A Proposal for Continuous and Silent User Authentication Through Mouse Dynamics and Explainable Deep Learning

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INTRODUCTION

The number of attacks on personal accounts has grown over time. Numerous user authentication techniques have been created throughout the years to avoid it.

Among these, there is biometric-based authentication. This type of technique exploits physical-biometric or behavior-biometric for user recognition.

For instance, touch dynamics, keyboard dynamics, and mouse dynamics belong to this second category.

THE PROPOSAL

We experimented on the “Balabit Mouse Dynamics Challenge” dataset [1], which outlined some tasks, and the users logged to a remote server where they executed them, to collect the mouse interactions between users and the system.

The data were saved in CSV files with the following structure: record timestamp in second, client timestamp in second, the current condition of the mouse buttons, additional information about the current state of the mouse, and x-y coordinate of the cursor on the screen.

This process has been applied for every ten users, and at the end, each CSV file created was labeled as legal behaviors and illegal behaviors.

DATASET COMPOSITION

For image generation, we developed a script that goes to insert the x and y coordinates for each file into each specific list, which takes the name of the action done by the user.

The coordinates represent the most significant data in a row.

After graph creation for each list, they are joined into a single image with a PNG extension.

After that, we divided them into two classes, such as legal behaviors (1271 samples) and illegal behaviors (405 samples).

We consider the data augmentation technique. Using this approach, we increased the number of components in our dataset to 8000 elements for each class.

PRELIMINARY EVALUATION

We conducted a preliminary evaluation using the VGG16 model using the hyperparameters reported in Table 1, and we achieved the results reported in Table 2.

| Table 3 – Results obtained for "legal behaviours" class |
| Loss | Precision | Accuracy | F-Measure | AUC |
| 0.896 | 0.902 | 0.902 | 0.902 | 0.902 |

The class labeled illegal behaviors found 2179 true positives, 2151 true negatives, 249 false positives, and 221 false negatives. Results are displayed in Table 3.

FUTURE WORKS

In future studies, we would consider different models to improve the performances. Furthermore, we would consider more data for model training and evaluation.

REFERENCES