PREDICTION AND CLASSIFICATION OF MENTAL HEALTH DISORDERS USING MACHINE LEARNING

APSV

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ABSTRACT

Not long ago, if someone acted “strange,” they were simply called crazy or weak. Mental illness wasn’t diagnosed—it was ignored, feared, or mocked. Today, science has changed that. We now recognize conditions that were once misunderstood, leading to a rise in diagnoses. Not because more people are sick, but because we finally know what to look for.

Our data is a compilation of surveys surrounding the following mental disorders: Schizophrenia, Bipolar Disorder, Eating Disorders like Anorexia, bulimia, and binge eating, Anxiety Disorders and Depression. Distinguished figures like Princess Diana, openly discussed her battle with bulimia while other examples of famous people with mental disorders are John Nash, the mathematician from A Beautiful Mind, and Jim Carrey, who suffered severe depression. Around 18% of the global population experiences an anxiety disorder each year, affecting women twice as much as it affects men. On the other hand, depression affects about 7% of the global population every year.

Today, instead of mocking or isolating people, we seek to understand and treat mental illness. The conversation is evolving, and with it, the way we view the human mind.

Keywords: mental health disorder, Machine Learning, modelling, classification, prediction.

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OBJECTIVES: BUSINESS UNDERSTANDING

As mentioned in our abstract, our project includes the following mental disorders:

- Schizophrenia: A severe mental disorder characterized by delusions, hallucinations, and disorganized thinking.
- Anxiety: An excessive fear or worry response that interferes with daily life.
- Depression: A mood disorder causing persistent sadness, loss of interest, and fatigue.
- Bipolar Disorder: A mental illness causing extreme mood swings between depressive and manic episodes.
- Eating Disorders: Disorders affecting eating behaviour and body perception, such as anorexia or bulimia.

Mental illnesses are often underdiagnosed in comparison to physical illnesses. According to the WHO, around 280 million people suffer from depression, but many do not receive treatment due to stigma and lack of access to mental healthcare. In addition to depression, it is estimated that 1 in 4 people will experience a mental disorder at some point in their lives. However, between 35% and 50% of people with mental disorders in developed countries do not receive treatment, a figure that is even higher in developing countries[1]. In Spain, according to the Ministry of Health, 12.5% of all health problems are related to mental disorders, a higher percentage than cancer and cardiovascular diseases. Despite this, many cases remain undiagnosed and untreated[2]. For example, in people living with HIV, it has been observed that 77% of mental illnesses are underdiagnosed, highlighting the need for greater attention and assessment in this group[3].

These statistics emphasize the importance of improving mental illness detection and treatment to reduce their impact on society. Nowadays, machine learning algorithms and the processing of large volumes of data are transforming many fields, and mental health is no exception. The ability of these models to identify patterns and make accurate predictions offers enormous potential to improve the detection and treatment of mental illnesses. In this project, our approach will be to apply different algorithms and models, evaluating the results to analyse their applicability and effectiveness in the field of mental health.

METHODOLOGY

TOOLS

For this project, we have used Python as the programming language within the Google Colab environment. We have followed the CRISP-DM (Cross Industry Standard Process for Data Mining) methodology to implement different Machine Learning algorithms learnt in APSV subject.

The code for data manipulation and visualization was developed using libraries such as Pandas, NumPy, Matplotlib, and Seaborn. Regarding the algorithms, the most used library in Python to work with ML is SciKit-Learn[4]. This module includes several implementations and functions for data handling and transformation.

[1] comunicalasaludmental.org
[2] sanidad.gob.es
[3] eresvihda.es
[4] https://scikit-learn.org/stable/

This project documentation outlines the process followed in our Jupyter Notebook files, with the source code included, all published on GitHub (https://github.com/Angelaruizalvarez/Mental-Health-ML-Algorithms). Specifically, the two following sections correspond to the *Data_preparation.ipynb* file.

DATA SOURCE & UNDERSTANDING

The data used in this project comes from a set of databases hosted on Kaggle, under the title *Mental Health*, published by Mohamadreza Momeni and updated two years ago. Specifically, we have worked with the first database in the repository, called '1-mental-illnesses-prevalence.csv'.

This data import and exploration corresponds to the "Data Visualization & Understanding" section. After downloading the file, it has properly been uploaded it to a new personal repository on Github and we have imported the database from GitHub into our Google Colab temporal workspace using the curl method, allowing us to easily access it for analysis in Python. Once imported, we have done a verification of the configuration of the work environment and used several commands to further understand our data. We have examined the different columns of the database and obtained general information about the variables and data formats contained in each column.

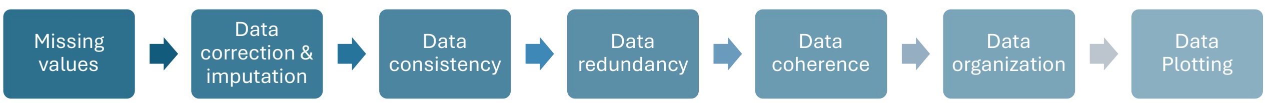
Column Name	Description
Entity	Name of the country, continent or group of countries according to income level
Code	Code of a few letters that identifies the entity
Schizophrenia disorders	Percentage of the population affected by each of the disorders. The data source indicates that these numbers are based on surveys that consider both sexes and a standardized age.
Depressive disorders	
Anxiety disorders	
Bipolar disorders	
Eating disorders	

Note: columns containing mental disorders also include a specification part:
"Schizophrenia disorders (share of population) - Sex: Both - Age: Age-standardized"
To simplify the database, this part of the name has been removed in the data cleaning section.

These initial steps allowed us to understand the data in our set for further analysis.

DATA PREPARATION

This data preparation corresponds to the "Data Cleaning & Preparation" section. We have prepared the data for subsequent modelling, following the steps shown to ensure good processing.



First, we analysed null values in some entries in the table, finding numerous null values in the 'Code' column. After visualizing which 'Entity' values were missing, we decided to manually impute them with codes that we considered appropriate. In this way, our database was free of null values. In addition, we checked that there were no duplicate entries.

We checked that all codes contained values for the percentage of the population with mental disorders for all years between 1990 and 2019, the range covered by our database. With this check, we ensured the consistency and completeness of the data.

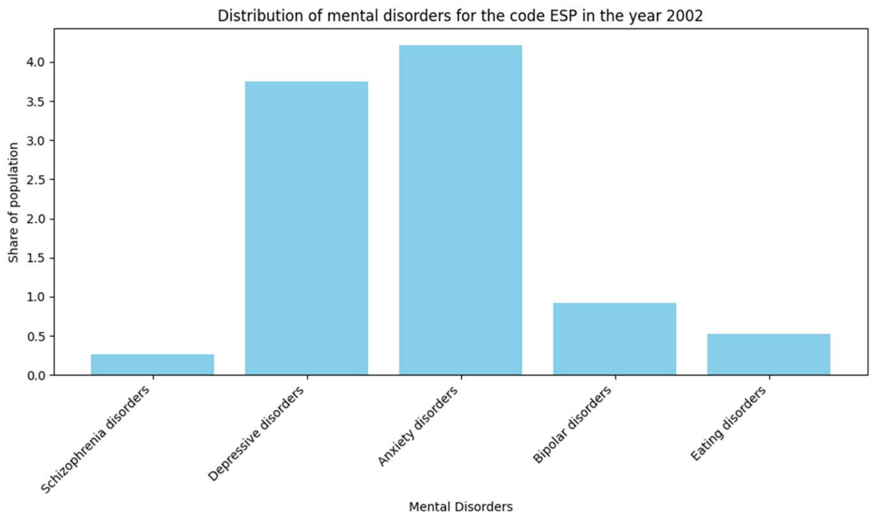
Additionally, as we have identified that the 'entity' and 'code' columns are somewhat redundant, we saved the Entity-Code relation table to a CSV file and implemented a retrieving code for future reference before dropping the 'Entity' column. This choice is based on the fact that one column has a much more abbreviated notation than the other. In this way, we avoid redundancies, since both columns act as identifiers, and we simplify the database so that it only contains relevant data.

Once we understand what the values in the mental disorders columns represent, we have shortened some column names to simplify the database, as they all indicate the share of population for both sexes and a standardized age. This ensures data coherence while maintaining clarity.

After a thorough understanding of our data, we have decided to split the dataset into three different databases, the content of which is shown below. Each one has been appropriately saved in its corresponding *csv* file within our local programming workspace for later download.

df_countries.csv	**df_continents.cv**	**df_income.csv**
Contains all individual country codes (150 in total)	Contains codes for different continents, also including the code for European Union - AFR_IHME: Africa - AMR_IHME: America - ASIA_IHME: Asia - EUR_IHME: Europe - EU27: European Union	Contains a categorization regarding income level. - HIGH_INC: high income - LOW_INC: low income - LOW_MID_INC: lower middle income - UP_MID_INC: upper middle income

Finally, we have implemented some data plotting code that allows the analysis of the values of the different mental disorders in a specific population, filtering the data by a manually selected country code and year, after a possible consultation of the codes of our three datasets. The code shows the percentage of the affected population in a bar graph, facilitating the analysis of mental health data. For example, the distribution for Spain in 2002 is shown below.



MACHINE LEARNING MODELS

This section corresponds to the *ML_cont.ipynb* file. In this section, we have implemented different classification and regression algorithms to our previously mentioned databases.

CLASSIFICATION OF CONTINENTS

ALGORITHM SELECTION

In this section we have selected and applied different classification algorithms to the database corresponding to continent codes: Logistic Regression, Decision Tree, Random Forest, K Nearest Neighbour and Perceptron; further plotting the results and evaluating their performance.

VARIABLE ASSIGNMENT

Our independent variable, X, consists of two mental disorders selected from the list of disorders, this means, two columns in the database that represent the population percentages for those two selected disorders in each case. The variable Y, which the model will try to predict, is the encoded version of Code. We use *LabelEncoder* to transform the Code column into numerical values, so that the classification algorithms can process them.

The five algorithms have been applied in two different approaches: one using all available data for each year of each continent, and another grouping by code calculating the average of the values across all years. In the first case, we obtain a more robust implementation whereas the second approach results in a simplified version, only plotting one value per code. To implement either approach, we have used a common code, adding sections that can be commented or uncommented depending on the approach we want to calculate This allows the performance of the algorithms to be compared in different situations.

MODEL IMPLEMENTATION & RESULT PLOTTING

Once trained and deployed, the models predict the relationship between the selected mental disorders (X) and the continents (Y). The results are shown in 10 graphs, corresponding to all possible combinations of our five mental disorders. The plot shows how the population percentages for the two selected disorders (principal axes) are distributed across the different continents, creating a coloured map described in the legend shown on the side. This allows us to observe whether continents with similar patterns in these disorders can be effectively classified by the model, helping to visualize the borders that the model has learned during training. We created the scatter plot by adjusting the graph boundaries with a margin of 0.25 from the extreme values on both axes to ensure that all points are well framed, as well as using the *viridis* colour map for good visual representation.

Regarding the chosen parameters, for the Random Forest algorithm we have defined $n\_estimators = 100$, as it as it provides stability without making the model unnecessarily expensive. For the K Nearest Neighbour algorithm, we have chosen $k = 5$ as the number of neighbors, a common choice in KNN because it balances smoothing and accuracy, avoiding both overfitting with very low k and loss of detail with very high k.

The results for the first approach using all available data for all the years are shown in Appendix 1, where we can observe and analyse the results for the five models. Similarly, the results for the second approach using mean values are available in Appendix 2.

VISUAL EVALUATION OF CLASSIFICATION ALGORITHMS

For the first approach we can see that the **Logistic Regression model** does not draw the scatter plot perfectly in some cases. For example, this algorithm sometimes does not predict the EUR_IHME category in the decision region in one case. Moreover, most graphs using values for eating disorders versus the rest of the disorders show very irregular decision regions and instability at the decision edges. For the **Decision Tree model**, in certain graphs (Schizophrenia vs. Anxiety Disorders graph), you see very tightly segmented and classified regions, indicating that the model is making decisions based on a very small number of samples in those areas, resulting in the space being divided in an unintuitive way. Visually, the **Random Forest model** appears to classify the data reasonably well, capturing general trends accurately. However, some areas where classes are mixed near the boundaries between regions suggest that the model might struggle with data that is intermixed (Eating vs. Anxiety disorders graph). The **KNN model** appears to produce more irregular and data-inconsistent decision regions, suggesting greater overfitting compared to previous models. The **Perceptron model** generates smoother and more gradual boundaries between classes. In general, the scatter plots define each class well, except in the Schizophrenia vs. eating disorders graph, where one of the regions shows a strange shape. This could be due to how the model models the decision space in areas with low data density.

When the same models are used but with only one feature in the second approach, the decision boundaries are much simpler and more apparent randomness is shown, since the models have less information to separate the classes. Specifically, for the KNN, since it has only one value for each class, the model is unable to classify each region, resulting in grey scatter plots that do not offer us any information. We can visually observe that for all algorithms, plotting the complete data generally results in a more robust prediction of the colour map. Using only the mean values could simplify the case but, in this case, it does not result in a useful approach.

ANALYTIC EVALUATION OF CLASSIFICATION ALGORITHMS

Now using metrics such as F1 Score and Accuracy, we evaluate the models for the first approach. For each pair of disorders, we train and evaluate each model in the KFold iterations, obtaining values for the two metrics that we use to perform a quantitative evaluation of the models. We perform cross-validation using KFold with n_splits = 3 p, since it allows us to evaluate the model in a robust way and avoid the results depending on a single division of the data, thus obtaining a reliable evaluation.

In addition to displaying the results for each iteration, we also create a dictionary for each metric (*global_results_f1* and *global_results_accuracy*) to store the results of each model in each KFold iteration. We obtain the average of both metrics for each pair of disorders and for each model in general, which gives us a clear view of the overall performance of each model. This approach guarantees a good and accurate evaluation of the models in different combinations of disorders.

The detailed **accuracy** values obtained through all iterations for each model and disorder pair are detailed in Appendix 3, showing the average values below.

Pair of disorders	Logistic Regression	Decision Tree	Random Forest	Nearest Neighbors	Perceptron	Mean Value
Schizophrenia + Depressive disorders	0,6333	0,9800	0,9733	0,8534	0,7867	**0,8453**
Schizophrenia + Anxiety disorders	0,8933	1,0000	1,0000	0,9933	1,0000	**0,9773**
Schizophrenia + Bipolar disorders	0,5867	1,0000	1,0000	1,0000	1,0000	**0,9173**
Schizophrenia + Eating disorders	0,5867	1,0000	1,0000	1,0000	1,0000	**0,9173**
Depressive + Anxiety disorders	0,9067	0,9467	0,9467	0,9267	0,9200	**0,9293**
Depressive + Bipolar disorders	0,6533	0,9533	0,9467	0,9400	0,8933	**0,8773**
Depressive + Eating disorders	0,7333	0,9800	0,9667	0,9667	0,9133	**0,9120**
Anxiety + Bipolar disorders	0,8933	0,9267	0,9267	0,9400	0,9333	**0,9240**
Anxiety + Eating disorders	0,9400	1,0000	1,0000	0,9933	1,0000	**0,9867**
Bipolar + Eating disorders	0,7467	1,0000	1,0000	1,0000	1,0000	**0,9493**
Model Accuracy	**0,7573**	**0,9787**	**0,9760**	**0,9613**	**0,9447**	**0,9236**

Similarly, the obtained F1 Score Values are also shown below.

Pair of disorders	Logistic Regression	Decision Tree	Random Forest	Nearest Neighbors	Perceptron	Mean Value
Schizophrenia + Depressive disorders	0,631	0,9799	0,9800	0,8497	0,7674	**0,8416**
Schizophrenia + Anxiety disorders	0,873	1,0000	1,0000	0,9933	1,0000	**0,9733**
Schizophrenia + Bipolar disorders	0,482	1,0000	1,0000	1,0000	1,0000	**0,8964**
Schizophrenia + Eating disorders	0,4587	1,0000	1,0000	1,0000	1,0000	**0,8917**
Depressive + Anxiety disorders	0,9322	0,9387	0,9525	0,9364	0,9127	**0,9345**
Depressive + Bipolar disorders	0,5492	0,9525	0,9397	0,9177	0,9094	**0,8537**
Depressive + Eating disorders	0,5152	0,9803	0,9803	0,9669	0,9186	**0,8723**
Anxiety + Bipolar disorders	0,8848	0,9313	0,9252	0,9318	0,9513	**0,9249**
Anxiety + Eating disorders	0,8854	1,0000	1,0000	0,9866	1,0000	**0,9744**
Bipolar + Eating disorders	0,5158	1,0000	1,0000	1,0000	1,0000	**0,9032**
Model F1 score	**0,6727**	**0,9783**	**0,9778**	**0,9582**	**0,9459**	**0,9066**

<0,65
0,65-0,9
0,9-0,99
1

Using the colour scale shown, we have analysed all the cases. We have calculated both metrics since accuracy is simpler and provides an overview but may not be sufficient if the classes are uneven. The F1 Score is more robust when both accuracy and the ability to detect all classes are considered. The joint analysis of these two variables shown previously allows us to estimate which models to use depending on the pair of disorders we want to classify. The **Logistic Regression model** generally does not show good results in any case. In particular, some graphs (Schizophrenia vs. depressive disorders and depressive vs bipolar disorders) are the ones that present the most difficulties for the models, due to the results obtained. **K Neighbours model** shows a very good classification behaviour, with high F1 scores and accuracy values in most cases. However, the **Perceptron**, **Random Forest** and **Decision Tree models** show in most cases an accuracy and F1 score of 100%, standing out as the most effective.

CLASSIFICATION OF COUNTRIES PER INCOME

After observing the results obtained for the classification of continents, we have applied the three best learning models to our database containing the categorization regarding income level. The results obtained for the **Random Forest**, **Perceptron** and **Decision Tree models** are shown in Appendix 4. All the graphs obtained show very well-defined borders and good classification models for the four categories. This time we do not find strangely shaped decision zones in the Perceptron model, since the data are better distributed in the scatter plot, allowing the model to make a more precise classification.

PREDICTION OF FUTURE VALUES

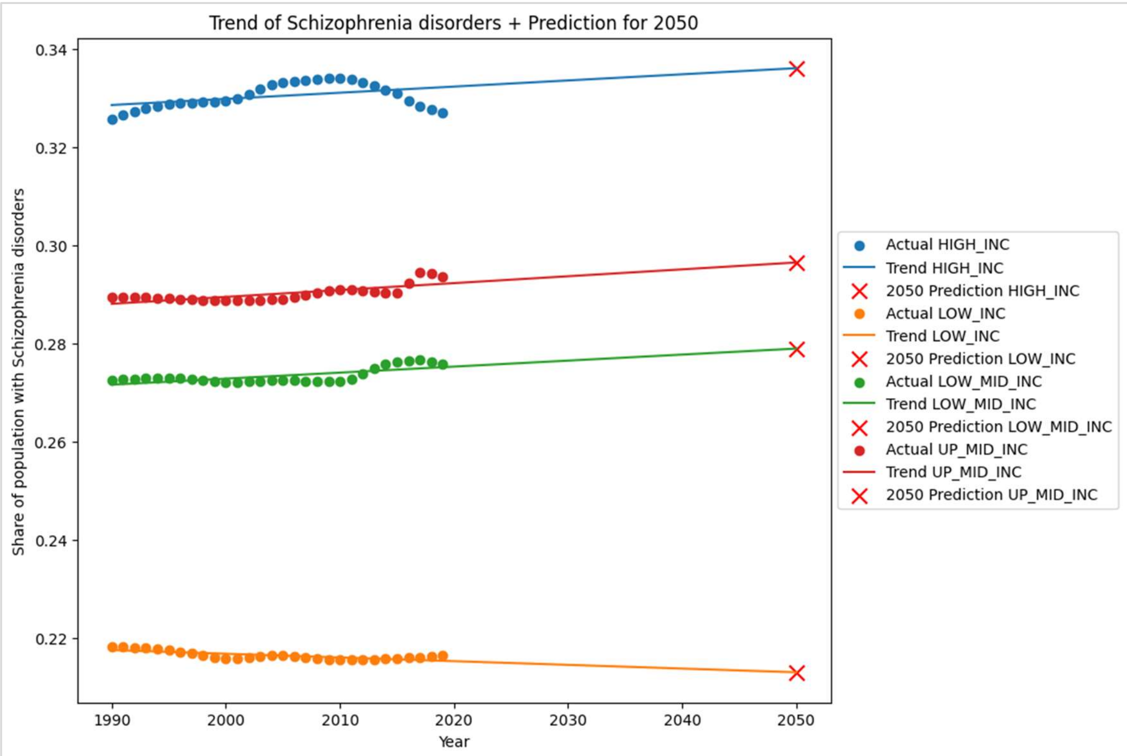
Furthermore, in this section we have selected and applied different regression algorithms to the database corresponding to continent codes: Linear Regression, Decision Tree and Random Forest. We have developed a regression model to analyse the evolution of the percentage of the population with different mental disorders over time, using data from our database between 1990 and 2019.

We have defined a *disorder_index* variable, which allows us to select the disorder we want to analyse, thus reusing the same code and saving us complexity.

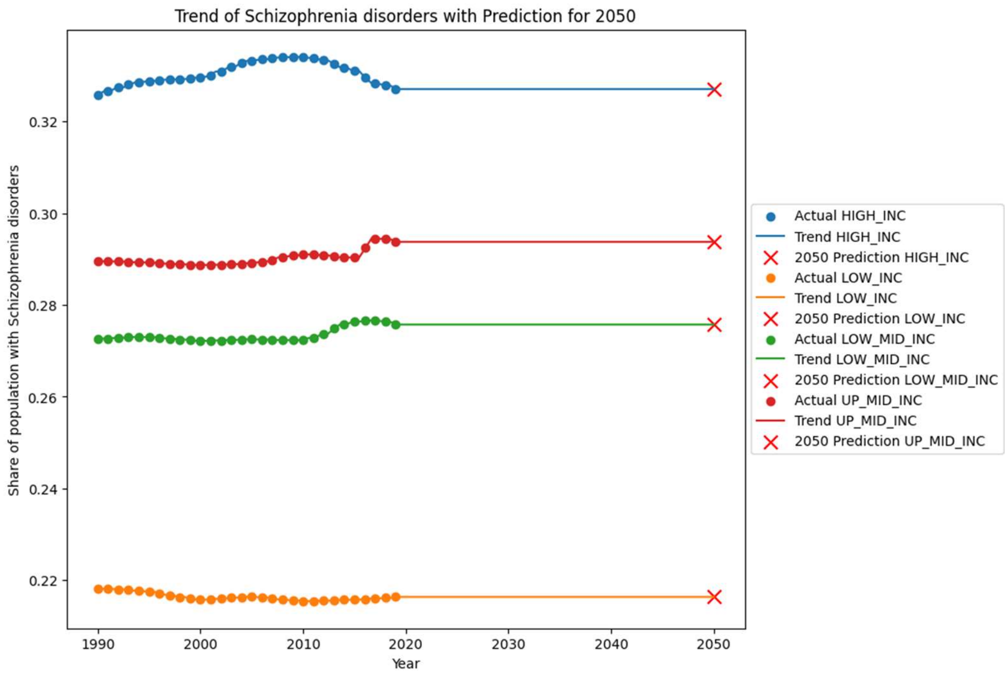
Disorder_index	Real disorder
0	Schizophrenia disorders
1	Depressive disorders
2	Anxiety disorders
3	Bipolar disorders
4	Eating disorders

We have used three machine learning models to analyze the evolution of the disorders and predict their value in 2050. For each model, we have plotted the values between 1990 and 2019, with data obtained directly from the database. After applying the corresponding model to generate the trend line, using different colours for each of the four categories, we have been able to predict the evolution until 2050, where its predicted value has been marked with a red cross. Additionally, we have created a summary table with the values of each category in the years 1990, 2019 and the prediction for 2050.

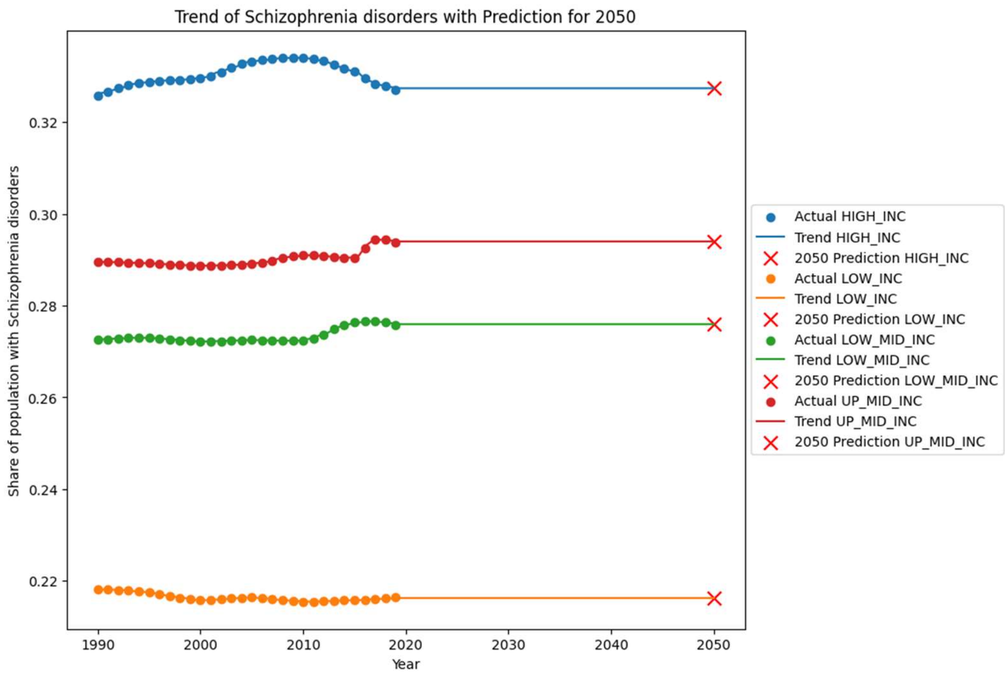
An example of predicted values for **Schizophrenia disorder** is shown below for model comparison.



Linear Regression



Decision Tree



Random Forest

After a thorough analysis of the results obtained, it is clear that the **Linear Regression model** is the only one that allows us to predict a value beyond the original data range, which was the main objective of this section. The **Decision Tree** and **Random Forest** models adjust their trend line too closely to the real data, which prevents extrapolating longer-term trends. This is why both models show a straight line between the value of 2019 and that of 2050. The linear regression model, however, does provide us with prediction values with a certain consistency, as shown below.

Code	1990	2019	2050
HIGH_INC	0.328651	0.332285	0.336170
LOW_INC	0.217510	0.215317	0.212974
LOW_MID_INC	0.271626	0.275183	0.278985
UP_MID_INC	0.288119	0.292190	0.292190

From all this observation, we can conclude that while linear regression seeks a global fit, the other two models focus on learning local patterns, which prevents them from projecting values outside the training interval and are not useful for this task.

CONCLUSIONS

In this project, we emphasize the importance of proper cleaning and preparation of the datasets we work with, as well as an initial plotting of the data to better understand how to handle them. All of this, combined with a solid application of the CRISP process, allows us to clearly define our objectives and validate whether they are achieved or not.

Firstly, after applying different classification algorithms, we have concluded that Random Forest, Decision Tree, and Perceptron are the most efficient, both analytically and visually, by precisely delimiting the decision zones. By plotting graphs for all possible combinations of the five mental health disorders we work with, we have added validity and robustness to our study, enhancing both the qualitative and quantitative evaluations.

Regarding the regression algorithms, we conclude that only the Linear Regression algorithm is useful in predicting values for different mental health disorders on a future date. While Random Forest and Decision Tree offer advantages, such as a trend line more closely aligned with real values, they are less suitable in this case and serve other purposes in different contexts.

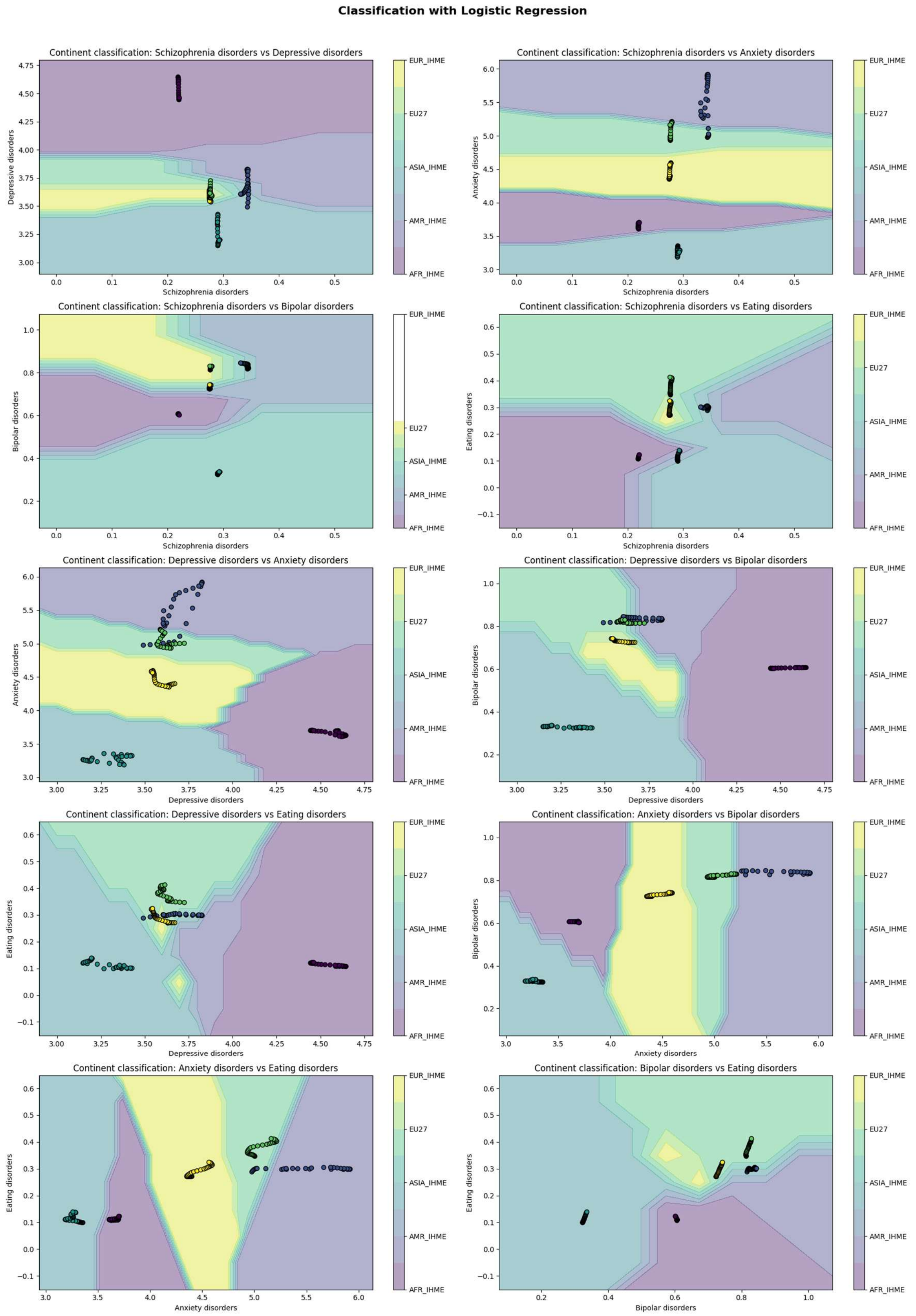
In general, we have conducted a very exhaustive, visual analysis of the data, which opens a crucial path for experts in fields like psychology or sociology for further analysis of patterns related to mental illness. This type of analysis can help understand global population distribution and how factors like a country's income level can influence the mental health of its population. It also provides a solid foundation for other experts to build upon with their knowledge, leading to deeper analyses of trends and potential solutions.

In summary, this analysis demonstrates how machine learning algorithms can model the evolution of mental disorders and predict potential trends. Always taking into account that the validity of predictions depends on the quality of the data and the characteristics of the algorithm. These algorithms can play a crucial role in detecting mental illnesses, and as citizens, it is our responsibility to apply our knowledge and collaborate with experts to improve detection for further treatment, working together for a healthier and more aware society.

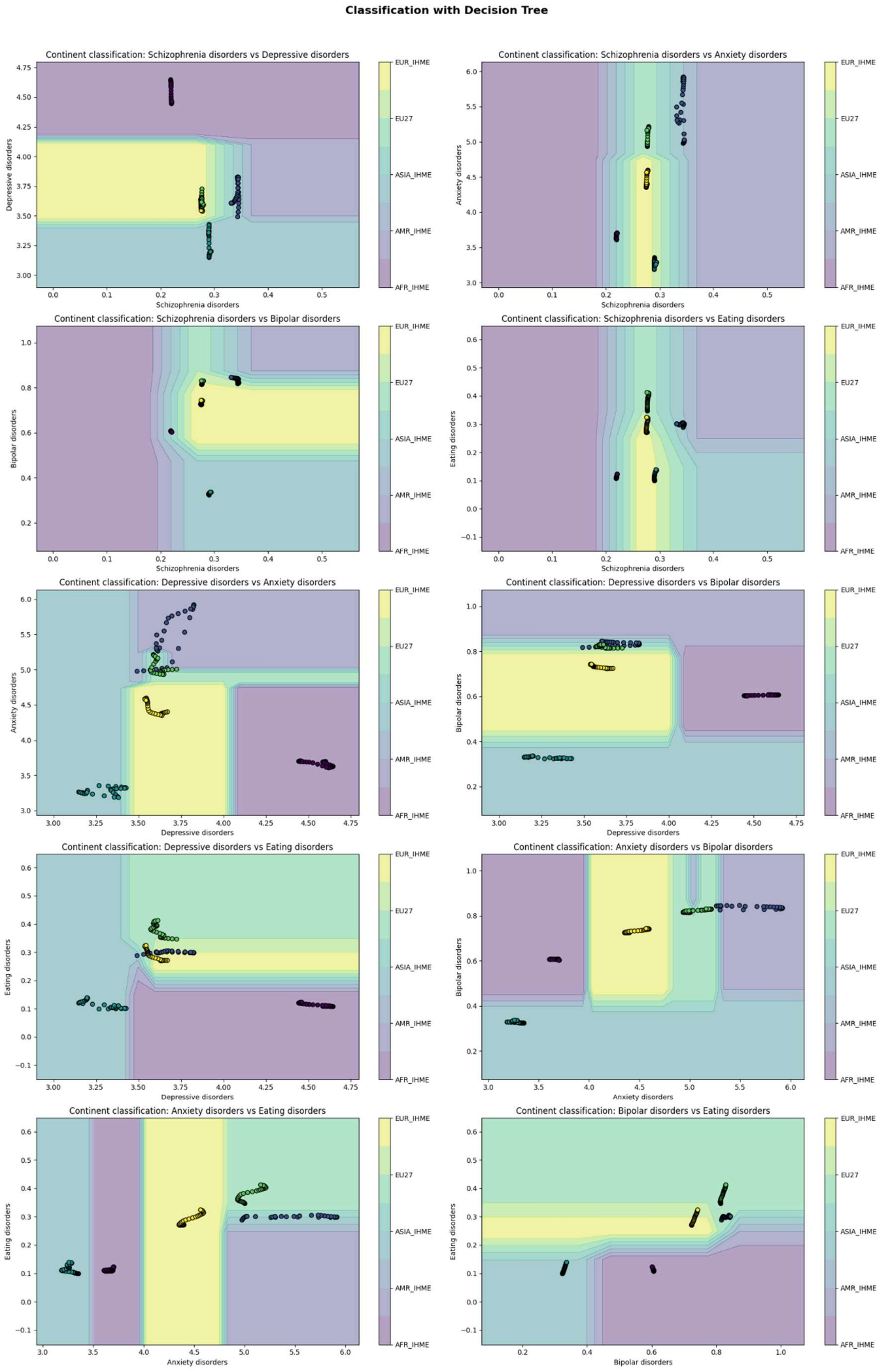
APPENDIX

APPENDIX 1. RESULTS USING ALL VALUES

LOGISTIC REGRESSION

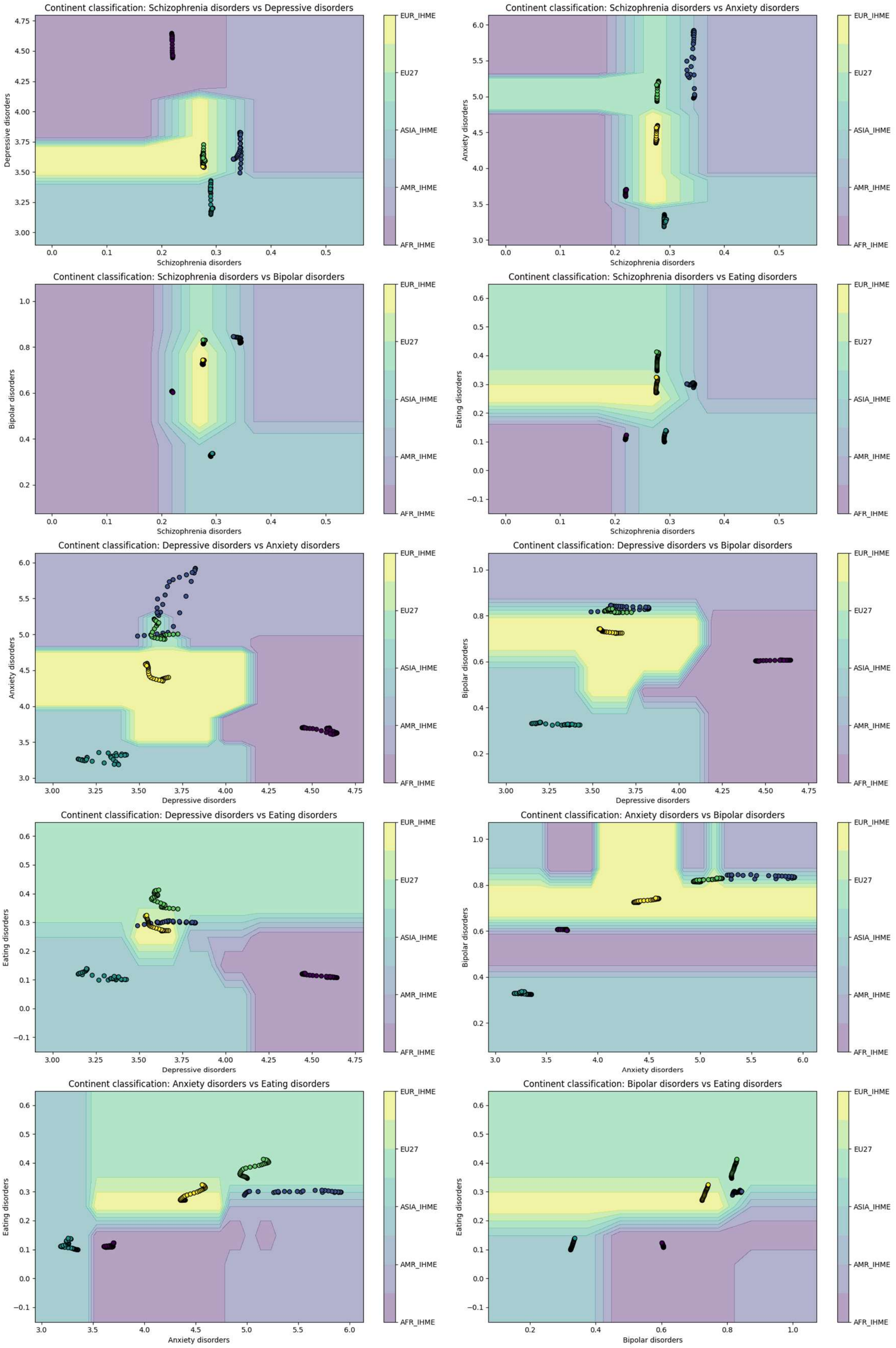


DECISION TREE



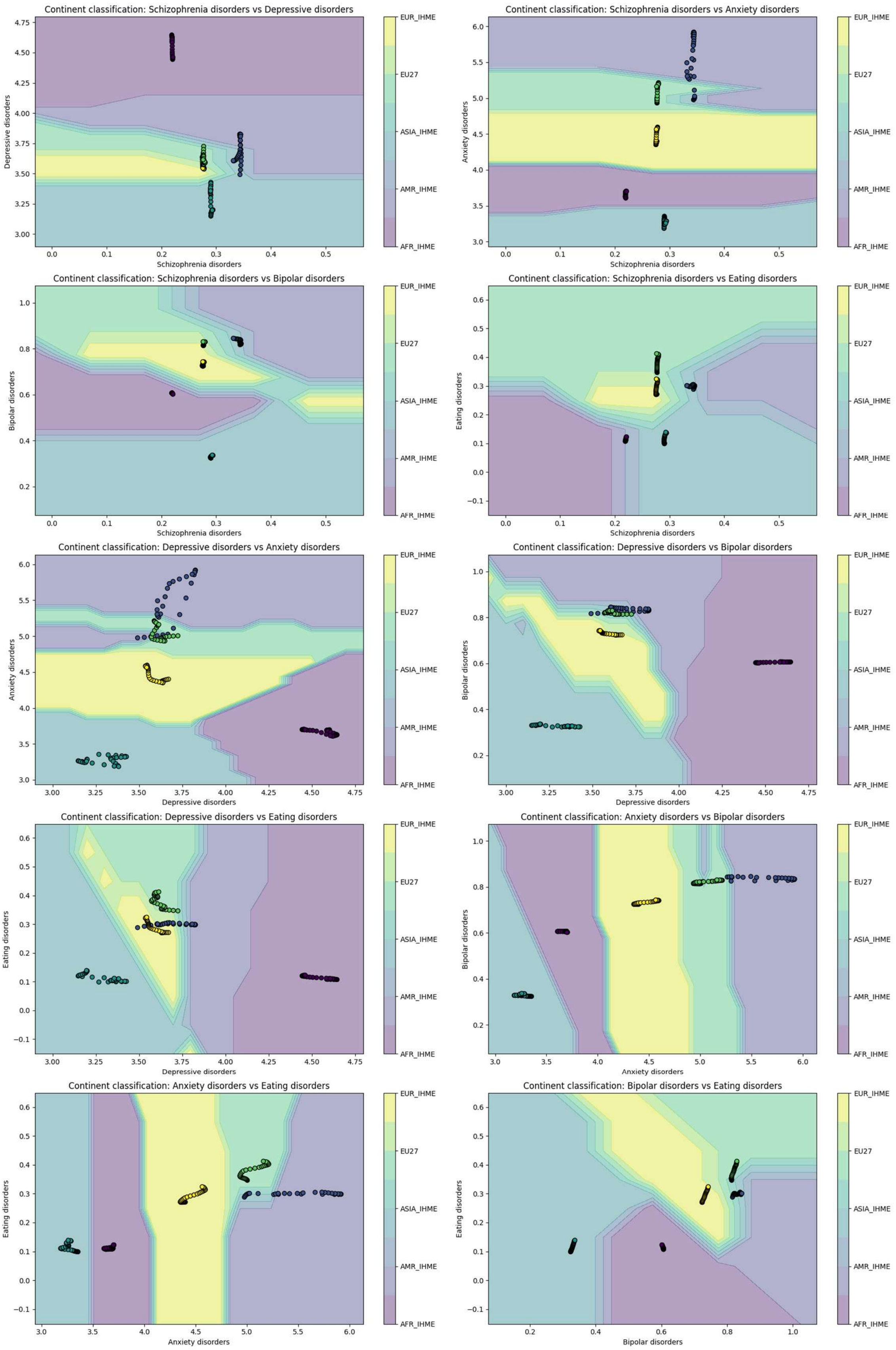
RANDOM FOREST

Classification with Random Forest



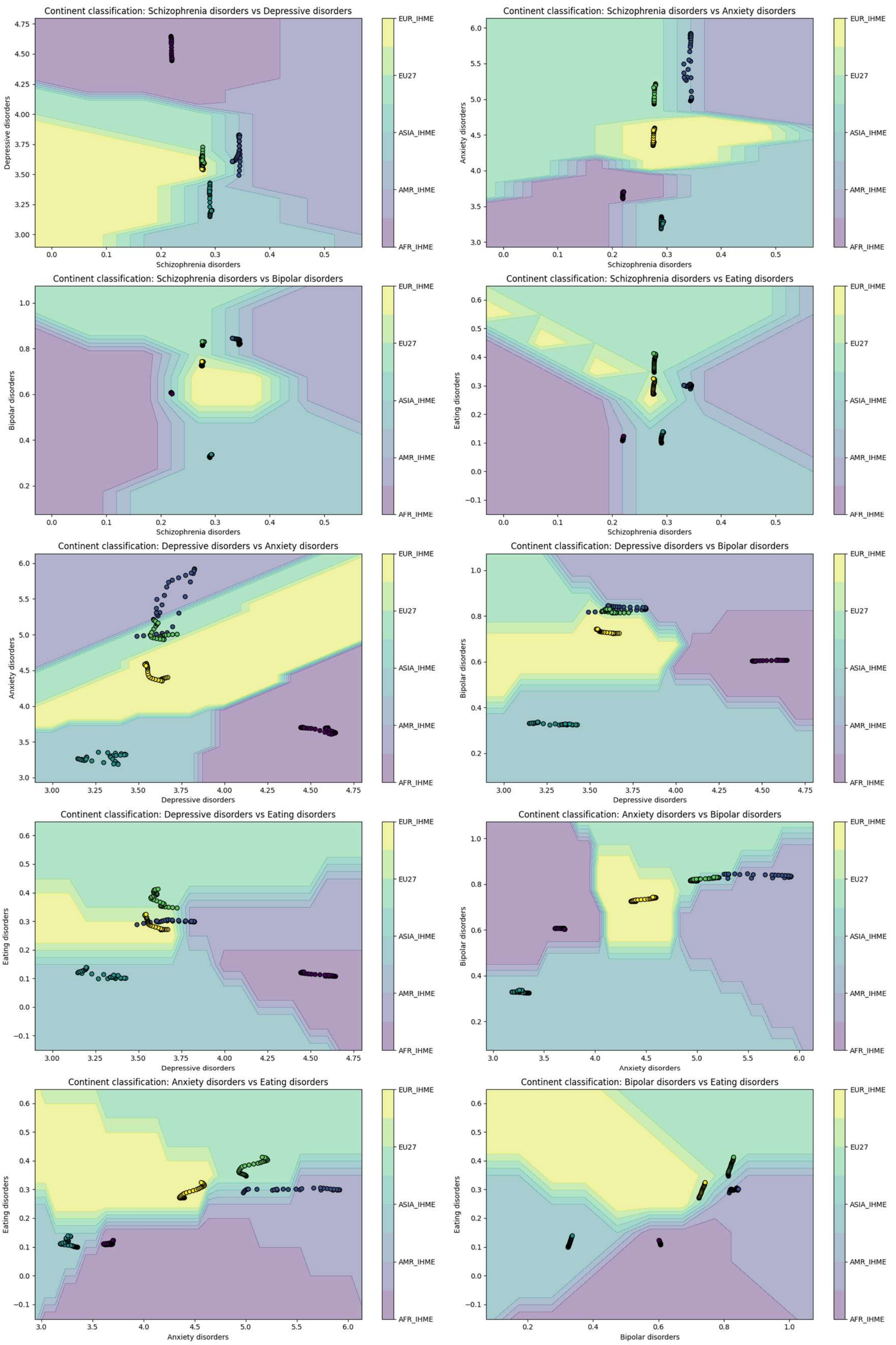
K NEAREST NEIGHBOUR

Classification with KNN



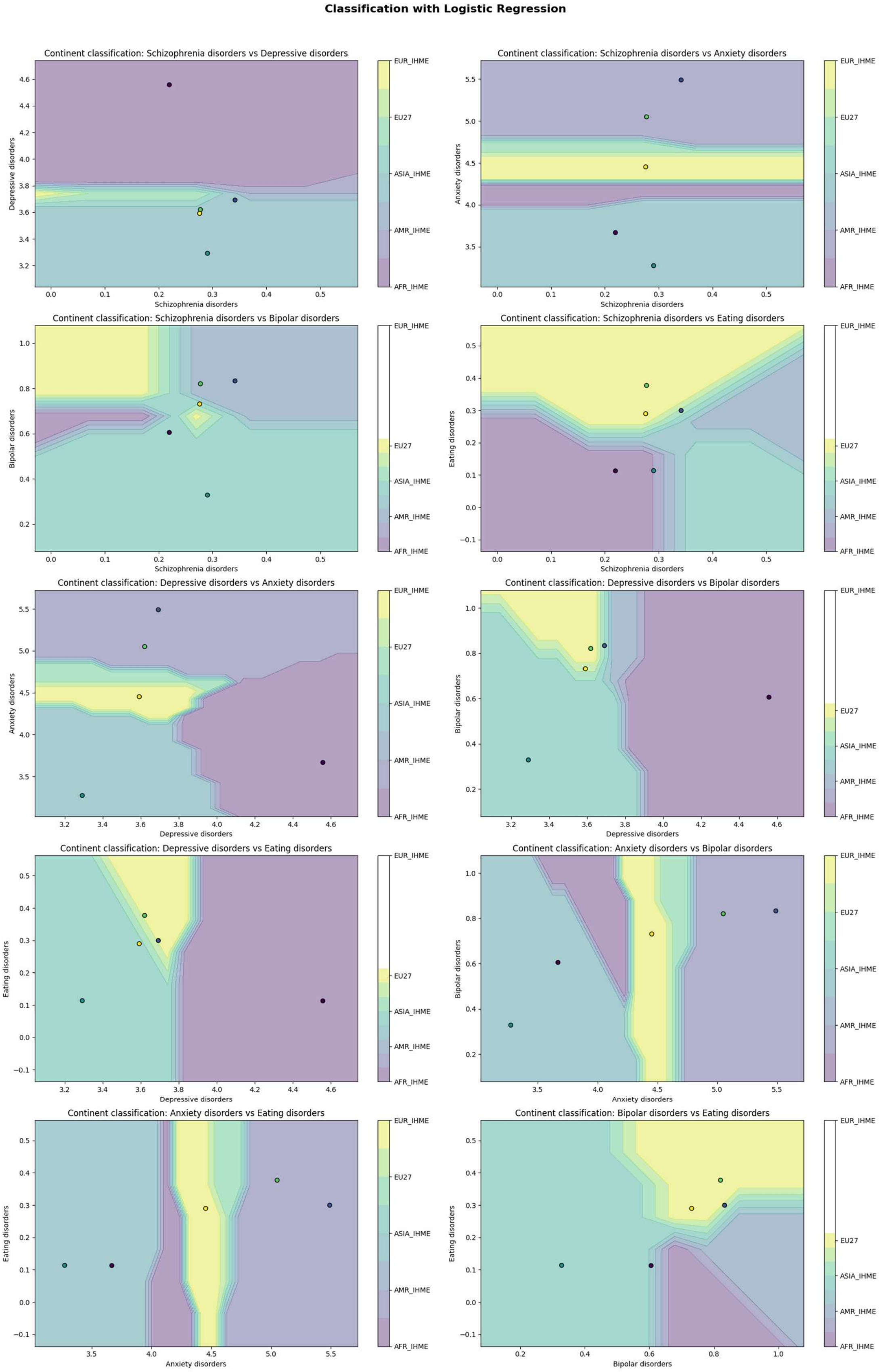
PERCEPTRON

Classification with Perceptron (MLP)



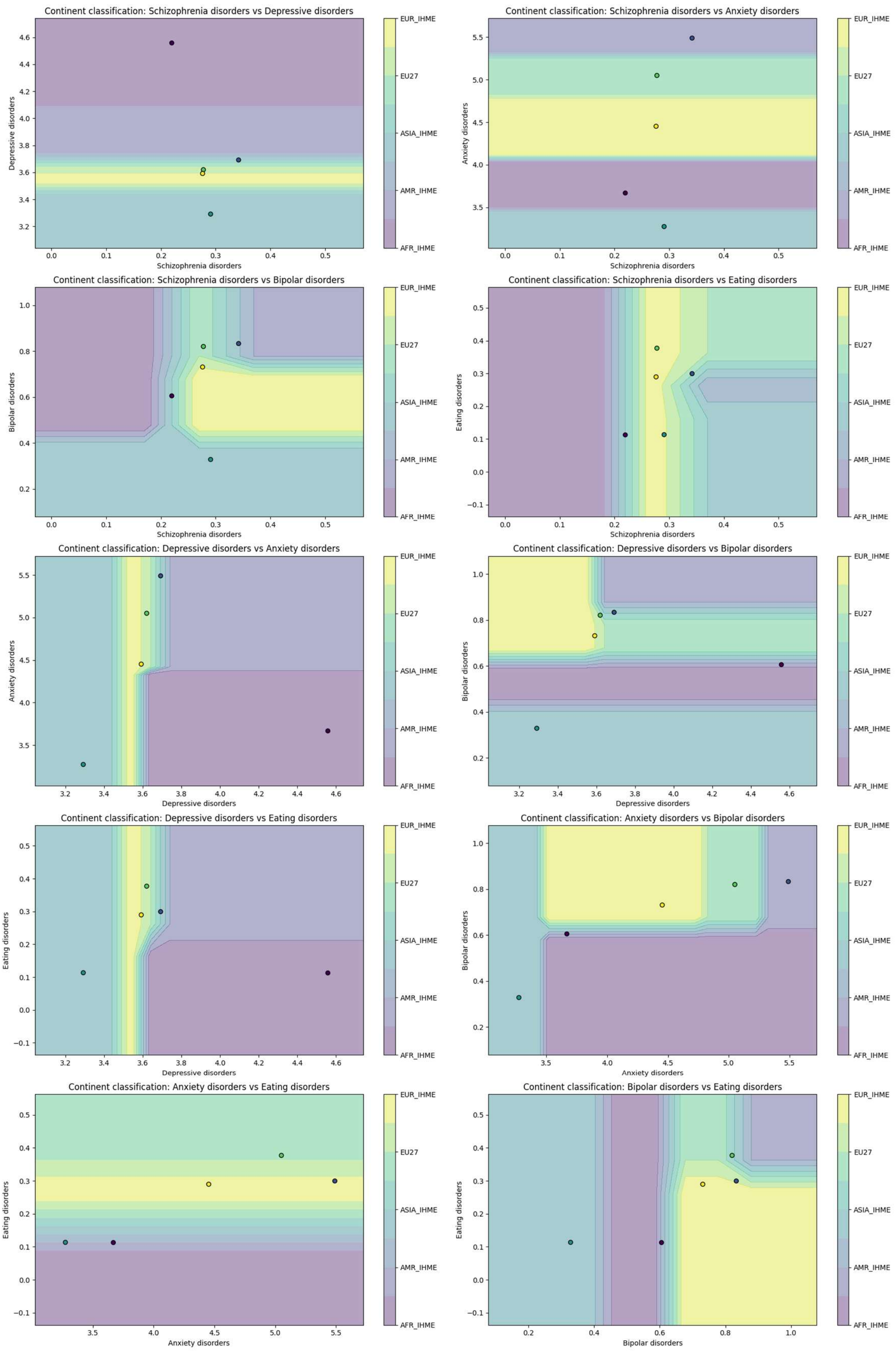
APPENDIX 2. RESULTS USING MEAN VALUES

LOGISTIC REGRESSION

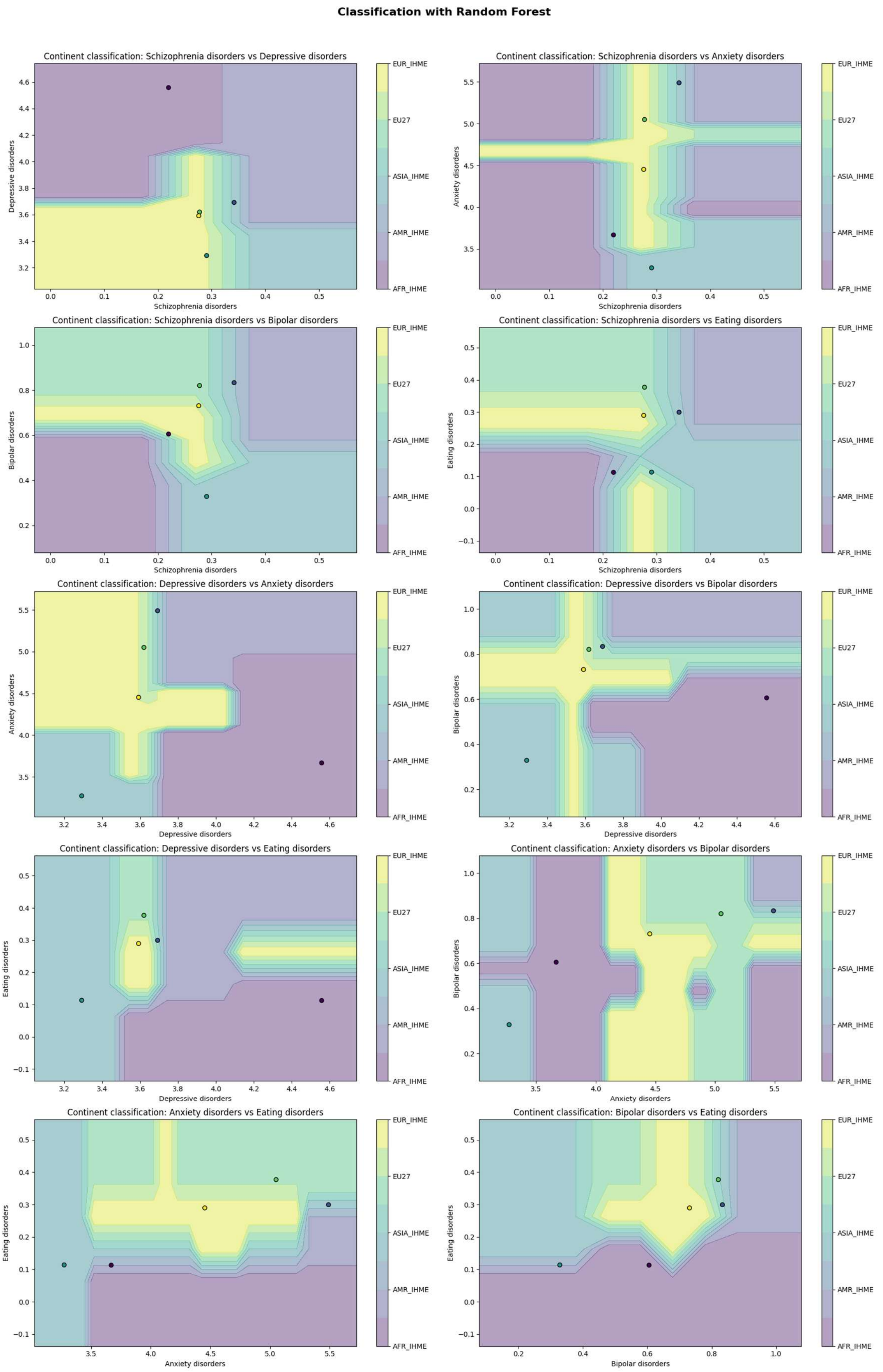


DECISION TREE

Classification with Decision Tree

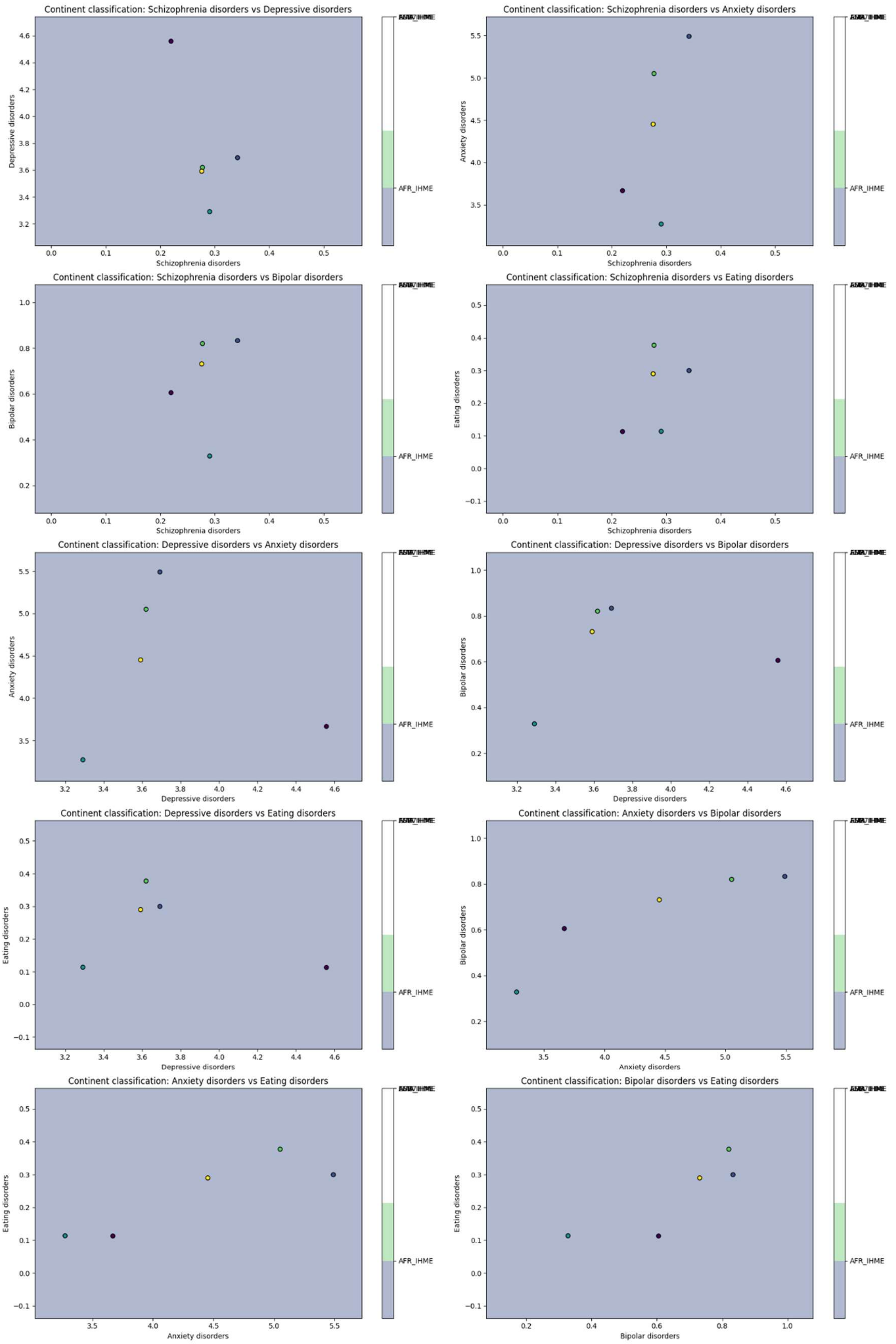


RANDOM FOREST

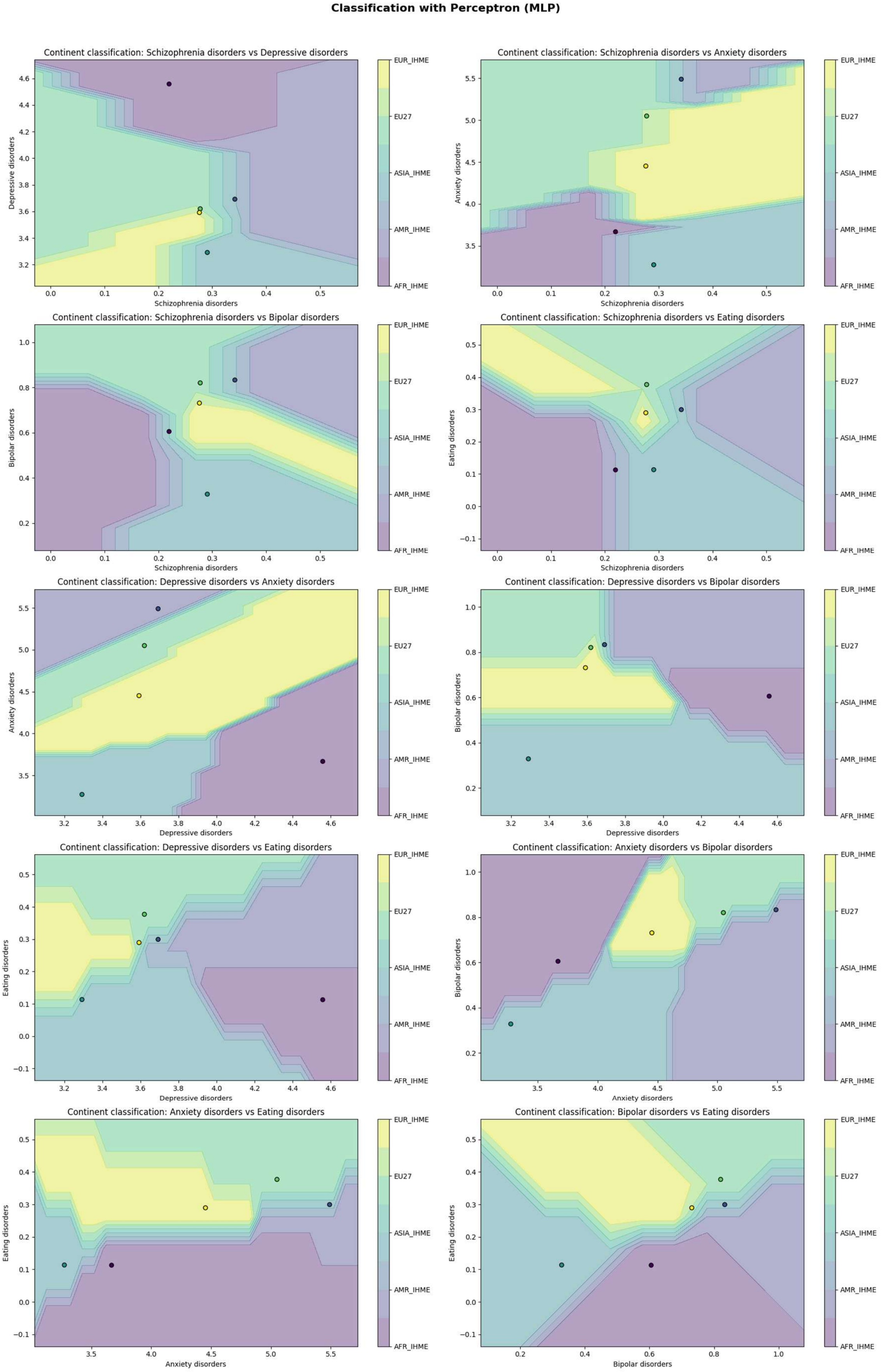


K NEAREST NEIGHBOUR

Classification with KNN



PERCEPTRON


Classification with Perceptron (MLP)
Continent classification: Schizophrenia disorders vs Depressive disorders
Continent classification: Schizophrenia disorders vs Anxiety disorders
Continent classification: Schizophrenia disorders vs Bipolar disorders
Continent classification: Schizophrenia disorders vs Eating disorders
Continent classification: Depressive disorders vs Anxiety disorders
Continent classification: Depressive disorders vs Bipolar disorders
Continent classification: Depressive disorders vs Eating disorders
Continent classification: Anxiety disorders vs Bipolar disorders
Continent classification: Anxiety disorders vs Eating disorders
Continent classification: Bipolar disorders vs Eating disorders
Schizophrenia disorders
Depressive disorders
Anxiety disorders
Bipolar disorders
Eating disorders
EUR_IHME
EU27
ASIA_IHME
AMR_IHME
AFR_IHME

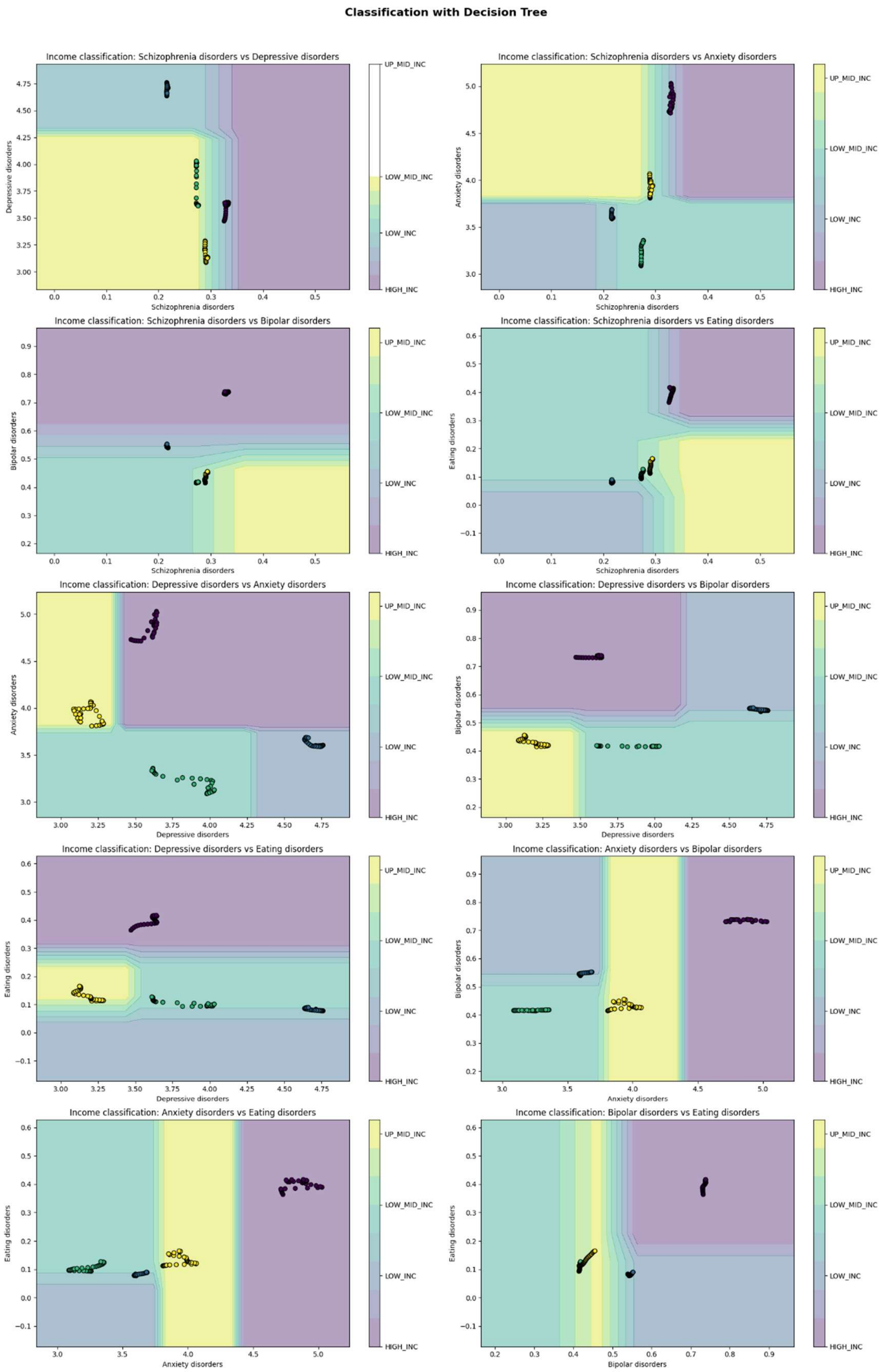
APPENDIX 3. DETAILED ACCURACY VALUES PER ITERATION

Accuracy Evaluation

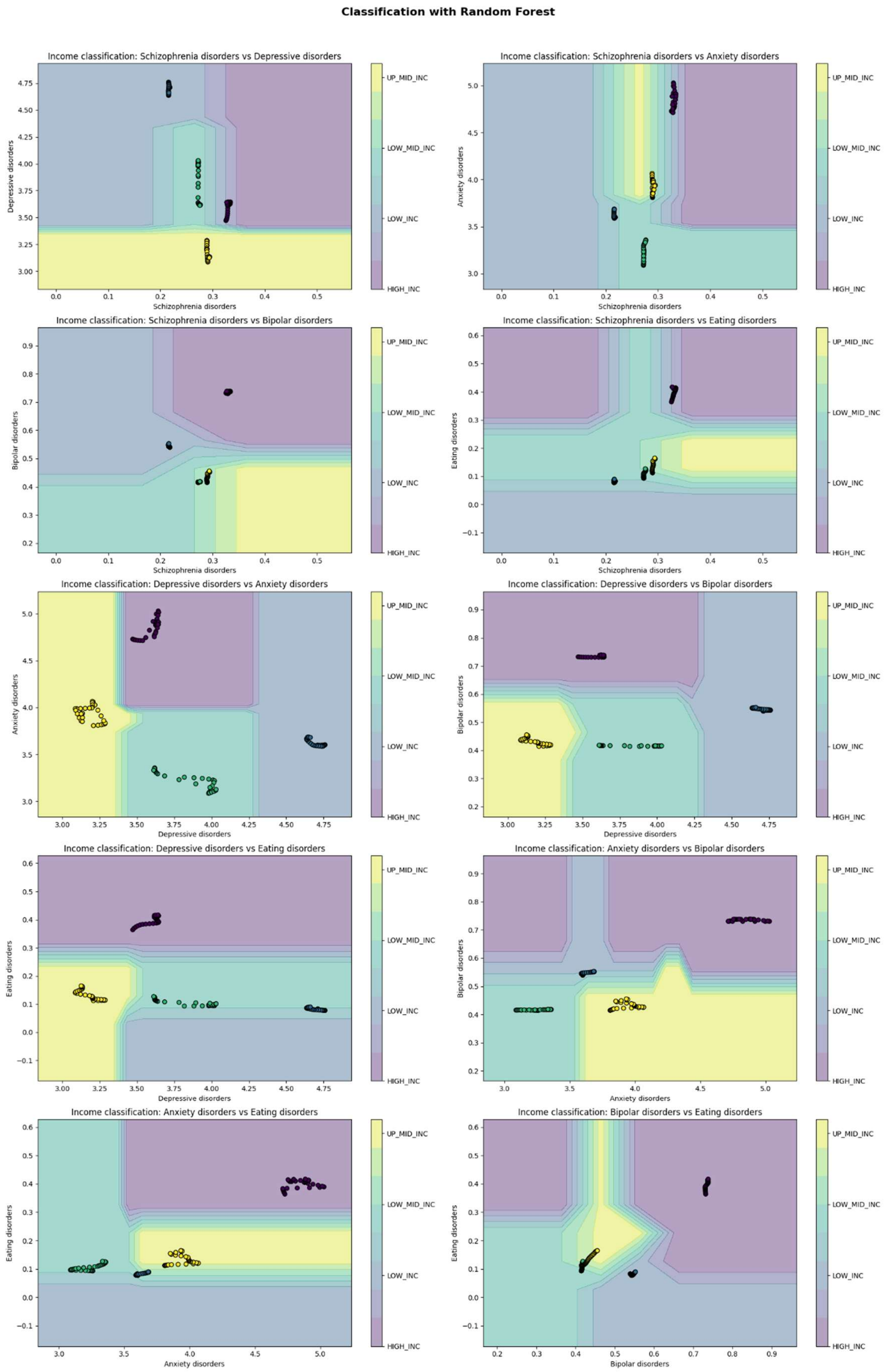
	Iteration	Logistic Regression	Decision Tree	Random Forest	K Nearest Neighbors	Perceptron	Mean Value
Schizophrenia disorders vs. Depressive disorders	1	0,6330	1,0000	1,0000	0,7667	0,7667	
	2	0,8000	0,9667	1,0000	0,9667	0,8333	
	3	0,4333	1,0000	1,0000	0,8667	0,7667	
	4	0,7333	1,0000	0,9667	0,8667	0,7667	
	5	0,5667	0,9333	0,9000	0,8000	0,8000	
	Mean	0,6333	0,9800	0,9733	0,8534	0,7867	0,8453
Schizophrenia disorders vs. Anxiety disorders	1	0,8333	1,0000	1,0000	0,9667	1,0000	
	2	0,9000	1,0000	1,0000	1,0000	1,0000	
	3	0,9000	1,0000	1,0000	1,0000	1,0000	
	4	0,9333	1,0000	1,0000	1,0000	1,0000	
	5	0,9000	1,0000	1,0000	1,0000	1,0000	
	Mean	0,8933	1,0000	1,0000	0,9933	1,0000	0,9773
Schizophrenia vs Bipolar Disorders	1	0,7667	1,0000	1,0000	1,0000	1,0000	
	2	0,6333	1,0000	1,0000	1,0000	1,0000	
	3	0,4333	1,0000	1,0000	1,0000	1,0000	
	4	0,6333	1,0000	1,0000	1,0000	1,0000	
	5	0,4667	1,0000	1,0000	1,0000	1,0000	
	Mean	0,5867	1,0000	1,0000	1,0000	1,0000	0,9173
Schizophrenia vs Eating Disorders	1	0,7667	1,0000	1,0000	1,0000	1,0000	
	2	0,6333	1,0000	1,0000	1,0000	1,0000	
	3	0,4333	1,0000	1,0000	1,0000	1,0000	
	4	0,6333	1,0000	1,0000	1,0000	1,0000	
	5	0,4667	1,0000	1,0000	1,0000	1,0000	
	Mean	0,5867	1,0000	1,0000	1,0000	1,0000	0,9173
Depressive vs Anxiety Disorders	1	0,8667	0,9667	0,9333	0,8333	0,8667	
	2	0,9000	0,9333	0,9667	0,9667	0,9333	
	3	0,9000	0,9000	0,9000	0,9000	0,9000	
	4	0,9333	0,9333	0,9333	0,9333	0,9667	
	5	0,9333	1,0000	1,0000	1,0000	0,9333	
	Mean	0,9067	0,9467	0,9467	0,9267	0,9200	0,9293
Depressive vs Bipolar Disorders	1	0,7000	0,9667	1,0000	0,9000	0,8667	
	2	0,9333	0,9667	0,9333	0,9667	0,9333	
	3	0,4333	0,9000	0,9000	0,9000	0,8667	
	4	0,7333	0,9333	0,9000	0,9667	0,9000	
	5	0,4667	1,0000	1,0000	0,9667	0,9000	
	Mean	0,6533	0,9533	0,9467	0,9400	0,8933	0,8773
Depressive vs Eating Disorders	1	0,8333	0,9333	0,9333	0,9333	0,8667	
	2	0,9333	0,9667	0,9667	0,9667	0,9667	
	3	0,4333	1,0000	1,0000	1,0000	0,9667	
	4	0,8333	1,0000	1,0000	0,9667	0,9333	
	5	0,6333	1,0000	0,9333	0,9667	0,8333	
	Mean	0,7333	0,9800	0,9667	0,9667	0,9133	0,9120
Anxiety vs Bipolar Disorders	1	0,8333	0,9000	0,9000	0,9000	0,8333	
	2	0,9000	0,9667	0,9667	0,9333	0,9333	
	3	0,9000	0,8667	0,8667	0,9000	0,9000	
	4	0,9333	0,9000	0,9000	0,9667	1,0000	
	5	0,9000	1,0000	1,0000	1,0000	1,0000	
	Mean	0,8933	0,9267	0,9267	0,9400	0,9333	0,9240
Anxiety vs Eating Disorders	1	0,9000	1,0000	1,0000	0,9667	1,0000	
	2	0,9667	1,0000	1,0000	1,0000	1,0000	
	3	0,9000	1,0000	1,0000	1,0000	1,0000	
	4	0,9667	1,0000	1,0000	1,0000	1,0000	
	5	0,9667	1,0000	1,0000	1,0000	1,0000	
	Mean	0,9400	1,0000	1,0000	0,9933	1,0000	0,9867
Bipolar vs Eating Disorders	1	1,0000	1,0000	1,0000	1,0000	1,0000	
	2	1,0000	1,0000	1,0000	1,0000	1,0000	
	3	0,4333	1,0000	1,0000	1,0000	1,0000	
	4	0,6000	1,0000	1,0000	1,0000	1,0000	
	5	0,7000	1,0000	1,0000	1,0000	1,0000	
	Mean	0,7467	1,0000	1,0000	1,0000	1,0000	0,9493
Model accuracy		0,7573	0,9787	0,9760	0,9613	0,9447	**0,9236**

APPENDIX 4. RESULTS FOR INCOME-LEVEL DATABASE

DECISION TREE



RANDOM FOREST



PERCEPTRON

Classification with Perceptron (MLP)