Analysis of Eye tracking data for the study of spatial memory
Correlation analysis of eye tracking variables
Machine learning and data prediction of performance

A Project Report

submitted by

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As a master's project for the
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DEPARTMENT OF COMPUTER SCIENCE OF FHNW

AND

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DECLARATION OF ORIGINALITY

I, **Constantin Jeremy**, with **Roll No: —-------** hereby declare that the material presented in the Project Report titled **Analysis of Eye tracking data for the study of spatial memory, Correlation analysis of eye tracking variables, Machine learning and data prediction of performance** represents original work carried out by me in the **DEPARTMENT OF COMPUTER SCIENCE OF FHNW and l'ECOLE SUPÉRIEURE D'INGÉNIEURIE LÉONARD DE VINCI PARIS,LA DEFENSE**

With my signature, I certify that:

- I have not manipulated any of the data or results.
- I have not committed any plagiarism of intellectual property. I have clearly indicated and referenced the contributions of others.
- I have explicitly acknowledged all collaborative research and discussions.
- I have understood that any false claim will result in severe disciplinary action.
- I have understood that the work may be screened for any form of academic misconduct.

Constantin Jeremy

Place: Paris, La Defense

Date: 10.02.2023

Acknowledgements

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Abstract

This project, on a broader scale, examines visual variables and many eye-related behaviors that can affect memory performance during a route learning experience in a variety of realism levels in a virtual environments

It also explores participant’s memory data from tests as It aims to correlate them with the learner's performance in memory acquisition.

This analysis is an extension of the VISDOM research project and focuses on spatial knowledge acquisition, navigational memory accuracy, and three different levels of realism (realistic, realistic, mixed real, and abstract).

The participants are composed of 39 older adults and 42 more youthful adults, with various cognitive abilities withinside the context of navigational reminiscence and are similarly cut up among the genders, and show off broadly varying accuracies [1].

We hypothesize that via the study the eye-movement data of the eighty one contributors, the usage of machine learning methods, it could supply us an a new perception into the reasons for variation within our group.

Additionally it might permit us to hint at less visible variables that affect the memory acquisition of the contributors for the duration of spatial experiment. Since eye-motion information (fixation, blinks, pupil dilation etc…) is an extremely precise indicator of the emotions and visual strategies of the learner [2], it could additionally tell us on how they respond to the cognitive load and stress while taking tests on every digital education environment.

In addition, the usage of machine learning could help to confirm previous work and theories on certain variables linked to participants and their effect on the contributor’s performances.

I additionally try to recreate similar but artificial data to the one taken in the midst of the experiment as an attempt to test the machine learning algorithm further.

Table of Content

Abbreviations

VR - **V**irtual **R**eality
SVM - **S**upport **V**ector **M**achine

Introduction

1.1 Background

Navigation is a critical aspect of everyday life. It allows individuals to encode, store, and retrieve information about their surroundings in order to move through a given environment. The ability to navigate effectively and efficiently is essential for daily life activities such as driving or walking. When memory retention is impaired, an individual may experience difficulty in navigating which can lead to stress, frustration and a decreased sense of independence. Additionally, navigation in virtual reality is complex because it relies on sensory information, spatial awareness and memory retention. Eye tracking technology has been widely used in virtual reality research to understand the visual attentional processes involved in navigation.

Eye tracking data and memory retention in virtual reality navigation have not been studied extensively. The purpose of this report is to investigate whether the gaze patterns and pupils behavior of participants as they navigate virtual environments can be used to predict their memory retention performance on a navigation task. By studying the gaze patterns and pupils behavior of participants as they navigate virtual environments, we aim to understand how eye tracking data can inform our understanding of the underlying cognitive mechanisms involved in VR navigation and memory retention. Furthermore, this research tries to provide new insights into how stress affects visual attentional processes during navigation and how that is related to memory retention.

1.2 Use of Eye tracking data for memory retention analysis.

Previous studies have demonstrated the effectiveness of using eye tracking data to show a correlation between navigational skills and eye behavior.

For instance, researchers have used eye tracking to examine the gaze patterns of individuals as they navigate through virtual environments and have found that individuals with better navigational skills tend to fixate on different spatial locations compared to those with weaker navigational skills.

Furthermore, studies have shown that individuals who fixate more on landmarks and other spatial cues tend to perform better on memory retention tasks related to navigation.

Other studies have been able to correlate stress with eye movement data and its effect on navigational memory retention.

For example, some studies have shown that individuals who experience stress while navigating virtual environments tend to fixate more on task-irrelevant information, such as the virtual avatar or other non-spatial elements in the virtual environment..

Additionally, some research has found that individuals who experience stress during navigation tend to perform worse on memory retention tasks. These studies highlight the importance of understanding the relationship between stress and eye movement data in the context of navigation and memory retention in virtual environments.

1.3 The Impact of Data and Machine learning

Recent advances in data collection and machine learning have greatly impacted the field of virtual reality research, particularly in the area of eye tracking and memory retention.

Using sophisticated eye tracking technology, researchers are able to collect large amounts of data on gaze patterns and analyze it using machine learning algorithms.

This has allowed for a deeper understanding of how gaze patterns relate to cognitive processes such as memory retention and navigation.

Past Studies of eye tracking data have identified patterns and predicted outcomes related to memory retention in virtual environments.

For example, researchers have used machine learning algorithms to classify gaze patterns based on navigational performance, identify factors that influence memory retention, and even predict memory retention performance from gaze data.

The use of machine learning in VR research can also enable researchers to identify individual differences in terms of memory and navigation performance.

1.4 Problem statement

The problem statement of this thesis is to investigate the validity of the following hypotheses:

1. There is a correlation between stress levels and eye tracking data in a virtual reality (VR) navigational environment.

2. There is a correlation between disorientation and eye tracking data in a virtual reality (VR) navigational environment.

The study aims to use eye tracking data to measure and analyze the impact of stress and disorientation on navigational performance and memory retention in a VR environment.
The research will identify patterns and variations in eye tracking data that may indicate changes in stress and disorientation levels.
The results of this study may provide insights on how to better support users' needs and enhance their memory retention.

1.5 Objectives of work

The objectives of this thesis are as follows:

1. Correlating eye tracking data (e.g., gaze patterns and fixations) with memory retention tasks will provide insight into virtual environments. This can be accomplished by analyzing eye tracking data collected from participants as they navigate virtual environments, and comparing this data to their performance on memory retention tasks.

2. Create a machine learning algorithm capable of predicting memory retention performance from eye tracking data. This will involve using machine learning models to analyze the eye tracking data and identify patterns, including how long it takes people to recall information after seeing it.

3. Correlate eye movement data to stress variables. This will involve observing participants' stress-related eye movements while navigating virtual environments, with the goal of understanding how stress affects visual attention and memory retention.

Literature Survey

2.1 Survey on existing connections proven between stress and eye movement

- **Eye fixation on relevant material improves memory retainment under stress.**

Researchers found that participants who fixated more on relevant information during a stress-inducing task had better memory recall than those who kept their attention on irrelevant details. Individuals who are prone to anxiety may benefit more from the ability to selectively focus on relevant information during a stress-inducing task. [7]

- **Effect of stress on eye behavior.**

The researchers found that participants who exhibited more frequent and longer fixations on negative stimuli during a stress-inducing task had a larger cortisol response. [8]

During the study, researchers measured eye gaze in students. They found that students with higher stress levels exhibited more frequent and longer fixations on neutral and negative stimuli, and fewer fixations on positive stimuli. Eye gaze could be a useful tool for identifying and monitoring stress levels in students.[10]

Facial cues from videos can provide a non-invasive and easy to use method for detecting stress and anxiety.[11]

Gaze behavior, such as increased fixations on negative stimuli and decreased fixations on positive stimuli, can be used as an indicator of stress.[12]

- **Using VR and eye Tracking as a mean to measure stress and anxiety**

The use of eye gaze in students as a measure of stress levels has the potential to provide an objective and accurate assessment of stress.[10]

Virtual environments and eye-tracking technology can be used to provide a nonintrusive, controllable method for measuring stress in a laboratory setting.[12]

2.2 Previous Work

In previous research led by Ismini Lokka and Arzu Coltekin as part of the completed project VISDOM, Geo-Virtual Environments (2 distinct paths) were designed. These environments were useful because some participants were asked to go through these paths before answering questions that would later be used as Data for this project. Moreover, while going through these paths a Tobii eye tracking device was placed in the optic of collecting eye movement data that would later be used to correlate memory with eye movement data. Furthermore, since these environments were in three levels of realism (abstract - realistic - semi-realistic) some assumptions on how realism affects memory were able to be made from these studies.[2]

Overall, older participants performed worse than younger ones in both the immediate and delayed recall stages. In general, both older as well as the younger participants performed better in the Mixed VE (vs Abstract VE) in both immediate and delayed recall stages.
In addition, relatively speaking, their performance was found to be better in the Realistic VE when compared to Abstract VE in both recall stages. This finding

supports previous research findings on visual encoding of information among age groups. Comparing accuracy of all three stages: The observed differences from previous research conducted so far are also demonstrated to be statistically significant with medium to huge effect sizes.[2]

In Experiment 2, participants were asked to rate their preferred visualizations before and after going through an experiment. Before the experiment, 98% of older people preferred the Realistic VE and the majority of younger people did too. After the experiment, however, most younger people shifted their preference to Mixed, but not most older people. Overall it seems that users would likely prefer Mixed over Realistic VE (69%) [3]. Second most preferred visualization would be Realistic VE (69%) [3] and none of users showed particular preference for Abstract VE . Those who switched from Realistic VE to Mixed VE also switched from Mixed over Realistic VE . However there was no instance when opposite happened - a user switching from Realistic over Mixed or vice versa.[2]

2.3 Disorientation Research in Virtual Environments

- **Change in eye behavior due to disorientation**

Both pilots and non-pilots exhibited changes in gaze behavior while undergoing spatial disorientation cues. Non-pilots were less efficient in scanning and attending to relevant visual cues when they experienced spatial disorientation cues.[13]

2.4 Hypotheses (Constructed from the Literature Survey

1. Stress observation from eye behavior is possible and can affect memory retention in a navigational environment:

Gaze behavior--increased/decreased fixations, blinking rate and other eye movements--can be used as an indicator of stress. Observing eye behavior provides an objective method for detecting stress; moreover, it can affect memory retention and attention to relevant information, which are crucial in a navigational environment. Therefore, stress observation from eye behavior can be utilized to predict memory retention in a navigational environment.

2. Disorientation has an impact on eye behavior and can affect memory retention in a navigational environment:

When exposed to spatial disorientation cues, participants' eyes tend to move more than they usually would when not in a disorienting environment. Disorientation can affect eye behavior and that attention to relevant visual cues may be affected when experiencing disorientation. Furthermore, spatial disorientation can affect memory retention and attention to relevant information, which is crucial for navigation. Therefore, understanding the effects of disorientation on eye behavior can help in predicting memory retention in a navigational environment.

2.5 Machine learning models common within Eye-Tracking Research

The Machine learning models generally used within eye-tracking research for carrying out the analyses and prediction constitute the following models

1. Support Vector Machine (SVM)
2. Random Forest
3. Neural Networks (NNs)
4. K-Nearest Neighbors (KNN)
5. Decision Trees

These are some of the machine learning methods that have been used in prior research for analyzing and predicting Tobii eye tracking data.
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2.6 Aging and lighting affect Eye-movement data

Age and lighting conditions can affect eye tracking data, which can potentially create biases in our study that focuses on that data. Age can affect eye tracking data as older adults may have decreased visual acuity, which can impact their ability to focus on certain objects or follow certain movements. Lighting conditions also affect eye tracking data as different lighting conditions can impact the visibility of objects and reduce the contrast of the display. Additionally, lighting conditions can affect pupil size, which impacts accuracy of gaze tracking. These biases can be mitigated by taking into account participant's age and lighting conditions when collecting and analyzing data; as well as recruiting a diverse range of participants to reduce impact of these factors on results.

2.7 Summary from the Literature

1. Studies have consistently shown that changes in gaze behavior, such as increased fixations on negative stimuli and decreased fixations on positive stimuli, can be used as an indicator of stress.

2. Observing eye behavior can provide a non-invasive and objective method for detecting stress.

3. Stress can affect memory retention and attention to relevant information, which is crucial in a navigational environment.

4. Disorientation can have an impact on eye behavior and that attention to relevant visual cues may be affected when experiencing disorientation.

5. Spatial disorientation can affect memory retention and attention to relevant information, which is crucial for navigation.

6. The use of virtual environments and eye-tracking technology can provide a non-intrusive and controllable method for generating and measuring stress in a laboratory setting.

7. Facial cues from videos can provide a non-invasive and easy to use method for detecting stress and anxiety.

8. Eye gaze can be used as a potential indicator of stress levels in students.

Work Done

Repository : https://github.com/JeremyConstantin/Eye-Movement-Data-Project.git

3.1 Data collection and adaptation

3.1.1 Data collection using Python (Will need more details)

We used Tobii eye tracking technology in combination with Python programming to collect data from a virtual reality (VR) navigation experiment. The participants were tasked with remembering different paths within a virtual environment. The eye tracking data was then transferred to a Python algorithm for processing and analysis. First, it performed data cleaning and filtering to remove any noise or null values in the data. Next, it calculated various gaze-based metrics such as gaze duration, fixation points, and saccadic movements relevant to our research. Finally, the data was transformed into a readable Excel format that made it easy to visualize and analyze results.
The processed data was then used as input for a machine learning algorithm to further analyze the participants' navigational strategies and memory retention. The use of Python allowed for easy manipulation of the data, efficient implementation of various data processing and analysis techniques, and powerful results from an eye tracking research study.

	ParticipantName	Blink_Counter	left_avg_pupil_dill	Start_Timestamp	RecordingTimestamp	FixationIndex	SaccadeIndex	Ga:
0	o01.01.A	3037.50000	-2.069561e-06	8.903217e+05	1.137997e+06	1923.849646	3727.393615	
1	o02.01.A	2343.50000	-2.628735e-06	6.377481e+05	7.952424e+05	1955.450345	2682.489554	
2	o03.01.A	5455.50000	-4.339637e-06	7.381119e+05	9.366817e+05	2040.530155	3167.136285	
3	o04.02.A	63.50000	4.963551e-08	1.270209e+06	1.692247e+06	4809.399911	7401.217459	
4	o05.02.A	1844.56879	-2.646829e-06	6.525738e+05	8.211633e+05	2264.712946	7063.154909	
...	...	...	...	...	...	...	...	
68	y36.02.A	2519.50000	-9.484141e-06	4.899007e+05	5.986756e+05	889.351359	3712.775818	
69	y37.02.A	569.50000	-7.170527e-08	5.207757e+05	6.481532e+05	1864.115157	2467.908383	
70	y38.01.A	394.50000	4.105912e-06	5.556030e+05	6.933407e+05	1772.701999	2176.515095	
71	y40.04.A	367.00000	1.041408e-06	5.109857e+05	6.370528e+05	1937.950781	2448.516270	
72	y41.01.A	684.00000	-1.378570e-06	4.893362e+05	5.939090e+05	1995.482102	4663.346545	

73 rows × 21 columns

Figure 3.1.1 : Dataset after collection and treatment with python

3.1.2 Main interesting Variables

To fully understand the participants' performance, it was important to consider a variety of variables that have been highlighted by previous research.

1. Age is known to be a significant factor in memory retention and cognitive functioning. We tested the computer's ability to detect a correlation between age and performance on the memory retention task by considering the age of our participants. As age increases, there is a decline in cognitive abilities, memory retention decreases, pupil size changes and brain activity changes.

2. Fixation is defined as keeping one's gaze on a particular object or point. Variables such as fixation duration and number of fixations provide insight into how the participants were processing the information presented in the virtual environment. These variables can help identify if the participants spent enough looking at relevant AOIs, which can indicate better navigation performance.

3. Saccadic movement is the rapid movement of the eyes from one point to another. Saccadic variables such as saccadic amplitude and saccadic velocity provide insight into the participants' visual scanning strategies and how they were navigating the virtual environment. This could indicate slight disorientation, thus affecting memory retention.

4. Gaze duration measures the amount of time the participant spent looking at a particular point or object. By measuring gaze duration, we were able to see if participants spent time looking at the horizon instead of relevant landmarks and how that related to their performance on the task.

5. Sleep is known to be an important factor in memory retention and cognitive functioning. By considering the number of hours the participants slept the night before the experiment, we were able to see if there was a correlation between sleep and performance on the VR navigational task. Lack of sleep affects cognitive abilities and memory retention.

By considering these variables, we were able to gain a more comprehensive understanding of the factors that influence memory retention in virtual environments. This helped us to identify patterns and trends in the participants' performance and make meaningful conclusions about the effect of virtual environments on memory retention.

3.1.3 Variables creation and changes

To better analyze the eye behavior of our participants, we created new variables to supplement the data collected by the Tobii eye tracking technology. These variables included:

1. Blinking rate: To simulate and count the number of times a participant blinked during the experiment, we counted the number of times the tracking of the participant's eyes was lost for around 0.3 seconds. This variable provided insight into the participant's blink patterns and how they may hint at their stress level.

2. Average pupil dilatation: To understand how the virtual environment affected the participant's cognitive state, we calculated the average pupil dilatation of the participants while they took the VR navigational test. This variable provided insight into the participant's level of attention, engagement and stress level with the task.

3. Grade: To classify the participants' results, we assigned a letter grade to each participant based on their performance on the memory retention task. This variable provided a straightforward way to compare the participants' results and identify patterns in their performance.

These variables were used in combination with other gaze-based metrics collected by the eye tracking technology to gain a comprehensive understanding of the participants' eye behavior and how it relates to their navigational performance, stress level and memory retention.

3.2 Machine learning

3.2.1 Variables correlation in python

We explored the correlation between variables collected during the experiment and performance on a memory retention task by using Python programming to conduct linear regression analysis.
We used several methods including Pearson's correlation coefficient and Spearman's rank correlation coefficient to quantify the strength and direction of the relationship between variables collected during the experiment and performance on our memory retention task.
Additionally, we used visualization techniques like heatmaps to identify patterns in the relationship between our variables.
These methods provided us with a more comprehensive understanding of the factors that influence memory retention in virtual environments, helping us to make meaningful conclusions about the effect of virtual environments on memory

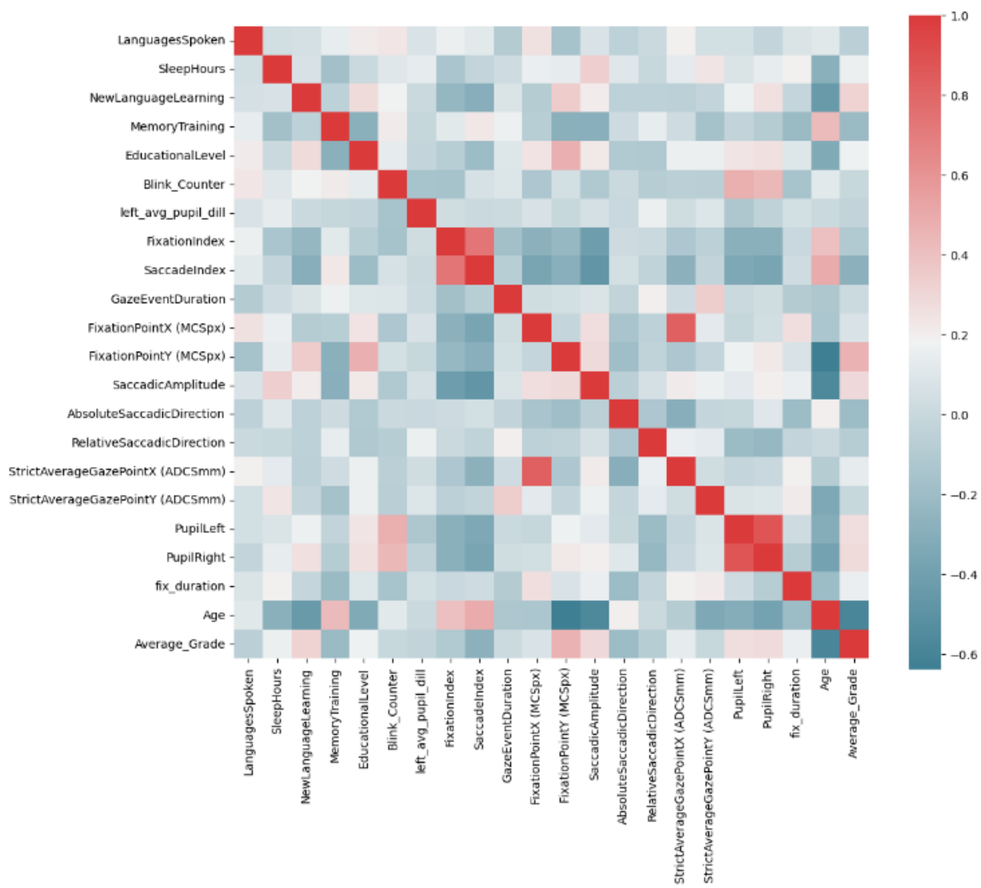

Figure 3.2.1: Heatmap of variable correlation

	LanguagesSpoken	SleepHours	EducationalLevel	Blink_Counter	left_avg_pupil_dill	F
LanguagesSpoken	1.000000	0.034452	0.212986	0.234222	0.075155	
SleepHours	0.034452	1.000000	0.004369	0.100721	0.134053	
EducationalLevel	0.212986	0.004369	1.000000	0.134404	-0.029263	
Blink_Counter	0.234222	0.100721	0.134404	1.000000	-0.153684	
left_avg_pupil_dill	0.075155	0.134053	-0.029263	-0.153684	1.000000	
FixationIndex	0.161464	-0.142945	-0.078942	-0.163639	0.030377	
SaccadeIndex	0.115130	-0.028408	-0.207836	0.064131	0.005789	
GazeEventDuration	-0.096690	0.024186	0.093209	0.087295	0.010356	
ixationPointX (MCSpx)	0.255799	0.154651	0.244960	-0.127463	0.066814	
ixationPointY (MCSpx)	-0.163270	0.131919	0.472520	0.046301	-0.006784	
SaccadicAmplitude	0.072236	0.335353	0.221609	-0.119030	0.048070	
ɔluteSaccadicDirection	-0.053904	0.102977	-0.108653	0.007522	-0.004263	
ativeSaccadicDirection	0.005487	-0.007591	-0.119586	-0.083735	0.160809	
ictAverageGazePointX (ADCSmm)	0.188757	0.125178	0.160359	-0.068060	0.032845	
ictAverageGazePointY (ADCSmm)	0.040877	0.240253	0.155537	-0.069195	0.090575	
PupilLeft	0.041899	0.080316	0.239869	0.477054	-0.120262	
PupilRight	-0.027653	0.141130	0.258438	0.438422	-0.047886	
fix_duration	0.082852	0.190303	0.095414	-0.153727	0.045006	
Average_Grade	-0.067864	0.161249	0.174318	-0.007181	-0.034684	

Figure 3.2.2: Numerical value of correlation between variables (between -1 and 1)

3.2.2 Machine learning model creation and comparisons

Another crucial aspect was to use machine learning models to predict the participants' performance on the memory retention task based on the variables collected during the experiment, specifically eye tracking data.
I coded multiple machine learning models using Python and compared them in an attempt to find the best model.

1. k-Nearest Neighbors (KNN): This is a simple algorithm that classifies a new data point based on the majority class of its k-nearest neighbors. KNN is simple to implement for classification and is a good choice for small

datasets like ours. However KNN is sensitive to irrelevant features and the scale of the data.
Thus KNN can be used to classify gaze patterns and predict cognitive states, but it may be affected by the high dimensionality of the data, which can increase the computational cost and decrease the accuracy.

2. Support Vector Machine (SVM): This is a supervised learning algorithm that can be used for classification or regression problems.
   SVM tries to find a hyperplane that maximizes the margin between the classes.
   SVM is effective in high dimensional spaces, and it can work well for datasets with a lot of variables like ours.

3. Random Forest: This is an ensemble learning method that uses multiple decision trees to make predictions.
   Random Forest is robust to outliers and noise, and it can also be used for classification.
   On the down side, Random Forest can be difficult to interpret.
   For eye tracking data, Random Forest may be less sensitive to outliers.

3.2.3 Hyperparameters

In order to improve the accuracy of our models, we coded an algorithm in Python to find the best possible hyperparameters for our models.
The technique we used was grid search and random search. Grid search involves specifying a range of possible values for each hyperparameter and training the model with all possible combinations of these values.
Random search is a technique that involves randomly sampling hyperparameter values and training the model with these values.
By using these techniques, we were able to find the optimal hyperparameters for our models and improve their accuracy.
By using these techniques, we were able to optimize the parameters of our models using eye tracking data, which resulted in higher accuracy and better predictions for the participants' performance on the memory retention task.

3.3 Fictional data creation

3.3.1 Mathematical information about the data

Our investigation was based on the task of extracting mathematical and statistical information about the data, including average, standard deviation, and other measures of central tendency and dispersion.
This information will be used to prepare means to recreate fictional data and expand our database.
The algorithm we coded uses Python libraries such as NumPy and Pandas to calculate these statistics.
These libraries provide various functions that allow us to perform calculations such as mean, median, standard deviation, variance and other measures of central tendency and dispersion on our data.
By employing these techniques, we were able to extract valuable information about the data that could be used to generate fictional data that mimic reality.
This helped us make more accurate predictions.

Column	Mean	Median	Mode
Unnamed: 0	36.0	36.0	0
Blink_Counter	960.0688958813963	684.0	42.0
left_avg_pupil_dill	-1.3671455355959058e-08	1.3509291035220196e-07	-0.000111213226021
Start_Timestamp	655585.75663288	643526.5889336346	352173.3494517002
RecordingTimestamp	828965.6395938683	811249.4533089071	442784.95524931146
FixationIndex	2163.1361198709037	2060.896579154456	889.3513588465055
SaccadeIndex	3484.617263086963	3261.810031324125	1338.710014463596
GazeEventDuration	2204.2321205486173	665.4448075847561	210.52172373320016
FixationPointX (MCSpx)	608.2694444742119	611.3539253409376	496.66759070375
FixationPointY (MCSpx)	1116.7191348227104	1382.2210287488738	373.5343503463285
SaccadicAmplitude	5.47700809289834	5.476163149217583	3.9128314367359742
AbsoluteSaccadicDirection	178.00915414732881	178.06649734579443	166.49347306682836
RelativeSaccadicDirection	179.90148931371178	180.03807755652252	173.03558252863718
StrictAverageGazePointX (ADCSmm)	1051.8797737908085	1051.5784772942532	912.7921279448854
StrictAverageGazePointY (ADCSmm)	642.7355004098002	642.9353721231868	446.15814308027535
PupilLeft	3.8124138377196317	3.823376660551467	2.75520037278658
PupilRight	3.786897693522387	3.716053565852033	2.488967658940788
Timestamp_n	173379.88296098876	164746.79894881666	81532.18417529584
fix_duration	146.63572007988083	145.37381887963824	138.81950166341585
Age	0.5205479452054794	1.0	1
Average_Grade	0.557267541451588	0.5647617831606596	0.2553476174262691

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Figure 3.3.1.1: 3/7 Measures of central tendency and dispersion for our data

3.3.2 Creation of fictional data

To expand our dataset, we created a model that used the statistical information extracted from our small database. We used Python libraries to generate random data points from distributions. This allowed us to create new data points that were similar to real data, but with random variations. The algorithm also used techniques such as bootstrapping and simulation to generate new data points. Bootstrapping is a technique that involves generating new data by randomly sampling with replacement from the original dataset.[6] Simulation is a technique that involves generating new data by using mathematical models and assumptions about the data.[7]

Once the new data points were generated, we added them to the original dataset to create a larger dataset that we could use to train and test our machine learning model. I repeated this process several times to generate a sufficient amount of new data.

By creating fictitious data based on a small dataset, we were able to extend the dataset and make more data available for machine learning. This allowed us to understand the direction in which machine learning models were trying to predict memory retention.

	Unnamed: 0	ParticipantName	Blink_Counter	left_avg_pupil_dill	Start_Timestamp	RecordingTimestamp	FixationIndex
0	0	o01.01.A	3037.50000	-2.069561e-06	8.903217e+05	1.137997e+06	1923.849646
1	1	o02.01.A	2343.50000	-2.628735e-06	6.377481e+05	7.952424e+05	1955.450345
2	2	o03.01.A	5455.50000	-4.339637e-06	7.381119e+05	9.366817e+05	2040.530155
3	3	o04.02.A	63.50000	4.963551e-08	1.270209e+06	1.692247e+06	4809.399911
4	4	o05.02.A	1844.56879	-2.646829e-06	6.525738e+05	8.211633e+05	2264.712946
...	...	...	...	...	...	...	...
995	48	y20.04.A	2355.50000	5.477422e-07	1.270209e+06	5.939090e+05	2281.716890
996	11	y24.05.A	42.00000	-4.339637e-06	5.556030e+05	8.534881e+05	1250.871318
997	5	o18.04.A	995.00000	3.503784e-07	6.386481e+05	7.472544e+05	1749.070832
998	17	o25.06.A	42.00000	-1.075063e-06	1.016220e+06	7.815757e+05	1238.131590
999	38	o34.04.A	155.00000	6.262034e-07	6.260260e+05	6.481532e+05	1895.534058

1073 rows × 22 columns

Figure 3.3.1 : Dataset of 1000 fictional data created based on prior information

3.3.3 Prediction on fictional data

After creating fictitious data, we used a pre-built KNN model to analyze the data to better understand how computers classify the data.
This allowed us to identify shortcomings in our model and determine the next steps needed to improve its performance. By testing the model on fictitious data, we were able to see how well the model generalized to new and unseen data and determine if changes were needed.
This provided valuable insight into the strengths and weaknesses of KNN models and how they process the data they feed.
By carefully examining the results of testing the model on fictitious data, we were able to make informed decisions about how to improve the machine learning model so that it could accurately classify data in the future. . Traditional machine learning researchers often use fictitious data to test models in a controlled environment.
Creating synthetic datasets gives researchers complete control over the data distribution, helping to assess the performance and robustness of machine learning models.
This approach helps them understand the limitations of their model and identify areas for improvement.

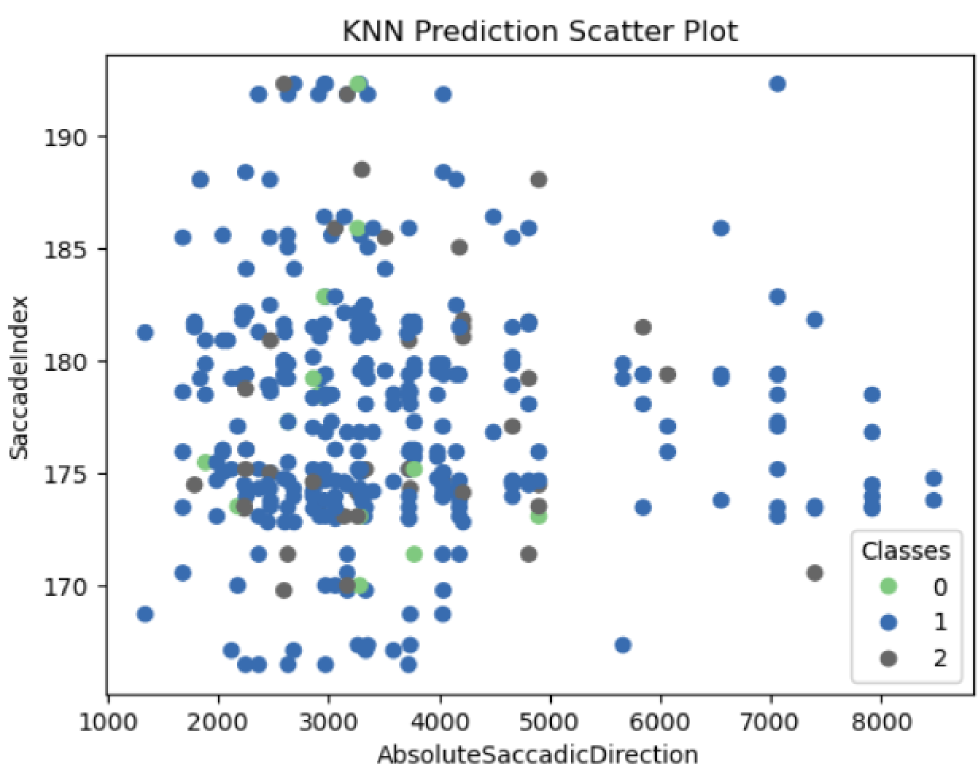


Figure 3.3.3: Scatter plot of the Knn-prediction on fictional data

Results and Output

4.1 Correlation found and meaning

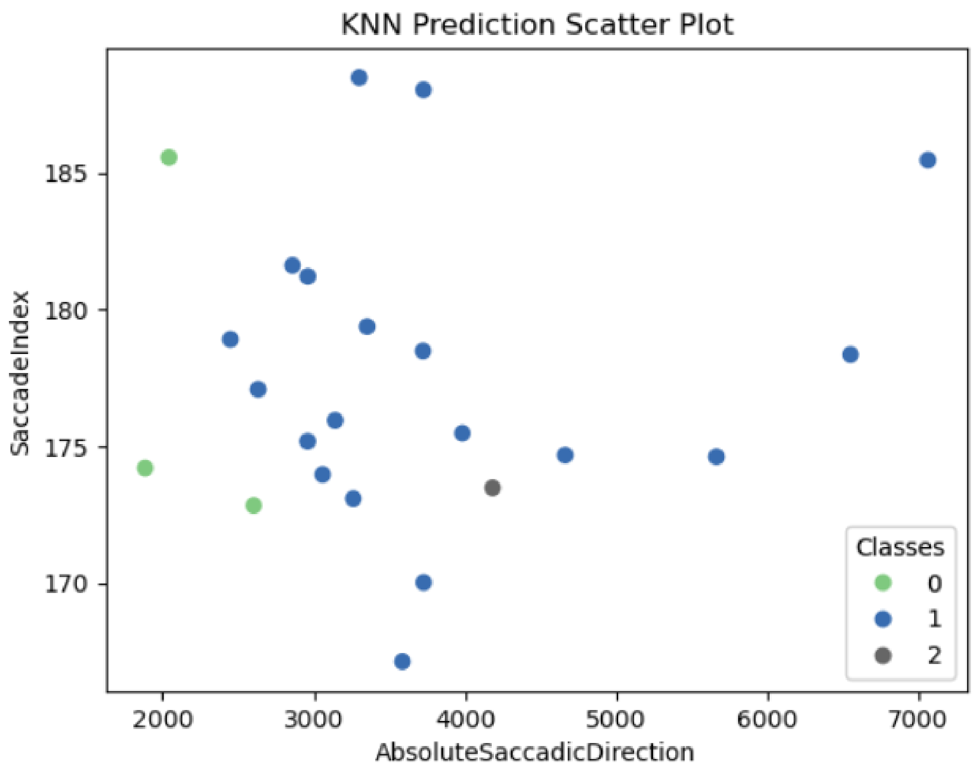
In our study, we carefully analyzed the correlation matrix of the eye movement data to better understand the relationships between variables.
To do this, I first looked at the raw data to see if there was a correlation.
We then examined the normalized and scaled data to see the correlations preserved by normalization.
Our results showed a strong positive correlation between AbsoluteSaccadicDirection, SaccadeIndex and mean performance on memory tasks.
This finding could help prove that there is a link between eye movements and memory performance, and can be further investigated using machine learning algorithms.
By using this data to train a predictive model, it may be possible to predict human memory based on eye movement patterns.
After a correlation analysis of eye movement data and mean performance on memory tasks, it was disappointing to find no visible correlation between the stress index and mean performance.
This suggests that in our particular case there may not be a strong relationship between stress levels and memory.
Despite this result, the strong positive correlation between AbsoluteSaccadicDirection, SaccadeIndex and mean grades on memory tasks remains valuable information.
This finding could be used in later machine learning algorithms to better understand the relationship between eye movements and memory performance, leading to new insights and insights.

4.2 Prediction accuracy and uses

Using the collected eye movement data, we utilized machine learning algorithms and hyperparameter tuning to identify the best-fit model for predicting the average grade of a patient based on their eye movement patterns.
After evaluating multiple models, we found that the best-fit model was a K-Nearest Neighbor (KNN) classifier with 24 neighbors.
This model achieved an accuracy of around 57% on our testing data, along with other satisfactory performance metrics such as 60% recall.

	precision	recall	f1-score	support
0	0.40	0.67	0.50	3
1	0.85	0.58	0.69	19
2	0.00	0.00	0.00	1
accuracy			0.57	23
macro avg	0.42	0.42	0.40	23
weighted avg	0.75	0.57	0.63	23

These results demonstrate correlations between eye movement data and average scores on memory tasks, highlighting the potential for using eye movement patterns as indicators of cognitive performance.
In addition, we visualized the distribution of the results by plotting a scatterplot of the prediction results using the two variables that showed the highest correlation in the correlation matrix (SaccadeIndex and AbsoluteSaccadicDirection) to determine whether clusters exist or not.
This scatterplot helped us better understand the relationship between these two variables and the grade average predictions made by the computer.
Overall, these results suggest that eye movement data may provide valuable information on cognitive performance and aid in further research in this area.



However, despite these positive results, it is important to note that the data are concentrated in one class and the mean grades are very close.
This concentration means that the predictive model could only detect one class and might not be representative of the entire population.
The results suggest an association between eye movement data and memory task performance, but more studies with more diverse data are needed to confirm these results and draw firmer conclusions.

Conclusion and Next Steps

Our studies of correlations between eye movement data, disorientation, and stress have not been successful in providing evidence for those correlations. On the other hand, it was a good predictor of findings showing associations between eye movement data and memory performance.
In fact, the correlations we found, along with the experiential accuracy of machine learning, prove that there are ways to use eye movement data to predict memory performance.
However, the results regarding the correlation between stress measures and memory performance grades were disappointing as no strong correlation was observed.
It's also important to note that the data set is concentrated in one class, making it difficult to fully validate the results. In fact, the lack of sparsity in the average scores on memory tasks makes it difficult to understand if a machine learning model is truly efficient, or if the model just knows how to classify the majority of data belonging to the same class.
Therefore, future studies should use larger datasets with large standard deviations of mean grades and a large number of classes.
In next steps, different machine learning algorithms should be investigated to further validate correlations and better understand the relationship between eye movement data and memory performance.
Regarding stress and disorientation indicators, next steps may include better methods to determine if participants are stressed/disoriented such as questions about how the participant felt at the time of the test and/or saliva samples to analyze her level of stress.

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