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Human Activity Recognition using Machine Learning

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Abstract: Nowadays, activity recognition is one of the most popular uses of machine learning algorithms. It's utilized in biomedical engineering, game production, and producing better metrics for sports training, among other things. Data from sensors linked to a person may be used to build supervised machine learning models that predict the activity that the person is doing. We will use data from the UCI Machine Learning Repository in this work. It contains data from the phone's accelerometer, gyroscope, and other sensors, which is used to build supervised prediction models using machine learning techniques like as SVM, Random Forest. This may be used to forecast the person's kind of movement, which is separated into six categories: walking, walking upstairs, walking downstairs, sitting, standing, and lying. We'll use a confusion matrix to compare the accuracy of different models.
Keywords: Human Activity Recognition, SVM, Random Forest, Decision Tree, Confusion Matrix.

I. INTRODUCTION

The number of smart phones available on the market has grown at an exponential rate over the previous decade. In India alone, the number of smart phone users is predicted to more than double in 2014, from 156 million to 364 million. As the number of smart phones increases, so does the amount of data that can be generated by the smart phone's sensor. The Smartphone is equipped with a gyroscope and an accelerometer, among other inertial sensors. The readings of these sensors vary depending on how the smart phone is moved. These smart phones have easily incorporated into the daily lives of those around us. The majority of the day is spent using mobile devices. Using the data from the smart phone's sensors, we can follow the activity of the person holding the phone. Activity recognition takes this information into consideration and utilizes it to create models that can anticipate the person's current activity. We use data from the UCI machine learning repository that has been adjusted for our study in this publication. The data will be analysed using supervised machine learning algorithms to generate prediction classification models that will be used to categories the person's physical activity into six categories: sitting, standing, lying down, walking, walking upstairs, and walking downstairs. The accuracy of the various models developed will be assessed using SVM (Support Vector Machine), Random Forest Classifier and the construction of a confusion matrix. The following is how this paper has been organized: Section 2A discusses the data set used in the study and the operations performed on it before it was utilized in the experiment. Section 3 contains a description of the methodology employed. The Section 4 discusses observations.

II. DATA SET

The Human Activity Recognition database was built from the recordings of 30 study participants performing activities of daily living (ADL) while carrying a waist-mounted smartphone with embedded inertial sensors. The objective is to classify activities into one of the six activities performed. The following information is supplied for each entry in the dataset:

1) The accelerometer's overall acceleration (triaxial acceleration) and the predicted body acceleration.
2) The gyroscope's triaxial angular velocity.
3) A 561-feature vector having variables in the time and frequency domain.
4) Its designation of activity.
5) An identification for the person who conducted the experiment.

III. LITERATURE SURVEY

For years, experts have researched human activity recognition and presented several solutions to the problem. Existing methods usually employ vision sensors, inertial sensors, or a combination of the two. The use of machine learning and threshold-based algorithms is common. Machine learning algorithms are more accurate and dependable, but threshold-based methods are faster and easier to use. Body posture has been captured and identified using one or more cameras [7-8]. The most typical methods are several accelerometers and gyroscopes mounted to various body locations [9-11]. Aims have also been set for approaches that integrate visual and inertial sensors.

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Data processing is an important component of all of these methods. The quality of the input characteristics has a significant influence on performance. Previous research has focused on extracting the most useful elements from the Human Activity Recognition data set utilizing Smart phones [12]. The signal is often analyzed in both the temporal and frequency domains. The accuracy of the 6 tasks completed by the group of 30 participants was predicted using machine learning algorithm on the activity column.

IV. METHODOLOGY

The trials were conducted on a group of 30 participants ranging in age from 19 to 48 years old. Each participant did six activities while wearing a Smartphone. We recorded 3-axial linear acceleration and 3-axial angular velocity at a constant rate of 50Hz using the device's internal accelerometer and gyroscope. The tests were videotaped so that the data could be manually labelled. The resulting dataset was randomly divided into two sets, with 70 percent of the volunteers providing training data and 30 percent generating test data.

The sensor data (accelerometer and gyroscope) were pre-processed using noise filters before being sampled in 2.56 sec fixed-width sliding windows with 50% overlap (128 readings/window). A Butterworth low-pass filter was used to separate the gravitational and body motion components of the sensor acceleration data into body acceleration and gravity. Because it is expected that the gravitational force has only low frequency components, a filter with a cutoff frequency of 0.3 Hz was utilized. Calculating variables from the time and frequency domain yielded a vector of characteristics from each frame.

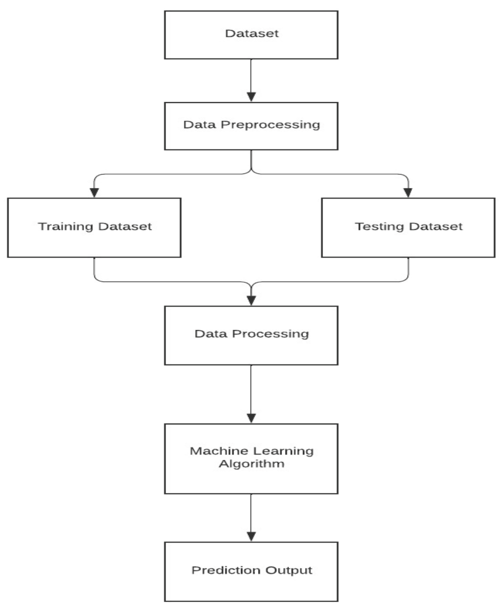


Figure 1: implementation of system model

A. Importing Data

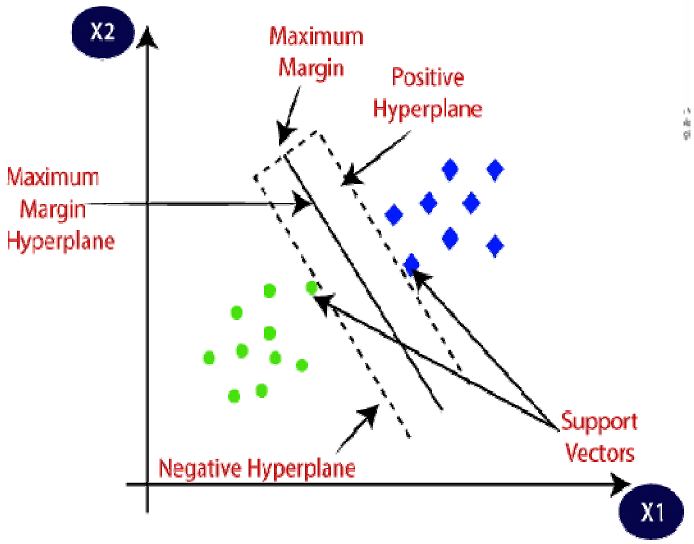
As a csv file, the data was imported into Kaggle. The data was shuffled to ensure that the observations were distributed randomly. Different models are now used in SVM (Support Vector Machine), Random Forest Classifier and the construction of a confusion matrix.

B. Data Pre-processing

Data preprocessing is the procedure for preparing raw data for use in a machine learning model. It's the first and most important stage in building a machine learning model. It is not always the case that we come across clean and prepared data when working on a machine learning project. It is also necessary to clean and format data before doing any action with it. As a result, we employ the data preparation task.

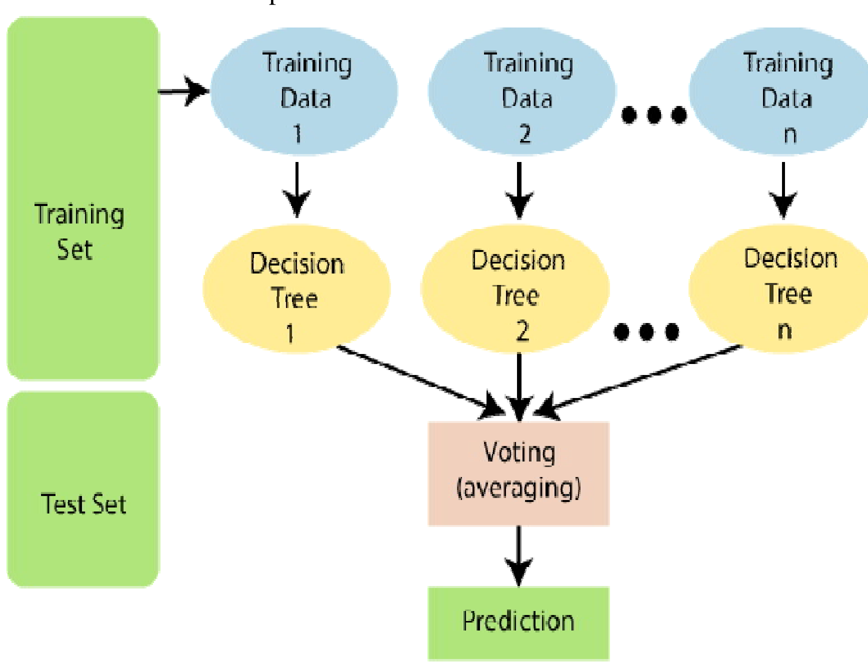
C. SVM Support Vector Machine

The support vector machine, or SVM, is a machine learning approach for analyzing data and recognizing patterns. It may create classification or regression models. SVM models portray classification categories as points in space when used for classification analysis. Simple linear SVM is constructed if the points can be separated using linear lines. If the points in a specific dimension cannot be clearly separated using hyperplanes, the points are transported to a higher dimension using Kernel Tricks. Hyperplanes are used to demarcate the borders between distinct categories once the points have been translated to higher dimensions.



D. Random Forest

Random forest (RF) is a classification approach that employs an ensemble of unpruned decision trees, each of which is constructed using a bootstrap sample of the training data and a randomly chosen subset of variables. Random Forest is a machine learning approach in which many trees, generally more than 500, are produced and observations are attempted to be categorized through each tree. Each tree provides a categorization for a certain class, which we refer to as "voting" for that class. The categorization that has received the most votes is chosen by Forest. For our research, we utilized the random Forest package from Kaggle to build a Random Forest model. A total of 1000 trees were planted.



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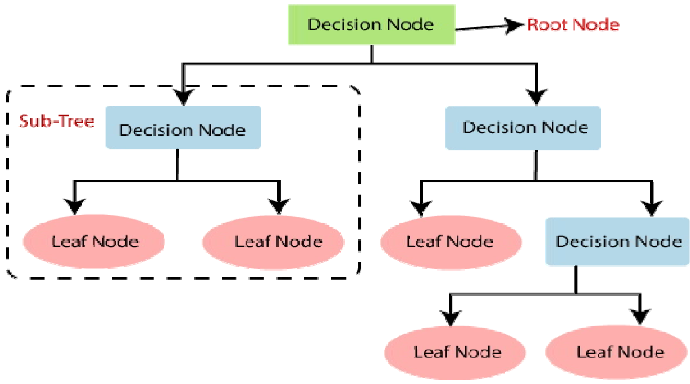
E. Decision Tree

Decision Tree is a supervised learning approach that may be used to classification and regression issues; however, it is most commonly employed to solve classification problems. Internal nodes contain dataset attributes, branches represent decision rules, and each leaf node provides the conclusion in this tree-structured classifier.



F. Confusion Matrix

Confusion Matrixes are used to assess an algorithm's effectiveness in the Machine Learning process; they are most commonly employed in supervised learning. The actual value of the class to be predicted is represented by each row of the matrix, while the predicted value is represented by each column. The rate of misclassification of the various models produced was measured using the Confusion Matrix in our study.

		Predicted Class		
		Positive	**Negative**	
Actual Class	**Positive**	True Positive (TP)	False Negative (FN) **Type II Error**	**Sensitivity** $\frac{TP}{(TP+FN)}$
	Negative	False Positive (FP) **Type I Error**	True Negative (TN)	**Specificity** $\frac{TN}{(TN+FP)}$
		Precision $\frac{TP}{(TP+FP)}$	**Negative Predictive Value** $\frac{TN}{(TN+FN)}$	**Accuracy** $\frac{TP+TN}{(TP+TN+FP+FN)}$

V. DATA VISUALIZATION

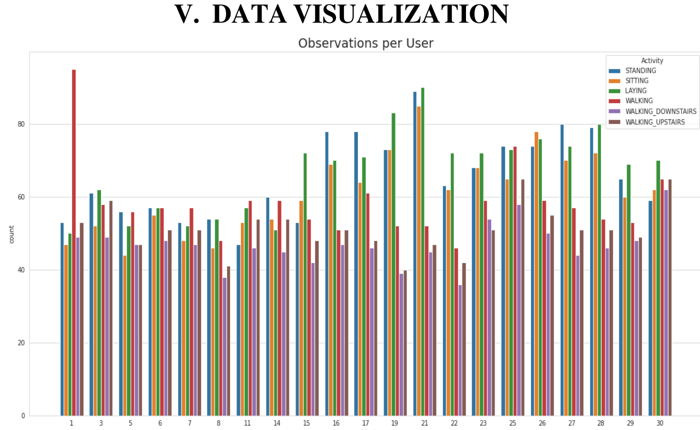


Figure 2: Observation Per User

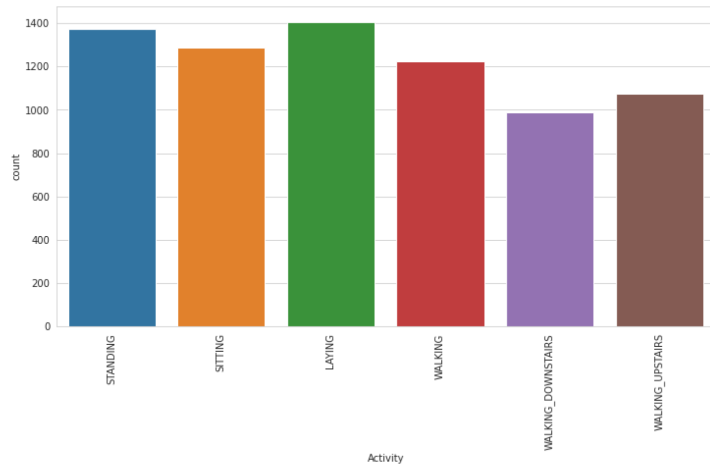


Figure 3: Activity Per User

VI. EXPERIMENTAL RESULT

Sl. No.	Algorithm Used	Accuracy Score
1.	Default SVC Score	0.9748
2.	Some Hyperparameter where Kernel used rbf and C=100.0	0.9884
3.	Random Forest Classifier	0.9816
4.	Confusion Matrix	0.9748
5.	Decision Tree	0.94

VII. CONCLUSION

Recognition of human activity has a wide range of applications in medical research and human survey systems. We created a smartphone-based identification system that detects six human behaviors in this project: walking, standing, lying, sitting, walking upstairs and downstairs. Using a built-in accelerometer, the system gathered time series signals, created 561 features in both the time and frequency domains, and then lowered feature dimensionality to increase performance. Four passive learning approaches were used to train and assess the activity data: random forest classifier, decision tree, support vector machine, and confusion matrix. In our experiment, the best classification rate was 98.8 percent, which was attained using SVC with rbf and c=100.0. The performance of SVM with default hyperparameters, Random Forest, Decision Tree, and Confusion Matrix is likewise quite close to the processed data. Algorithms were investigated in order to lower the cost of data tagging. After applying the supervised learning method to the four classifiers, SVM improves the most and SVM predicts the best accuracy for our situation. Future development may include new activities and the implementation of a real-time smartphone system.

REFERENCES

[1] Aggarwal, J. K., and Ryoo, M. S. (2011). Human activity analysis: a review. ACM Comput. Surv. 43, 1–43. doi:10.1145/1922649.1922653
[2] BishoySefen, Sebastian Baumbach et. al. / Human Activity Recognition Using Sensor Data of Smart phones and Smart watches/ ICAART 2016
[3] Wearable Sensor-Based Human Activity Recognition Using Hybrid Deep Learning Techniques
[4] M. Berchtold, M. Budde, D. Gordon, H. Schmidtke, and M. Beigl, “Actiserv: Activity recognition service for mobile phones,” in International Symposium on Wearable Computers, pp. 1–8, 2010.
[5] L. Bao and S. S. Intille, “Activity Recognition from User-Annotated Acceleration Data,” in Pervasive, pp. 1–17, 2004.
[6] O. Lara, M. Labrador, "A survey on human activity recognition using wearable sensors", IEEE Common. Surveys Tuts., vol. 15, no. 3, pp. 1192-1209, 2013.
[7] U. Maurer, A. Smailagic, D. P. Siewiorek, and M. Deisher, “Activity recognition and monitoring using multiple sensors on different body positions,” in Int. Workshop on Wearable and Implantable Body Sensor Networks, (Washington, DC, USA), IEEE Computer Society, 2006.

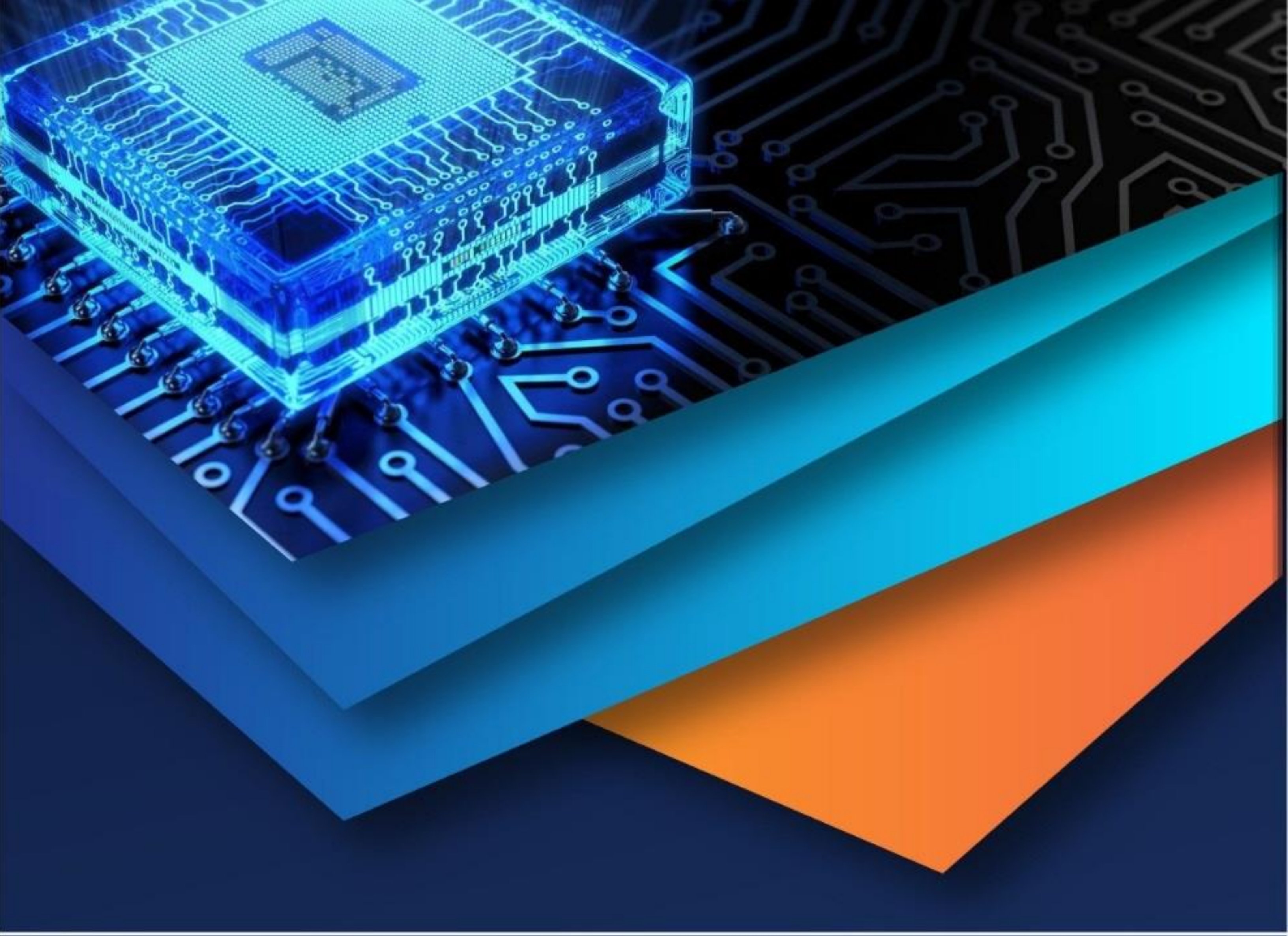
[8] J. Parkka, M. Ermes, P. Korpipaa, J. Mantyjarvi, J. Peltola, and I. Korhonen, "Activity classification using realistic data from wearable sensors," IEEE Trans. Inf. Technol. Biomed., vol. 10, no. 1, pp. 119–128, Jan. 2006.

[9] Davide Anguita, Alessandro Ghio, Luca Oneto, Xavier Parra and Jorge L. Reyes-Ortiz. Human Activity Recognition on Smartphones using a Multiclass Hardware-Friendly Support Vector Machine. International Workshop of Ambient Assisted Living (IWAAL 2012). Vitoria-Gasteiz, Spain. Dec 2012.

[10] Davide Anguita, Alessandro Ghio, Luca Oneto, Xavier Parra, Jorge L. Reyes-Ortiz. Energy Efficient Smartphone-Based Activity Recognition using Fixed-Point Arithmetic. Journal of Universal Computer Science. Special Issue in Ambient Assisted Living: Home Care. Volume 19, Issue 9. May 2013.

[11] Davide Anguita, Alessandro Ghio, Luca Oneto, Xavier Parra and Jorge L. Reyes-Ortiz. Human Activity Recognition on Smartphones using a Multiclass Hardware-Friendly Support Vector Machine. 4th International Workshop of Ambient Assited Living, IWAAL 2012, Vitoria-Gasteiz, Spain, December 3-5, 2012. Proceedings. Lecture Notes in Computer Science 2012, pp 216-223.

[12] Jorge Luis Reyes-Ortiz, Alessandro Ghio, Xavier Parra-Llanas, Davide Anguita, Joan Cabestany, Andreu Català. Human Activity and Motion Disorder Recognition: Towards Smarter Interactive Cognitive Environments. 21st European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, ESANN 2013. Bruges, Belgium 24-26 April 2013.



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