# **Progress Report 2**

Capstone Project: Gaming Addiction and Mental Health

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During Weeks 3 and 4 of the project, I focused on cleaning the dataset, preparing new features, and training a machine learning model that could help identify people at risk of gaming addiction based on their behavior and mental health indicators.

# 1. Getting the Dataset Ready

Before doing any kind of analysis or modeling, I had to make sure the dataset was in a good shape. Think of it like clearing your workspace before starting a big project.

Here's what I did:

#### Cleaned Column Names

Some column titles had extra spaces or inconsistent formatting. I fixed those so that everything was standardized and easier to work with.

# Removed Duplicate Entries

I checked for and removed any repeated rows to make sure every record represented a unique individual.

#### Converted Yes/No Answers to 1s and 0s

Survey responses like "Yes" and "No" were turned into numbers. This helps the machine learning model understand them better. For example:

"Yes" 
$$\rightarrow$$
 1

"No" 
$$\rightarrow$$
 0

#### Ordered Categories for Social Withdrawal

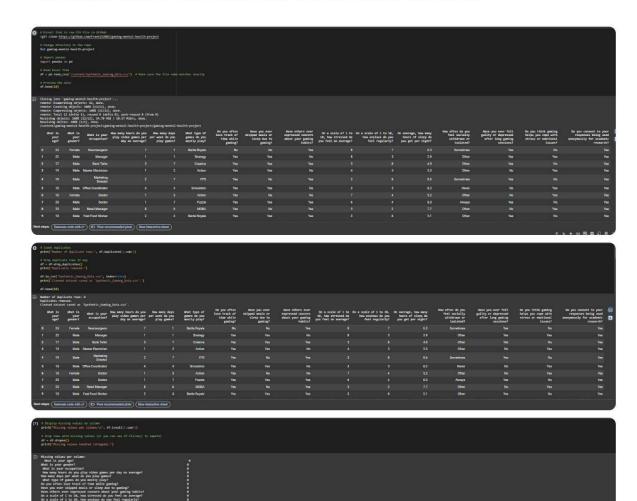
People described their social withdrawal using words like "Never," "Rarely," "Sometimes," and "Often." I converted those into a scale:

Never 
$$= 0$$

Rarely 
$$= 1$$

Sometimes = 2

This made it easier to treat social withdrawal as a measurable factor.



# 2. Creating New Features

We added new columns to help the model learn better patterns.

I counted how many risky behaviors a person had:

- Skipping meals or sleep due to gaming
- · Losing track of time
- · Feeling guilty after gaming
- Others showing concern about their habits

Each "yes" added 1 point, so the final score showed how serious the behavioral risks were.

# Mental Burden

This score was the sum of someone's stress and anxiety ratings. It helped measure their overall emotional load.

#### Sleep Deprivation

If someone got less than 5 hours of sleep, I marked them as "sleep-deprived." It's a red flag that gaming might be affecting their daily life.

# 3. Defining the Risk Score

I created a custom scoring system to rate how "at risk" a person might be. The score went from 0 to 10, based on five behaviors. Each behavior added 2 points if it was present:

- Plays more than 5 hours a day
- Plays more than 5 days a week
- · Skips sleep or meals due to gaming
- · Feels guilty after gaming
- · Loses track of time

This scoring system helped quantify the seriousness of someone's gaming habits.

### 4. Turning Scores into Risk Levels

After calculating the score, I grouped people into three categories:

• Low Risk: Score between 0 and 3

• Medium Risk: Score between 4 and 6

High Risk: Score between 7 and 10

This made the results easier to understand. For example, someone with a score of 9 would clearly fall into the High Risk group.

#### 5. Training the Model

Once everything was ready, I used a machine learning model called a Random Forest Regressor. I chose this model because:

- It works well with different kinds of data
- It's good at finding patterns
- It doesn't overfit easily (meaning it won't just memorize the data)

I trained the model to predict the risk score based on everything I'd prepared (gaming habits, stress, sleep, etc.).

#### 6. Evaluating the Model

To check how well the model was performing, I tested it using a portion of the data it hadn't seen before. The results were very encouraging:

- Mean Absolute Error (MAE): The average prediction error was only 0.08 points, which is very low.
- R<sup>2</sup> Score: The model explained about 99% of the variation in the risk scores.

This means the model was very accurate and didn't seem to be overfitting — it worked well on both training and test data.

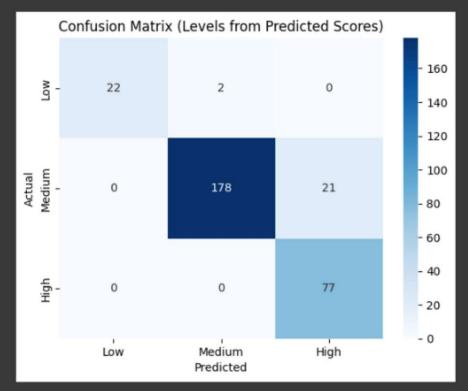
# 7. Converting Predictions Back into Risk Levels

After the model predicted a risk score for each person, I converted those scores back into Low, Medium, and High categories (using the same thresholds I created earlier).

Then I compared the predicted categories to the actual ones. The model was correct 92% of the time, and most of the mistakes were between neighboring levels like Medium and High — which is acceptable.

# Regression Evaluation: MAE: 0.07619999999999998 RMSE: 0.21812228985899934 R<sup>2</sup>: 0.9877456614313842 Classification Evaluation precision

| Classification | n Evaluation<br>precision |      | f1-score | support |
|----------------|---------------------------|------|----------|---------|
| High           | 0.79                      | 1.00 | 0.88     | 77      |
| Low            | 1.00                      | 0.92 | 0.96     | 24      |
| Medium         | 0.99                      | 0.89 | 0.94     | 199     |
| accuracy       |                           |      | 0.92     | 300     |
| macro avg      | 0.92                      | 0.94 | 0.93     | 300     |
| weighted avg   | 0.94                      | 0.92 | 0.93     | 300     |



Overfitting Check:

Train R²: 0.999 | Test R²: 0.988