of categorizing newly-arrived data.

LSTM:

Document categorization, time series analysis, voice and speech recognition, and many more applications are explored by LSTM, a subset of RNNs. Unlike feedforward networks, RNN predictions rely on previous guesses. Due to a few shortcomings that lead to unrealistic estimations, RNNs are not often used in experimental research.

Convolution Neural Network (CNN):

This is a primary class for neural networks to use for classifying and recognizing images. Many applications rely on convolutional neural networks, including scene labeling, object detection, face recognition, and many more.

Table 1: COMPARISON WITH STATE-OF-THE-ART APPROACHES

	1	2	3	4	5	6	7	8	9	10
	Conv	Max Pool	Conv	Max Pool	Conv	Max	Conv	Global Max Pool	Fc	Fc
Kernel Size	16	32	3	2	64	2	128			
Neurons	3	2	3	2	3	2	3		128	2
Activation	ReLU		ReLU		ReLU		ReLU		ReLU	SoftMax

4. Results

The names of the algorithms are shown on the x-axis of the graph, while the values of accuracy, precision, recall, and FSCORE are shown on the y-axis, with various colored bars representing each metric. According to the data shown above, XGBOOST is a very accurate graph extension. A comparison table of all algorithms is displayed in the screen below.

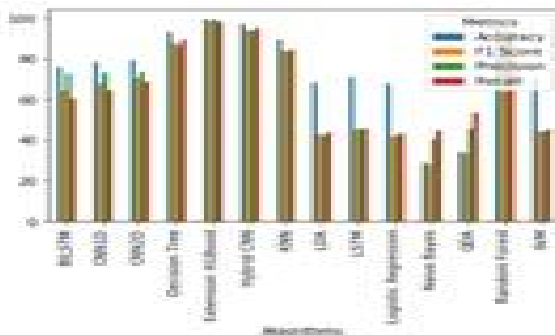


Fig 3. Valuations for accuracy, precision, recall, and FSCORE, represented by separate colored bars

Table 2: HYBRID (2D-CNN) FOR POSTURE PREDICTION

Feature	Accuracy	Precision	Recall	F-score
Mean	92.19	0.92	0.92	0.92
Mean, SD	92.8	0.92	0.92	0.91
Mean, SD, SR	93.9	0.93	0.93	0.93
Mean, SD, SR, percentile	94.29	0.94	0.94	0.94
Mean, SD, SR, percentile, kurtosis	94.51	0.94	0.94	0.94
Mean, SD, SR, percentile, kurtosis, skew	96.51	0.96	0.96	0.96
Raw data	96.23	0.96	0.95	0.96

Table 3: COMPARISON WITH STATE-OF-THE-ART APPROACHES

Ref	Accuracy	Precision	Recall	F-score
Rizwan et al. [17]	71.21	0.71	0.71	0.71
Xu et al. [18]	85.69	0.85	0.85	0.85
Castellini et al. [19]	79.08	0.88	0.73	0.76
Sanghvi et al. [20]	81.23	0.81	0.80	0.81
Winters et al. [21]	82.64	0.79	0.76	0.77
Winters et al. [21]	82.64	0.79	0.76	0.77
Lee et al. [3]	75.04	0.75	0.74	0.75
Our Approach	98.14	0.98	0.98	0.98

Table 4: SUMMARY OF HYBRID (BILSTM) FOR POSTURE PREDICTION

Feature	Accuracy	Precision	Recall	F-score
Mean	90.29	0.90	0.90	0.90
Mean, SD	91.9	0.91	0.91	0.91
Mean, SD, SR	92.78	0.92	0.91	0.92
Mean, SD, SR, percentile	92.99	0.92	0.92	0.92
Mean, SD, SR, percentile, kurtosis	93.73	0.93	0.93	0.93
Mean, SD, SR, percentile, kurtosis, skew	93.8	0.93	0.93	0.93
Raw data	94.52	0.94	0.94	0.94

In above comparison Graph you can see propose HYBRID CNN 2D and Extension XGBOOST got high accuracy and other value

5. Conclusion

Remote health monitoring is essential for allowing those with frail health or advanced age to live independently. This is why we offered a fresh design for posture detection—which encompasses sitting, standing, and walking—in this project, one that relies on deep learning classifiers. Furthermore, a novel hybrid methodology is created to compute the posture prediction, with DL methods serving as its foundation. A novel blend of deep learning and machine learning predictions is used to train the meta-learning. Experiments showed that the suggested hybrid approach worked better than DL and ML alone.

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