Physical Human Activity Recognition Using Machine Learning

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Abstract. Human activity recognition (HAR) is the outcome of the desire to make everyday lives smarter and easier with technology owing to the rise in ubiquitous computing. This study is designed to perform HAR by using two dimensionality reduction techniques followed by five different supervised machine learning algorithms as an aim to receive better predictive accuracy over the existing benchmark research. The study resulted in LR performing the best classification by achieving 92% accuracy using the PCA as feature reduction technique. The ANN also provided satisfactory results and has received predictive results greater than the benchmark test. However, KNN, decision tree, and Naive Bayes algorithms didn't prove efficient.

Keywords: Human Activity Reduction, Supervised Machine Learning, Wearable sensors, Dimensionality Reduction Techniques

1 Introduction

Activity recognition is the task of recognizing the current physical action performed by one or more users from a set of observations recorded during the user activity in the context of a definitive environment. Recent times have seen the theory of Human Activity Recognition (HAR) catering to multiple challenging applications built on the increase in ubiquitous, wearable and persuasive computing. Human Activity recognition has become an important technology that is changing the landscape of people's daily routine contributing to a wide range of applications as assistive technology, health and fitness tracking, elder care and automated surveillance to name a few. Additionally, the research in activity recognition has been so rapid and advanced that it is starting to cater applications that go beyond activity recognition. However, as the field is rich in practical applications, the challenges emerging for activity recognition are multifold. There are issues and challenges encountered in Human Activity Recognition such as selecting the right tools and techniques for gathering, storing and manipulating data. Picking the right algorithm to perform predictions is of utmost importance as there is a necessity to capture the inter-class variability and the intra-class similarity. Typical resource constraints as processing power, availability of time and sufficient storage form a huge hurdle. There is also a necessity to have a trade-off between system latency, accuracy and processing power. The initial stages of HAR deal with a different set of issues altogether. Picking the right sensor or combination of sensors, selecting the attributes and metrics to be measured, placing the sensor at the right location are all crucial in their corresponding way. Furthermore, all these must be done by considering the user privacy and usability in context. The process must not be obtrusive for the user and must adapt to the user's behavior and their environment as entire process can be highly sensitive to the participation and the interaction with the user.

The research question that is planned to be addressed in the current study is:

To what extent can supervised machine learning algorithms significantly enhance the recognition of physical human activity with inertial sensor?

The rest of the paper is organized as follows. Section 2 describes related work performed previously in the field of HAR. Section 3 explains the design and methodology of the experiment sequentially in the order of the experiment undertaken. Section 4 showcases the results achieved in the experiment and also performs a critical analysis on it. Finally, section 5 concludes the study by highlighting the work performed and underlines the scope for future work.

2 Related work

Human activity recognition has gained much importance in the past decade due to its numerous applications in human centric applications as in the field of medical, security and also military (D. Lara and Labrador, 2013). The initial research on HAR involved detecting gestures and activities from still images and videos in restricted environments and under constrained settings Turaga et al (2008); Mitra and Acharya (2007). A significant number of domains have been discovered to benefit due to HAR as in the case of Activities of Daily Living (ADL's) by Katz et al (1970), which was one of the initial researchers performed as an application of activity recognition, which further boosted the research by Bao and Intille (2004); Ravi et al (2005); Logan et al (2007); Tapia et al (2004). The traditional medical procedures were challenged by introducing the HAR to support patients' daily activity monitoring especially for patients with chronic impairments, medical diagnosis or even for rehabilitation (Starner et al, 1997; Chen et al, 2006; Oliver and Flores-Mangas, 2007; Bachlin et al, 2009; Tessendorf et al, 2011). HAR also provided great results for other areas of lesser severity as the entertainment and sports category (Kunze et al, 2006; Minnen et al, 2006; Ladha et al, 2013), the industrial and operations sectors (Maurtua et al, 2007; Stiefmeier et al, 2008). One of the most recent and popular usages of human activity recognition was for gaming consoles such as Microsoft Kinect where body gestures/movements are recognized to enhance gaming experience (Shotton et al, 2013).

A combination of different sensors at various locations have been utilized previously to produce varying results. One of the most popular sensors used quite frequently for similar studies involving repetitive actions is an accelerometer. An accelerometer is an electromechanical device which is used to measure static and dynamic acceleration forces. For instance, the angle of tilt or inclination of the device can be calculated by measuring the gravity acceleration. The accelerometer was used in multiple studies as a motion sensor, yielding good results for their area of application (Bao and Intille, 2004; Mi-hee et al, 2009; Khan et al, 2008). Others as image and audio based sensors, Global positioning system (GPS) sensors, biosensors and infrared sensors are also widely used in HAR applications. There are also combinations of sensors utilized together for better detection of the signals. The accelerometer was combined with the physiological sensor to detect signals as skin temperature and energy expenditure (Yang and Cho, 2008). Apart from the various types of sensors, the simplest and one of the efficient is the accelerometer in a combination with a gyroscope, which is a device used to detect angular velocity (Lazzarini, 2007). Due to development of mobile phone technology, the smart phones have built in accelerometers and gyroscopes which make the study of activity detection furthermore simplified (Brezmes et al, 2009; Oh et al, 2010). Anguita et al (2013); Kwapisz et al (2011) utilize the sensors in the mobile phone to perform the task of human activity recognition.

Cleland et al (2013) investigates the importance of sensor and the optimal placement of it on the body of the user. Their study demonstrates that the acceleration signal values gradually increase in magnitude as the placement of the sensor moves from head to feet. So, it is evident that the location has direct impact on the results obtained for the HAR process. Various studies have utilized the sensor placed at various body parts of the user and have received various ranges of accuracies. Parkka et al (2006) have studied HAR by placing the multiple sensors at the wrist and chest and performed various activities for the duration of 2 hours. The best results out of the three classifiers yielded were of 83% accuracy. Observing the studies that utilized only a single sensor at one location of the body, a sensor at waist or on the lower back have been yielding good results. Mathie et al (2004); Gupta and Dallas (2014) have performed HAR task using a single sensor placed at the Waist and have received a classification accuracy of 98% and Bonomi et al (2009) have received an accuracy of 93% while detecting for similar activities. Hence, placement of sensor on the waist can be seen as an ideal position as it is proven and additionally it is also closer to the centre of mass of the body (Yang and Hsu, 2010).

Anguita et al (2013) dealt with creating an activity database by recording Activities of Daily Life (ADL) of 30 users. They have utilized the inertial sensors on a smart phone device to record the activities. A multiclass Support vector machine algorithm has been employed to detect these activities. Authors have received improved classification accuracy when compared to their previous work which was an SVM classifier with additional usage of fixed point arithmetic algorithm which as stated in the research would reduce additional computational cost (Anguita et al, 2012). This database has been selected in this research study. The Hidden Markov Model (HMM) is the most popular algorithm used in activity recognition for this dataset and various researchers performed one, two and three staged HMMs on it (Zhu and Qiu, 2016; Ronao and Cho, 2014; San-Segundo et al, 2016b,0). Also, Gaussian mixture models which are slightly more complicated, have been utilized to perform activity recognition on the same data. However, the algorithm could not manage to yield results as accurate as the others (San-Segundo et al, 2016a).

In summary, with growing industry of the wearable tech, activity recognition has become one of the popular studies with increasing number of practical applications and questions it can solve. The motivation behind the study is to utilize the best activity recognition techniques combined with suitable machine learning algorithms to obtain high predictive accuracies. As the 'No-Free Lunch theorem' states that there can never be one particular model that may be suitable for an application and that the assumptions generated for a single research question might not hold true to another question, it is common for researchers to utilize multiple machine learning classifiers to detect the one that best fits the data and underlying domain (Wolpert, 2002). So the next direction in this research would be to evaluate the popular algorithms in activity recognition with a popular dataset with suitable evaluation techniques. The research question tackled by the current study is as follows:

> *To what extent can supervised machine learning algorithms significantly enhance the recognition of physical human activity with inertial sensor data when compared to a traditional SVM model?*

3 Design & Methodology

This chapter details the plan and the design methodology for the current study. Several data mining methodologies were studied to identify a robust and well structured approach for the data mining project. The Cross Industry Standard Process for Data Mining (CRISP–DM), a well proven method is identified to conduct the current study, which at its core is a data mining project (Piatetsky, 2014). This methodology is an ideal sequence of events and the current section will deal with each of these phases as a separate task. However, the steps can always be traced back to previous stages to repeat or manipulate a step to better suit the following stage.

3.1 Business Understanding

Human activity recognition, as seen from the previous section, has tremendous business value. The primary motive of this study is to enable patients, senior citizens or infants with immediate medical attention during a case of physical accident or emergency. This can be ensured by detecting their current physical activity with the assistance of a wearable device connected to them. As it is a case of providing medical support, recognizing the right activity of the user is of utmost importance as it acts as a trigger to the chosen emergency action as notifying the guardian or the hospital. From an analytical perspective, in order to recognize the activities right, we must target onto high accuracy levels of prediction. To achieve the targeted accuracy levels, multiple machine learning models from various families of machine learning algorithms will be employed.

Business Objective – As the current study deals with enabling quick assistance to provide emergency services, they must be reported with high accuracy. So the objective of the experiment is to implement machine learning models with high classification accuracy.

Business Success Criteria – The solution must not only result in high classification accuracy, but also provide evidence in proving that the experiment and results are significant and would always yield similar results when attempted to replicate the solution.

In view of the above objectives and constraints, below hypothesis is utilized to address the research question –

> *Each supervised machine learning algorithm, modeled on the HAR dataset yields a different classification accuracy that is significantly greater than the benchmark SVM model, with a p value < 0.05*

Formally, the null hypothesis can be stated as –

$$\Big[\big(\text{Accuracy (Decision Tree)}\big) \neq \big(Accuracy(KNearestNeighbor)\big) \neq \big(Accuracy(NaiveBayes)\big) \\ \neq \big(Accuracy(MultinomialLogisticRegression)\big) \neq \big(Accuracy(ArtificialNeuralNetwork)\big)\Big] \\ > \big(\text{Accuracy (Base Support Vector Machine) }\big)$$

3.2 Data Understanding

The dataset used in the current study is generated at the International Workshop of Ambient Assisted Living (IWAAL) held in Spain in 2012. Anguita et al (2012) designed an experiment by recording a set of six activities performed by a group of 30 volunteers. The tri-axial linear acceleration and the tri-axial angular velocity from the built-in accelerometer and gyroscope of a smart phone device are captured. Time and frequency domain vector of features were obtained from each of the window created. A set of derived features were created for each of these obtained features. To understand the data and its elements, the data must be initially integrated and put in an ideal format to inspect it; this process of data integration is performed and specified under the data preparation stage. The first element of investigation performed on the integrated data is calculating the dimensions using the function 'dim'. There were 10299 rows, which is the train and test set combined and 563 columns consisting of 561 features, the subject and the activity variable. The structure of the dataset and the six point summary of the data were attempted to be analyzed but as the data size was high, it was not quite comprehensible. The users and the activity levels were tabulated to inspect their distribution using simple aggregation methods. It is observed that their composition was quite uniform, with respect to each other and the entire data. It is also observed that both the activity and subject fields were free of any class noise or data inconsistency issues.

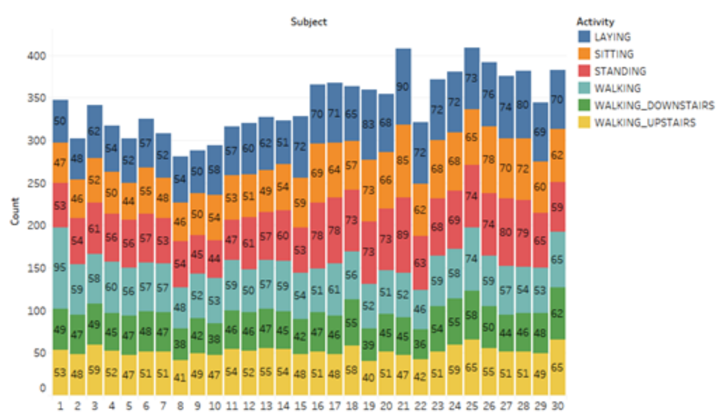

Fig. 1: Histogram of records per user grouped by target

3.3 Data Preparation

– **Data Integration**
  The first step under preparing the data is the data integration which is performed before the data understanding stage as the original data is provided as a .zip folder containing multiple text files each representing different components of the full dataset. A consolidated dataset is created initially

to perform data manipulations and finally the individual train and test datasets are created by dividing as per the original dataset composition.

– **Data Manipulation**
  The next step under the data preparation is converting the data into their right primitive data types. The Activity and Subject variable are converted into categorical variables using the function ”as.factor”. All the other independent features are converted into numeric using ”as.numeric”. The feature names are further edited to remove unnecessary spaces and special characters as brackets, quotes and dots, hyphens were replaced with underscores to have syntactically correct character names using the ’gsub’ function.
– **Dimensionality Reduction**
  High dimensionality as seen previously can cause severe difficulties as it could be increasingly hard for analysis. An ideal solution to this problem is to use dimensionality reduction techniques to bring down the size of the data. The study utilized two techniques to decrease the size of the feature set.
  • Correlation Analysis
    Highly correlated features can downgrade the performance of a model. Moreover, it’s not ideal to have multiple features measuring the same variability of the target feature. So in order to decrease multicollinearity in the data, highly correlated variables are identified and removed from the dataset. For this, initially, a correlation matrix is generated for all the 561 independent features. This produces a 561x561 matrix with correlation values between all the features.
    This correlation matrix is given as input to the ’findCorrelation’ function in the caret package along with a cut off value of 0.8 of pairwise absolute correlation, which denoted strong correlation between the features (Taylor, 1990). This function resulted in a list of 389 feature names which are highly correlated with the other features and in a pair possess a higher mean absolute correlation over the other. Finally, an uncorrelated dataset is created using only the features not in the highly correlated list generated above. This resulted in a dataset with 174 uncorrelated features. From this data the Subject feature which acts as an identifier is removed. The final uncorrelated dataset is inspected for dimensions and has 173 columns and the original intact 10299 rows.
  • Principal Component Analysis
    This technique replaces all the set of features with a linear combination of them called as principal components. To generate the principal components of the feature set, the ’prcomp’ function is utilized. The input to the function are the full list of features without the subject and the activity fields and a boolean variable of scaling given as true, to ensure that the features are scaled to have unit variance. The resultant object has 5 elements as standard deviation, rotation, centre, scale and a matrix with the new components which are ordered on basis of decreasing importance and relevance levels with respect to the variability being captured.
    The individual component variance measured is calculated by squaring the standard deviation values. Using the first 100 features, about 94.6% of the total variance is captured which is enough data captured for the proportion of data reduced.

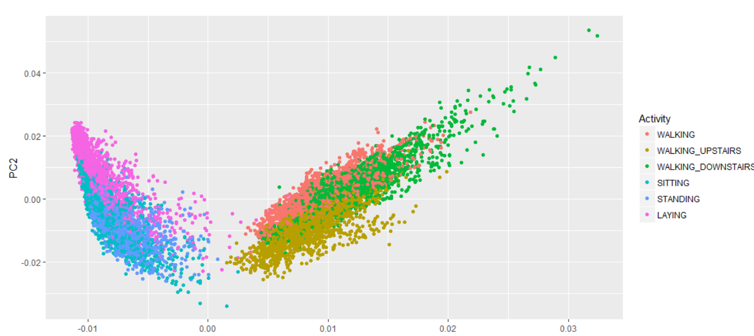

Fig. 2: Variable space approximated by the top 2 principal components

The variable space approximation captured in figure 2 showcase the components differentiating between the cluster of activities. From the figure 2 it is evident that the original data can be approximated using principal components. A new data frame is hence created with the Activity field and the first 100 principal components. The resultant dataset has 101 columns and the original 10299 rows.

3.4 Modeling

The models must be implemented in accordance to the model validation technique. K fold validation technique was deemed the best technique on basis of the reviewed studies. To perform the K fold validation, the caret package is utilized with the number of folds selected as 10 and the method as cross validation. The train function of the caret package is used for inducing each of the models. The first model to be created is the decision tree with the splits being performed using the Gini impurity as it is faster and better for continuous attributes as in this scenario Gini impurity also works in accordance to minimize the misclassification rate, which is the aim of the study. For K-Nearest neighbors' algorithms, the tune length is set to '15', which seems an ideal solution to compensate between increasing value of accuracy and tuning and execution time of the model. To iterate the training procedure over K, the model used cross validation technique. Due to cross validation over multiple values of K, the modeling took a lot of time to converge. It is observed that K value of 5 is best suited for the data. For the Naive bayes, the default settings are used with no use of kernel function. It was the quickest execution out of all the models. The penalized multinomial logistic regression is also run on default settings, but the maximum weights had to be set high enough to enable the model to be executed. The model summary provided an AIC value of 2178.446. The neural net is initially modeled with a combination of units of hidden layer and decay value. It is identified that by using 30 units in the hidden layers with a decay value of 0.1 the algorithm converges considerably faster and the model doesn't over-fit.

3.5 Evaluation

The evaluation is performed by predicting the target values for the testing datasets using their corresponding models. The prediction is implemented using the 'predict.train' function, from the caret package, by supplying the model and the test dataset to it. It is important to remove the original target feature from the test dataset. Once the predictive model results are generated, a confusion matrix is plotted using the function 'confusionMatrix' with data input as the predicted values and reference as the original target feature labels. The overall component of the confusion matrix generated has the overall statistics as accuracy levels, sensitivity, specificity, kappa value etc. An accuracy value is generated for every model under each of the feature engineering technique and values are analyzed to pick the best algorithm for the data. A final statistical test is performed on the distribution obtained from the validation stage to get the statistical significance of the tests in order to answer the research question.

4 Results & Discussion

4.1 Data Understanding

The Data Understanding phase proved to be quite insightful in establishing the context of the data preparation to be performed or in order to estimate the complexity in terms of space and time for creation of the models as well as predicting the final results. The initial analysis of the data depicted that the Activity feature, the subject feature, individually and with respect to each other are completely balanced. It is also seen that all the independent features fall in a specific range of $+1$ to -1. It can be understood that the data was range normalized to fit to this particular range. It permits the algorithms to provide equal emphasis on every feature and allow better standardized data into the next stages and not allowing various ranges of the data to affect the significance of any feature.

4.2 Data Preparation

The independent features of the experiment are derived from the raw signals from two sensors of a single device. When performing an action, it is evident that the data is highly correlated and that multiple values could be representing the same component of variance in the target feature as in any tri-axial dataset (Mannini and Sabatini, 2010). Furthermore, each of these features measure tiniest aspects of the activity performed as for instance, the magnitude of the jerk measured through the body acceleration in the x- axis. This value would not be as different as the value measure in y or z axis or that of its minimum or maximum value during the sampling period of 2.5 seconds. It can be understood that there is a potential for redundant data to mislead the algorithm. In addition, excessive and irrelevant data might also lead to over fitting in the model. As dimensionality reduction was a crucial step in preparing the data for the modeling stage, the idea was to choose more than one technique for this task. Under correlation analysis, a not very stringent value of the correlation coefficient was chosen but it proved quite significant by identifying about 70% of the total features as highly correlated with each other, such features were eliminated. Principal component analysis was thought to be a better dimensionality technique during the design phase, due to the fact that the features could be replaced with their linear combination, with each component capturing certain amount of measurable variance in the target feature. The results of the technique were quite impressive too. With just 18% of the total number of features, about 95% of the total variance was being captured. Plotting all the principal components against the target feature in figure 2 also demonstrated a good understanding of the activity as all the stationary activities as standing, sitting and lying down were differentiated from the motile activities as walking in a line and on the stairs.

4.3 Modeling

To utilize the K fold cross validation technique for the evaluation phase, each of the models was trained and validated on 10 different combinations of the training data to ensure that the entire dataset was used for training the models and additionally that the created models and the prediction results were significant and can be replicated when necessary. In order to create the different samples of train and validation datasets for each fold, stratified sampling technique was used. However, the random sampling could have worked equally good as the data is well balanced in terms of the target feature but stratified sampling provides greater certainty in avoiding any bias in the models due to the dataset composition.

The first model implemented was the decision tree, which is one the most powerful algorithms and yet can be highly influenced by its structure and thus yield drastically different results. The decision tree has suffered in differentiating the activities from each other. Especially, the sitting and walking downstairs activities were repeatedly misclassified. In the current study, as the independent features are all numeric, it must be been challenging for the algorithm to find the right value that can be used to bifurcate the tree to create partitions as the algorithm typically works best with categorical variables. Additionally, the decision trees are sought out due to its ability to provide highly interpretable results but in this case, with such huge amounts of data features, interpreting the rules and the tree partitions could add very little value.

The next model generated is the K nearest neighbors algorithm. It was one of the models that has performed remarkably in producing results with accuracies better than the benchmark result. Considering the nature of the activity, the two clusters of activities, stationary and mobile, the KNN algorithm ensured high inter cluster classification accuracy. But the intra cluster classification accuracy was not very satisfying especially for the stationary activities. As the current experiment involves detecting the user activity over the span of 2.5 seconds, it is evident that the activity is influenced by the actions preceding and following it. So the KNN algorithm which takes into account the specified number of neighbours for performing classification justifies its satisfactory performance. But it must be noted that the modeling and evaluation of the algorithm was computationally very demanding and has taken the highest amount of time.

The Naive bayes model is simple generative model that performed an indirect computation of the required probability through the Bayes function. The classification accuracy is not noteworthy compared to the results from other models and is also inadequate compared to the benchmark results.

The poor performance of the Naive bayes can be implied to the innate assumption of parameter independence. In the current experiment, each of the features is a derived attribute from the originally collected metrics and hence neglecting the interactions between the features can result in loss of plenty of information and proved damaging. But it must also be noted that the algorithm was the fastest to converge compared to all the other algorithms.

The multinomial logistic regression model was one of the best performing models and provided exceptional classification accuracy and was greater than the benchmark accuracy value. The ability of the algorithm to handle any non linear effects and reduce the influence of noise could have been the factors corresponding to the increased predictive accuracies. It can be observed that there is low inter cluster misclassification by the model but some amount of intra cluster misclassification for the stationary activities.

The final algorithm was the artificial neural net. The ability of the ANN to implicitly detect complex nonlinear relationships and also to acknowledge and utilize the interactions amongst the independent variables are two of the biggest advantages of the algorithm that have permitted in capturing the essence of the data resulting in the high accuracy values.

4.4 Comparison of Dimensionality Reduction Techniques

The dimensionality reduction techniques utilized to defend the experiment from the curse of dimensionality have helped in executing the algorithms on the given machine with limited space and time constraints. The figure 3 demonstrates the accuracy values for each of the model grouped by the corresponding feature reduction technique. It is evident that the Principal Component Analysis technique has increased accuracy values for every algorithm. The Correlation analysis despite being a strong technique failed in providing sufficient results. It could be as though the features were highly correlated, eliminating them completely resulted in loss of important information. However, by creating the principal component, the data was better approximated.

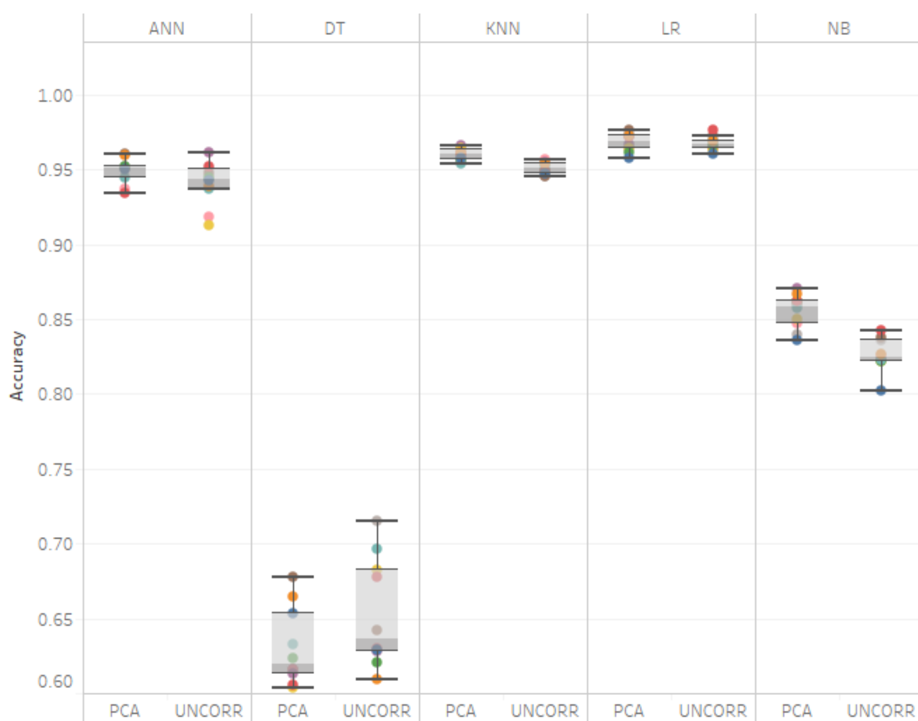

Fig. 3: Boxplots of accuracies grouped by dimensionality reduction technique

4.5 Distribution of Accuracies

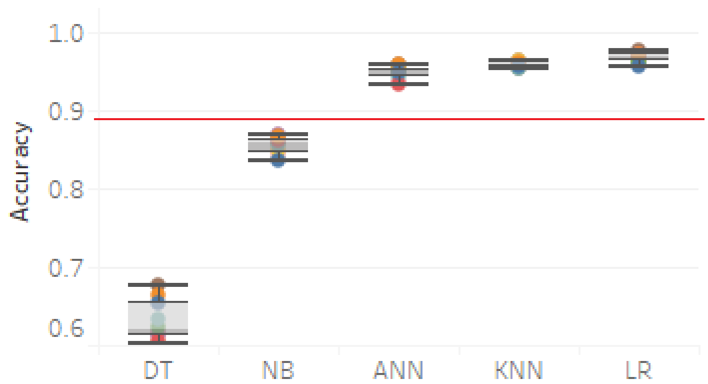

Fig. 4: Distribution of accuracies grouped by modeling technique

The figure 4 illustrates the distribution of the accuracies for each of the classification algorithm. The accuracy distributions for KNN, ANN and LR seem to be quite normal with low standard deviation but the distributions of KNN and NB seem slightly skewed. The red line depicts the accuracy value of the baseline test. The algorithms ANN, KNN and LR have performed extremely well and have achieved classification accuracies better than the baseline test. The results report that the logistic regression has slightly better classification accuracy over the K nearest neighbor which in turn has slightly better classification accuracy over artificial neural net. The figure 5 illustrates the results of the ANN, KNN and the LR models. It can be observed that the results of these tests overlap. Hence, they were individually tested for statistical significance in order to prove that the results of the LR algorithm are significant over the KNN algorithm and KNN was better over the ANN algorithm.

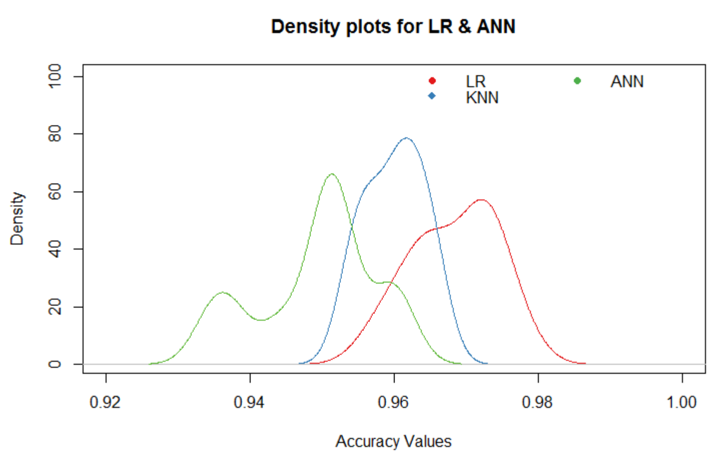

Fig. 5: Density plot for ANN, KNN and LR models

The hypothesis of the Wilcoxon test is that the two accuracy lists are from an identical population and don't differ. The tests resulted in a p value of 0.009152 and 0.008004, which are both quite less than 0.05, so the hypothesis can be rejected. So at a significance level of 0.5, it can be concluded that all the three accuracies are from a different populations and that the algorithms have increasing classification accuracy.

4.6 Hypothesis Evaluation

Model	Final Accuracy
Decision Tree	0.5744825
Naive Bayes	0.8316932
Artificial Neural Network	0.9029522
K Nearest Neighbors	0.8791992
Logistic Regression	0.9250085
Baseline SVM	**0.8915**

Table 1: Predictive Classification Accuracy List

From the results tabulated in table 1 depict the final predictive accuracies obtained when predicting against the test dataset. It is evident that Logistic Regression performed significantly better than all the other machine learning algorithms created in this experiment followed by the ANN which managed to perform better than the benchmark test. However, though the KNN model performed extremely well under validation data, the algorithm couldnt perform as per expectations when predicting activities for the test dataset. The NB and DT continued to perform poorly compared to the baseline test. Finally, the research hypothesis requires every model to perform significantly better than the base SVM model but only 2 of the models were able to do so.

Hence, combining all the experiment and statistical test results, it can be stated that there isnt enough evidence to reject the null hypothesis.

5 Conclusion

Primarily, the research aimed to recognize the physical human activity of a user using the data generated from a wearable sensor device. The initial study was concentrated on understanding the current state of the art techniques in performing human activity recognition. After acquiring relevant data for the research, the next main area of focus in the research was to perform suitable feature engineering to alter the data to be compliant to apply machine learning algorithms in the restricted time and memory conditions. Correlation analysis and Principal component analysis were the techniques utilized. Both these techniques have been proved effective for the experiment as they minimized the total number of features to about 30% of the original dataset. The goal of the research was to model the condensed data using machine learning algorithms in order to obtain high predictive accuracies. The experiment resulted in two out of the five induced models achieving a classification accuracy higher than the benchmark study, providing partial evidence to reject the null hypothesis. Additionally, it is also proved that principal component analysis serves better for HAR compared to correlation analysis. Under future work of this study, multiple other feature reduction techniques and more complex machine learning algorithms can be utilized to yield different results. Additionally, more complex activities can be added to the original experiment to have a bigger and better dataset.

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