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# HUMAN ACTIVITY RECOGNITION

## *and Explainable AI*

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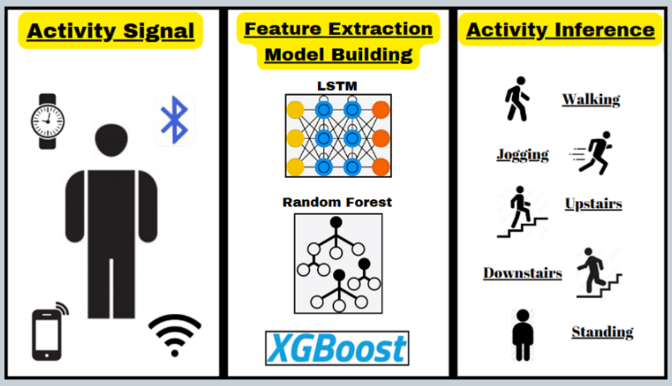
**In this project, I explore how machines understand human activities, like walking or sitting, using sensor data. I compare modern machine learning models with complex methods like LSTM and HMM, evaluating their effectiveness. My goal is to uncover advancements and trade-offs, making the artificial intelligence behind these decisions more understandable for practical trust and clarity, with the usage of explainable AI.**

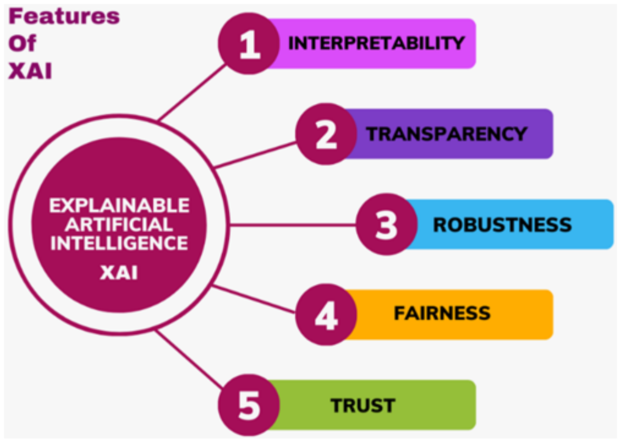
## 01. HAR

Machines understanding and categorizing human actions through data for diverse applications and insights.
Dataset records user activities (walking, jogging) with timestamp and three-axis accelerometer readings, in structured formats.



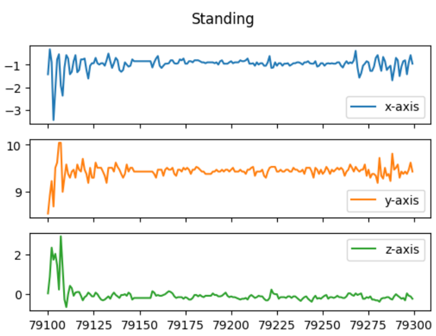

## 02. XAI

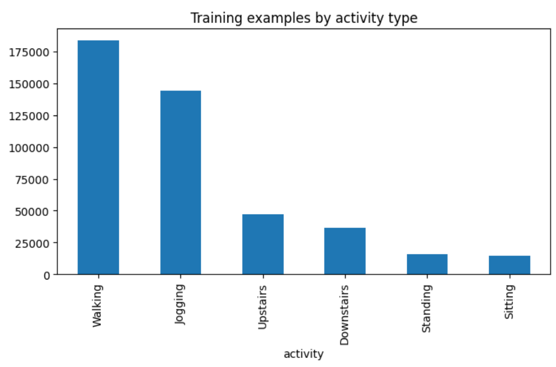
Explainable AI enhances transparency by providing interpretable insights into complex models, fostering trust. It empowers users to understand, validate, and make informed decisions based on machine learning outputs, bridging the gap between intricate model predictions and human understanding




## 03.INSIGHTS

Accelerometer readings reveal user activities. Insights identify the most frequent activity.



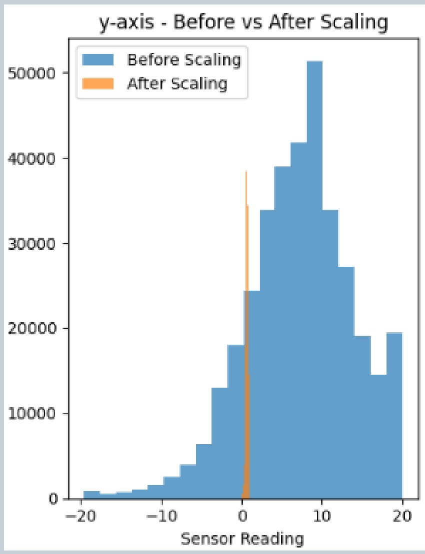

Analyzing impact, determine which activity significantly influences and least affects accelerometer readings.

## 04. EDA

Addressed imbalance in y-axis data only, for better model performance and accurate representation of Human Activity Recognition.

Encoded 'activity' labels using label encoding, enhancing model interpretability for Human Activity Recognition in sensor data.

| Activity | Encoded Value |
|---|---|
| Downstairs | 0 |
| Jogging | 1 |
| Sitting | 2 |
| Standing | 3 |
| Upstairs | 4 |
| Walking | 5 |

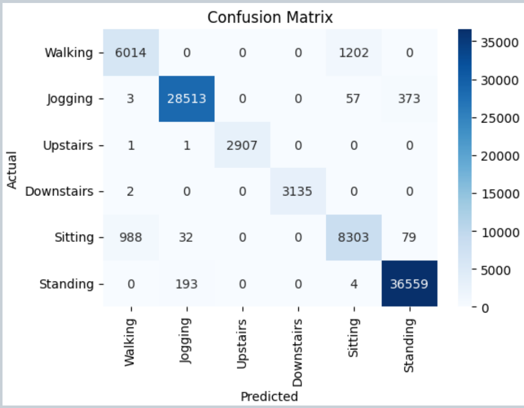



## 05.MODEL-EVAL

**Employed ML models:**
**Decision Tree - 75%**
**Logistic Classifier - 54%**
**XGBoost - 97%**
**KNN - 78%**

Classification Report:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.86 | 0.83 | 0.85 | 7216 |
| 1 | 0.99 | 0.99 | 0.99 | 28946 |
| 2 | 1.00 | 1.00 | 1.00 | 2909 |
| 3 | 1.00 | 1.00 | 1.00 | 3137 |
| 4 | 0.87 | 0.88 | 0.88 | 9402 |
| 5 | 0.99 | 0.99 | 0.99 | 36756 |
| accuracy | | | 0.97 | 88366 |
| macro avg | 0.95 | 0.95 | 0.95 | 88366 |
| weighted avg | 0.97 | 0.97 | 0.97 | 88366 |

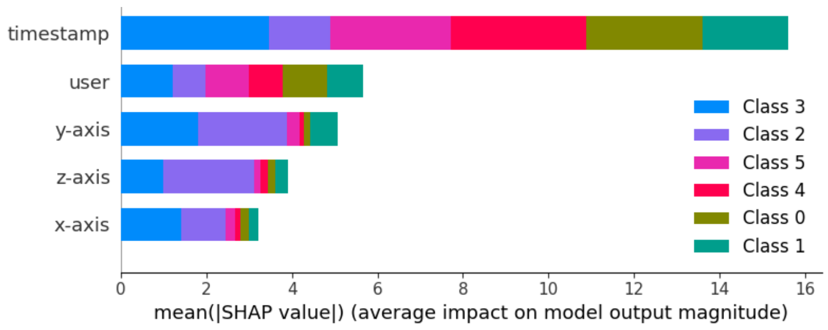



Confusion matrix used to evaluate performance. A Heat Map to visualize the matrix, for XGB.

## 06. EXPLAIN PREDICTIONS W/ SHAP

We used SHAP Values to tell how each feature contributes to models' decision, for better explanation. dissect model predictions, revealing the impact of each feature, simplifying understanding and boosting transparency.

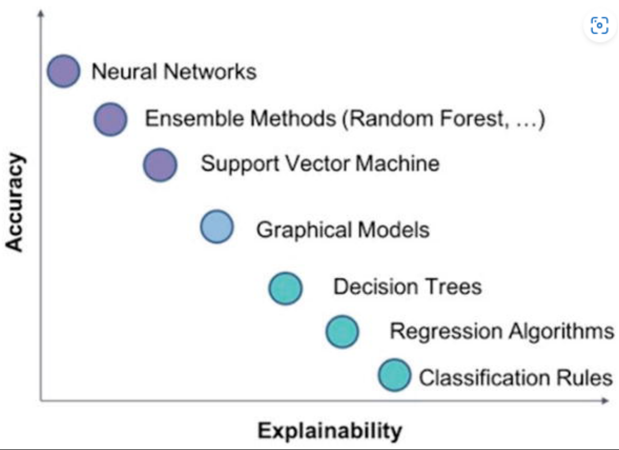
Each bar represents a feature's contribution to the model's output across all instances.




## 07. THESE MODELS VS. THOSE MODELS

Several key points for choosing the above models then LSTM or HMM.

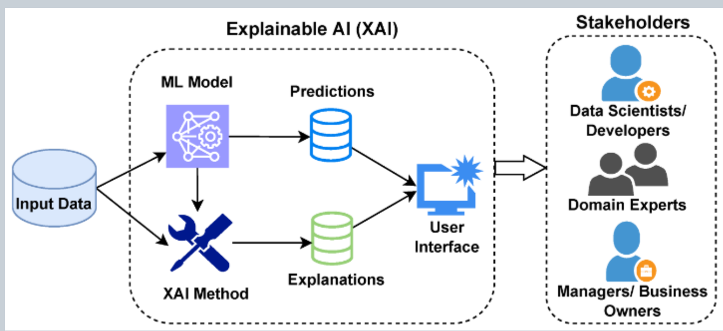
**Better Explainability**
**Easy Visualization**
**Feature Importance**
**Robust to Outliers**
**Better Noise Handling**
**Less Complex Architecture**
**Cheaper then DL Models**




## 08. SUMMARY

Chose interpretable Decision Trees and XGBoost for HAR, balancing accuracy and interpretability. Visualize SHAP values' impact on model transparency.

XAI enhanced model interpretability, offering insights into decision-making and enabling detailed examination of feature importance.




(N.D.). EXPLAINABLE AI - HOW HUMANS CAN TRUST AI - ERICSSON. RETRIEVED JANUARY 17, 2024, FROM <HTTPS://WWW.ERICSSON.COM/EN/REPORTS-AND-PAPERS/WHITE-PAPERS/EXPLAINABLE-AI--HOW-HUMANS-CAN-TRUST-AI> BROWNLEE, J. (2020). LSTMS FOR HUMAN ACTIVITY RECOGNITION TIME SERIES CLASSIFICATION. MACHINELEARNINGMASTERY.COM. RETRIEVED JANUARY 17, 2024, FROM <HTTPS://MACHINELEARNINGMASTERY.COM/HOW-TO-DEVELOP-RNN-MODELS-FOR-HUMAN-ACTIVITY-RECOGNITION-TIME-SERIES-CLASSIFICATION/>