תמונה שמכילה גופן, טקסט, לוגו, גרפיקה

התיאור נוצר באופן אוטומטי

**Capstone Project Phase A**

**ParkSmart**

Research of Pattern Recognition and Visualization Based on Personal Data for Support and Quality of Life Improvement for Parkinson's Patients.

**Supervision: Ph.D. Julia Sheidin**

**Ph.D. Avital Shulner Tal**

**Noam Vallach –** [**Noam.vallach@e.braude.ac.il**](mailto:Noam.vallach@e.braude.ac.il)

**Yuval Shekel –** [**Yuval.shekel@e.braude.ac.il**](mailto:Yuval.shekel@e.braude.ac.il)

**Table of Contents**

[Abstract 1](#_Toc187947060)

[1.Introduction 1](#_Toc187947061)

[2.Background and Related Work 3](#_Toc187947062)

[2.1. Parkinson's Disease 3](#_Toc187947063)

[2.2. Processing the Data Collected from the Patient 3](#_Toc187947064)

[2.3. Tools (technologies) for identifying patterns in medical data 5](#_Toc187947065)

[2.4. visual and textual presentation for understanding medical information 7](#_Toc187947066)

[3. Expected Achievements 8](#_Toc187947067)

[4. Research Process 9](#_Toc187947068)

[4.1 Data Pre-Processing 9](#_Toc187947069)

[4.2 Pattern Identifying Tool Selection 9](#_Toc187947070)

[4.3 XAI type selection 10](#_Toc187947071)

[4.4 Next Phase Process – activity diagram 10](#_Toc187947072)

[4.5 Challenges 11](#_Toc187947073)

[5. Evaluation Plan 12](#_Toc187947074)

[References 13](#_Toc187947075)

Abstract  
Parkinson's disease is a neurodegenerative disorder characterized by motor symptoms such as tremor, bradykinesia, and rigidity, as well as non-motor symptoms such as depression, sleep disturbances, and cognitive impairment. While there is no cure for the disease, research has shown that a combination of physical activity, proper nutrition, medication, and emotional support can significantly improve patients' quality of life and mitigate symptom progression.

Managing the daily routine of Parkinson's patients consistently and continuously, while relying on personal data, provides essential insights for improving disease management. However, existing tools and methods are not always tailored to the unique needs of each patient and are often cumbersome or limited in their utility.

The goal of our research project is to identify patterns in Parkinson's patients' personal data and to present those patterns in the most effective method, aiming to enhance their understanding and as a result, their quality of life.

To achieve this goal, we will review various tools for identifying patterns in medical data. The identified patterns, based on the patient personal data, may enable Parkinson's patients to gain insights about their disease. Additionally, we will review various formats for presenting these patterns in an understandable way and select the most effective method for presenting the patterns, whether visual, textual, or a combination, to ensure clarity and accessibility.

This project could serve as a significant initial step toward the future development of a personalized recommendation system (based on the patterns of the patient) that will benefit Parkinson's patients and improve their quality of life.

**Keywords:** Parkinson's disease, health data, recommendation system.

1.Introduction  
Parkinson’s disease is a neurodegenerative disorder affecting the nervous system, caused by a deficiency of the neurotransmitter dopamine due to the degeneration of cells in the substantia nigra of the brain. Parkinson’s disease is characterized by slowed movements, and its clinical symptoms include reduced mobility, muscle stiffness, involuntary tremors, impaired balance, and instability [1,2]. The disease significantly impacts the quality of life, with patients often struggling to perform simple daily activities [8].

Parkinson’s disease is incurable, and its treatment typically involves medication alongside alternative therapies aimed at delaying the progression of the disease [6]. Additionally, daily physical activity plays a critical role in improving the functionality of various bodily systems. However, despite the efficacy of medical treatments, physicians face challenges in optimizing medication regimens due to variations in disease progression among patients [7].

In recent years, with the advent of personalized medicine, there is growing recognition that analyzing the habits of Parkinson’s patients, interpreting her personal data, and funding patterns in the data can help in providing tailored recommendations and therefore, can improve their quality of life [9]. This is particularly relevant given the availability of advanced technologies such as artificial intelligence and deep learning. These tools have demonstrated significant effectiveness in analyzing extensive datasets and generating personalized recommendations [10].

In this project, we will examine the daily habits of a specific Parkinson’s patient who keeps a daily log of events and activities. Our project is a continuation of a previous project whose goal was data collection on various aspects, including meal types and times, medication types and schedules, physical activities performed, and their durations. These data will serve as the foundation for analyzing information, finding patterns in the data and presenting them, and as a result, the patient will be able to draw insights, and his doctor may use these patterns to create personalized recommendations aimed at improving her quality of life. The recommendations are made by identifying patterns, after which doctors, in combination with artificial intelligence systems, can observe and understand these patterns, thereby generating tailored recommendations.

In addition to finding patterns based on the patient’s individual data, we aim to identify the most effective method for delivering this information to patients. Our study investigates how insights can be presented to Parkinson’s patients in a way that maximizes their utility, whether through visual, textual, or combined formats.

Hence, the objective of this research is to review pattern recognition tools for Parkinson’s patients, analyze it, and present them in the most comprehensible and effective manner. By doing so, we aim to empower patients to implement these insights to enhance their quality of life.

2.Background and Related Work

2.1. ****Parkinson's Disease****

Parkinson's disease (PD) is a neurodegenerative disorder of the central nervous system that affects both motor and non-motor systems. The symptoms of this disease typically develop gradually, with non-motor issues becoming more prevalent as the disease progresses. Common motor symptoms include tremors, bradykinesia (slowness of movement), rigidity, and difficulty maintaining balance (parkinsonism) [1,2]. In later stages, additional conditions such as Parkinson’s disease dementia, involuntary falls, and neuropsychiatric problems like sleep disorders, psychosis, mood changes, or behavioral alterations may develop [11].

Parkinson's disease occurs due to a deficiency of the neurotransmitter dopamine, caused by the degeneration of nerve cells in the substantia nigra [3]. The exact cause of this neuronal degeneration is unknown. However, it appears to result from a combination of genetic and environmental factors [4]. For instance, some patients exhibit a mutation in the **SCAN** gene, which encodes the alpha-synuclein protein. This mutation leads to the accumulation of large quantities of the protein, causing neuronal dysfunction and cell death [5]. In other cases, exposure to toxins such as manganese or neurotoxins has been linked to neurological damage, ultimately leading to the development of Parkinson's disease.

Parkinson's disease is incurable, and treatment aims to slow its progression and prevent severe deterioration of the nervous system. Pharmacological treatments include dopamine agonists and dopamine inhibitors [6]. Additionally, physical activity and cognitive exercises are significant for preserving brain function [7].

2.2. Processing the Data Collected from the Patient

Since each patient experiences Parkinson's symptoms uniquely, accurate assessment of symptoms and medication efficacy is essential to enable specialists to evaluate disease progression and patient response to interventions [12]. Typically, Parkinson’s patients receive holistic care from a multidisciplinary team of professionals, including neurologists, movement disorder specialists, physiotherapists, psychologists, and dietitians, aimed at improving the independence and quality of life of Parkinson's patients [13]. Monitoring and evaluating Parkinson's symptoms and disease progression are primarily based on medical history, self-reported data, and neurological assessments such as the Unified Parkinson's Disease Rating Scale (UPDRS).

The system we are researching is designed to be personalized for a specific patient and is based on data collected in a previous project focused on patient data gathering. This dataset includes detailed information about the patient's daily routine, such as mealtimes and contents, sleep and wake times, physical activities performed, medication schedules and types, and records of relevant symptoms. However, the collected data is currently presented in a raw and unstructured form, necessitating pre-processing to make it suitable for use with advanced analytical tools. Table 1 presents the data that is collected by the patient and how it is presented currently

Table 1. Patient data

|  |  |  |  |
| --- | --- | --- | --- |
| **יום חמישי 2.11.2023** | | **יום רביעי 1.11.2023** | |
| **פעילות** | **שעה** | **פעילות** | **שעה** |
| קימה דופיקר | 06:00 | קימה דופיקר | 07:30 |
| מעדן סויה, אפרסקים עם צימוקים | 06:50 | חצי מעדן סויה | 07:50 |
| שירותים | 07:50 | קפה, טוסט עם חמאה וחצי מעדן סויה עם גרנולה | 08:10 |
| 2 טוסטים עם ביצה קשה ומיונז | 08:15 | דופיקר לקראת אימון  ירקות חתוכים, רבע פיתה עם חרדל ופסטרמה | 09:55 |
| דופיקר | 09:00 | אימון אישי | 11:00 |
| רסק תפוחים | 09:30 | ירקות חתוכים | 11:45 |
| דיקור | 10:10 | סיום אימון | 12:00 |
| תפו"א מבושלים ושעועית ירוקה | 11:20 | דופיקר  כ3  פ3  ירקות חתוכים | 12:15 |
| דופיקר | 12:10 | חצי פיתה עם חרדל ופסטרמה | 12:45 |
| התכווצויות בכפות הרגליים עד 14:30 | 12:30 | דופיקר | 15:25 |
| קומפוט | 13:40 | נסיעה לאלומות  ירקות חתוכים חצי פיתה עם גבנ"צ ומיונז  ריבר | 16:00 |
| פשטידת פטריות | 14:15 | דופיקר | 18:25 |
| דופיקר, מנוחה עד 16:15 | 15:00 | התכווצויות בכפות הרגליים | 18:30 |
| מעדן סויה, אפרסקים עם גרנולה | 16:15 | סיום התכווצויות | 19:20 |
| שירותים  קניות בקיבוץ | 16:30 | א.ערב תפו"א מבושלים שעועית ירוקה | 19:30 |
| דופיקר ויציאה לכדורי | 17:45 | רבע דופיקר סינמט שבור | 21:30 |
| ירקות חתוכים  בטן רגישה | 18:45 | לילה טוב | 22:30 |
| מנוחה בבית קשת  ירקות חתוכים, חצי לחמניה עם ביצה קשה ומיונז | 19:00 | רבע דופיקר סינמט שבור  חצי שעה בסלון  5 עוגיות | 01:20 |
| דופיקר | 20:40 |  |  |
| שירותים ומקלחת | 22:00 |  |  |
| סינמט שבור | 22:45 |  |  |
| לילה טוב | 23:00 |  |  |
| רבע דופיקר סינמט שבור  5 עוגיות | 02:00 |  |  |
| חזרה לישון | 02:25 |  |  |

2.3. Tools (technologies) for identifying patterns in medical data

The analysis of large volumes of digital patient data is essential for deriving characteristics and patterns of patient groups. Pattern recognition provides essential tools for data analysis tasks in the healthcare domain. Specifically, machine learning and deep learning techniques have been successfully applied to various tasks in healthcare, such as risk prediction, disease progression forecasting, and patient sub-classification [19].

For this purpose, tools for pattern recognition are utilized. Below, we present two key tools: Weka and SVM. These tools are used, among other applications, for recognizing patterns in medical information and are widely employed in academic research in this field due to their advanced classification capabilities and their ability to perform sophisticated regression analyses.

The Waikato Environment for Knowledge Analysis (Weka) is a machine learning toolkit developed by the University of Waikato in New Zealand. It is open-source software written in Java (licensed under the GNU General Public License) and is particularly suitable for academic research due to its user-friendly design. The software operates on Windows, Linux, and Mac operating systems. Weka includes a collection of machine learning algorithms designed for performing data mining tasks. The tool is based on a graphical user interface (GUI) and is primarily used for data preprocessing, evaluation methods, and comparing learning techniques [18].

Due to its ease of use and operation, Weka is considered popular among data scientists and researchers, as mentioned. This is attributed to several main features: First, the graphical user interface (GUI) allows users to explore data, apply machine learning algorithms, and predict outcomes without requiring extensive programming knowledge. Second, the software's rich algorithm library enables its use for various tasks, including regression, classification, and association rule mining. Third, the software offers extensive options for data preprocessing, such as data cleaning, normalization, and feature selection, to prepare data for analysis.  
Fourth, Weka can be integrated with other programming languages, such as R and Python.  
Fifth, data can be easily imported and exported from the software, as it supports various data formats (CSV, ARFF, Excel). Sixth, the software provides multiple data visualization tools, including histograms, scatter plots, and decision trees. Seventh, as an open-source platform, the software can be extended by adding algorithms or new features, allowing for customization and tool enhancement. Despite these advantages, the software also has limitations. Its scalability is limited, as it struggles to handle very large datasets. In addition, the software does not support multi-relational data mining and does not natively support sequence modeling, which restricts its use in certain applications [20].

Support Vector Machine (SVM) is a supervised learning technique used for data analysis in classification and regression tasks. In this method, training examples are represented as vectors in a linear space. For classification problems, the training phase involves fitting a classifier that separates positive and negative training examples as accurately as possible. The classifier generated by SVM is a linear separator that maximizes the margin between itself and the nearest examples from both categories. When a new point is presented, the algorithm determines whether it falls within the boundary defining the group or outside of it.

SVM is not restricted to linear classification and can also perform non-linear classification by employing a kernel function, which maps the input into a higher-dimensional space [21].

SVM performs well with high-dimensional data, which is common in medical datasets that contain numerous features. Additionally, SVM is robust to overfitting, making it particularly effective when the number of dimensions exceeds the number of samples. This ability helps the model generalize well to unseen data. The kernel trick is another strength of SVM, as it can handle non-linear relationships, which is beneficial for identifying complex patterns in medical data. Moreover, SVM tends to offer high accuracy in classification tasks, which is crucial for medical diagnostics. However, SVM can be computationally intensive, often being slow and consuming considerable memory, particularly with large datasets. Another limitation is the need for careful tuning of hyperparameters, such as the regularization parameter and kernel parameters. This tuning process can be complex and time-consuming.

2.4. visual and textual presentation for understanding medical information

The use of advanced algorithms and technologies to identify patterns in medical information, including patterns of Parkinson's disease, is thriving. However, most artificial intelligence algorithms operate as black boxes and lack explainability. Therefore, Explainable Artificial Intelligence (XAI) helps understand the decisions and reasoning behind computational model predictions, provides explanations for how a particular conclusion was derived, and enhances trust among both users and experts regarding the reliability of the results.

We will briefly introduce the most popular tools for providing AI explainability (XAI): Local Interpretable Model-Agnostic Explanations (LIME) and Shapley Additive Explanations (SHAP). LIME and SHAP are general-purpose, ready-to-use tools designed to offer explainability to users, mainly suited for developers of AI algorithms [16]. These explanations can be presented visually, textually, or in a combined manner.

SHAP (Shapley Additive Explanations) is a method for explaining model predictions by calculating the contribution of each feature to a specific prediction. The method is based on Shapley values, which estimate the marginal contribution of each feature across all possible coalitions. In other words, it quantifies how each feature influences the model's prediction compared to other features. This approach enables a clear understanding of which features contributed to the model's predictions and why. It presents their impact visually, especially for models involving images [14].

LIME (Local Interpretable Model-Agnostic Explanations) is a method that explains model predictions by approximating them locally with a simple and interpretable model. The method focuses on local fidelity, meaning it provides explanations for individual predictions tailored to the specific conditions under which the prediction was made. The process involves generating new samples that yield predictions from the original model, with each sample evaluated based on its proximity to the instance being analyzed. LIME then constructs a linear model to describe the contribution of each feature in the decision-making process for that prediction. This method is applicable to any machine learning model, regardless of its type [15].

In summary, SHAP provides consistent, theory-based explanations suitable for complex models, while LIME offers flexible local explanation solutions that are adaptable to different models and provide simpler insights.

**3. Expected Achievements**

In our project, we focus on identifying patterns based on the collected data and present them to the patient. This data is particularly relevant for Parkinson's patients, as it enables monitoring of factors influencing symptoms and treatment response, such as sleep patterns, physical activity, and adherence to medication schedules. Our project will serve as a continuation of the previous project, with the goal of advancing the data collection and analysis process. The identified patterns may help patients to improve their quality of life and adapt treatment to their individual condition.

The identified patterns and their presentation will benefit Parkinson's patients by simplifying the process of understanding the impact of various activities on their condition, so the patients will be able to make informed decisions and maintain a high quality of life.

The success of the project will be evaluated based on several criteria, including a comparison between the different tools used for pattern detection. We will examine whether the tools identified the same patterns, the relevance of the patterns found, and whether meaningful insights can be drawn from them. Additionally, we will assess the effectiveness of the patterns through feedback from the system's user (Michael) to determine whether the patterns are beneficial to him and whether he intends to make any lifestyle changes based on the information provided.

Ultimately, this project has the potential to serve as a foundation for future advancements in personalized medical tools, particularly for neurodegenerative diseases, by demonstrating the value of combining data-driven insights with accessible user interfaces.

4. Research Process

The project began under the guidance of our supervisors, who introduced the idea of analyzing and presenting Parkinson's patients data. During the initial meetings, they presented the data collected from a Parkinson's patient as part of a previous project. This data included information about daily activities, medication schedules, sleep routines, diet, and symptoms. These datasets served as a foundation for understanding the complexity and challenges of managing the disease and inspired us to explore ways to utilize this information for the purpose of improving treatment and the patient's quality of life.

Following the initial discussions, we focused on researching a system that could analyze daily routines and provide actionable patterns that enable gaining insights to enhance the quality of life for Parkinson's patients. Our research centered on identifying the most effective methods for utilizing the data and generating relevant patterns and presenting them to the patient. We reviewed existing literature on similar systems and explored tools and techniques in data analysis, machine learning, explainable ai and user experience design to ensure our approach was both scientifically robust and user-friendly.

4.1 Data Pre-Processing

At the current stage of the project, we focused on understanding the collected data to identify its structure and key characteristics. In the next stage, we will perform preprocessing of the data to convert it into a format suitable for the analytical tools we plan to use. This process will ensure that the data is prepared and optimized for complex analyses, enabling accurate identification of relevant patterns.

4.2 Pattern Identifying Tool Selection

After evaluating both tools, Weka and SVM, we decided to use Weka due to its user-friendly interface and the ability to integrate multiple algorithms, which can assist in preliminary analysis and understanding of the research data. However, as the research progresses, there may be a need to consider combining both tools, especially if the dataset becomes more complex and involves intricate relationships that demand higher precision and reliability.

4.3 XAI type selection

When examining the advantages and disadvantages, it appears that SHAP is more suitable for the project. While LIME offers an advantage in providing localized explanations that lead to clear insights, it may be less stable in cases of random sampling and is better suited for simpler models. On the other hand, SHAP provides both global and local explanations, giving it an edge in handling complex models. It is more stable and consistent, with the ability to explain the contributions of each feature, though it can be more complex to implement. SHAP seems to be the preferred choice when stability and comprehensive understanding are required, whereas LIME is more appropriate for focused explanations in simpler models [17].

4.4 Next Phase Process – activity diagram

In the next stage, we will review the tools presented in the literature review and choose the most suitable tool for identifying patterns from the collected data. Afterward, we will preprocess the patient’s data and integrate it into the selected tool for pattern recognition. Subsequently, we will evaluate the two tools we introduced for presenting the patterns and ultimately select the one most appropriate for displaying the identified patterns. The entire process will be presented in an activity diagram to help understand the workflow of the project.

**תמונה שמכילה טקסט, צילום מסך, תרשים, גופן

התיאור נוצר באופן אוטומטי**

4.5 Challenges

The challenges we expect in the project are our lack of medical knowledge, which makes it difficult to analyze the data and determine whether the identified patterns are correct or how they can be used effectively. In addition, using the tools may pose a challenge, as there is a need for a deep understanding of the tools themselves to extract maximum benefit from them. Furthermore, we must consider the challenge of ensuring compatibility between the tools to ensure they operate smoothly and are well-integrated within the project framework.

5. Evaluation Plan

To evaluate our work, we can present the identified patterns to Michael, a Parkinson's patient, in various formats, such as visual, textual, or a combination of both. We can then ask him which presentation method is the clearest and most understandable for him and whether the identified patterns are relevant and meaningful to him. Additionally, we can ensure the clarity and understanding of the patterns with various stakeholders (doctors, dietitians, physiotherapists, etc.) to confirm that the results are not only clear and comprehensible but also provide practical insights. In other words, we aim to determine whether conclusions can be drawn from the presented patterns, develop personalized recommendations, and ultimately help Michael significantly improve his quality of life. Furthermore, we can evaluate the work using the metrics of the tools we use (in terms of performance, accuracy, etc.).

References

[1] Bhattacharyya, K. B. (2017). Hallmarks of clinical aspects of Parkinson's disease through centuries. In K. P. Bhatia, K. R. Chaudhuri, & M. Stamelou (Eds.), Parkinson's Disease. International Review of Neurobiology (Vol. 132, pp. 7). Academic Press.

[2] Stanford Parkinson's Community Outreach. (2025). *Stanford University School of Medicine*. Retrieved January 3, 2025.

[3] Ramesh, S. D., & Arachchige, A. S. (2023). Depletion of dopamine in Parkinson's disease and relevant therapeutic options: A review of the literature. *AIMS Neuroscience, 10*(3), 201–203.

[4] Morris, H. R., Spillantini, M. G., Sue, C. M., & Williams-Gray, C. H. (2024, January). The pathogenesis of Parkinson's disease. *Lancet, 403*(10423), 293–304.

[5] Calabresi, P., Mechelli, A., Natale, G., Volpicelli-Daley, L., Di Lazzaro, G., & Ghiglieri, V. (2023). Alpha-synuclein in Parkinson's disease and other synucleinopathies: From overt neurodegeneration back to early synaptic dysfunction. *Cell Death & Disease, 14*(3), 176, 1–5.

[6] Bie, R. M., Clarke, C. E., Espay, A. J., Fox, S. H., & Lang, A. E. (2020, March). Initiation of pharmacological therapy in Parkinson's disease: When, why, and how. *Lancet Neurology, 19*(5), 452–461.

[7] Ahlskog, J. E. (2011, July). Does vigorous exercise have a neuroprotective effect in Parkinson disease? *Neurology, 77*(3), 288–294.

[8] Bohanec, M., Miljković, D., Valmarska, A., Mileva Boshkoska, B., Gasparoli, E., Gentile, G., Konitsiotis, S. (2018). A decision support system for Parkinson disease management: expert models for suggesting medication change. *Journal of Decision Systems*, *27*(sup1), 164–172. <https://doi.org/10.1080/12460125.2018.1469320>.

[9] Titova, N., & Chaudhuri, K. R. (2017). Personalized medicine in Parkinson's disease: Time to be precise. *Movement disorders : official journal of the Movement Disorder Society*, *32*(8), 1147–1154. [https://doi.org/34.1002/mds.27027](https://doi.org/10.1002/mds.27027)

[10] Coelho, B. F. O., Massaranduba, A. B. R., Souza, C. A. d. S., Viana, G. G., Brys, I., & Ramos, R. P. (2023). Parkinson’s disease effective biomarkers based on Hjorth features improved by machine learning. *Expert Systems with Applications, 212*, 118772

[11] Bohanec, M., Miljković, D., Valmarska, A., Mileva Boshkoska, B., Gasparoli, E., Gentile, G., Konitsiotis, S. (2018). A decision support system for Parkinson disease management: expert models for suggesting medication change. Journal of Decision Systems, 27(sup1), 164–172. <https://doi.org/10.1080/12460125.2018.1469320>

[12] Evers, L. J. W., Peeters, J. M., Bloem, B. R., & Meinders, M. J. (2023). Need for personalized monitoring of Parkinson's disease: the perspectives of patients and specialized healthcare providers. Frontiers in neurology, 14, 1150634. <https://doi.org/10.3389/fneur.2023.1150634>

[13] J. Cancela, M. Pastorino, M. T. Arredondo, and O. Hurtado. 2013. A telehealth system for Parkinson’s disease remote monitoring. In Proceedings of the 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). 7492–7495.

[14] Zhang, K., Xu, P., & Zhang, J. (2020, October). Explainable AI in deep reinforcement learning models: A shap method applied in power system emergency control. In *2020 IEEE 4th conference on energy internet and energy system integration (EI2)* (pp. 711-716). IEEE.‏

[15] Lundberg, S., & Lee, S. (2017). A unified approach to interpreting model predictions. *CoRR, abs/1705.07874*.

[16] Hossain, M. I., Zamzmi, G., Mouton, P. R., Salekin, M. S., Sun, Y., & Goldgof, D. (2023). Explainable AI for Medical Data: Current Methods, Limitations, and Future Directions. *ACM Computing Surveys*.‏

[17] Mane, D., Magar, A., Khode, O., Koli, S., Bhat, K., & Korade, P. (2024). Unlocking machine learning model decisions: A comparative analysis of LIME and SHAP for enhanced interpretability. *Journal of Electrical Systems*, *20*(2s), 1252-1267.‏

[18] Singhal, S., & Jena, M. (2013). A study on WEKA tool for data preprocessing, classification and clustering. *International Journal of Innovative technology and exploring engineering (IJItee)*, *2*(6), 250-253.

[19] Baytaş, İ. M., Peng, Y., & Özgür, A. (2023). Editorial: Pattern recognition for healthcare analytics. *Frontiers in digital health*, *5*, 1186713. ‏

[20] (August 22, 2024) *Introduction to Weka: Key Features and Applications*<https://www.geeksforgeeks.org/>.

[21]Cervantes, J., Garcia-Lamont, F., Rodríguez-Mazahua, L., & Lopez, A. (2020). A comprehensive survey on support vector machine classification: Applications, challenges and trends. *Neurocomputing, 408*, 189-215. <https://doi.org/10.1016/j.neucom.2019.10.118>.