Predicting Enuresis Treatment Outcomes with the Help of AI

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***Abstract*—15% of all five year olds and 5-10% of all 7 year olds struggle with bedwetting, a condition medically known as enuresis. Current treatment methods rely primarily on the family to carry out an 8 week treatment. In order to involve healthcare providers in the process and create an opportunity for individualized treatments, Pjama AB has developed an enuresis alarm system. This system directly shares patient data with nurses through a patient portal. Throughout this project, data collected employing Pjama alarm systems is analyzed with the help of AI classifiers in Python. Classifiers when trained on patient data curated predictions concerning the outcome of a patient's enuresis treatment with an accuracy of up to 90%. Further analysis needs to be done on predictions made with trained classifiers in order to reveal at which point in the treatment predictions are reliable. However early observations indicate that this point lies somewhere around 2 to 3 weeks into the treatment. Previously information surrounding treatment outcome could only be concluded after the 8 week treatment period was over. Being able to foresee an outcome of a patient treatment after roughly 2-3 weeks not only involves healthcare providers in the treatment process but simultaneously allows them to individualize patient treatments. In the case of unsuccessful patients, treatments can be halted at 3 weeks instead of 8 saving families weeks of sleepless nights. The hope is that overtime, individualizing treatments early in the treatment period will increase the number of patients which reach a successful outcome and simultaneously make the treatment process easier for families.**

I. Introduction

BEDWETTING, enuresis, is one of the most common health problems among children worldwide, in Sweden it is the second most common condition after asthma. Enuresis is defined as the involuntary discharge of urine. Nocturnal enuresis is most prevalent as circa 15% of all five-year-olds and 5-10% of all 7-year-olds wet the bed, boys make up two thirds of these children [1]. As a child, suffering from enuresis (bedwetting) it often means avoiding activities in which overnight stays are involved. Due to the constant obstacle that enuresis poses, these individuals are at a high risk for developing poor self-esteem, anxiety and stress. When introduced at a young age these factors have the ability to affect the child's social development.

Currently enuresis is treated using two methods, an enuresis alarm or a Desmopressin hormone treatment. Initially treatments are performed with an enuresis alarm. With this system the child activates a sensor when they urinate which in turn causes an alarm in the room to sound, waking the child. Over time the child should learn to wake up before they urinate. Treatments utilizing the bedwetting alarm continue for at least 6 weeks and are often continually used for 2-3 months. This time period is defined by Swedish standards for enuresis treatments which state that the first treatment evaluation can be done after 6 weeks [2]. If the enuresis alarm fails to cure a child, which occurs in 40% of cases, the hormone Desmopressin is introduced [3]. However Desmopressin is not curative, it is solely a temporary solution [1].

Both treatments mentioned above rely almost solely on the patient's family in conducting the treatment and can be an enormous strain on both them and the patient [1]. Pjama AB is a Malmö based company that aims to minimize the strain that enuresis treatment causes for patients and their families. The company has developed an enuresis alarm system that allows families to collect data during the enuresis treatment in hope of tying healthcare providers into the treatment process. Data points such as the distribution of wet to dry nights and time of night when the urination takes place are collected. Throughout the treatment a database of information is built up surrounding each patient.

As of today Pjama AB enuresis alarms have been actively collecting patient data for two years and exist in more than half of Sweden's healthcare regions. This has resulted in large databases of information which have never existed before, their existence opens up an opportunity for data analysis.

A. Project Outline

This project will analyze Pjama AB patient data with the help of artificial intelligence(AI). Data from inactive patients, those who have completed their treatments, is to be studied for possible patterns and trends. Patterns in the data that are found to affect the final outcome of a treatment will be used to curate predictions regarding the treatment outcome of future patients.

Patients will first be separated into four outcome groups based upon their treatment progression and eventual outcome. These four groups are successful, partially successful, unsuccessful and dropout. Their data will then be analyzed in order to identify what data patterns result in a successful, partially successful, or unsuccessful treatment. Throughout the process it will also be especially important to be able to identify patients which are dropouts. This in order to implement measures to change the course of their treatment and simultaneously reduce the number of patients which drop out of the treatment process.

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A prediction as to the outcome of the patient treatment is first made before the treatment process begins. This prediction will be based on the answers to a 23 question survey that patients took before their treatment process began. The questions were formulated by Pjama AB with the help of Tryggve Nuveus, Professor at Department of Women's and Children's Health, Paediatric Inflammation, Metabolism and Child Health Research Uppsala, in order to gain information surrounding the patient's enuresis profile. After this initial prognosis a prediction concerning treatment outcome and dropout risk will be made every day throughout the treatment process. Subsequently allowing healthcare professionals to observe the daily progression of patients.

The ability to predict the outcome of a treatment will not only allow nurses to be a part of the treatment process but simultaneously allow them to individualize patient treatments. Healthcare providers will have the ability to monitor patient progress, assist in diagnosis, and determine which treatment method is best suited for each patient. If a patient is predicted to be a dropout the nurse may check in with the family to motivate them. The aim is to be able to make these changes earlier in the process than the now standardised 6 weeks. This will give patients a greater chance at reaching a successful treatment outcome and allow unsuccessful patients to quit the stress inducing treatment earlier. An individualized treatment will in this way give each patient a greater chance at reaching a successful treatment outcome.

This report will first explain how enuresis data analysis is performed with the help of Python code and AI. Results and implementation of the code will be presented thereafter in order to highlight how predictions can be utilized in a patient treatment.

II. Method

A. Classifying patients - manual

To begin the analysis of data, all patients which have completed their treatment are manually separated into four groups. These groups represent four possible outcomes of the enuresis treatment. Groups are defined according to the following criteria:

1) Successful treatment criteria: 14 consecutive dry nights, this must occur within 12 weeks of treatment. A first progress evaluation is made after 8 weeks, if needed the treatment can be extended to 12 weeks.
2) Partially successful treatment criteria: Wet nights even after 8 weeks. The number of wet nights during week 7 and 8 is at most 50% of the same number during the first 2 weeks
3) Unsuccessful treatment criteria: Wet nights even after 8 weeks. The number of wet nights during week 7 and 8 is more than 50% of the same number during the first 2 weeks. At least four days of data are registered during week 8.
4) Dropout criteria: The patient / family does not report data in the portal. No data registered for 7 consecutive days, no registered data week 8 and at least 1 week active data reporting.

B. Initial Evaluation

A 23 question survey has been answered during each patient registration. The first step in patient data analysis is to organize the collected answers in a pandas dataframe. The data points are answers to questions such as:

1) Child birth date
2) Child gender
3) How many nights a week does the child wet the bed?
4) Has the child tried treatment with an enuresis alarm before?
5) Does your child usually wet once or twice during a night?

The results from the completed surveys must be sorted and controlled for missing values. Data points that are not considered to be predictors of treatment outcome, e.g. e-mail, are removed from the data set. The data which remains is stored in different formats, some in text form, and the majority as integers. All data points which are stored as text are subsequently substituted with integers. This through means such as changing all "yes" data points to ones and all "no" data points to zeros. This change produces a dataframe with a homogeneous data type.

The final step in organizing the data is replacing missing values with one of three options: the mean value of patient answers, patient data from the previous day or values taken from similar patients. Patient treatment outcome is then added, completing the dataframe. It is this detail which separates each patient data set into one of the four classes.

AI averaging algorithms are then used to create predictions surrounding the outcome of patient treatments. This algorithm is referred to as a classifier and specializes in using existing data sets in order to separate new data into categories. [4] In this case classifiers are trained to recognize patterns within the data set of 23 questions that contribute to the outcome of a patient treatment.

The best classifier for a data set depends on the nature of the relationship between data points in a specific data set. When initiating the classification of patient enuresis data, the nature of the relationship between data points is unknown. This unknown relationship implies that several types of classifiers have to be tested on the data to determine which of them is the best match. Six different classifiers (Decision Tree, Random Forest, KNN, Logistic Regression, SVM and Naive Bayes) are trained using patient data, in this case the 23 questions in order to identify treatment outcome.

The four different outcomes can be separated into two groups. Patients which are dropouts and those which are not. In the case of dropout patients one classifier is trained to identify if a patient risks being a dropout or not. Those which are not dropouts (successful, partially successful, and unsuccessful), are tested using two methods. In method one, three classifiers are trained, each specializing in recognizing patterns for one specific outcome. For instance, one classifier is asked the question "will this patient be partially successful or not partially successful?". In method two, one classifier is trained to recognize all three outcomes. To illustrate, "will this patient be successful, partially successful or unsuccessful?".

These methods will be referred to as ”Method 1” and ”Method 2” throughout the text.

The testing of classifiers produced through Methods 1&2 is done by first splitting the input data set into two groups, 70% for training and 30% for testing. The classifiers are then trained to recognize patterns in the training data. The trained classifier is then introduced to the 30% test set. The predictions that the classifiers make concerning the treatment outcome for a patient are compared to the factual result and each classifier is subsequently evaluated for its ability to predict the correct outcome. The classifier which has the highest prediction accuracy score is used during implementation of the code into the patient portal.

C. Data evaluation as treatment begins

The next step in the process is to evaluate the data that has been collected after the treatment process has begun. Each night during the 8 week treatment parents enter the following information into the Pjama app:

1) When did the child go to bed?
2) Did the child wet the bed? (Dry, Wet, Very Wet)
3) If the child wet the bed, What time?
4) Did the child wake up by the alarm or did the parents have to wake the child?
5) Technical problem?

All data from the initial 142 patients over 8 weeks is mixed together in such a way that the information within can not be understood. The first task is to organize the data into a comprehensible dataframe. The organization process begins with the same steps explained above, deletion of data points which have been deemed irrelevant, and conversion of text to integers.

The dataframe now contains only relevant data points expressed as integers. To further organize the information a new column is added to the dataframe which calculates the date that each data point was created.

Utilizing the newly created date column, all information registered to the patient on day one of the treatment is recorded in the new dataframe under the 19 specified columns for day one (Table I). The process is then repeated for each day through day 56 (8 weeks). This same process is now repeated for all patients.

TABLE I: Explanation of a few of the 19 data points recorded each day.

	Explanation of data point
14 days wet rolling	Number of wet days within the last two weeks.
14 days dry rolling	Number of dry days within the last two weeks.
Enuresis latency	Time of night when urination occurred.
Wet second time	Did the child urinate twice.

While transferring information from one dataframe to another there sometimes happen to be missing values. These missing values are managed in distinct ways depending on which data point it is. These were either replaced with mean values, the value from the night before or values taken from similar patients.

Enuresis latency (the time at which the child urinates during the night) is predicted to be an indicator of the progression of the treatment. Due to this extra care is taken in predicting cases where enuresis latency is a missing value. The first step in curating an accurate prediction is to find the patients with the most accurate data sets, in other words those patients with the least amount of missing values. The times at which these patients urinated during the night is then plotted against the outcome of their treatment. The pattern which emerges within these plots determines how enuresis latency is to be predicted.

If a pattern emerges an algorithm must be curated so that predicted values follow the pattern and do not become outliers. If a pattern does not arise enuresis latency can be randomly predicted within a reasonable range with the use of functions such as KNN-imputer [5].

Following the revision and organization of data points the dataframe is then combined with the dataframe containing each patient’s answers to the 23 survey questions. This process creates a large dataframe containing all collected data about every patient over their completed treatment.

Classifiers are then created for the data using both Method 1 and Method 2. To train these classifiers the data set is separated into two groups as done for the 23 questions. 70% of the data is used to train different types of classifiers. Once the classifiers are trained they are then tested on the remaining 30% of the data.

In order to increase accuracy scores of all classifiers the data set is balanced. The four classes (successful, partially successful, unsuccessful and dropout) contain differing amounts of patients, with the class dropout containing the majority. This is referred to as an imbalanced data set. If the distribution of classes is not uniform among samples the prediction of AI classifiers will often lean towards that of the majority classes [6].

To balance the data set two different methods are tested, RandomUnderSampler and SMOTE (Synthetic Minority Oversampling Technique). Utilizing RandomUnderSampler the majority groups are identified and reduced to the size of the smallest group by randomly removing patients from the larger groups. When using SMOTE samples of the majority class are counted and synthetic patients are created for the minority classes until they have the same amount of occurrences as the majority class [7]. Receiver Operating Characteristic-curves (ROC-curves) are plotted to examine which of the two methods give the highest prediction accuracy.

After balancing of the input data, classifiers are retrained using the 70 - 30 method described above. However in this case they are trained on differing amounts of data. One classifier is trained for each day of the treatment process. The first being trained on only patient data from day one and the last classifier being trained on 56 days of data. The classifiers trained for day one are used to predict the patients outcome after day one, the classifiers trained for day two predict outcome after day two and so on. Outcome predictions are then made for every patient every day.

D. Classifying patients - code

Separation of inactive patients into the four outcome classes was previously done by hand. A code is now written to simplify the process. This is done by importing three parameters for each patient for each of the 56 days. The parameters are, how many wet and dry nights there have been the last 2 weeks and whether there is data missing that day. Using this information the patients can now be classified according to the criteria stated in Table 1.

E. Implementation

The code which is written throughout this project is then implemented into the Pjama portal giving healthcare providers access to a myriad of new functions.

F. Prediction analysis

In order to discover initial trends regarding at which point in the treatment predictions are reliable, the Pjama portal was used. A number of patient profiles of those which have completed the treatment process were selected. The presented prediction graph was then manually observed. This in order to try to find a trend in the point of time at which the prediction matched the true treatment outcome.

III. Results

A. Initial evaluation

The following data presents the accuracy of each classifier in predicting the correct treatment outcome of a patient. Table 2 presents data obtained using classifier Method 1, Table 3 presents data obtained using classifier Method 2. In both cases the Random Forest classifier produces the most accurate predictions.

TABLE II: Accuracy scores for each outcome and classifier for the initial 23 questions using classifier Method 1.

	Successful	Part. succ.	Unsucc.	Dropout
Decision Tree	0.7674	0.8139	0.7441	0.6744
Random Forest	0.7906	0.7906	0.7674	0.7674
KNN	0.6511	0.7906	0.7674	0.7674
Logistic Regression	0.6046	0.7906	0.6976	0.6976
SVM	0.6511	0.7906	0.6976	0.7441
Naive Bayes	0.3953	0.3720	0.4651	0.7209

TABLE III: Accuracy scores for each outcome and classifier for the initial 23 questions using classifier Method 2.

	Succ., Part. succ., Unsucc.	Dropout
Decision Tree	0.6129	0.6744
Random Forest	0.6207	0.7674
KNN	0.4516	0.7674
Logistic Regression	0.4516	0.6976
SVM	0.4516	0.7441
Naive Bayes	0.3953	0.7209

B. Results of data evaluation as treatment progresses

The graphs in Figure 1 represent the plotted enuresis latency of 40 patients. Observing these graphs it becomes clear that the only obvious pattern to emerge in the enuresis data is that successful patients do not wet the bed as often in the later weeks of the treatment. The time of night when the child wets the bed seems to have no correlation to treatment outcome in this data set. Due to this all missing enuresis latency values in the data set were predicted with the help of KNN imputer.

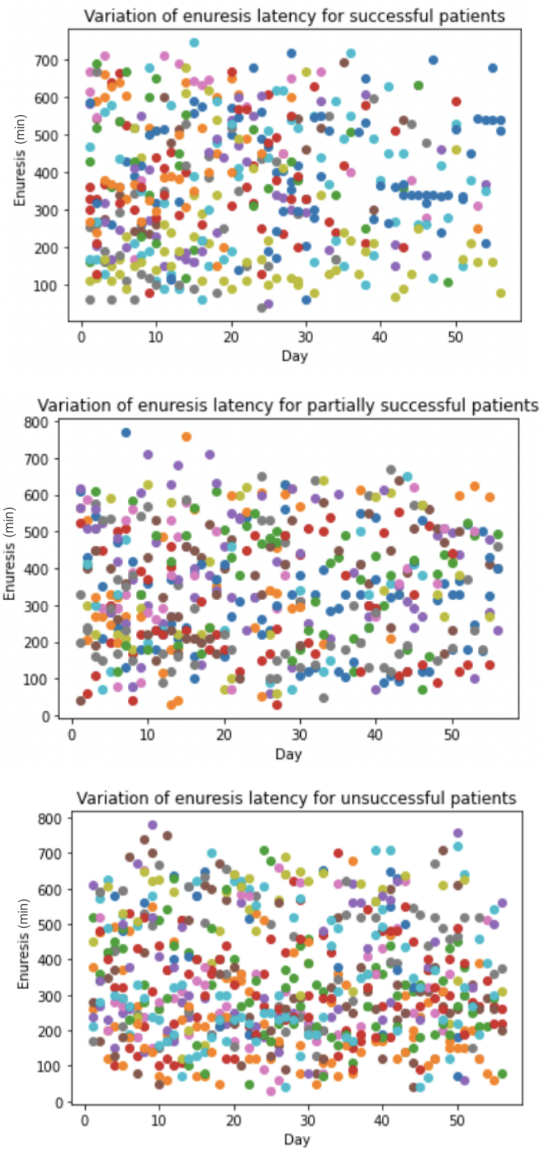

Fig. 1: Plot of enuresis latency where each color represents a patient. A point is plotted on the graph on those days that the patient wet the bed and represent the time of night when the accident occurred.

As all patient data now is organized and missing data is filled in the best possible manner, classifiers can now be tested. Table 4 contains the data captured when classifier Method 1 is used. The prediction accuracy of each classifier highlights that the Random Forest classifier has the highest rate of success throughout the different categories and days. Table 5 contains the predictive accuracy of Random Forest classifiers when classifier Method 2 is used. Here only Random Forest is tested as it has already been confirmed as the classifier which best fits the data set.

TABLE IV: Accuracy scores for each outcome and each classifier for the daily questions created utilizing Method 1.

Successful	All days	Day 1	Day 3	Day 5	Day 7
Decision Tree	0.8372	0.7441	0.7441	0.6744	0.6976
Random Forest	0.8604	0.8372	0.7906	0.7441	0.7674
KNN	0.8139	0.6279	0.7209	0.6744	0.6279
Logistic Regression	0.5348	0.7674	0.7441	0.6511	0.6511
SVM	0.7674	0.8372	0.7906	0.6976	0.7674
Partially successful	All days	Day 1	Day 3	Day 5	Day 7
Decision Tree	0.6976	0.7674	0.6511	0.6511	0.7441
Random Forest	0.8837	0.8139	0.8139	0.8372	0.7906
KNN	0.7674	0.7906	0.8139	0.8139	0.7441
Logistic Regression	0.8139	0.7674	0.7209	0.7674	0.7441
SVM	0.7441	0.8139	0.6744	0.7209	0.7209
Unsuccessful	All days	Day 1	Day 3	Day 5	Day 7
Decision Tree	0.7209	0.6976	0.6744	0.7209	0.6511
Random Forest	0.7906	0.7441	0.7441	0.7441	0.7441
KNN	0.7441	0.6744	0.7674	0.7906	0.7441
Logistic Regression	0.5581	0.7674	0.6744	0.7674	0.6976
SVM	0.6279	0.7906	0.6279	0.7674	0.6744
Dropout	All days	Day 1	Day 3	Day 5	Day 7
Decision Tree	0.9066	0.6976	0.6279	0.6046	0.6976
Random Forest	0.9069	0.7674	0.6511	0.7906	0.7674
KNN	0.8372	0.6744	0.7997	0.6976	0.7674
Logistic Regression	0.8604	0.7674	0.6744	0.7441	0.6744
SVM	0.8129	0.7906	0.6976	0.6511	0.7209

TABLE V: Accuracy scores utilizing classifier Method 2 on all patient data.

Successful, Partially successful, & Unsuccessful	All days	Day 1	Day 3	Day 5	Day 7
Random Forest	0.6451	0.3548	0.3870	0.3548	0.2903
Dropout	All days	Day 1	Day 3	Day 5	Day 7
Random Forest	0.9069	0.7674	0.6511	0.7906	0.7674

C. Undersampling and Oversampling

The ROC curves (Figure 2) show the true and false positive rates for the three classes successful, partially successful and unsuccessful. The area under the curve represents how capable the model is of identifying each class (Table 6).

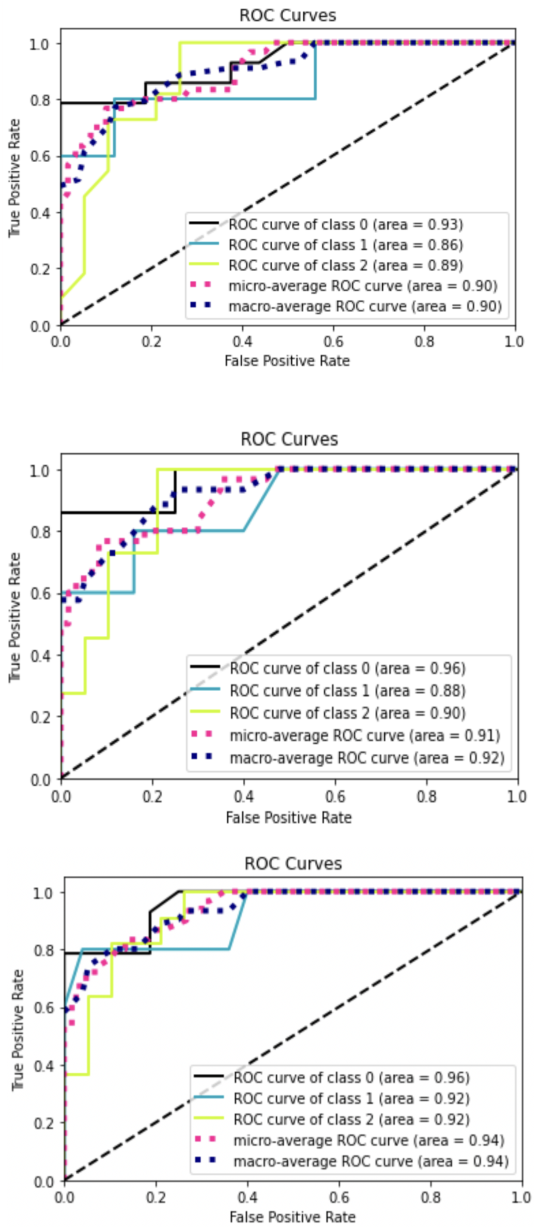

Fig. 2: ROC curves for one of the classifiers where class 0 is successful, class 1 partially successful and class 2 unsuccessful. From top to bottom; Imbalanced, Undersampled, Oversampled.

TABLE VI: Comparing degree of separability for each outcome in the two classifiers for finished treatments before and after balancing the dataset.

	Successful	Part. succ.	Not succ.	Dropout
Imbalanced	0.93	0.86	0.89	0.97
Undersampled	0.96	0.88	0.90	0.98
Oversampled	0.96	0.92	0.92	0.97

D. Implementation

The new implemented functions allow healthcare professionals to be a part of the enuresis treatment process in a way that has not been possible before.

New functions include :

- Re-training the Random Forest classifiers as new patients finish the treatment process - The original code written throughout this project is utilized to retrain the classifiers on a greater amount of data.
- Predicting the treatment outcome for a specific patient - Trained classifiers are used to make predictions using data from the specified patient each day.
- Predicting the treatment outcome for all active patients - The process above is executed on all active patients.
- Classifying newly treated patients into one of the four outcomes (successful, partially successful, unsuccessful, and dropout).

Results of patient outcome predictions are presented as both a bar graph and a line graph over the days which they have been active (Figure 3). The prediction made for the most plausible outcome after each day is represented as a color in the bar graph. If on day one the data points towards a successful treatment, the bar on day one will be green. If the prediction leans towards a partially successful outcome - a yellow bar, unsuccessful - red bar and dropout - gray bar. Simultaneously a line graph will track the probability for each treatment outcome throughout the treatment (Figure 4). In order to clearly display the current predicted outcome of the treatment a traffic light will highlight the color of the predicted most probable outcome (Figure 3).

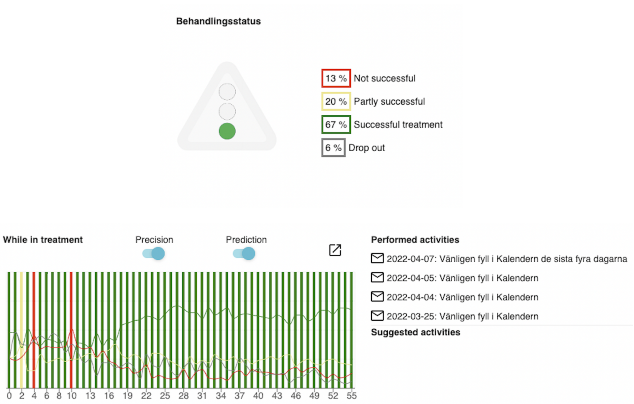

Fig. 3: Image of the patient portal that will be displayed for nurses.

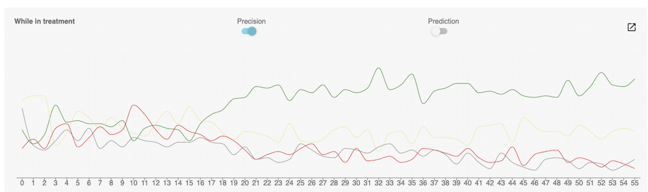

Fig. 4: An mage of the web portal which highlights the predictions made for each day. The red line correlates to probability of an unsuccessful treatment, the yellow - partially successful treatment and the green - successful treatment. As seen in this example the patient is clearly predicted to achieve a successful outcome around day 21.

As predictions are made each day healthcare providers will be given suggestions as to what can be done to achieve the best possible results. Active suggestions can be seen under “Suggested activities” (Figure 3). If a patient has stopped registering data over a number of days and therefore is predicted to become a dropout, healthcare providers may be urged to send a motivational message to the family.

E. Prediction analysis

Observing the patient profiles in the Pjama portal gives an early indication that accurate predictions are made 2 to 3 weeks into the treatment.

IV. Discussion

Early indications show that the code produced in this project may be able to predict a trend in patient data after approximately 2-3 weeks. Predictions based upon these trends may enable healthcare providers to make informed decisions about a patient treatment early in the process.

As described above two methods were used to train classifiers, creating predictions using classifier Methods 1 & 2. The resulting accuracy of the Method 2 was much lower than that in the Method 2 (Table 3 & 4). This outcome stems from the fact that the AI classifier has to identify three different outcomes instead of one, making the chance of guessing the correct outcome circa 33% instead of 50%. However the decision was still made to use the two classifier method (Method 2) primarily because results are presented in a more comprehensible manner. Nurses are clearly presented with 3 predictions which add up to 100%, giving a clear image of the patient’s treatment outcome. Although Method 1 gave a higher accuracy score, it was concluded that it was of greater importance that healthcare providers could understand the information presented to them.

When implementing Method 1, the code written above may allow healthcare providers to predict the correct outcome of a patient enuresis treatment with an accuracy of 29.03% - 64.51%. The lower accuracy scores occur in the early days of the treatment as there is not much data to base predictions on. As the treatment progresses more data is added bringing the predictive accuracy up to 64.51%.

However it can be discussed whether 64.51% accuracy is ideal for making medical predictions. An explanation for the low success rate can be attributed to a number of different factors. The first factor being that all collected data points are not relevant in predicting treatment outcomes. Signs of non relevance have been detected in the data point enuresis latency. Initially enuresis latency was thought to be a significant predictor of treatment progression yet a closer inspection (Figure 1) revealed that there is no clear correlation shown between urination time and treatment progression. In the future, points such as this one may not be included when calculating outcome predictions in order to increase the accuracy of the classifiers and simultaneously increase the ease of data registration for families.

An alternate factor which may be contributing to low prediction accuracy is an inadequate data volume, both in terms of missing data and patient quantity. Missing data points were replaced using varying methods. However these replacement data points are not entirely accurate representations of patient data, and may therefore have swayed predictions. A lack of patients may also have contributed to low accuracy as the classifiers simply may not have enough input to detect an accurate data pattern and create an AI prediction.

The consequences of the information deficiency described above will wane as time progresses. Prediction accuracy should rise as more patients join the treatment as classifiers will have access to greater amounts of information to be trained on and later base predictions on. Over time prediction accuracy has a high probability of improving resulting in a more reliable system for healthcare workers.

Classifiers trained to make predictions concerning dropout patients are made in the same way throughout both methods. This is primarily due to the importance of high predictive accuracy in identifying potential dropouts. The changes above will also help to raise the accuracy of dropout predictions. A majority of patients end up being dropouts making it essential to identify patients which are headed to this outcome. Predictions made in the Pjama portal will give healthcare providers the tools to identify these patients early. If the patient is likely to be a dropout, they can contact the family and sort out what the cause is. Are they having technical problems? Do they lack motivation? Investigating subjects like these and solving them may lead to the patient continuing the treatment. Hopefully giving more patients a chance at curing their enuresis.

Initial observations made using the Pjama portal highlight that nurses may even be able to foresee the outcome of patient's enuresis treatments after approximately 2-3 weeks. However the way in which the result was achieved, observing patient profiles in the portal, is not the most accurate way of achieving results. In order to confirm the initial conclusion above more analysis will need to be done concerning predictions made on new patients.

Before the Pjama portal was developed, health care providers were unaware of how their patients' treatments were progressing over long periods of time. Implementation of this system will enable daily observations and may subsequently allow healthcare providers to make informed decisions about individual treatments. This would be an extreme improvement to previous treatment methods in which healthcare providers were not involved in the process at all.

If a treatment is predicted to be unsuccessful or partially successful an informed decision may be made to introduce Desmopressin earlier into the treatment than the now standardised six weeks. Early observations indicate that this might be at 2-3 weeks into the treatment, however more studies are needed to confirm that this course of action is the best one for the patient. If a treatment is predicted to be unsuccessful, an informed decision may be made to discontinue the treatment. This would allow the families of these patients to return to a normal night-time routine. In theory if the enuresis alarm is not working for the patient there is no need to complete 8 weeks of waking up to an alarm in the middle of the night if the treatment will not help the patient. The hope is that treatments can be individualized to the point were they are as effective as possible, benefiting both the patient and family.

A. *Ethics*

Every patient deserves access to the best possible healthcare. Predictions made within the Pjama portal are a big step in the right direction in terms of giving enuresis patients access to better care. Healthcare providers will gain access to information that may enable them to fully change the course of certain patient treatments. If more time and focus is placed on each patient they may have a higher chance at succeeding.

As previously mentioned, better care often leads to more successful treatments. A successful treatment may lead to a decrease in patient disorders associated with enuresis such as anxiety, stress and poor social development. Success would simultaneously relieve patient families of a major burden. The hope is that the implementation of daily predictions will allow more patients and families to release the stress that enuresis often causes.

B. *Sustainable development*

As mentioned above there is a hope that disorders and stresses associated with enuresis will eventually decrease. If greater amounts of children were to achieve a successful treatment there would hopefully be a simultaneous positive affect on society as a whole. This due to a better general mental health among children and a lightened stress on their families. In this way individualized treatments with the help of predictions would be working towards a more positive sustainable social society. Fewer enuresis patients would also reduce household waste. "It's estimated that in an average household with children who wear diapers, disposable diapers make up to 50% of household waste" [9]. An increase of successful patient treatments would decrease the diaper usage among these families thus reducing the amount of diaper waste which ends up in landfills. The hope is that use of predictive analysis within enuresis treatments will eventually contribute to a more sustainable society both in terms of mental health and diaper waste production.

V. Conclusion

Early observations have lead to the conclusion that treatment predictions may become a reliable indicator of treatment outcome after roughly 2-3 weeks. The next step is to prove this observation through further analysis of predictions within a larger study. The ability to produce predictions may allow health care providers to make informed decisions regarding the individualization of each patient's treatment process. Instead of a family struggling through the treatment for 8 weeks on their own, they will now be able to receive individualized treatment advice. Our hope is that the predictive capabilities of the Pjama portal will change the way enuresis treatment is conducted in the future.

VI. Epilogue

Thank you to Kalle Åström and Christian Balkenius for your guidance concerning machine learning and Tryggve Nevéus for bringing us your knowledge regarding enuresis. A special big thank you to Torbjörn Gärdenfors who has supported and guided us throughout this project with his expertise and encouragement.

The labor within this thesis has been distributed evenly between Mia Johnson and Klara Halling as they worked together in the early stages of the project but worked more independently as they gained knowledge within Python and patient data. Even as work was completed independently they were involved in each others work throughout both the programming and writing process.

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