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Patient-Handling Tasks and Posture Classification with Machine Learning

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Introduction

A 2016 survey conducted by Venditelli et al [1] indicated that 39% of registered nursing respondents had reported musculoskeletal injuries after two years of regularly performing patient-handling tasks. Optical marker systems (considered the gold standard) can be accurately used in laboratory settings to explore mechanisms of injury during patient-handling tasks, but deploying inertial measuring units (IMUs) in biomechanics allows data collection in both laboratory and clinical environments. IMU-based capture systems are also preferable to optical marker systems because they avoid marker occlusion during more complicated patient-handling tasks. The purposes of our study are (1) to identify machine learning models that can accurately predict the task performed and the quality of posture adopted by participants performing patient-handling tasks (using data from wearable sensors - IMUs - and force plates), and (2) to determine an optimal combination of those IMUs.

Time Series Classification

Time series classification (TSC) is a type of supervised machine learning classification problem where the data is sequentially ordered by time. It can be further categorized into univariate (TSC) and multivariate (MTSC) problems. Our data is multivariate time series data as it comprises multivariate forces, accelerations, and angular velocity measurements.

Recently, researchers have made significant progress in machine learning techniques for multivariate time series classification. In [2], Fawaz et al developed a Convolutional Neural Network ensemble called InceptionTime that is highly accurate and scalable for large datasets. Similarly, Dempster et al [4] used a convolutional kernel based approach (ROCKET) to perform very fast and accurate classifications on time series data. We compared the performances of the following multivariate time series classifiers on our dataset: MiniRocket [5], MultiRocket [6], HIVE-COTE 2.0 [7], InceptionTime [2], and ResNet [3].

Methodology

For our preliminary model, data was collected from two college-aged, able-bodied volunteers who were fitted with 8 IMU devices on the trunk, pelvis, thighs, calves, and feet (see fig. 1). The subjects performed 3 different patient-handling tasks while standing on two force plates placed side by side, with a foot on each force plate. The 3 tasks were: standing a patient up from a wheelchair, rolling a patient onto their side, and sitting a patient up on a table. For each of the 3 tasks, 36 trials were performed, with 3 repetitions per trial, and 2 or 3 categories of posture (good vs poor, or good, neutral, poor). We used a 50 pound nursing manikin as our patient for repetition consistency.

fig. 1: IMU, force plate, and markers setup

Each of the 8 IMUs placed on the participants comprises a tri-axial accelerometer and a gyroscope which each produced 3 dimensions of data. Only the accelerations were used (i.e. 24 acceleration dimensions per IMU). Each of the two force plates provided 8 dimensions, but only the vertical GRF (vGRF) dimension (force in the z-direction) was used. We selected 5 different IMU combinations to serve as inputs to the MTSCs: (1) vGRFs, trunk, and pelvis; (2) trunk and pelvis; (3) only trunk; (4) only pelvis; and (5) only vGRFs. Each model was trained and validated on 80% of the data, while the remaining 20% of the data (which were not used in training the model) were used to test the models to evaluate accuracy and precision.

Results

After training and testing the models on 216 instances, (each instance is 1 trial; each trial has 300 rows and 58 columns of data) we found that the trunk and pelvis combination produced the highest scores across models. MiniRocket yielded the best scores with accuracy at 98.1% and precision at 97.8% (see fig. 3). MiniRocket was also by far the fastest model, training in just over 2 minutes.

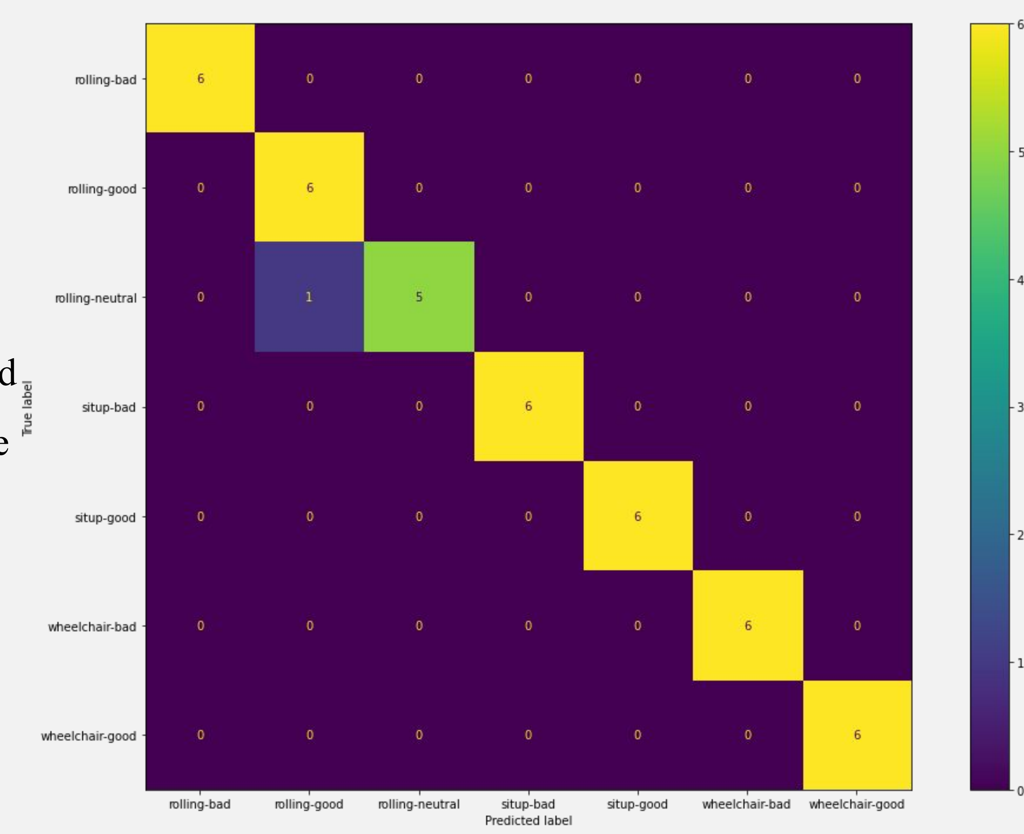

fig. 2: Confusion matrix for trunk and pelvis data

MultiRocket followed close behind MiniRocket in all metrics. HIVE-COTE 2.0 frequently scored equal or slightly less than the ROCKET variants at the expense of time, taking between 10-15 times as long to train, validate, and test the dataset. The neural networks, ResNet and InceptionTime, performed significantly worse, with higher training times and lower model scores than the ROCKET variants or HIVE-COTE 2.0. When analyzing the confusion matrices (see fig. 2), we saw that the rolling tasks were the most frequently incorrectly identified by the model. Having the additional (intermediate) category "neutral" seemed to cause the model to struggle in predicting between "bad" and "neutral", or "good" and "neutral".

Conclusion

Results from four MTSCs that predict patient-handling tasks and quality of posture when provided with force plate and IMU input data were analyzed, with a couple achieving very high levels of accuracy. Our findings show that MiniRocket produced the most accurate and reliable results for our dataset. Future work will investigate classifying additional manual patient-handling tasks, determining the specific location from which poor posture is emanating, and possibly deploying the model for use in real time during task performance. Combined with electromyography, this may provide insight on low back loads experienced by caregivers while performing manual patient-handling tasks. It is also important to determine specifically in what location the quality of posture is poor (e.g. upper body or lower body). Ultimately, we hope our model can be applied within an application that can provide real time automated feedback on the postures adopted by caregivers during task performance to help minimize workplace injury.

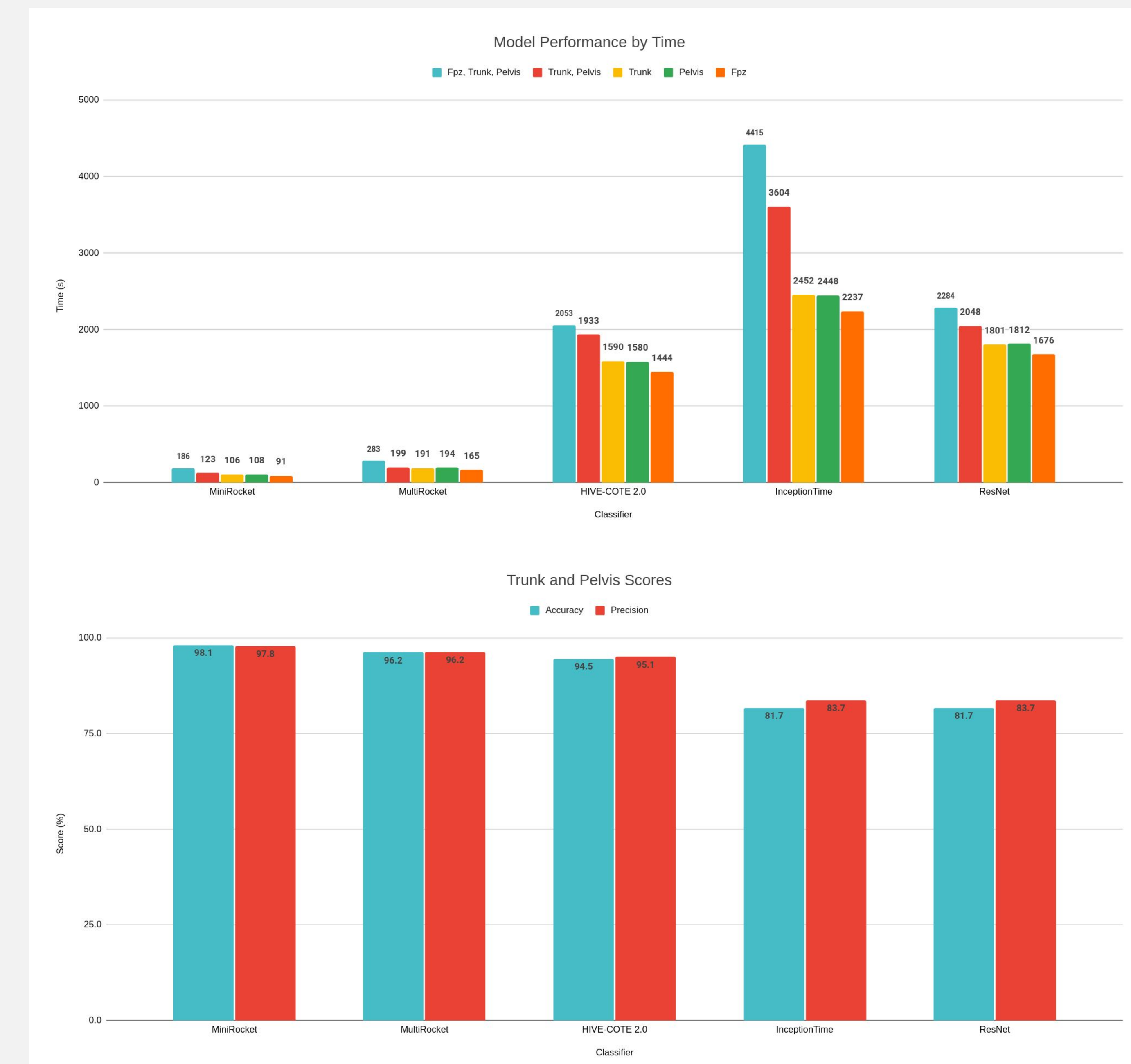

fig. 3: Model performance for trunk and pelvis data

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