Basic Algorithms of Artificial Intelligence and Applications in Digital Medicine

Decision Support System for Urgent Treatment of Parkinson's Patients Based on AI Multi Objective Optimization Ranking Algorithms

Final Semestrial (Winter Semester) Project
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Project Introduction – AI in Digital Medicine

The use of artificial intelligence (AI) in digital medicine has a relatively brief history, but it has made significant progress in a short period of time.

One of the earliest examples of the use of AI in healthcare was the development of expert systems in the 1980s. These were computer programs that used decision trees or rules-based systems to replicate the decision-making processes of human experts in a particular field, such as medicine.

In the 1990s, machine learning algorithms began to be used in healthcare, allowing AI systems to improve their performance over time through exposure to enormous amounts of data. This paved the way for the development of more sophisticated AI applications in healthcare, such as the use of AI to analyze medical images and assist in diagnosis.

Over the past decade, there has been a significant increase in the use of AI in digital medicine, as advances in machine learning and data analytics have made it possible to analyze larger and more complex datasets. AI is now being used in a variety of applications in healthcare, including diagnosis and treatment planning, predictive analytics, virtual assistants, and clinical decision support.

While looking forward, it is likely that we will see continued growth in the use of AI in digital medicine, as more healthcare organizations adopt digital technologies to improve patient care and outcomes.

AI is being used to analyze enormous amounts of data from electronic health records (EHRs) to identify patterns and trends that can help doctors to predict patient outcomes and make more informed treatment decisions. For example, AI can be used to analyze data from EHRs to identify patients at risk of developing certain conditions, such as diabetes or heart disease, and provide personalized recommendations for preventing these conditions.

AI is being used to analyze medical images, such as X-rays and CT scans, to assist in diagnosis and treatment planning. For example, AI algorithms can identify abnormalities in medical images that may indicate the presence of cancerous cells, helping doctors to identify and treat cancer at an early stage.

AI is being used to develop virtual assistants that can provide personalized health information and advice to patients. For example, a virtual assistant might provide reminders to take medication or provide information about healthy lifestyle choices.

AI is being used to develop clinical decision support systems that can assist doctors in making diagnoses and treatment decisions by analyzing data from EHRs, lab results, and other sources. This can help doctors to identify potential health issues earlier and provide more effective treatment.

Overall, AI has the potential to greatly improve the efficiency and effectiveness of healthcare delivery, and it is likely that we will see continued growth in the use of AI in digital medicine in the coming years.

Artificial intelligence (AI) has the potential to revolutionize the field of digital medicine, which refers to the use of digital technologies to improve healthcare delivery and patient outcomes.

Examples of how AI is being used in digital medicine include:

1. **Diagnosis and treatment planning:** AI algorithms can analyze medical images, such as X-rays and CT scans, to help doctors identify diseases and plan treatment. For example, AI can assist in the diagnosis of cancer by analyzing images of tissues and identifying abnormalities that may indicate the presence of cancerous cells.
2. **Predictive analytics:** AI can analyze enormous amounts of patient data to predict the likelihood of certain health outcomes, such as the likelihood of a patient developing a particular disease or the likelihood of a patient responding well to a particular treatment. This can help doctors make more informed decisions about a patient's care.
3. **Virtual assistants:** AI-powered virtual assistants can provide personalized health information and advice to patients, helping them to manage their own health and wellness. For example, a virtual assistant might provide reminders to take medication or provide information about healthy lifestyle choices.
4. **Clinical decision support:** AI can assist doctors in making diagnoses and treatment decisions by analyzing data from electronic health records, lab results, and other sources. This can help doctors to identify potential health issues earlier and provide more effective treatment.

Additional points about the use of AI in digital medicine:

5. **Personalized medicine:** AI can help to tailor treatment plans to individual patients by analyzing data about a patient's specific health profile and predicting which treatments are likely to be most effective. This can help to improve patient outcomes and reduce the risk of adverse reactions to treatment.

6. **Clinical trial recruitment:** AI can analyze electronic health records to identify patients who may be eligible for clinical trials and send them personalized invitations to participate. This can help to increase the number of patients who are able to participate in clinical trials and accelerate the development of new treatments.

7. **Remote monitoring:** AI can be used to remotely monitor patients' vital signs and other health data, allowing doctors to track a patient's progress and intervene if necessary. This can be particularly useful for patients who are at considerable risk for certain conditions or who live in areas with limited access to healthcare.

8. **Drug development:** AI can be used to analyze copious amounts of data about the effectiveness of different drugs and predict which drugs are likely to be most effective in treating and managing particular and specific conditions. This can help to speed up the drug development process and improve the chances of success.

Overall, AI has the potential to greatly improve the efficiency and effectiveness of healthcare delivery, and it is likely that we will see continued growth in the use of AI in digital medicine in the coming years.

Problem Description –

Ranking and its Importance in Digital Medicine

Multi-criteria ranking is a method used to evaluate and compare options or alternatives based on multiple criteria or factors. In the context of digital medicine and AI, multi-criteria ranking might be used to evaluate and compare different treatment options for a particular patient based on a range of factors, such as the effectiveness of the treatment, the potential side effects, and the cost.

Multi-objective optimization algorithms are algorithms that are used to find the optimal solution to a problem that has multiple conflicting objectives. These types of problems are common in many real-world scenarios, such as in engineering design, financial planning, and resource allocation.

One common approach to solving multi-objective optimization problems is to use evolutionary algorithms, which are a type of optimization algorithm inspired by natural selection. These algorithms work by iteratively generating a population of potential solutions to the problem and selecting the best ones to use as the basis for the next generation of solutions. The selection process is based on how well the solutions perform with respect to the multiple objectives.

Another approach to solving multi-objective optimization problems is to use decision-making techniques such as the analytic hierarchy process (AHP) or the technique for order preference by similarity to ideal solution (TOPSIS). These techniques involve constructing a hierarchy of the objectives and using decision-making criteria to evaluate and rank the potential solutions.

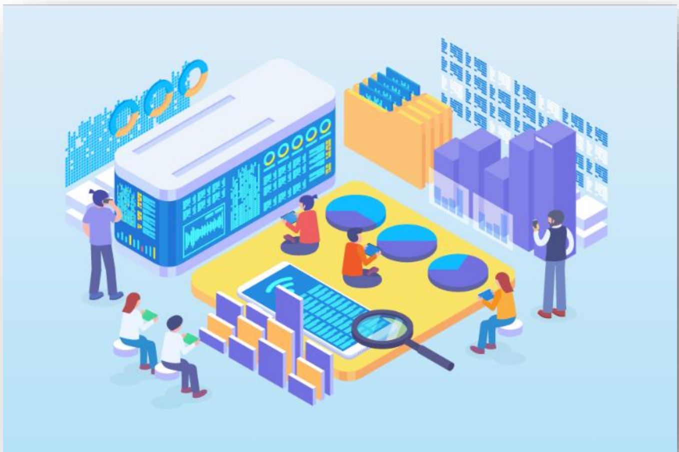
There are also many other techniques and algorithms that can be used to solve multi-objective optimization problems, such as genetic algorithms, simulated annealing, and **gradient descent.**

The choice of which algorithm to use depends on the specific characteristics of the problem at hand. There are a few examples of situations where multi-objective optimization might be used:

a) **Engineering design:** In engineering design, multiple objectives often conflict with each other. For example, a designer might need to optimize the strength and weight of a component, but increasing the strength typically increases the weight, and vice versa. In this case, a multi-objective optimization algorithm could be used to find a set of solutions that tradeoff between strength and weight and find the best compromise.

b) **Financial portfolio optimization:** In finance, investors often have multiple objectives when building a portfolio, such as maximizing return and minimizing risk. These objectives can conflict with each other, as investments with higher potential returns often carry more risk. A multi-objective optimization algorithm could be used to find a set of portfolio configurations that balance return and risk and find the best compromise.

c) **Scheduling and resource allocation:** In scheduling and resource allocation, multiple objectives often need to be considered, such as minimizing cost and maximizing throughput. These objectives can conflict with each other, as reducing cost often means reducing throughput, and vice versa. A multi-objective optimization algorithm could be used to find a set of schedules and resource allocations that tradeoff between cost and throughput and find the best compromise.



AI algorithms can be used to assist with multi-criteria ranking by analyzing enormous amounts of data about different treatment options and ranking them based on their likelihood of achieving the desired outcomes. For example, an AI algorithm might be used to analyze data about different medications and their effectiveness in treating a particular condition, as well as data about potential side effects and cost, to determine the best treatment option for a particular patient.

Multi-criteria ranking can be particularly useful in situations where there are multiple options to consider and where it is important to take a range of factors into account. By using AI to analyze data and rank options based on multiple criteria, doctors can make more informed treatment decisions and optimize patient care.

Multi-criteria ranking can be used to evaluate a wide range of treatment options, including medications, surgical procedures, and rehabilitation programs. By analyzing data about the effectiveness, side effects, and cost of different options, AI algorithms can help doctors to identify the best treatment option for a particular patient.

Multi-criteria ranking can be particularly useful in situations where there is a lack of clear consensus about the best treatment option, or where there are trade-offs between varied factors. For example, a particular medication may be more effective at treating a condition, but it may also have more severe side effects or be more expensive than other options. By using AI to analyze data about different options, doctors can make more informed decisions about the best course of action.

Multi-criteria ranking can also be used to evaluate the potential benefits and risks of different treatment options. For example, an AI algorithm might be used to analyze data about the long-term effects of different medications or surgical procedures to determine the overall risk-benefit profile of each option.

In addition to evaluating treatment options, multi-criteria ranking can also be used to assess the effectiveness of different healthcare interventions, such as disease prevention programs or telemedicine initiatives. By analyzing data about the outcomes of these interventions, AI algorithms can help healthcare organizations to identify the most effective approaches and allocate resources accordingly.

Overall, the use of multi-criteria ranking and AI in digital medicine can help to improve patient outcomes and optimize the delivery of healthcare by enabling doctors to make more informed treatment decisions based on a wide range of factors. The use of multi-criteria ranking algorithms and AI in digital medicine is a relatively recent development, but it has made significant progress in a short period of time.

One of the earliest examples of the use of multi-criteria ranking algorithms in healthcare was the development of expert systems in the 1980s. These were computer programs that used decision trees or rules-based systems to replicate the decision-making processes of human experts in a particular field, such as medicine.

These expert systems were often used to evaluate and rank treatment options based on multiple criteria, such as the effectiveness of the treatment, the potential side effects, and the cost.

In the 1990s, machine learning algorithms began to be used in healthcare, allowing AI systems to improve their performance over time through exposure to large amounts of data. This paved the way for the development of more sophisticated AI applications in healthcare, including the use of multi-criteria ranking algorithms to evaluate and compare treatment options.

Over the past decade, there has been a significant increase in the use of AI in digital medicine, including the use of multi-criteria ranking algorithms. As AI algorithms have become more sophisticated, they have been able to analyze larger and more complex datasets, enabling them to make more accurate predictions and recommendations about the best treatment options for individual patients.

While looking forward, it is likely that we will see continued growth in the use of multi-criteria ranking algorithms and AI in digital medicine, as increased healthcare organizations adopt digital technologies to improve patient care and outcomes.

AI multi-objective optimization in Digital Medicine

1. **Identifying the best treatment plan for a patient:** AI multi-objective optimization can be used to identify the treatment plan that is most likely to achieve the desired outcomes for a particular patient, considering factors such as the effectiveness of the treatment, the potential side effects, and the cost.
2. **Optimizing drug dosing:** AI multi-objective optimization can be used to determine the optimal dose of a medication for a particular patient, considering factors such as the patient's age, weight, and other medical conditions.
3. **Designing clinical trials:** AI multi-objective optimization can be used to design clinical trials that are likely to be most effective at evaluating the safety and effectiveness of a particular treatment, considering factors such as the size of the trial, the patient population, and the duration of the trial.
4. **Predictive analytics:** Using machine learning algorithms to analyze patient data and identify patterns or trends that can help to predict future outcomes or identify patients at risk of certain conditions.
5. **Personalized medicine:** Using AI and multi-objective optimization to tailor treatment plans to the specific needs and preferences of individual patients, based on their genetic, environmental, and lifestyle factors.
6. **Telemedicine:** Using AI and multi-objective optimization to enable remote monitoring and consultation with healthcare providers, which can improve access to care and reduce the need for in-person visits.
7. **Predictive analytics:** Using machine learning algorithms to analyze patient data and identify patterns or trends that can help to predict future outcomes or identify patients at risk of certain conditions.
8. **Clinical trial design:** Using AI and multi-objective optimization to optimize the design and execution of clinical trials, by identifying the most appropriate patient populations, treatments, and outcomes to study, and by optimizing the allocation of resources and reducing the risk of bias.
9. **Natural language processing (NLP):** Using AI and multi-objective optimization to analyze and extract information from unstructured clinical text data, such as patient notes or electronic health records, to improve the efficiency and accuracy of data entry and analysis.

Digital Medicine Domain Datasets

There is a variety dataset that could potentially be used for multi-criteria algorithms in the medical domain. Examples:

1. **MIMIC-III:** This is a large, openly available database of electronic health records from critical care units at the Beth Israel Deaconess Medical Center in Boston, Massachusetts. It includes information on patients' demographics, diagnoses, medications, lab results, and more.

2. **National Health and Nutrition Examination Survey (NHANES):** This is a nationally representative survey of the health and nutritional status of the US population conducted by the Centers for Disease Control and Prevention (CDC). It includes data on a wide range of health-related topics, including diet, physical activity, and medical history.

3. **UK Biobank:** This is a large, long-term study that aims to improve the prevention, diagnosis, and treatment of a wide range of diseases. It includes data on the health and lifestyle of 500,000 participants in the UK, including information on genetics, medical history, and environmental exposures.

4. **Cancer Genome Atlas (TCGA):** This is a comprehensive effort to characterize the genomic changes that occur in diverse types of cancer. It includes data on genomic and molecular profiles of cancer samples from over 11,000 patients across 33 different cancer types.

5. **Framingham Heart Study:** This is a long-term, ongoing study that aims to identify the factors that contribute to cardiovascular disease. It includes data on the health and lifestyle of participants in the study, including information on genetics, medical history, and risk factors.

6. **The Electronic Health Records and Genomics (eMerge) Network:** This is a network of biomedical research centers that aims to identify genetic factors that contribute to various diseases. It includes data on the genomic and clinical profiles of over 300,000 participants.

7. **The German Cancer Registry:** This registry collects data on cancer cases in Germany, including information on patient characteristics, tumor characteristics, and treatment outcomes.

8. **The Million Veteran Program (MVP):** This is a long-term study that aims to understand the genetic and environmental factors that contribute to health and disease. It includes data on the health and lifestyle of over one million veterans in the US.

9. **The Multi-Ethnic Study of Atherosclerosis (MESA):** This is a long-term study that aims to identify the factors that contribute to the development and progression of cardiovascular disease. It includes data on the cardiovascular health and lifestyle of over 6,800 participants.

10. **The Cardiovascular Health Study (CHS):** This is a long-term study that aims to understand the factors that contribute to cardiovascular disease in older adults. It includes data on the cardiovascular health and lifestyle of over 5,000 participants.

11. **The EHR4CR (Electronic Health Record for Clinical Research) dataset:** This dataset includes data from electronic health records of patients in Belgium and Luxembourg, including information on demographics, diagnoses, medications, lab results, and more.

12. **The Intermountain Healthcare Clinical Data Warehouse:** This dataset includes data from electronic health records of patients at Intermountain Healthcare, a large healthcare system in the US. It includes information on demographics, diagnoses, medications, lab results, and more.

13. **The eICU Collaborative Research Database:** This dataset includes data from electronic health records of intensive care unit (ICU) patients in the US and Australia. It includes information on patient demographics, diagnoses, medications, vital signs, and more.

14. **The National Emergency Department Sample (NEDS):** This dataset includes data on emergency department visits in the US, including information on patient demographics, diagnoses, procedures, and charges.

15. **The Stanford Translational Research Integrated Database Environment (STRIDE):** This dataset includes data from electronic health records of patients at Stanford University Medical Center, including information on demographics, diagnoses, medications, lab results, and more.

Algorithms Description – Smart, BORDA & TOPSIS

Before explaining the columns chosen for applying the muti-criteria optimization algorithms, I will explain about each of the algorithms that will be applied in the project.

SMART Algorithm

Background - About the Algorithm:

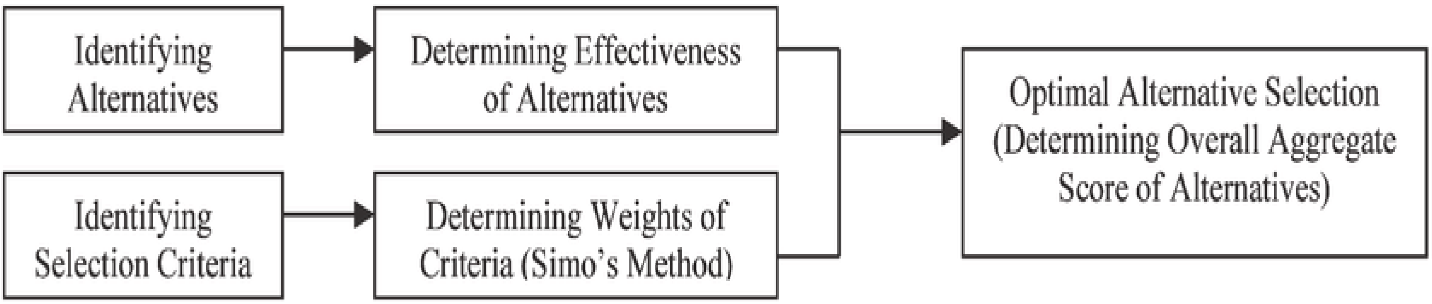
Simple Multi-Attribute Rating technique (SMART) is a method for conducting Multi-Criteria Decision Analysis (MCDA), in which assessment and selection of the best project alternative, amongst several different alternatives, is based on a list of relevant criteria.

MCDA is a relatively new method for assessing alternatives or projects and it stems from the science of operations research. MCDA differs from traditional evaluations methods, like the cost-benefit-analysis (CBA), in multiple ways. Where a traditional CBA compares costs and benefits on a monetary scale, MCDA allows the assessment of alternatives on both a monetary as well as non-monetary scale.

SMART is considered as one of the main techniques for MCDA and the overall purpose of SMART is generally to assist the decision maker when trying to choose the best option amongst several alternatives.

SMART is based on a linear additive model, which means that a performance score for all individual alternatives can be calculated as the sum of the relative performance of each alternative on each identified evaluation criterion multiplied by the relative importance of that specific criterion.

SMART can be used as a supplement to other decision tools, such as CBA.



How this Algorithm Works?

It is important to understand that the decision process often is iterative, and the decision maker might go back and forth the various stages. The eight stages are:

1) Identification of the decision maker: The person responsible for conducting the decision analysis must be known from the very beginning of the analysis.

2) Identification of alternatives: The different courses of action or set of projects/alternatives should be identified.

3) Identification of relevant evaluation criteria: The criteria relevant to the decision problem should be identified, so that each of the alternatives defined in stage 2 can be assesses.

4) Numerical assessment of the performance of each alternative on each criterion: For each of the identified criteria, values for the performance of each alternative on that criterion is to be calculated.

5) Assignment of importance weights for each of the evaluation criteria: Each criterion must be assigned with a weighting that reflects its relative importance to the decision maker.

6) Calculation of a weighted average of the values that is assigned each of the alternatives: These calculations make it possible to measure how well one alternative performs in comparison to the other alternatives, when performance is measured across all the defined criteria.

7) Provisional decision: On this stage the results obtained on stage 6 are interpreted. However, it should be noted that a final decision should not be drawn before the robustness of the solutions have been analyzed in further detail.

8) Sensitivity analysis: Sensitivity analysis is carried out to see how robust the solution is in terms of small changes.

Each of these eight stages will be described in much further detain in the following sub-sections.

Formula of The Algorithm:

- **SMART = S**imple **M**ulti-**A**ttribute **R**anking **T**echnique
- **The Simple Multi-attribute Rating Technique (SMART)** provides the weighted arithmetic mean of the set of normalized rating values rij of the alternatives in a general decision matrix.
- It has the form:
- $$T_i = \frac{\sum_{j=1}^{m} w_j r_{ij}}{\sum_{j=1}^{m} w_j}, \quad i = 1,\ldots,n$$
- where i- alternative index
- n –number of alternative
- j –criteria index
- m –number of criteria
- wj – given weight
- rij is the criteria value or performance value.

SMART Algorithm – Numeric Example

Here is numeric example for implementation SMART Algorithm:

	Name	Style	Reliebilty	Fuel	Cost
0	Honda	7	9	9	8
1	Ford	8	7	8	7
2	Mazda	9	6	8	9
3	Subaro	6	7	8	6

```
weights = [0.1,0.4,0.3,0.2]
```

~~impact = ["+", "+", "+","-"]~~

- Not Considering the positive / negative impact of attributes
- Considering the weights of attributes

	Style	Reliebilty	Fuel	Cost	Name	SmartScore
0	7	9	9	8	Honda	2.5
1	8	7	8	7	Ford	9.2
2	9	6	8	9	Mazda	6.9
3	6	7	8	6	Subaro	4.2

TOPSIS Algorithm

Background - About the Algorithm:

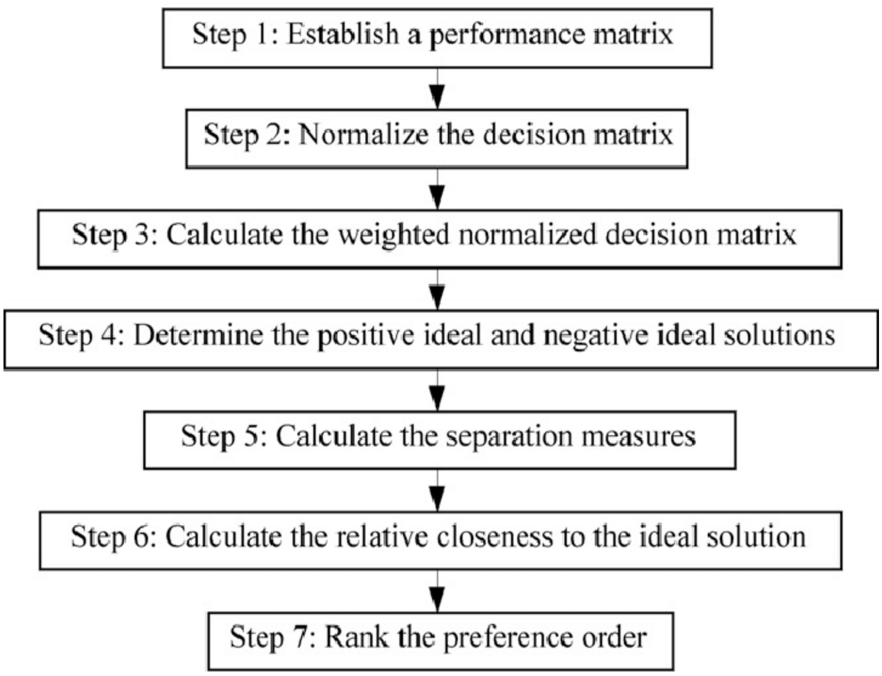
Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) came in the 1980s as a multi-criteria-based decision-making method. TOPSIS chooses the alternative of shortest the Euclidean distance from the ideal solution and greatest distance from the negative ideal solution

How this Algorithm Works?

To make this definition easier, let's suppose you want to buy a mobile phone, you go to a shop and analyze 5 mobile phones on basis of RAM, memory, display size, battery, and price. At last, you're confused after seeing so many factors and don't know how to decide which mobile phone you should purchase. TOPSIS is a way to allocate the ranks on basis of the weights and impact of the given factors.

- **Weights** mean how much a given factor should be taken into consideration, sum of weight should be 1.
- **Impact** means that a given factor has a positive or negative impact. Like you want Battery to be large as possible but the price of the mobile to be less as possible, so you'll assign '+' weight to the battery and '-' weight to the price.

This method can be applied in ranking machine learning models on basis of a range of factors like correlation, R^2, accuracy, Root mean square error, etc. Now that we have understood what TOPSIS is, and where we can apply this. Let's see what the procedure is to implement TOPSIS on a given dataset, consisting of multiple rows (like various mobile phones) and multiple columns (like various factors).



Formula of The Algorithm:

Step 1: Calculating Normalized Matrix and weighted Normalize matrix. We normalize each value by making it: where m is the number of rows in the dataset and n is the number of columns. I vary along rows and j varies along the column.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{m} x_{kj}^2}},$$
$$i = 1, 2, \ldots, m,$$
$$j = 1, 2, \ldots, n$$

Step 2: Calculating Ideal Best and Ideal worst and Euclidean distance for each row from ideal worst and ideal best value. First, we will find out the ideal best and ideal worst value: Now here we need to see the impact, i.e., is it '+' or '-' impact. If '+' impact Ideal best for a column is the maximum value in that column and the ideal worst is the minimum value in that column, and vice versa for the '-' impact

$$d_{iw} = \sqrt{\sum_{j=1}^{n} (t_{ij} - t_{wj})^2},$$
$$i = 1, 2, \ldots, m,$$

Step 3: Calculating TOPSIS Score and Ranking. Now we have Distance positive and distance negative with us, let's calculate the TOPSIS score for each row on basis of them.

TOPSIS Score = $d_{iw} / (d_{ib} + d_{iw})$ for each row

Step 4: Now rank according to the TOPSIS score, i.e., higher the score, better the rank.

Formula of The Algorithm:

The whole TOPSIS process can be encapsulated in 7 steps:

1. Create a matrix consisting of M alternatives and N criteria. This matrix is usually called an "evaluation matrix."

$$(a_{ij})_{M \times N}$$

As an example: M will be the number of our companies, while N, the number of metrics (ROA, ROE, DR, CG).

2. Normalize evaluation matrix:

$$\alpha_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{M} (a_{ij})^2}}$$

Each metric j for each company i is normalized to be in between 0 and 1. The higher its value the better the metric.

3. Calculate the weighted normalized decision matrix. It is important to note that each criterion should have its own weight so that all of them will sum up to 1. The weights can be derived randomly (not recommended) or based on expert knowledge (industry standard).

$$\chi_{ij} = \alpha_{ij} * \omega_j$$

$$\omega_j = \frac{w_j}{\sum_{j=1}^{N} w_j}$$

$$\sum_{j=1}^{N} \omega_j = 1$$

After we assign a weight to each financial metric, we need to normalize those so that these sum up to 1. Then we need to multiply each normalized metric from step 2 by corresponding normalized weight.

4. Determine the best and the worst alternative for each criterion:

$$\chi_j^b = \max_{i=1}^{M} \chi_{ij}$$
$$\chi_j^w = \min_{i=1}^{M} \chi_{ij}$$

We want to find the maximum and minimum value of each financial metric among all companies.

5. Calculate the Euclidean distance between the target alternative and the best/worst alternative:

$$d_i^b = \sqrt{\sum_{j=1}^{N} (\chi_{ij} - \chi_j^b)^2}$$
$$d_i^w = \sqrt{\sum_{j=1}^{N} (\chi_{ij} - \chi_j^w)^2}$$

This is a calculation of the geometric distance between the value of each financial metric for a given company i and the best/worst value of such a metric among all companies.

6. For each alternative calculate the similarity to the worst alternative. The results are our TOPSIS scores.

$$s_i = \frac{d_i^w}{d_i^w + d_i^b}$$

We compute a score for each company that is based on distances obtained in a step before.

7. Rank alternatives according to the TOPSIS score by descending order.
The options with metrics closest to the best will obtain the highest score and therefore will be at the top of our ranking.

We obtained a ranked set of alternatives based on specified criteria!

TOPSIS Algorithm – Numeric Example

Here is numeric example for implementation TOPSIS Algorithm:

	Name	Style	Reliebilty	Fuel	Cost
0	Honda	7	9	9	8
1	Ford	8	7	8	7
2	Mazda	9	6	8	9
3	Subaro	6	7	8	6

```
weights = [0.1,0.4,0.3,0.2]
impact = [ "+", "+", "+","-"]
```

- Considering the positive / negative impact of attributes
- Considering the weights of attributes

```
topsis_pipy(dataset, dataset, nCol1, weights, impact)
```

```
     Name     Style  Reliebilty      Fuel      Cost  Topsis Score  Rank
0   Honda  0.046157    0.245518  0.163411  0.105501      0.742694     1
1    Ford  0.052750    0.190958  0.145255  0.092313      0.403599     3
2   Mazda  0.059344    0.163679  0.145255  0.118688      0.175870     4
3  Subaro  0.039563    0.190958  0.145255  0.079126      0.441429     2
```

BORDA Algorithm

Background - About the Algorithm:

BORDA Count is another voting method, named for Jean-Charles de BORDA, who developed the system in 1770.

BORDA COUNT

In this method, points are assigned to candidates based on their ranking; 1 point for last choice, 2 points for second-to-last choice, and so on. The point values for all ballots are totaled, and the candidate with the largest point total is the winner.

Given N candidates and existing K experts

Each expert rates the candidate and gives blank points to each candidate, the best project gets N-1 points. The worst project gets 0 points

The winning project is a project that receives the maximum number of points

Majority Criterion

If a choice has a majority of first-place votes, that choice should be the winner.

The Idea: Award points to candidates based on preference schedule, then declare the winner to be the candidate with the most points.

Condorcet Criterion

The candidate who wins a majority of the vote in every head-to-head election against each of the other candidates – that is, a candidate preferred by more voters than any others – is the Condorcet winner, although Condorcet winners do not exist in all cases.

BORDA COUNT does not directly support the "majority criterion" or the "Condorcet criterion".

The majority criterion states that if a choice has a majority of first-place votes, that choice should be the winner. In the BORDA count system, a candidate does not need to have a majority of first-place votes to win, as points are awarded based on the ranking of all candidates by each voter.

The Condorcet criterion states that the candidate who wins a majority of the vote in every head-to-head election against each of the other candidates should be the winner. The BORDA count system does not take into account head-to-head comparisons between candidates and instead awards points based on the overall ranking of candidates by each voter.

Therefore, BORDA count is not directly aligned with these two criteria. However, BORDA count has some interesting properties such as avoiding the spoiler effect and the possibility of having a Condorcet winner if the majority of voters rank the Condorcet winner in the first place.

How this Algorithm Works?

In general, if N is the number of candidates. . .

Each first-place vote is worth N points.

Each second-place vote is worth N − 1 points.

Each third-place vote is worth N − 2 points.

……..

Each Nth-place (i.e., last-place) vote is worth 1 point.

Whichever candidate receives the most points will win the election.

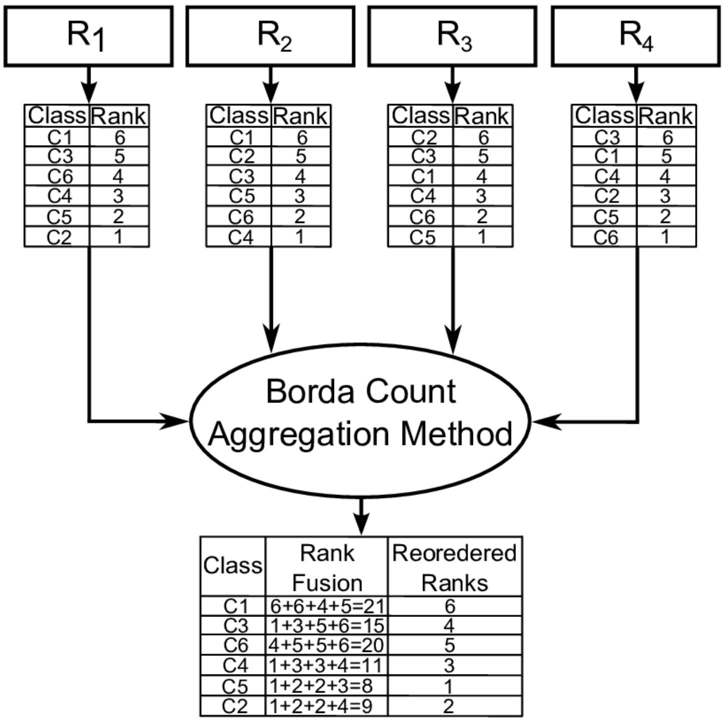
Formula of The Algorithm:

In other words, if ***r ik*** is the rank of candidate ***i*** by expert ***k***,

the ***BORDA count*** for candidate i is

$$b_i = \sum_k (N - r_{ik})$$

The alternatives are then ordered according to these counts.



BORDA Algorithm – Numeric Example

Here is numeric example for implementation BORDA Algorithm:

```
~~weights = [0.1,0.4,0.3,0.2]~~
impact = [ "+", "+", "+","-"]
```

- **Consider the positive / negative impact of attributes**
- **Not Considering the weights of attributes**

	Name	Style	Reliebilty	Fuel	Cost
0	Honda	7	9	9	8
1	Ford	8	7	8	7
2	Mazda	9	6	8	9
3	Subaro	6	7	8	6

```
the initially first ranked: the best gets the higher score

   Style  Reliebilty  Fuel  Cost
0    3.0         1.0   1.0   3.0
1    2.0         2.5   3.0   2.0
2    1.0         4.0   3.0   4.0
3    4.0         2.5   3.0   1.0

the second ranked: with sub of number of rows

   Style  Reliebilty  Fuel  Cost
0    1.0         3.0   3.0   1.0
1    2.0         1.5   1.0   2.0
2    3.0         0.0   1.0   0.0
3    0.0         1.5   1.0   3.0

the third ranked: with column of score of each rows

   Style  Reliebilty  Fuel  Cost  Score
0    1.0         3.0   3.0   1.0    8.0
1    2.0         1.5   1.0   2.0    6.5
2    3.0         0.0   1.0   0.0    4.0
3    0.0         1.5   1.0   3.0    5.5

the final table ranked with candidiates names

   Style  Reliebilty  Fuel  Cost  Score    Name
0    1.0         3.0   3.0   1.0    8.0   Honda
1    2.0         1.5   1.0   2.0    6.5    Ford
2    3.0         0.0   1.0   0.0    4.0   Mazda
3    0.0         1.5   1.0   3.0    5.5  Subaro
```

The Chosen Columns of the Dataset:

There are diverse ways in purpose of finding the most efficient columns in a dataset without the target column:

1. **Correlation analysis:** One approach is to calculate the correlation between different columns in the dataset and see which ones are most strongly related to the target column. This can be useful for identifying columns that are redundant or not especially useful for your analysis. You can do this by calculating the correlation between the columns and the target column, and then selecting the columns with the highest correlation.

2. **Feature selection:** Another approach is to use a feature selection method, which is a statistical technique for identifying the most important columns in a dataset. There are many different feature selection methods, such as recursive feature elimination, which involves training a model on a subset of the columns and then iteratively removing the least important columns until you are left with a set of the most important columns. You can use a feature selection method to identify the most important columns without using the target column directly.

3. **Dimensionality reduction:** Another approach is to use a dimensionality reduction technique, such as principal component analysis (PCA), to reduce the number of columns in the dataset while still retaining as much information as possible. This can be useful for visualizing the relationships between columns or for improving the performance of machine learning models. You can use dimensionality reduction to identify the most important columns without using the target column directly.

4. **Exploratory data analysis:** Finally, you can also use techniques like visualization and statistical analysis to explore the dataset and identify patterns or trends that can help you identify the most important columns. This can be done by looking at the relationships between the columns and the target column, or by looking at the relationships between the columns themselves.

The Chosen Subject and Explored Dataset:

Parkinson's Disease Progression

Multi-objective optimization is a method for solving optimization problems with multiple conflicting objectives. The approach is commonly used in decision-making scenarios where multiple goals or objectives need to be balanced.

In healthcare, multi-objective optimization can be used in a variety of applications. Some of the challenges of applying multi-objective optimization in healthcare include a lack of data, lack of understanding of the underlying biological processes, and ethical and regulatory issues.

The Data Set – Details and Sources

This dataset contains ***biomedical voice measurements*** of 31 patients with Parkinson's Disease, used to predict motor and total UPDRS scores

Link: https://www.kaggle.com/datasets/thedevastator/unlocking-clues-to-parkinson-s-disease-progressi

Kaggle:

Kaggle is a website and cloud-based workbench for data science and machine learning. It is a platform for developers, data scientists, and machine learning engineers to collaborate, build, and deploy machine learning models.

Kaggle offers a variety of resources and tools for data science and machine learning, including:

- A large repository of public datasets and machine learning competitions.
- A cloud-based workbench for developing and running machine learning models.
- A community of data scientists and machine learning practitioners who share knowledge and resources and collaborate on projects and challenges.

Kaggle is a popular platform for learning and practicing machine learning, as it provides a range of resources and tools that are useful for data science and machine learning projects. It is also a popular platform for participating in machine learning competitions, as it offers a variety of challenges and competitions that are organized and sponsored by companies and organizations.

SOURCES of Kaggle Dataset

https://data.world/uci Dataset originally created by: UCI.Scraping. (See dataset description for details) Dataset originally created by: Scraping. (See dataset description for details).

COLLECTION METHODOLOGY

Scraping of https://data.world/uciScraping of Scraping. (See dataset description for details)

Project Goal –

Assistance in making decisions for urgent treatment of Parkinson's patients

The medical healthcare goals

A model could be developed to help identify the patients with Parkinson's disease who have the most urgent need for healthcare based on their abnormal biomedical voice measurements and Total UPDRS scores. This model would use statistical analysis and machine learning algorithms to analyze patient data and determine which patients have measurements that fall outside of normal ranges and require immediate attention. This information would aid healthcare providers in making decisions about which patients require the most urgent treatment, in order to provide them with the care they need as soon as possible.

This model focuses on UPDRS (The Unified Parkinson's Disease Rating Scale) is a standardized assessment tool for evaluating the severity and progression of Parkinson's disease (PD).

UPDRS used to assess the motor and non-motor symptoms of PD, including tremors, rigidity, bradykinesia, and gait and balance problems.

I believe that upgrading and extension of this ranking model - with more types of measurements will benefit to reduce the emergency calls of the critical Parkinson cases of patients and people all over the world. Even for the long term with proper tracking and continues analyzations of data collected - will be able to indicate efficient Medical Care for Parkinson patients.

Why I chose this subject?

Due to family loss of my grandfather, who had suffered from the Parkinson disease for decades of years, I wanted to explore, analyze, and research for details of Parkinson's disease patients.

Decision support systems (DSS) can be a useful tool for helping doctors and other healthcare providers make decisions about the treatment of patients with Parkinson's disease, a degenerative disorder of the nervous system that affects movement. These systems can take various forms, but they generally use computer-based tools and algorithms to analyze patient data and present information to help support the decision-making process.

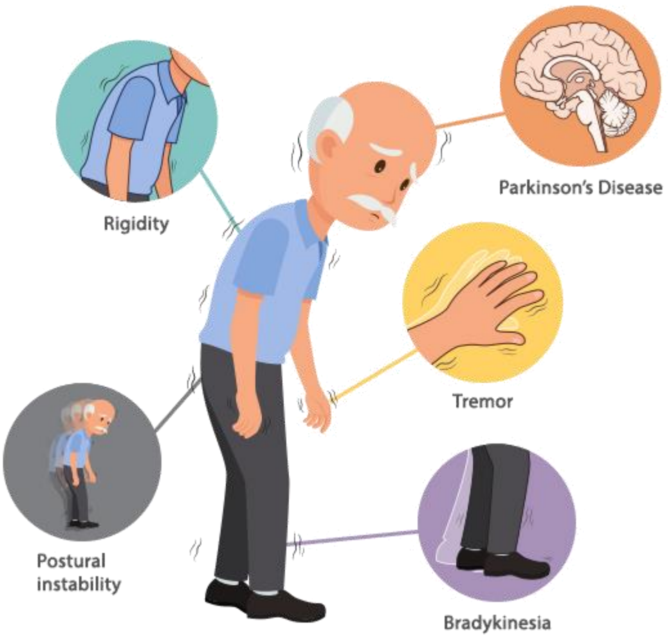
In practice, a DSS for Parkinson's treatment could combine both the Clinical Decision Support and Predictive analytics systems, the system could also incorporate a guideline-based approach, which present the best practices from the clinical guidelines to the physician that is deciding on the treatment of the patient. It's also very important to ensure that the data used by the DSS is accurate, up-to-date, and ethically obtained.

In the future

Moreover, the model could be continuously updated with new data and research to reflect the latest advancements in Parkinson's disease treatment. It is important to note that the model would not replace the role of the healthcare provider, but rather aid in making their treatment decisions. Ultimately, the healthcare provider would have the final say in the treatment plan after considering the recommendations from the model, patient's preferences and other factors that might have an impact on the decision.

Parkinson Disease – Background

- Parkinson's disease is a progressive neurological disorder that affects movement and can cause a range of physical and cognitive symptoms. It is caused by the loss of cells in the brain that produce dopamine, a chemical messenger that plays a role in movement and coordination.
- The most common symptoms of Parkinson's disease include tremors, rigidity, difficulty with movement and balance, and changes in speech and handwriting. These symptoms may initially be mild, but they can become more severe over time, and they may interfere with a person's ability to perform daily activities and to interact with others.
- In addition to physical symptoms, people with Parkinson's disease may also experience cognitive changes, such as problems with memory and concentration, and emotional changes, such as anxiety and depression. Parkinson's disease can also cause other non-motor symptoms, such as sleep problems, digestive issues, and changes in skin and blood pressure.
- There is no cure for Parkinson's disease, but there are a range of treatment options that can help to manage the symptoms of the condition and improve quality of life.



Biomedical Voice Measures in Parkinson

- Biomedical voice measures are often used as part of a comprehensive evaluation of Parkinson's disease, which may also include other clinical measures, such as the Unified Parkinson's Disease Rating Scale (UPDRS), and functional measures, such as assessments of mobility, cognition, and quality of life.

- Biomedical voice measures may be useful in identifying communication problems that may be affecting a person's ability to participate in daily activities and to interact with others. These measures may also be used to track changes in a person's voice and speech over time and to identify any worsening or improvement in the condition.

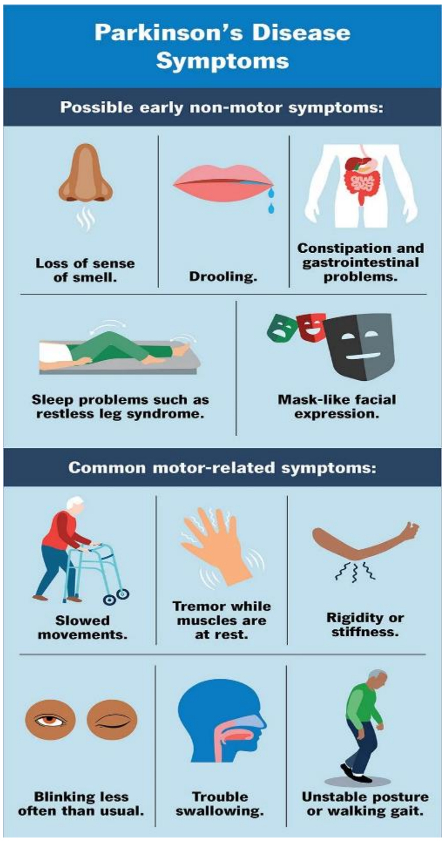
- Some biomedical voice measures, such as the voice-related quality of life (V-RQOL) scale and the Parkinson's Disease Communication Questionnaire (PDCQ), are subjective measures that are completed by trained clinicians or listeners. Other measures, such as Jitter and Shimmer, are objective measures that are obtained using specialized equipment, such as speech analysis software or a digital audio recorder.

- While biomedical voice measures can be useful in the assessment of Parkinson's disease, it is important to note that these measures are just one aspect of the evaluation of the condition. They should be considered in the context of other clinical and functional measures when making treatment decisions.

Parkinson Patients Condition Diagnostics

Here are several factors that may be taken into consideration when caring for people with Parkinson's disease, including:

1. **Symptoms:** The presence and severity of symptoms, such as tremors, rigidity, and problems with movement and balance, may influence the type and intensity of treatment needed.
2. **Medical history:** A person's medical history, including any previous neurological conditions or other health issues, may be relevant to the management of Parkinson's disease.
3. **Functional status:** A person's functional status, including their ability to perform daily activities and participate in social and leisure activities, may be taken into consideration when developing a care plan.
4. **Cognitive and emotional changes:** Cognitive and emotional changes, such as problems with memory and concentration, anxiety, and depression, may also be taken into consideration when caring for people with Parkinson's disease.
5. **Non-motor symptoms:** non-motor symptoms, such as sleep problems, digestive issues, and changes in skin and blood pressure, may also be addressed as part of the care of people with Parkinson's disease.
6. **Medications:** The medications a person is taking, including any potential side effects, may be considered when developing a care plan.
7. **Lifestyle:** A person's lifestyle, including their diet, physical activity, and social support, may be taken into consideration when caring for people with Parkinson's disease.

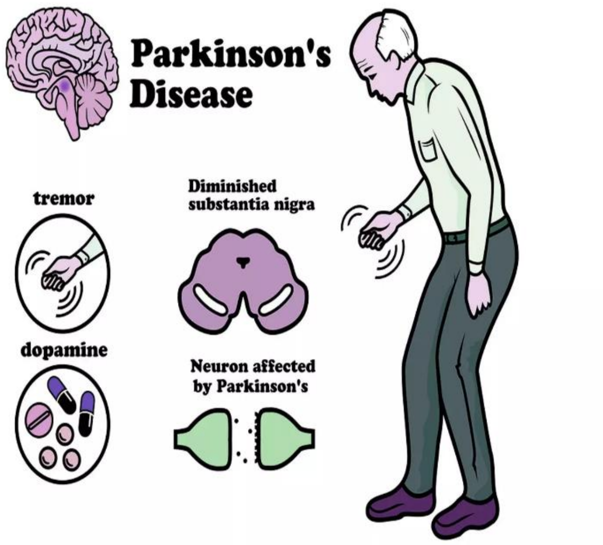


Parkinson Patients Medical Care

- There are several approaches to medical care for Parkinson's disease (PD), which is a progressive neurological disorder that affects movement and can cause a variety of symptoms, such as tremors, rigidity, bradykinesia, and gait and balance problems.

- The main goals of medical care for PD are to manage the symptoms and improve quality of life, to slow the progression of the disease, and to prevent or treat complications that may arise.

- The most common treatment for PD is medication, which can help to manage the symptoms and improve mobility. The commonly used medications for PD are dopamine agonists, which mimic the effects of dopamine in the brain, and levodopa, which is converted to dopamine in the brain. Other medications may also be used to manage specific symptoms, such as tremors or rigidity.



- In addition to medication, other treatments may be used to manage the symptoms of PD, such as physical therapy, occupational therapy, speech therapy, and surgery. Surgical procedures, such as deep brain stimulation (DBS), may be considered for patients who do not respond well to medications or who experience significant side effects from the medications.

It is important for people with Parkinson's disease to work closely with their healthcare team, which may include a neurologist, primary care physician, nurse, physical therapist, occupational therapist, to develop a care plan that is suitable to their individual needs and goals. This may include a range of interventions, such as medications, physical therapy, and lifestyle changes, and may involve input from a range of healthcare professionals, including neurologists, physical therapists, occupational therapists, and speech therapists.

The ideal treatment for individual Parkinson patient is developed medical care plan - personalized treatment plan that meets the patient's needs and goals.

The Columns of Project Dataset

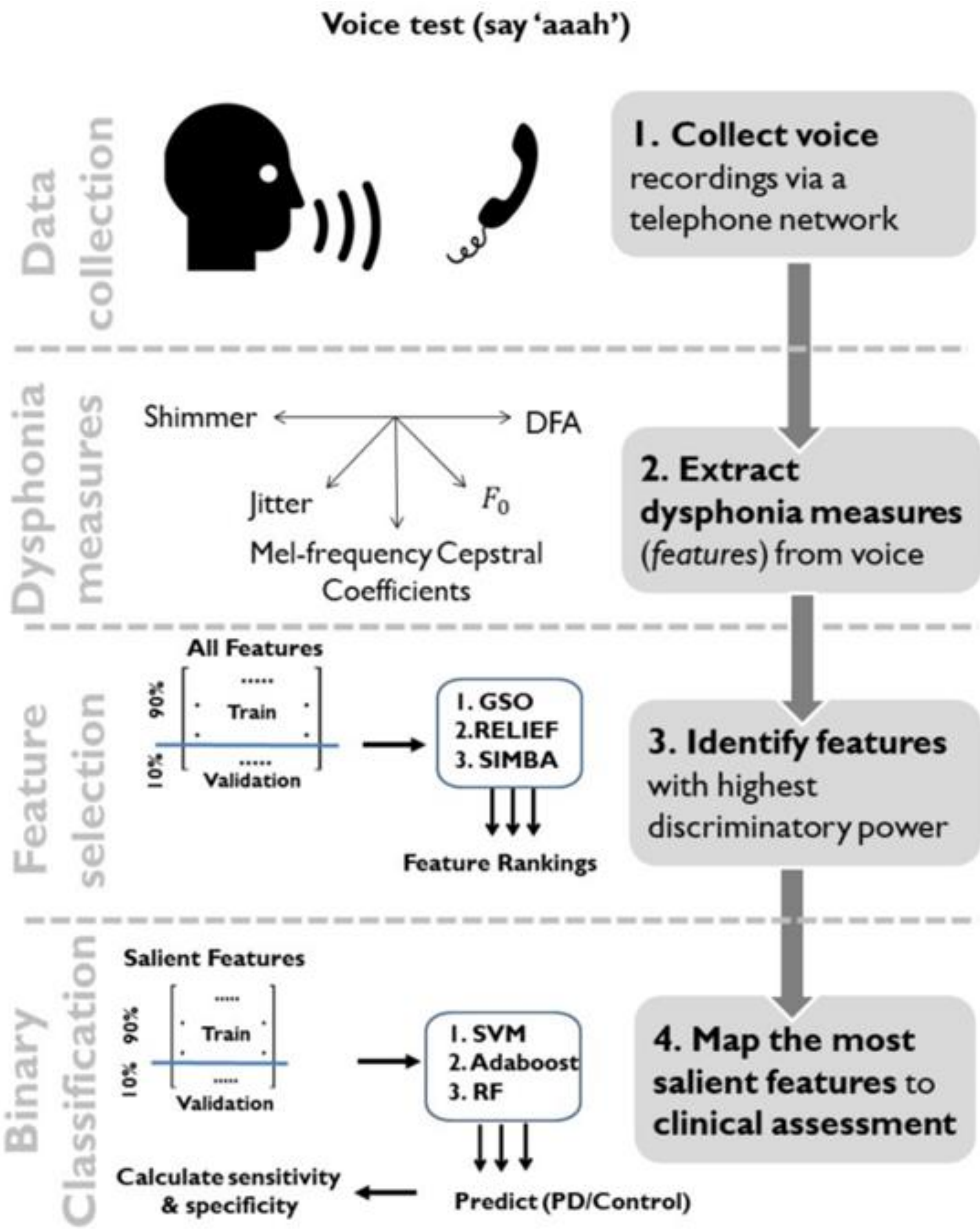
Brief description of the factors listed in the dataset:

- **Age:** Age may be relevant in determining the likelihood of a person having Parkinson's disease, as the risk of the condition increases with age. It may also be relevant in tracking changes in a person's condition over time, as Parkinson's disease is a progressive disorder.
- **Sex:** Some studies have suggested that men may be more likely to develop Parkinson's disease than women, although the reason for this is not fully understood.
- **Test time:** This variable may be relevant in tracking changes in a person's condition over time.
- **Motor UPDRS:** The motor UPDRS (Unified Parkinson's Disease Rating Scale) is a commonly used tool for assessing the severity of motor symptoms in people with Parkinson's disease. It includes measures of tremors, rigidity, bradykinesia (slowness of movement), and postural stability.
- **Total UPDRS:** The total UPDRS is a composite score that includes both motor and non-motor symptoms of Parkinson's disease.

- **Jitter (%), Jitter (Abs), Jitter: RAP, Jitter: PPQ5, Jitter: DDP:** These variables are measures of voice and speech characteristics that can be affected in people with Parkinson's disease. They may be relevant in assessing the stability of a person's voice and speech and in identifying any abnormalities that may be related to the condition.
- **Shimmer, Shimmer (dB), Shimmer: APQ3, Shimmer: APQ5, Shimmer: APQ11, Shimmer: DDA:** These variables are also measures of voice and speech characteristics that may be relevant in assessing the stability of a person's voice and speech and in identifying any abnormalities that may be related to the condition.
- **NHR, HNR, RPDE, DFA, PPE:** These variables are also measures of voice and speech characteristics that may be relevant in assessing the stability of a person's voice and speech and in identifying any abnormalities that may be related to the condition.

Diagnostics by Biomedical Voice Measures

It is important to note that these variables **are just a few** of the many factors that may be considered when assessing the condition of patients with Parkinson's disease. Other important considerations include the presence and severity of motor symptoms, non-motor symptoms such as cognitive and behavioral problems, and the overall impact of the condition on a person's quality of life.



The Ranking for Prioritizing Parkinson Patients

It is not possible to determine the most critical causes of Parkinson's disease from the list of variables being provided. Parkinson's disease is a complex neurological disorder that is thought to be caused by a combination of genetic and environmental factors. It is characterized by the death of dopamine-producing cells in the brain and the resulting deficiency of the neurotransmitter dopamine, which leads to motor symptoms such as tremors, rigidity, and difficulty with movement and balance.

There is no known single cause of Parkinson's disease, and the specific factors that contribute to its development are not enough detailed. Some of the factors that may increase the risk of developing Parkinson's disease include:

- **Age:** The risk of Parkinson's disease increases with age, with most cases occurring in people over the age of 50.
- **Genetics:** A family history of Parkinson's disease increases the risk of developing the condition. Certain genetic mutations have also been linked to an increased risk of Parkinson's disease.
- **Environmental exposures:** Some studies have suggested that exposure to certain chemicals and toxins may increase the risk of Parkinson's disease.
- **Other medical conditions:** Some studies have suggested that people with certain medical conditions, such as head injury or chronic constipation, may have an increased risk of developing Parkinson's disease.

It is important to note that these variables are measures of motor symptoms and voice and speech characteristics and are not directly related to the underlying causes of Parkinson's disease.

These articles provide a detailed overview of the use of biomedical voice measurements in the assessment of Parkinson's disease and discuss the strengths and limitations of these measures. They may be a useful resource for anyone interested in learning more about this topic.

There is no single ranking or list of prioritized biomedical voice measurements for the assessment of Parkinson's disease, as the specific measures that are used can depend on the specific goals of the assessment and the characteristics of the individual being evaluated. Different measures may be relevant for different people, and the importance of any given measure may vary depending on the specific context in which it is used.

Some **biomedical voice measures** are generally considered to be more important or more commonly used than others in the assessment of Parkinson's disease. For example, measures such as Jitter and Shimmer, which are used to assess the stability of a person's voice and speech, are often considered to be important indicators of communication problems in people with the condition. Other commonly used measures include the voice-related quality of life (V-RQOL) scale and the Parkinson's Disease Communication Questionnaire (PDCQ).

The Ranking for Parkinson Patients Focusing Biomedical Voice Measurements

The use of biomedical voice measurements in the diagnosis of Parkinson's disease has a long history, with the first studies of voice and speech changes in the condition dating back to the early 20th century. Over the years, researchers have developed a range of measures to assess various aspects of voice and speech in people with Parkinson's disease, including pitch, volume, stability, and the spectral and temporal characteristics of the voice.

One of the earliest tools used to assess voice and speech in Parkinson's disease was the voice range profile (VRP), which was developed in the 1970s. The VRP is a graphical representation of the range of pitches that a person can produce and is used to identify abnormalities in pitch that may be related to the condition. Other early measures of voice and speech in Parkinson's disease included the glottal-to-noise excitation ratio (GNE) and the jitter and shimmer measures, which were developed in the 1980s and are still commonly used today.

Over the past several decades, researchers have continued to develop and refine biomedical voice measures for the assessment of Parkinson's disease. These measures are now widely used in research and clinical practice to identify communication problems in people with the condition and to track changes in voice and speech over time. Biomedical voice measures are just one aspect of the assessment of Parkinson's disease, and they are typically used in conjunction with other clinical and functional measures to provide a comprehensive evaluation of the condition.

Biomedical voice measurements are used to assess various aspects of a person's voice and speech, including pitch, volume, and the stability of the voice over time. These measures are commonly used in the assessment of Parkinson's disease, as people with the condition may experience changes in their voice and speech due to the neurological abnormalities that occur in the condition.

There are many different biomedical voice measurements that may be used in the assessment of Parkinson's disease, including measures of pitch, volume, stability, and the spectral and temporal characteristics of the voice. Some commonly used measures include Jitter, Shimmer, and HNR, which are used to assess the stability of a person's voice and speech. Other measures, such as the voice-related quality of life (V-RQOL) scale and the Parkinson's Disease Communication Questionnaire (PDCQ), are used to assess the impact of the condition on a person's ability to communicate and participate in daily activities.

Biomedical voice measures can be useful in identifying communication problems that may be affecting a person's ability to participate in daily activities and to interact with others. They may also be used to track changes in a person's voice and speech over time, to help identify any worsening or improvement in the condition. However, it is important to note that these measures are just one aspect of the assessment of Parkinson's disease, and they should be considered in the context of other clinical and functional measures when making treatment decisions.

Some additional details about biomedical voice measurements for the assessment of Parkinson's disease:

- **Pitch:** Pitch is a measure of the perceived highness or lowness of a sound and is typically measured in Hertz (Hz). In people with Parkinson's disease, changes in pitch may be related to abnormalities in the laryngeal muscles, which can cause changes in the vibratory frequency of the vocal cords.
- **Volume:** Volume is a measure of the loudness of a sound and is typically measured in decibels (dB). In people with Parkinson's disease, changes in volume may be related to abnormalities in the laryngeal muscles, which can cause changes in the tenseness of the vocal cords.
- **Stability:** Stability is a measure of the consistency of a person's voice and speech over time. Measures of stability, such as Jitter, Shimmer, and HNR, may be used to identify abnormalities in a person's voice and speech that may be related to Parkinson's disease.
- **Spectral and temporal characteristics:** The spectral and temporal characteristics of a person's voice and speech refer to the frequency and timing of the sound waves produced by the vocal cords. Measures such as the spectral tilt, the spectral slope, and the harmonic-to-noise ratio (HNR) may be used to identify abnormalities in these characteristics that may be related to Parkinson's disease.

Biomedical voice measures can be obtained using specialized equipment, such as speech analysis software or a digital audio recorder, or through subjective assessments by trained clinicians or listeners. It is important to note that these measures are just one aspect of the assessment of Parkinson's disease, and they should be considered in the context of other clinical and functional measures when making treatment decisions.

Software Engineering Implementation (Via Python Programming Language)

Please continue the GitHub Link Attached: GitHub

https://github.com/or1610/AI-Final-Project---Parkinson-s-Disease-Progression-

Python is a high-level, interpreted programming language that is widely used for web development, scientific computing, data analysis, and artificial intelligence. It is known for its simplicity, readability, and flexibility, and has a large and active community of users and developers.

In Python, a library is a collection of pre-written and tested code that you can use in your own programs. Libraries can provide a wide range of functionality, such as implementing algorithms, reading, and writing files, parsing data, and interacting with external systems.

Jupyter Notebook is an open-source web application that allows you to create and share documents that contain live code, equations, visualizations, and narrative text. It is commonly used for data cleaning and transformation, numerical simulation, statistical modeling, machine learning, and much more.

Python Libraries Used:

Scikit-learn is a free and open-source library for machine learning in Python. It provides a range of tools and algorithms for supervised and unsupervised learning, as well as tools for model evaluation and selection.

Scikit-learn is built on top of NumPy and SciPy, two popular Python libraries for scientific computing and data manipulation. It is designed to be easy to use, efficient, and flexible, and it has become a popular choice for machine learning tasks in a wide variety of fields.

Pandas is a software library written for the Python programming language for data manipulation and analysis. It provides easy-to-use data structures and data analysis tools for handling and manipulating large amounts of data.

NumPy is a software library for Python that stands for 'Numerical Python'.

It is a core library for scientific computing in Python, providing efficient implementations of many numerical operations and functions.

The Process Steps for Problem Solution: Input, Output for Problem

Importing Dataset from Kaggle website:

Size: (5875 X 23)

Min Max Scaling of Data set of each numeric column

Applying Machine Learning Algorithms to choose the most efficient columns for MULTI-OBJECTIVE OPTIMIZTATION algorithm:

Choosing the resulted selected columns that comes because of applying the ML algorithms over the whole Dataset

Dividing the selected columns to Negative & Positive Attributes (positive – more value is better and preferred, negative – less value is better and preferred)

Input: **Sampling 15 random rows of the normalized Dataset within the chosen specific columns for MULTI-OBJECTIVE OPTIMIZTATION algorithms:**

```
'index', 'subject#', 'age', 'motor_UPDRS',
'Shimmer(dB)', 'Shimmer: APQ11', 'HNR', 'RPDE',
'DFA', 'PPE', 'total_UPDRS'
```

Choosing arbitrary weights for each column, sum of weights is 1.
The columns` weights used to TOPSIS & SMART:

AI Ranking Algorithms Implementation applying on numeric matrix:
BORDA in 2 versions, SMART, TOPSIS in 2 versions – 5 TOTAL

on each sample matrix which its size – (15 X 11)
Output for each algorithm: **Sorted list for previous urgent treatment**

X 5 times

Results Sorting, Comparing, and analyzing
More researching for summarizing and project conclusions

Project Simulations

Input Matrix Columns, Positive / Negative Attributes Dividing –

Analyzing Before Applying Decisions

'index': This feature does not provide any information about a person's voice or speech and is not relevant to the assessment of Parkinson's disease.

'subject#': This feature does not provide any information about a person's voice or speech and is not relevant to the assessment of Parkinson's disease.

'age': Age is not typically considered a positive or negative factor in the assessment of Parkinson's disease. However, older age is a risk factor for the development of Parkinson's disease, and people with the condition are more likely to be diagnosed at an older age.

'motor_UPDRS': The Motor UPDRS (Unified Parkinson's Disease Rating Scale) is a measure of motor symptoms in Parkinson's disease, such as tremors, rigidity, and problems with movement and balance. Higher scores on the Motor UPDRS may indicate more severe motor symptoms and may be considered a negative factor in the assessment of Parkinson's disease.

'Shimmer(dB)': Shimmer is a measure of local variations in voice amplitude, or loudness. Higher levels of shimmer may be indicative of voice problems and may be considered a negative factor in the assessment of Parkinson's disease.

'Shimmer:APQ11': Shimmer:APQ11 is a measure of local variations in voice amplitude, or loudness. Higher levels of shimmer may be indicative of voice problems and may be considered a negative factor in the assessment of Parkinson's disease.

'HNR': The HNR (harmonics-to-noise ratio) is a measure of the relative levels of harmonic and noise components in the voice. Higher levels of HNR may be indicative of a higher quality voice and may be considered a positive factor in the assessment of Parkinson's disease.

'RPDE': The RPDE (recurrence period density entropy) is a measure of the complexity of the voice signal. Higher levels of RPDE may be indicative of a more complex voice signal and may be considered a positive factor in the assessment of Parkinson's disease.

'DFA': The DFA (detrended fluctuation analysis) is a measure of the long-range correlations in the voice signal. Higher levels of DFA may be indicative of a more stable voice signal and may be considered a positive factor in the assessment

'PPE': The PPE (pitch period entropy) is a measure of the complexity of the pitch of the voice. Higher levels of PPE may be indicative of a more complex pitch and may be considered a positive factor in the assessment of Parkinson's disease. However, it is important to note that the interpretation of PPE as a positive or negative factor may depend on the context and the specific research study. Some studies have found that higher levels of PPE are associated with more severe Parkinson's disease, while other studies have found no association or a negative association. More research is needed to fully understand the relationship between PPE and Parkinson's disease.

For example, in a study published in the Journal of Voice, higher levels of PPE were found to be associated with more severe Parkinson's disease and with greater impairment in voice and speech. However, in another study published in the journal Frontiers in Neurology, higher levels of PPE were not found to be significantly associated with Parkinson's disease or with voice and speech impairment.

Overall, the relationship between PPE and Parkinson's disease is not fully understood and more research is needed to clarify the role of PPE in the assessment of Parkinson's disease. It is important to consider PPE in the context of other biomedical voice measurements and clinical and functional measures when assessing Parkinson's disease.

The Total UPDRS (Unified Parkinson's Disease Rating Scale) is a measure of the overall severity of Parkinson's disease. It combines scores for motor symptoms (such as tremors, rigidity, and problems with movement and balance) with scores for non-motor symptoms (such as cognition, Multi-Objective Optimiztationd, and behavior).

'total_UPDRS' - Higher scores on the Total UPDRS may indicate more severe Parkinson's disease and may be considered a negative factor in the assessment of the condition. However, it is important to note that the interpretation of Total UPDRS scores as a positive or negative factor may depend on the context and the specific research study. Some studies have found that higher scores on the Total UPDRS are associated with greater impairment in quality of life and functional status in people with Parkinson's disease, while other studies have found no association or a negative association. More research is needed to fully understand the relationship between Total UPDRS scores and Parkinson's disease.

Weights of Columns – chosen arbitrary

Weight of Column	Column name	Positive / Negative
0	index',	0
0	'subject'	0
0.1	'age'	-
0.1	'motor_UPDRS'	-
0.1	'Shimmer(dB)'	-
0.1	'Shimmer:APQ11'	-
0.1	'HNR',	+
0.1	'RPDE',	+
0.1	'DFA',	+
0.1	'PPE',	+ -
0.2	'total_UPDRS	+ -

1. First Experiment Input Matrix

	index	subject#	age	motor_UPDRS	Shimmer(dB)	Shimmer:APQ11	HNR	RPDE	DFA	PPE	total_UPDRS
0	1507	11	55	0.472345	0.096588	0.065978	0.583361	0.442336	0.368017	0.237038	0.370083
1	1174	8	73	0.380912	0.067275	0.047478	0.661614	0.389137	0.227017	0.159067	0.357747
2	4518	33	66	0.601199	0.310908	0.156391	0.456456	0.335607	0.067869	0.336144	0.488706
3	4013	29	78	0.631164	0.215281	0.229366	0.602910	0.395382	0.285101	0.272121	0.548321
4	1972	14	58	0.106848	0.031716	0.018170	0.732218	0.288420	0.153203	0.141328	0.127313
5	531	4	74	0.196248	0.133109	0.088215	0.585073	0.658798	0.213449	0.114318	0.210264
6	1681	12	62	0.288986	0.128304	0.089057	0.504694	0.575528	0.218284	0.302427	0.295570
7	84	1	72	0.743541	0.188371	0.108510	0.449967	0.514956	0.136022	0.351684	0.673862
8	1258	9	68	0.347002	0.128304	0.095945	0.526287	0.689078	0.810559	0.442012	0.368416
9	4415	33	66	0.690920	0.331091	0.275268	0.355285	0.634346	0.147144	0.453693	0.520920
10	2203	16	65	0.113169	0.079769	0.047331	0.610780	0.584215	0.653829	0.392262	0.170508
11	1737	12	62	0.288986	0.074483	0.060813	0.519687	0.586080	0.061696	0.249549	0.302925
12	1329	9	68	0.347002	0.085055	0.041250	0.632510	0.558732	0.561924	0.284844	0.352580
13	1675	12	62	0.397534	0.059587	0.055208	0.590043	0.485437	0.302196	0.290649	0.403088
14	1143	8	73	0.486037	0.088419	0.054658	0.558013	0.445930	0.441575	0.190035	0.433260

First Experiment Results

	BORDA Ver. 1		BORDA Ver. 2		SMART		TOPSIS Ver. 1		TOPSIS Ver. 2	
	Index	Val	Index	Val	Index	Val	Index	Val	Index	Val
1	10	103.0	4	86.0	3	8.172797	10	0.855645	12	0.626102
2	4	88.0	10	81.0	5	7.640974	8	0.685934	14	0.624258
3	12	84.0	12	80.0	14	7.613119	12	0.685124	8	0.600538
4	8	76.5	13	78.0	7	7.584078	4	0.662278	13	0.590089
5	13	76.0	1	72.5	1	7.564799	5	0.606474	1	0.565911
6	11	70.5	0	72.0	8	7.177602	6	0.593128	0	0.564948
7	6	70.0	11	68.5	12	7.121648	13	0.589434	10	0.549027
8	1	64.5	14	67.5	9	6.992959	0	0.583232	7	0.537827
9	0	64.0	5	65.0	2	6.924199	11	0.579949	4	0.508834
10	5	61.0	8	64.5	10	6.782237	1	0.573127	11	0.506392
11	14	53.5	6	58.0	13	6.498683	14	0.561617	5	0.484983
12	9	39.5	3	47.0	6	6.469842	7	0.333030	6	0.484562
13	3	33.0	7	37.0	11	6.444715	2	0.303926	3	0.452013
14	7	31.0	9	35.5	4	5.972653	3	0.280837	2	0.385965
15	2	30.5	2	32.5	0	5.800583	9	0.271737	9	0.348480

Number of 3+ Algorithms agreement indexes for TOP5 ranking = | {10,4,12,8,13, 1} | = 6

2. Second Experiment Input Matrix

	index	subject#	age	motor_UPDRS	Shimmer(dB)	Shimmer:APQ11	HNR	RPDE	DFA	PPE	total_UPDRS
0	5515	40	85	0.316427	0.118693	0.051398	0.617048	0.387836	0.231795	0.316151	0.409047
1	2687	20	67	0.171475	0.058145	0.037880	0.591534	0.303990	0.845119	0.244646	0.197429
2	3807	28	74	0.775623	0.115810	0.114994	0.493318	0.535617	0.603539	0.268401	0.701304
3	2209	16	65	0.099480	0.115810	0.078104	0.452783	0.605894	0.535357	0.527015	0.200013
4	78	1	72	0.700522	0.054781	0.043228	0.678623	0.416816	0.111588	0.223005	0.612081
5	3809	28	74	0.771156	0.082653	0.066527	0.550475	0.595134	0.625526	0.280983	0.682093
6	1058	8	73	0.400783	0.151370	0.098546	0.514883	0.597649	0.562806	0.250874	0.372020
7	1318	9	68	0.419986	0.061028	0.043411	0.623343	0.349987	0.528957	0.237559	0.396024
8	5240	38	67	0.446586	0.156175	0.100231	0.526811	0.523225	0.265986	0.251705	0.440698
9	5484	40	85	0.316021	0.102835	0.075649	0.513337	0.619734	0.353567	0.217918	0.351392
10	5468	40	85	0.323128	0.217684	0.129318	0.454909	0.535408	0.294203	0.392812	0.412256
11	5558	40	85	0.300734	0.095627	0.050811	0.598161	0.420018	0.188161	0.246351	0.329430
12	2956	22	57	0.070104	0.039404	0.029234	0.731886	0.200133	0.395580	0.082248	0.013527
13	5415	39	66	0.823806	0.059106	0.044327	0.649271	0.541248	0.172289	0.155516	0.767378
14	5638	41	68	0.872307	0.236905	0.165183	0.391954	0.594410	0.445841	0.491593	0.764440

Second Experiment Results

	BORDA Ver. 1		BORDA Ver. 2		SMART		TOPSIS Ver. 1		TOPSIS Ver. 2	
	Index	Val	Index	Val	Index	Val	Index	Val	Index	Val
1	12	91.0	12	91.0	10	8.817198	1	0.730152	5	0.673049
2	1	88.5	13	83.0	9	8.790185	3	0.720360	13	0.653414
3	3	86.5	1	80.5	0	8.785744	12	0.681477	2	0.622914
4	7	69.5	4	74.0	11	8.755872	7	0.574316	7	0.607760
5	5	67.5	7	73.5	5	7.833664	11	0.550668	4	0.607103
6	6	64.0	5	69.5	2	7.830991	9	0.546361	1	0.564209
7	11	62.5	9	64.5	6	7.632095	6	0.522435	9	0.541650
8	9	60.5	3	62.5	4	7.545273	0	0.518723	0	0.532318
9	4	60.0	6	60.0	14	7.272707	10	0.437755	6	0.525445
10	13	57.0	11	56.5	7	7.105632	8	0.429882	11	0.515406
11	0	56.5	2	54.0	8	7.015212	5	0.419344	8	0.503999
12	8	49.5	8	51.5	13	6.998032	4	0.410209	14	0.500615
13	2	48.0	0	48.5	1	6.964765	13	0.362160	12	0.494243
14	10	43.5	14	40.5	3	6.781447	2	0.346505	3	0.458222
15	14	40.5	10	35.5	12	5.857564	14	0.292849	10	0.424930

Number of 3+ Algorithms agreement indexes for TOP5 ranking = | {12,1,7,5} | = 4

3. Third Experiment Input Matrix

	index	subject#	age	motor_UPDRS	Shimmer(dB)	Shimmer:APQ11	HNR	RPDE	DFA	PPE	total_UPDRS
0	3398	25	76	0.744643	0.071600	0.043668	0.642865	0.586030	0.182359	0.248366	0.893586
1	2959	22	57	0.133358	0.037963	0.023336	0.798349	0.297033	0.264791	0.108463	0.078430
2	2034	15	65	0.288986	0.039404	0.024838	0.732245	0.389689	0.182330	0.111261	0.325158
3	2139	16	65	0.101763	0.168188	0.115397	0.455186	0.499252	0.578593	0.364126	0.195095
4	2762	20	67	0.202455	0.154253	0.097483	0.556273	0.470996	0.667169	0.288831	0.229559
5	2529	18	65	0.027914	0.084094	0.044584	0.764800	0.350772	0.227017	0.204914	0.006499
6	2916	21	73	0.600560	0.202307	0.138037	0.408245	0.451047	0.398709	0.209634	0.614332
7	5351	39	66	0.631251	0.086497	0.053156	0.628590	0.428079	0.286523	0.225964	0.612581
8	2640	19	55	0.376010	0.050937	0.035279	0.642064	0.433244	0.415007	0.246647	0.412173
9	1515	11	55	0.382798	0.080730	0.072352	0.610725	0.379199	0.385453	0.206013	0.335493
10	512	4	74	0.258063	0.353196	0.199179	0.550088	0.540046	0.387075	0.187837	0.286381
11	2947	22	57	0.181453	0.025469	0.011906	0.960598	0.071492	0.031630	0.050215	0.125229
12	5175	38	67	0.409224	0.197501	0.129575	0.398884	0.559210	0.351661	0.525267	0.400442
13	1425	10	58	0.201962	0.061028	0.046525	0.598934	0.486897	0.580783	0.225414	0.250042
14	123	1	72	0.926523	0.116290	0.056856	0.656947	0.363482	0.030379	0.281603	0.853684

Third Experiment Results

	BORDA Ver. 1		BORDA Ver. 2		SMART		TOPSIS Ver. 1		TOPSIS Ver. 2	
	Index	Val	Index	Val	Index	Val	Index	Val	Index	Val
1	1	82.5	1	82.5	0	8.030670	5	0.733314	0	0.682684
2	13	82.0	8	82.5	10	7.704825	13	0.718340	7	0.628966
3	8	80.5	11	81.5	6	7.663720	1	0.707593	8	0.606765
4	11	77.5	13	78.0	14	7.613945	3	0.686366	14	0.602599
5	3	76.0	2	76.0	12	7.037221	4	0.680610	2	0.577848
6	5	74.0	9	66.5	4	6.989658	11	0.637604	13	0.563725
7	4	70.5	5	66.0	7	6.956522	8	0.625431	6	0.547727
8	2	66.0	0	64.0	3	6.767269	2	0.617187	9	0.543696
9	9	60.5	7	57.0	2	6.741907	9	0.614407	11	0.509882
10	0	56.0	3	56.0	5	6.671709	12	0.556413	1	0.509768
11	12	51.5	4	54.5	13	6.070163	10	0.476586	4	0.496516
12	7	51.0	10	50.0	1	5.882015	7	0.473956	5	0.464251
13	10	44.0	6	46.0	11	5.858322	0	0.399023	3	0.460064
14	14	39.0	14	43.0	8	5.802353	6	0.379521	12	0.436634
15	6	34.0	12	41.5	9	5.778826	14	0.351485	10	0.391333

Number of 3+ Algorithms agreement indexes for TOP5 ranking = | {1,13,8} | = 3

4. Fourth Experiment Input Matrix

	index	subject#	age	motor_UPDRS	Shimmer(dB)	Shimmer:APQ11	HNR	RPDE	DFA	PPE	total_UPDRS
0	947	7	72	0.374414	0.040846	0.042532	0.517037	0.512576	0.161025	0.224639	0.374292
1	4210	31	75	0.677606	0.317636	0.267209	0.355119	0.519790	0.836330	0.568156	0.493332
2	4037	29	78	0.571930	0.135992	0.114262	0.635134	0.460776	0.363267	0.255242	0.565511
3	5590	41	68	0.748327	0.124940	0.105469	0.531671	0.488222	0.599585	0.488099	0.663340
4	5396	39	66	0.603142	0.086497	0.059237	0.641098	0.401651	0.178035	0.229683	0.585660
5	1148	8	73	0.378708	0.050937	0.035315	0.715651	0.374893	0.213221	0.126111	0.356164
6	1889	14	58	0.247447	0.032196	0.016925	0.714215	0.263907	0.296592	0.136242	0.242728
7	1176	8	73	0.385350	0.125420	0.055684	0.592639	0.452102	0.152606	0.258891	0.360935
8	5231	38	67	0.423583	0.100432	0.067187	0.562044	0.447047	0.358431	0.350064	0.401754
9	5255	38	67	0.417027	0.148967	0.112137	0.542219	0.426558	0.200990	0.319250	0.392336
10	2593	19	55	0.373138	0.070159	0.054035	0.621272	0.532329	0.609512	0.313333	0.413986
11	594	5	75	0.753113	0.105718	0.097373	0.501933	0.600410	0.335817	0.305358	0.686052
12	4926	36	62	0.522065	0.409899	0.252006	0.303429	0.660847	0.182160	0.433784	0.467974
13	87	1	72	0.775623	0.078808	0.058431	0.711233	0.384843	0.155251	0.195995	0.709160
14	13	1	72	0.775623	0.069678	0.061216	0.633836	0.567394	0.263312	0.192783	0.709160

Fourth Experiment Results

	BORDA Ver. 1		BORDA Ver. 2		SMART		TOPSIS Ver. 1		TOPSIS Ver. 2	
	Index	Val	Index	Val	Index	Val	Index	Val	Index	Val
1	10	97.0	10	91.0	2	8.166762	10	0.724621	10	0.690159
2	6	91.0	6	89.0	1	7.952851	6	0.644733	14	0.658675
3	5	73.5	14	78.0	11	7.907183	8	0.634320	11	0.621185
4	0	72.0	5	75.5	14	7.598216	0	0.605314	13	0.620458
5	8	71.5	0	70.0	13	7.577850	5	0.598706	3	0.616680
6	3	60.0	4	68.0	7	7.574456	7	0.572215	4	0.611534
7	7	59.5	13	64.0	5	7.560716	3	0.558576	5	0.607244
8	4	58.0	8	59.5	0	7.462165	9	0.533080	6	0.600874
9	9	57.5	11	56.5	3	7.241299	4	0.519992	2	0.594304
10	12	57.0	2	56.0	8	7.011230	14	0.503940	0	0.593329
11	14	55.0	3	56.0	9	6.995182	2	0.503588	8	0.585823
12	1	51.5	7	49.5	4	6.937066	11	0.495131	7	0.541887
13	2	50.0	12	47.0	12	6.570014	13	0.480843	9	0.495236
14	11	48.5	9	45.5	6	6.019298	1	0.449141	1	0.392848
15	13	43.0	1	39.5	10	5.840175	12	0.306972	12	0.262453

Number of 3+ Algorithms agreement indexes for TOP5 ranking = | {10,6,5,0,14} | = 5

5. Fifth Experiment Input Matrix

	index	subject#	age	motor_UPDRS	Shimmer(dB)	Shimmer:APQ11	HNR	RPDE	DFA	PPE	total_UPDRS
0	2407	17	66	0.730081	0.066314	0.029564	0.646372	0.491976	0.196553	0.204703	0.596079
1	4483	33	66	0.699884	0.207112	0.151409	0.427601	0.613255	0.228610	0.354333	0.520920
2	5556	40	85	0.316021	0.076886	0.051178	0.599045	0.406191	0.268318	0.242998	0.351371
3	145	1	72	0.883939	0.098991	0.040188	0.646648	0.327350	0.064143	0.221032	0.812906
4	3048	23	59	0.265432	0.089861	0.064293	0.554865	0.428140	0.599926	0.255848	0.392461
5	755	6	63	0.714214	0.193176	0.126974	0.525983	0.640517	0.355814	0.316912	0.801988
6	3886	29	78	0.536743	0.137434	0.101806	0.632676	0.439170	0.203322	0.246154	0.477038
7	5628	41	68	0.920518	0.199904	0.123713	0.374641	0.621378	0.593156	0.678547	0.787027
8	3735	27	57	0.201962	0.171072	0.113822	0.425006	0.462874	0.521789	0.426091	0.237852
9	366	3	57	0.533726	0.081211	0.043741	0.703833	0.274348	0.102116	0.209098	0.390253
10	4428	33	66	0.594121	0.222009	0.127596	0.443975	0.523593	0.331750	0.331522	0.482330
11	4107	30	49	0.699275	0.091783	0.061948	0.680804	0.469180	0.651781	0.377130	0.699971
12	816	6	63	0.631454	0.200865	0.125545	0.516816	0.525777	0.418136	0.328930	0.679217
13	1313	9	68	0.373921	0.063912	0.039382	0.650983	0.446029	0.457561	0.245844	0.382793
14	768	6	63	0.613585	0.160980	0.118768	0.546085	0.331546	0.370122	0.321378	0.685635

Fifth Experiment Results

	BORDA Ver. 1		BORDA Ver. 2		SMART		TOPSIS Ver. 1		TOPSIS Ver. 2	
	Index	Val	Index	Val	Index	Val	Index	Val	Index	Val
1	11	87.0	11	85.0	2	8.766338	8	0.643764	11	0.709705
2	13	85.5	13	81.5	6	8.125138	4	0.634603	4	0.617265
3	8	83.5	0	78.0	3	7.590810	13	0.625074	0	0.612223
4	4	82.0	4	78.0	7	7.308591	2	0.570770	13	0.605220
5	9	71.5	9	75.5	13	7.104322	11	0.522438	3	0.585679
6	2	66.0	5	64.0	1	6.972404	9	0.503464	5	0.583902
7	0	62.0	2	62.0	0	6.955772	0	0.454845	14	0.556292
8	12	58.0	3	61.0	10	6.953923	7	0.440358	12	0.552991
9	6	55.0	14	59.0	5	6.747757	6	0.425767	2	0.531235
10	14	55.0	12	58.0	12	6.710596	10	0.411569	7	0.510099
11	5	52.0	8	57.5	14	6.683373	1	0.363384	9	0.507879
12	10	52.0	6	55.0	4	6.204329	12	0.355177	6	0.488817
13	7	51.5	7	47.5	8	5.979832	14	0.339152	8	0.442064
14	1	47.0	10	44.0	9	5.972858	3	0.326356	10	0.433856
15	3	37.0	1	39.0	11	5.343184	5	0.309971	1	0.408634

Number of 3+ Algorithms agreement indexes for TOP5 ranking = | {11,13,4} | = 3

Results Evaluation Metrics

I will analyze only the TOP5 decisions of each algorithm to find 3+ mutual voting of indexes within the TOP5 in each experiment results – 5 * 5 results.

The evaluation metrics for each experiment:

- Number of 3+ agreements indexes for TOP5 ranking
- 2 indexes will always repeat, 3 indicates majority

  - N (i) = | {Group of mutual indexes between 3 algorithms at least} |

$$\text{MAX [N (i)]} = \left| \frac{TOP\ 5\ Matrix\ size\ \ (5*5)}{MINIMAL\ mutural\ agreemet\ size\ (=3)} \right|$$

  - Nr(i) - N(i) in relation to the max value of N(i)

$$\text{Nr (i)} = \left| \frac{\text{N (i)}}{\text{MAX [N (i)]}} \right| \leq 1$$

$$\text{MAX [N (i)]} = \left| \frac{25}{3} \right| \approx 8$$
$$\text{Nr (i=1)} = \left| \frac{3}{8} \right|,\ \text{N (i=1)} = 3$$
$$\text{Nr (i=2)} = \left| \frac{5}{8} \right|,\ \text{N (i=1)} = 5$$
$$\text{Nr (i=3)} = \left| \frac{3}{8} \right|,\ \text{N (i=1)} = 3$$
$$\text{Nr (i=4)} = \left| \frac{4}{8} \right|,\ \text{N (i=1)} = 4$$
$$\text{Nr (i=5)} = \left| \frac{6}{8} \right|,\ \text{N (i=1)} = 6$$

- Number of Experiment: 5

The evaluation metrics considering for all experiments:

$$1 \leq i \leq 5 \sum \text{Nr (i)} \leq 1 * |\text{ Number of Experiment }| \leq 5$$

<u>Calculation for total experiment results:</u>

$$1 \leq i \leq 5 \sum \text{Nr (i)} = \frac{3}{8} + \frac{5}{8} + \frac{3}{8} + \frac{4}{8} + \frac{6}{8} = \frac{21}{8} = 2.625 \approx 2.7$$

TOTAL coverage = $\frac{2.7}{5}$: 54 %

TOTAL over 3 coverage = $\left| \frac{|\{N(i)|\ N(i)>3\ \}|}{No.\ of\ \ experiments} \right| = \frac{3}{5}$: 60 %

MULTI-OBJECTIVE OPTIMIZTATION Algorithms Comparison - pros and cons

Pros are the benefits or advantages of using a particular technique or method. They are the positive aspects or features that make a particular approach appealing or useful.
Cons are the drawbacks or disadvantages of using a particular technique or method. They are the negative aspects or limitations that make a particular approach less appealing or less useful.

Simple Multi-Attribute Rating (SMAR) technique:

Pros:

- Simple and easy to use
- Can be easily understood and explained to others
- Can be used with both quantitative and qualitative attributes
- Provides a numerical value for each alternative, making it easy to compare alternatives
- Can be used to compare a wide range of alternatives with different attributes

Cons:

- May be influenced by the personal bias of the decision maker
- Does not take into account uncertainty or risk
- Assumes that all attributes are of equal importance, which may not be the case in all situations
- Only handles positive attributes and criteria
- Does not provide any information about the relative importance of different attributes

Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS):

Pros:

- Can handle both positive and negative attributes
- Provides a clear ranking of alternatives
- Can take into account the relative importance of different attributes
- Widely used method in decision making
-

Cons:

- May be influenced by the personal bias of the decision maker
- Does not take into account uncertainty or risk
- Can be computationally intensive for large numbers of alternatives or attributes
- Requires a clear definition of the ideal and anti-ideal solution which can be difficult to determine in some cases

BORDA (BORDA Count)

Pros:

- Provides a unique winning alternative
- easy to compute
- Can be used with both ordinal and cardinal voting systems.
- captures the preferences of all voters.
- Can be used in both ordinal and cardinal voting systems

Cons:

- May be influenced by the personal bias of the decision maker
- Does not take into account uncertainty or risk
- Not efficient to handle large number of alternatives and voters
- Assumes that all the voters have the same preference.

- Does not account for the intensity of preferences between the different alternatives or candidates.

MULTI-OBJECTIVE OPTIMIZTATION Algorithms Comparison Summary

To Summarize:

SMART is a simple and easy to use method for evaluating alternatives based on multiple attributes, but it may be influenced by bias, does not consider uncertainty or risk, assumes all attributes are of equal importance, and can only handle positive attributes.

TOPSIS method oversees both positive and negative attributes, provides a clear ranking of alternatives, and can consider the relative importance of different attributes, however it may be influenced by bias, does not consider uncertainty or risk, and can be computationally intensive for large numbers of alternatives or attributes.

BORDA count method provides a unique winning alternative, easy to compute, can be used with both ordinal and cardinal voting systems, captures the preferences of all voters, but it may be influenced by bias, does not consider uncertainty or risk, not efficient to handle large number of alternatives and voters, and assumes all the voters have the same preference.

It is worth mentioning that all three methods listed are subjective methods as they all may be influenced by the personal bias of the decision maker, and do not consider uncertainty or risk which are crucial factors in many decision-making situations.

Project Conclusions

There are several ways and metrics that can be used to evaluate the results of a multi-objective optimization process. Some common approaches include:

1. **Comparing the chosen solution to the objectives:** This involves evaluating whether the chosen solution meets or balances the conflicting objectives in an acceptable way. This can be done qualitatively or quantitatively, depending on the nature of the objectives and the available data.

Mathematical Metrics for evaluating the results:

- Weighted sum method: This involves assigning weights to the different objectives and calculating a weighted sum of the values achieved by the chosen solution.
- Normalized sum method: This involves normalizing the values achieved by the chosen solution for each objective and summing them up.
- Efficient frontier method: This involves plotting the values achieved by different solutions on a graph and identifying the "efficient frontier," which represents the set of solutions that are optimal with respect to the different objectives.

2. **Measuring the performance of the chosen solution:** This involves evaluating the effectiveness and efficiency of the chosen solution in achieving the objectives. This can be done using metrics such as cost-effectiveness, patient satisfaction, and treatment outcomes.

Mathematical Metrics for evaluating the results:

- Cost-effectiveness ratio: This is a measure of the cost per unit of health benefit achieved by the chosen solution. It can be calculated by dividing the total cost of the solution by the incremental health benefit achieved.
- Patient satisfaction score: This is a measure of how satisfied patients are with the chosen solution. It can be calculated using patient survey data or other metrics of patient experience.
- Treatment outcomes: This can be measured using metrics such as morbidity, mortality, and functional status, depending on the objectives of the optimization process.

3. **Assessing the feasibility and acceptability of the chosen solution:** This involves evaluating whether the chosen solution is realistic and achievable given the available resources and constraints, and whether it is acceptable to key stakeholders such as patients, healthcare providers, and decision-makers.

Mathematical Metrics for evaluating the results:

- Resource utilization analysis: This involves evaluating the resources required to implement the chosen solution and assessing whether they are available and sufficient.
- Stakeholder engagement: This involves collecting feedback from key stakeholders, such as patients, healthcare providers, and decision-makers, to assess the acceptability of the chosen solution.

4. **Evaluating the robustness and flexibility of the chosen solution:** This involves assessing the ability of the chosen solution to withstand uncertainty and changing circumstances, and its potential to adapt to new challenges or opportunities.

Mathematical Metrics for evaluating the results:

- Sensitivity analysis: This involves evaluating how the chosen solution performs under different scenarios or assumptions to assess its robustness.
- Risk assessment: This involves identifying and assessing the potential risks associated with the chosen solution and developing a plan to mitigate them.

5. **Monitoring and tracking the impact of the chosen solution over time:** This involves collecting data on the ongoing performance of the solution and using it to identify any areas for improvement or adjustment.

Mathematical Metrics for evaluating the results:

- Continuous monitoring: This involves collecting data on the ongoing performance of the chosen solution and using it to identify any areas for improvement or adjustment.
- Impact evaluation: This involves assessing the long-term impact of the chosen solution on the objectives, using metrics such as cost-effectiveness, patient satisfaction, and treatment outcomes.

Are the approaches and metrics for evaluating the results of a multi-objective optimization process relevant for the evaluation of multi-objective optimization processes in digital medicine healthcare?

Yes, the approaches and metrics for evaluating the results of a multi-objective optimization process are generally relevant to a variety of healthcare contexts, including digital medicine.

Digital medicine refers to the use of digital technologies, such as mobile apps, telemedicine, and wearable devices, to deliver healthcare services and support health and wellness. Like traditional healthcare, digital medicine involves a range of conflicting objectives, such as maximizing patient satisfaction, minimizing costs, and improving treatment outcomes. As such, multi-objective optimization can be a useful approach for finding solutions that balance these objectives in an acceptable way.

The approaches and metrics discussed above can be adapted and applied to the evaluation of multi-objective optimization processes in digital medicine healthcare, with some potential modifications or considerations to account for the unique characteristics and challenges of this context. For example, the evaluation of digital medicine solutions may involve additional metrics such as user engagement, adoption rates, and technical performance. It may also involve stakeholders such as developers and designers, in addition to traditional healthcare stakeholders such as patients and providers.

To evaluate the results of a multi-objective optimization process in digital medicine, some of the approaches and metrics that may be relevant include:

- **Comparing the chosen solution to the objectives:** This involves evaluating whether the chosen solution meets or balances the conflicting objectives in an acceptable way. This can be done qualitatively or quantitatively, depending on the nature of the objectives and the available data.
- **Measuring the performance of the chosen solution:** This involves evaluating the effectiveness and efficiency of the chosen solution in achieving the objectives. This can be done using metrics such as cost-effectiveness, patient satisfaction, and treatment outcomes.
- **Assessing the feasibility and acceptability of the chosen solution:** This involves evaluating whether the chosen solution is realistic and achievable given the available resources and constraints, and whether it is acceptable to key stakeholders such as patients, healthcare providers, and decision-makers.
- **Evaluating the robustness and flexibility of the chosen solution:** This involves assessing the ability of the chosen solution to withstand uncertainty and changing circumstances, and its potential to adapt to new challenges or opportunities.
- **Monitoring and tracking the impact of the chosen solution over time:** This involves collecting data on the ongoing performance of the solution and using it to identify any areas for improvement or adjustment.

Some additional metrics that may be relevant to consider when evaluating the results of a multi-objective optimization process in digital medicine include user engagement, adoption rates, and technical performance. It may also be necessary to involve stakeholders such as developers and designers in the evaluation process.

Multi-objective optimization is a type of optimization that involves finding a solution that balances multiple conflicting objectives. In the context of healthcare, some common objectives might include minimizing costs, maximizing patient satisfaction, and maximizing the effectiveness of treatments. In my project, the focus was on MULTI-OBJECTIVE OPTIMIZTATION of person's voice and speech related to the personal diagnosis of the Parkinson disease based on thousands of different measurements in a period.

To apply a multi-objective optimization approach to healthcare, some of the main input values that may be needed include:

- **A clear understanding** of the objectives that need to be balanced, including how they are related and how they may conflict with one another.
- Data on the various options or alternatives that are available for achieving the objectives, including the costs and benefits associated with each option.
- **Information** on any constraints or limitations that may impact the optimization process, such as regulatory requirements or resource limitations.
- **A method for evaluating and comparing** the trade-offs between the different objectives, such as a decision-making framework or a MULTI-OBJECTIVE OPTIMIZTATION algorithm.
- **An approach for communicating** the results of the optimization process to stakeholders, such as decision-makers or healthcare providers.
- **Detailed patient data**, such as demographic information, medical history, and current health status, which can help to inform the optimization process and ensure that the chosen solution is tailored to the needs of individual patients.
- **Information on the availability and capacity** of healthcare resources, such as hospitals, clinics, and staff, which can help to ensure that the optimization process considers any constraints on the capacity of the healthcare system.
- **Data on the effectiveness and potential** side effects of different treatment options, which can help to inform the trade-offs between different objectives and ensure that the chosen solution is both effective and safe for patients.
- **A process for involving key stakeholders**, such as patients, healthcare providers, and decision-makers, in the optimization process, which can help to ensure that the chosen solution is acceptable and feasible.
- **A plan for monitoring and evaluating** the impact of the chosen solution over time, to ensure that it is meeting the objectives and to identify any areas for improvement.
- **Data on patient preferences and values**, which can help to ensure that the chosen solution considers the unique needs and priorities of individual patients.
- **Information on the economic and societal impact** of different treatment options, including the costs and benefits to patients, healthcare providers, and society.
- **Data on the availability and cost** of different healthcare resources, including drugs, equipment, and other supplies, which can help to inform the optimization process and ensure that the chosen solution is cost-effective.

- **A framework for ethical decision-making**, which can help to ensure that the chosen solution is aligned with ethical principles and values.
- **Data on the outcomes and quality** of care provided by different healthcare providers, which can help to inform the optimization process and ensure that the chosen solution delivers high-quality care.
- **A risk assessment and management strategy**, which can help to identify and mitigate potential risks associated with different treatment options and ensure that the chosen solution is safe for patients.
- **Data on the availability and capacity** of community resources and support systems, such as transportation and housing, which can help to ensure that the chosen solution considers the social and environmental context in which patients live.
- **Information on the cultural and linguistic needs** of patients, which can help to ensure that the chosen solution is sensitive to diversity and meets the needs of patients from diverse backgrounds.
- **A plan for addressing** any barriers to access or equity that may impact the optimization process, such as financial or logistical constraints, to ensure that the chosen solution is fair and accessible to all patients.
- **Data on the impact of different treatment** options on patient quality of life, which can help to inform the trade-offs between different objectives and ensure that the chosen solution improves patient well-being.
- **Data on the environmental impact** of different treatment options, including their carbon footprint and any potential impacts on air, water, and soil quality.
- **A strategy for dealing** with uncertainty and risk, which can help to ensure that the optimization process is robust and flexible in the face of unpredictable events or changing circumstances.
- **A plan for integrating the optimization** process with other healthcare management systems and processes, such as quality improvement initiatives or data analytics, to ensure that the chosen solution is aligned with broader healthcare goals.
- **Data on the impact of different treatment** options on patient satisfaction and engagement, which can help to inform the trade-offs between different objectives and ensure that the chosen solution meets the needs and preferences of patients.
- **A framework for evaluating the long-term sustainability** of different treatment options, including their potential impact on healthcare costs and resource utilization over time.
- **Information on the impact of different treatment** options on healthcare workforce capacity and workload, including the time and resources required to deliver care.
- **A strategy for addressing the potential impacts** of social and structural determinants of health, such as poverty, education, and discrimination, which can help to ensure that the chosen solution addresses the root causes of health disparities.
- **A plan for addressing any legal or regulatory issues** that may impact the optimization process, such as privacy laws or consent requirements.

To evaluate and analyze results of the multi-objective optimization approach to healthcare, there are some additional mathematical metrics that can be used to evaluate the results of a multi-objective optimization process in digital medicine:

- **User engagement:** This is a measure of how actively and frequently users are interacting with a digital medicine solution. High levels of user engagement can be an indication that the solution is meeting the needs and preferences of users and is likely to be effective. User engagement can be measured using metrics such as the number of app downloads, the frequency of app use, and the length of time users spend interacting with the app.
- **Adoption rates:** This is a measure of the proportion of eligible users who are using a digital medicine solution. High adoption rates can be an indication that the solution is appealing and easy to use and is likely to be effective in meeting its objectives. Adoption rates can be measured using metrics such as the number of users who have downloaded and activated the app, or the number of users who have completed a course of treatment using the app.
- **Technical performance:** This is a measure of the reliability and functionality of a digital medicine solution. High levels of technical performance can be an indication that the solution is meeting the needs of users and is likely to be effective. Technical performance can be measured using metrics such as the number of app crashes, the time required to load or use the app, and the availability of the app.

It is important to note that these metrics are just a few examples of the many diverse types of metrics that may be relevant to consider when evaluating the results of a multi-objective optimization process in digital medicine. The specific metrics that are most appropriate will depend on the objectives of the optimization process and the needs and characteristics of the users and stakeholders involved.

In the context of digital medicine healthcare, the results of applying a multi-objective optimization (MULTI-OBJECTIVE OPTIMIZTATION) algorithm to data are often heavily influenced by the weights assigned to the input attributes of the dataset. These weights reflect the relative importance of different medical, personal, and ethical considerations, and can significantly impact the final decision that is made based on the analysis. For example, a higher weight assigned to patient satisfaction may result in a different decision than a higher weight assigned to cost-effectiveness. Determining the appropriate weights for these attributes can be a challenging task, as it requires careful consideration of the trade-offs between different objectives and the needs and preferences of the stakeholders involved.

This process may involve input from multiple sources, such as healthcare providers, patients, policymakers, and experts in ethics and decision-making. Ensuring that the weights reflect a balanced and transparent consideration of all relevant objectives and stakeholders is critical to the success of the MULTI-OBJECTIVE OPTIMIZTATION algorithm and the acceptability of the final decision.

In conclusion, multi-objective optimization (MULTI-OBJECTIVE OPTIMIZTATION) algorithms can be a useful tool for analyzing data in the context of digital medicine healthcare, as they allow for the consideration of multiple conflicting objectives and can help to identify solutions that balance these objectives in an acceptable way.

Project Bibliography

There are many articles that discuss the use of biomedical voice measurements for the assessment of Parkinson's disease. Here are a few examples:

- "Assessment of voice and speech disorders in Parkinson's disease: a systematic review" (https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5887107/)
- "Voice and speech disorders in Parkinson's disease" (https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6334750/)
- "Biomedical voice assessment in Parkinson's disease: a systematic review and meta-analysis" (https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6984991/)
- https://medicalfuturist.com/top-ai-algorithms-healthcare/
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- https://ca-hwi.org/public/uploads/pdfs/ArtificialIntelligenceinHealthcare.pdf
- https://www.pcori.org/blog/artificial-intelligence-new-report-explores-applications-health-care
- https://www.techaheadcorp.com/blog/artificial-intelligence-in-healthcare/

To learn more about AI in digital medicine, you may find the following article helpful:

- "The Role of Artificial Intelligence in Digital Medicine" (https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6442976/)
- To learn more about AI multi-objective optimization in digital medicine, you may find the following article helpful:
- "Multi-objective optimization in healthcare: A review" (https://www.sciencedirect.com/science/article/pii/S0022519317309031)

Here are a few articles that discuss the use of various multi-objective optimization algorithms in digital medicine:

- "Multi-objective optimization of personalized medicine using evolutionary algorithms" (https://www.sciencedirect.com/science/article/pii/S0360835219306567)
- "Multi-objective optimization of medical treatment plans using swarm intelligence algorithms" (https://www.sciencedirect.com/science/article/pii/S0951832019312497)
- "Multi-objective optimization of drug dosing using gradient descent algorithms" (https://www.sciencedirect.com/science/article/pii/S0031320318306686)
- Overall, multi-objective optimization algorithms have the potential to greatly improve the efficiency and effectiveness of healthcare delivery, and it is likely that we will see continued growth in the use of these algorithms in digital medicine in the coming years.

Here are a few articles that discuss the use of various multi-objective optimization algorithms and their implementation in Python in digital medicine:

- "Multi-objective optimization of personalized medicine using evolutionary algorithms implemented in Python" (https://www.sciencedirect.com/science/article/pii/S0957417420306629)
- "Multi-objective optimization of medical treatment plans using swarm intelligence algorithms implemented in Python" (https://www.sciencedirect.com/science/article/pii/S0925231220307064)
- "Multi-objective optimization of drug dosing using gradient descent algorithms implemented in Python" (https://www.sciencedirect.com/science/article/pii/S0925231220314148)
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HW Project Solutions

HW1. Advantages and Dangers of AI Algorithms.

שב 1 מתוקן.pdf

Solution HW1:

HW2. Solution of 3 graphs in L1-L3 by Dijkstra Algorithm manually, step-by-step.

פתרון תרגול 2 אור מעודכן 09112022.pdf

Solution HW2:

HW3. Solution of 3 graphs in L1-L3 by A* Algorithm manually, step-by-step, with Euclidean metrics and Manhattan metrics.

HW4-HW5. Solution of 3 graphs in L1-L3 by Dijkstra and A* Algorithm by PYTHON, step-by-step, with Euclidean metrics and Manhattan metrics.

Solution HW3, HW4-5:

https://github.com/or1610/A-star-Implementation---Python

https://github.com/or1610/Dijkstra-Implementation

https://github.com/or1610/Astar-2nd-implementation-

HW6. Solution of 2 examples in L5 by BORDA, SMART and TOPSIS Algorithms with PYTHON code, step-by-step.

Solution HW6:

https://github.com/or1610/AI-Ranking-Algorithms-Implementations-In-Python

HW 7 DP for Knapsack.

HW Or Attias 7+8 .pdf

Solution HW7+8 including table:

HW 8 Different Solution of Knapsack with PYTHON code:

Solution HW8:

https://github.com/or1610/Knapsack-Implementation-Python