Instituto Tecnológico y de Estudios Superiores de Monterrey

MODELLING LEARNING WITH ARTIFICIAL INTELLIGENCE

TC2034

GROUP 301

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Data analysis for medical applications

TEAM

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1. Description of the implemented application along with the collected data, answering the following questions

    - What is the purpose of the application?

The application's purpose is to provide fitness and activity tracking for athletes when training with friends, especially those practicing boxing. It can detect a variety of movements, like walking, running, or jumping, which are tied to standard aerobic exercises, shadow boxing, a more specific sport exercise, and sitting down or waving your hand, which provide insight into when the athlete is resting or in a relaxed state. This can help a person track their movements and actions during training or sparring, which proves useful in further developing their skills and physical condition.

    - What is it expected to do?

The application is expected to receive data from a mobile device held in your right hand and, based on the phone's movement, accurately classify physical activities (or lack of them) in real-time.

    - Are there similar applications out there?

Some applications offer quite similar functionality, but there is not one that is flexible to the type of exercise one is working out. Some apps, such as PunchLab or Combat Go, provide tracking for boxing and other fighting-related exercises, while others, like Fitbit, track steps, cardiac rhythm, and data related to walking, running, or staying still. While not necessarily an app, there are cases of employing an optimized AI model to make a smartphone into a personalized activity recognition system, similarly to what we are attempting to do (STMicroelectronics, n.d.).

    - What type of information does it acquire and analyze?

The phone captures information on acceleration in all three axes and orientation of the phone using a gyroscope, all of this through the Phyphox app. It then analyzes different tendency measures for each of them, obtaining various features for the model to utilize.

2. Explanation of the features extracted from the data.

A total of 60 features were extracted from the data, characteristics of x, y, and z axes for acceleration and gyroscope readings, plus some global features that represent all 3 axes. The selected features are common in real applications and studies involving accelerometers and gyroscopes (D'Souza & Rajamohan, 2017; Zertuche, 2023; Capela et al, 2015).

Table 1: *Acceleration in the x, y, and z axes*

Feature	**Explanation**
Mean (3)	The average acceleration per axis indicates general motion.
Standard deviation (3)	Variation in acceleration. Higher values indicate more dynamic movements.
Maximum/minimum values (6)	Peak intensity for acceleration, both lowest and highest. It helps to distinguish high-intensity activities.
Skewness (3)	Indicates the symmetry (or lack of) in the motion distribution.
Kurtosis (3)	Measures how narrow/flat the peak is. It helps differentiate between sudden and smooth movements.
Energy (3)	Sum of squared signal values. It may reflect the intensity of the movement.
Root mean square (3)	Shows the magnitude of acceleration.
Zero-crossing count (3)	Frequency of changes in the direction of the movement. It is useful to identify periodic motions.
Global Mean (1)	Combined statistics of all axes that provide insight into total body movement and its intensity or patterns.
Global standard deviation (1)	
Global signal energy (1)	

Table 2: *Gyroscope magnitude in the x, y, and z axes*

Feature	**Explanation**
Mean (3)	The average angular velocity, or average rotational motion, per axis.
Standard deviation (3)	The variation in the rotational motion. It can be useful to identify sudden movements, such as punching.
Maximum/minimum values (6)	Peak rotational motions.
Skewness (3)	The predominant direction of the rotation.
Kurtosis (3)	It shows the concentration of extreme rotational motions.
Energy (3)	It reflects a total value for rotational movement.
Root mean square (3)	Magnitude of rotational motion. It may show movements that involve rotating the phone a lot.
Zero-crossing count (3)	Changes in the rotational movement of the phone. It can help identify repetitive movements.
Global Mean (1)	Measures of the combined axes that provide general insight into the rotational movement of the phone.
Global standard deviation (1)	
Global signal energy (1)	

3. A summary of the evaluation results for the tested classifiers, including hyperparameter tuning and feature selection.

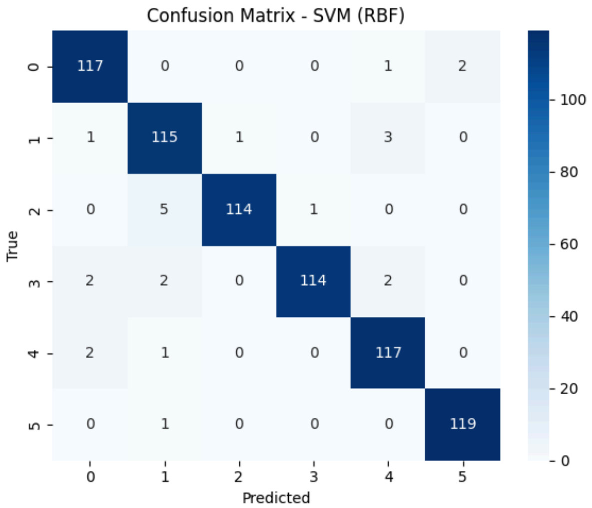
Table 3: *Summary of evaluation results for each of the 10 tested classifiers.*

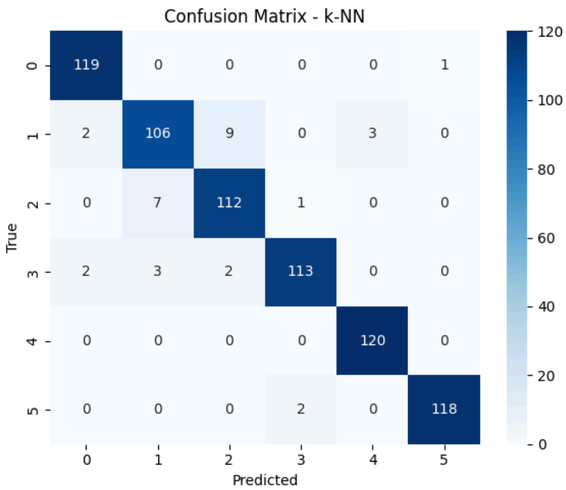
Model	Class	Precision	Recall	F1-Score	Support
SVM (RBF)	0	0.95901639	0.975	0.96694215	120
SVM (RBF)	1	0.92741935	0.95833333	0.94262295	120
SVM (RBF)	2	0.99130435	0.95	0.97021277	120
SVM (RBF)	3	0.99130435	0.95	0.97021277	120
SVM (RBF)	4	0.95121951	0.975	0.96296296	120

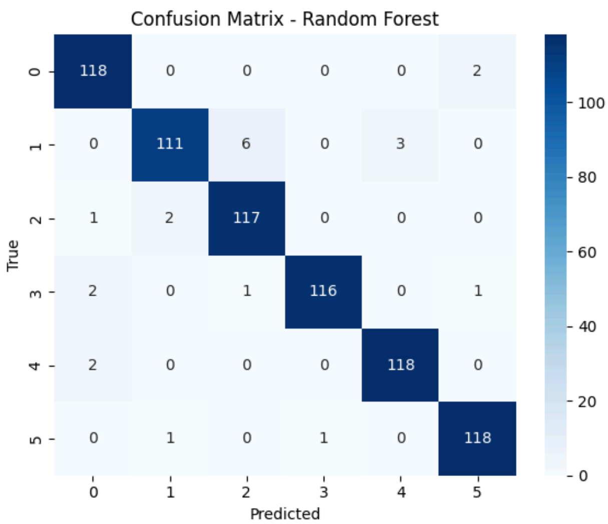
SVM (RBF)	5	0.98347107	0.99166667	0.98755187	120
k-NN	0	0.96747967	0.99166667	0.97942387	120
k-NN	1	0.9137931	0.88333333	0.89830508	120
k-NN	2	0.91056911	0.93333333	0.9218107	120
k-NN	3	0.97413793	0.94166667	0.95762712	120
k-NN	4	0.97560976	1	0.98765432	120
k-NN	5	0.99159664	0.98333333	0.9874477	120
Random Forest	0	0.95934959	0.98333333	0.97119342	120
Random Forest	1	0.97368421	0.925	0.94871795	120
Random Forest	2	0.94354839	0.975	0.95901639	120
Random Forest	3	0.99145299	0.96666667	0.97890295	120
Random Forest	4	0.97520661	0.98333333	0.97925311	120
Random Forest	5	0.97520661	0.98333333	0.97925311	120
Gradient Boosting	0	0.98319328	0.975	0.9790795	120
Gradient Boosting	1	0.90677966	0.89166667	0.89915966	120
Gradient Boosting	2	0.92248062	0.99166667	0.95582329	120
Gradient Boosting	3	0.97435897	0.95	0.96202532	120
Gradient Boosting	4	0.97478992	0.96666667	0.9707113	120
Gradient Boosting	5	0.98305085	0.96666667	0.97478992	120
Extra Trees	0	0.9516129	0.98333333	0.96721311	120
Extra Trees	1	0.95689655	0.925	0.94067797	120
Extra Trees	2	0.94354839	0.975	0.95901639	120
Extra Trees	3	1	0.95	0.97435897	120
Extra Trees	4	0.98333333	0.98333333	0.98333333	120

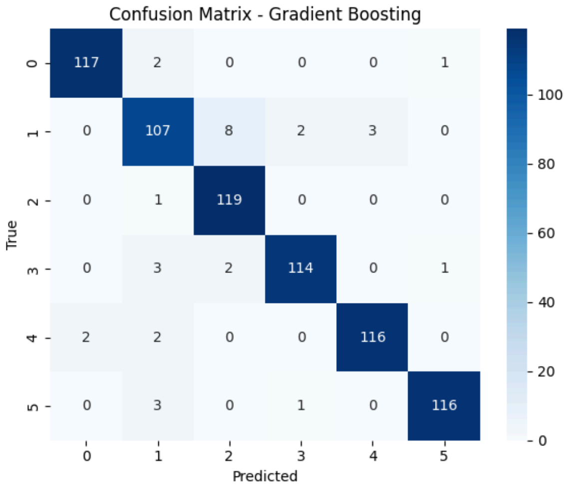
Extra Trees	5	0.98360656	1	0.99173554	120
XGBoost	0	0.98333333	0.98333333	0.98333333	120
XGBoost	1	0.94736842	0.9	0.92307692	120
XGBoost	2	0.928	0.96666667	0.94693878	120
XGBoost	3	0.97478992	0.96666667	0.9707113	120
XGBoost	4	0.97540984	0.99166667	0.98347107	120
XGBoost	5	0.99166667	0.99166667	0.99166667	120
MLP	0	1	0.99166667	0.9958159	120
MLP	1	0.93548387	0.96666667	0.95081967	120
MLP	2	0.97457627	0.95833333	0.96638655	120
MLP	3	0.99137931	0.95833333	0.97457627	120
MLP	4	0.98360656	1	0.99173554	120
MLP	5	0.99173554	1	0.99585062	120
LDA	0	0.99166667	0.99166667	0.99166667	120
LDA	1	0.9338843	0.94166667	0.93775934	120
LDA	2	0.97478992	0.96666667	0.9707113	120
LDA	3	1	0.95833333	0.9787234	120
LDA	4	0.96747967	0.99166667	0.97942387	120
LDA	5	0.98360656	1	0.99173554	120
Naive Bayes	0	0.98319328	0.975	0.9790795	120
Naive Bayes	1	0.92173913	0.88333333	0.90212766	120
Naive Bayes	2	0.91525424	0.9	0.90756303	120
Naive Bayes	3	0.87719298	0.83333333	0.85470085	120
Naive Bayes	4	0.98305085	0.96666667	0.97478992	120
Naive Bayes	5	0.86029412	0.975	0.9140625	120

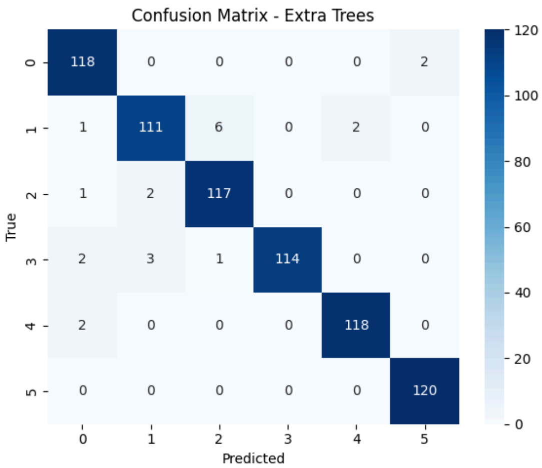
Confusion Matrices

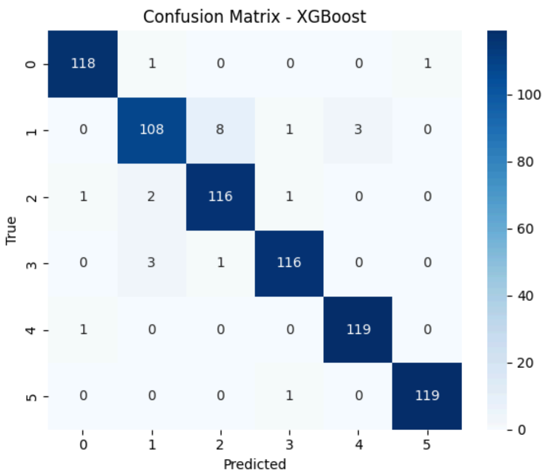


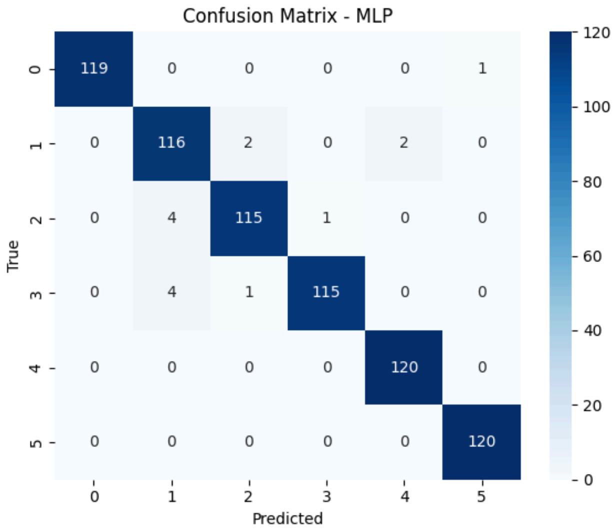


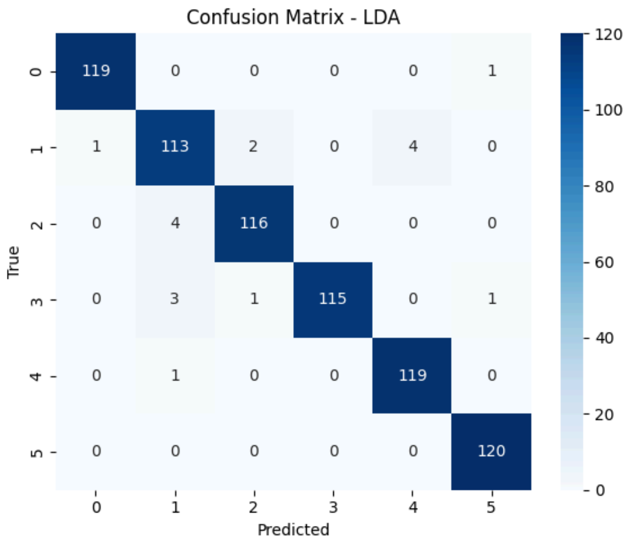


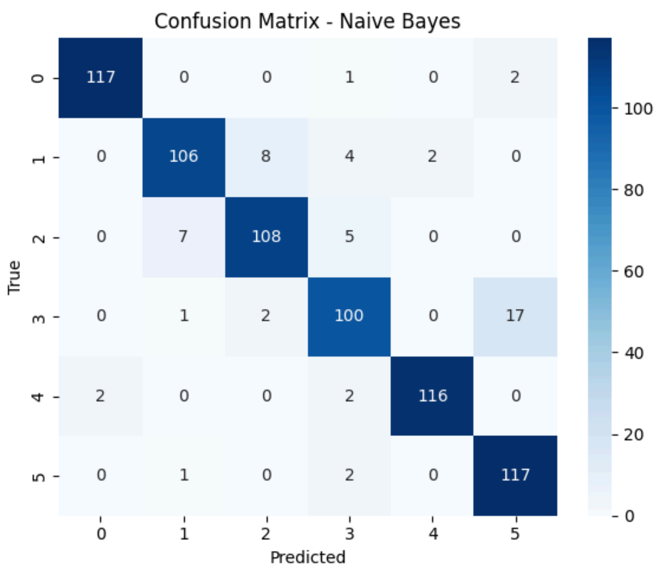

Confusion Matrix - Gradient Boosting
117 2 0 0 0 1
0 107 8 2 3 0
0 1 119 0 0 0
0 3 2 114 0 1
2 2 0 0 116 0
0 3 0 1 0 116
True
Predicted
0 1 2 3 4 5
0 20 40 60 80 100


Confusion Matrix - Extra Trees
118 0 0 0 0 2
1 111 6 0 2 0
1 2 117 0 0 0
2 3 1 114 0 0
2 0 0 0 118 0
0 0 0 0 0 120
True
Predicted
0 1 2 3 4 5
0 20 40 60 80 100 120


Confusion Matrix - XGBoost
118 1 0 0 0 1
0 108 8 1 3 0
1 2 116 1 0 0
0 3 1 116 0 0
1 0 0 0 119 0
0 0 0 1 0 119
True
Predicted
0 1 2 3 4 5
0 20 40 60 80 100


Confusion Matrix - MLP
119 0 0 0 0 1
0 116 2 0 2 0
0 4 115 1 0 0
0 4 1 115 0 0
0 0 0 0 120 0
0 0 0 0 0 120
True
Predicted
0 1 2 3 4 5
0 20 40 60 80 100 120


Confusion Matrix - LDA
119 0 0 0 0 1
1 113 2 0 4 0
0 4 116 0 0 0
0 3 1 115 0 1
0 1 0 0 119 0
0 0 0 0 0 120
True
Predicted
0 1 2 3 4 5
0 20 40 60 80 100 120


Confusion Matrix - Naive Bayes
117 0 0 1 0 2
0 106 8 4 2 0
0 7 108 5 0 0
0 1 2 100 0 17
2 0 0 2 116 0
0 1 0 2 0 117
True
Predicted
0 1 2 3 4 5
0 20 40 60 80 100

The evaluation results demonstrate that many of the models can accurately describe the data provenient from the motion during the different activities. These results fall in line with results obtained in similar studies and projects that employed the same classifiers (Casale & Radeva, 2011; Zertuche, 2023).

Selected model for online classification

Out of all the classifiers tested, **XGBoost** Classifier was selected for the final online classification system due to its combination of high accuracy, fast prediction speed, and robustness to overfitting. As shown in Table 3, XGBoost consistently achieved high F1-scores across all classes (often above 95%), and had near-perfect performance in classes involving more dynamic movements such as jumping or shadow boxing. Additionally, XGBoost supports efficient training and inference, which is crucial for real-time classification on a mobile device. This made it the most suitable option for deploying in an interactive application that responds instantly to motion inputs.

4. Online classification results, including responses to the following questions:
    - Does the application work with all team members?

The application worked correctly with all team members, successfully recording motion data and providing a classification for the actions performed in real-time. It is also capable of compatibility with different phones, with no significant effect on performance.

- Does the online classification performance align with the cross-validation results?

The online classification performance is generally aligned with the results obtained from cross-validation. For most activities, the application was able to accurately classify the team members' movements. However, the performance did drop minimally when performing shadow boxing, as it would occasionally return a single window of a different activity, such as running. This may be due to different speed or position of the punch, or due to the timing between punches.

5. An individual reflection on the work done.

Gustavo:

I feel like this project was a great opportunity to utilize the knowledge acquired during the course towards a real-life application. Not only that, but it also proved to be quite an interesting project to work, from the data recollection phase to the final product. It didn't feel like something that me from the start of this semester would have thought I could accomplish.

During the project we were able to compare the performance of different classifiers in a real example. One problem we did encounter during the process was that we initially got really low accuracy for all the models (around 60%). We attributed that low level of accuracy to our data recollection, since we had made the measurements with the phone inside our pocket, rather than on our hand. We also asked othe teams about how they were doing and some told us we could also use gyroscope, which we decided for. After doing these two adaptations and recollecting new data, we were able to accomplish around a 96-97% accuracy for multiple of the models evaluated. In the end, the online classification worked as expected, and the final result is one I am satisfied with. I think that this project and the abilities we used will prove useful further into my academic and professional lives.

Daniel Sanchez:

This project, in my opinion, was among the most comprehensive and useful ones we've completed for the semester. From using a smartphone to gather motion data to training and implementing a real-time machine learning model, there were several steps required. The poor performance of our models was one of the biggest issues we encountered in the beginning. We made the decision to hold the phone in hand and use gyroscope data in addition to accelerometer readings after consulting with other teams and conducting some research. This modification had a big impact. After employing feature selection to retain the top 30, we retrained our models using the 60 retrieved features..The application is simple to replicate and distribute because we were able to incorporate everything into a single Python script. It was really satisfying to observe that it replies very instantaneously and classifies activity in real time. I believe that this kind of practical project helps close the gap between theory and practical application, and I'm proud of how we were able to transform raw sensor data into a completely functional activity identification system. Additionally, it provided us with tools and insights that will be useful for upcoming AI or data science projects.

Diego Vértiz:

Working on this project has been one of the most eye-opening experiences of the semester. I’ve always thought machine learning models were powerful, but actually seeing them in action, detecting activities in real-time based on sensor data from a phone I was holding, was honestly amazing.

At first, the process felt overwhelming: collecting the right data, figuring out how to structure it, and testing so many different models. But as we kept improving our approach, especially by redoing our data collection and trying new techniques like feature selection, the results kept getting better and better. Watching the model go from barely working to giving over 96% accuracy felt like magic backed by science.

What impressed me the most was how these classification models can learn to “understand” human movement just by analyzing numbers. You’re literally teaching a computer to recognize how you’re walking, running, or even shadow boxing—and it actually gets it right!

This project made me appreciate how much potential there is in machine learning, not just as a technical field, but as a tool to create meaningful and useful applications. It also showed me that even when things look complicated at first, if you take it step by step, you can build something really cool.

References

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