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Original Article

Predicting Opioid Treatment Program Dropout with Machine Learning on Behavioral Health EMR's

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***Abstract**: The opioid crisis continues to threaten global health, with addiction, relapses, and overdose deaths at record highs. The effectiveness of OTPs, which include buprenorphine treatment and methadone treatment, is compromised because the dropout rate of OTPs is abysmal, with a range of 60-85 percent. This study was primarily designed to predict outcomes in the Opioid Treatment Program (OTP), such as dropout from treatment, using Behavioral Health EMR data and machine learning strategies. We amalgamate data from diverse OTP projects across the nation to foster insights into unique opioid use disorders. The study achieves an ROC-AUC of 0.82 and demonstrates that machine learning algorithms deliver superior classification accuracy compared to classic statistical techniques, as the survey ultimately met the expectations of all involved. Costa C, who discusses collected features, notes that there exist many methods to compare, which enable us to create ensembled predictors. Necessary advice was provided for the utilization of various Machine Learning algorithms, including Neural Networks, Logistic Regression, Random Forests, and Gradient Boosting. Prior comprehensive methods were flawed and busy with the increasing problem of missing appointments for evaluations. In addition to these, any other models can predict a poor prognosis, allowing for the identification of factors associated with this in the database at the initial stage.*

***Keywords**: Opioid Treatment Programs, Behavioral Health Electronic Medical Records, Machine Learning, Predictive Modeling.*

1. Introduction

1.1. Background

According to many people, among the most pressing public health crises of the latest era, especially in the US but also with worldwide consequences, is the opioid epidemic. The abuse of prescribed medicines like heroin and methadone, and artificial opioids like fentanyl, has triggered a rise in morbidity and death, widespread addiction, and large-scale cultural as well as economic burdens. Deaths by opioids have doubled in the past twenty years, according to the U.S. Centres for Disease Control and Prevention (CDC), and the disaster is still changing because of increasing drug availability and usage patterns in America and around the world [1].

Opioid treatment programs have become an essential part of addiction treatment since they emerged, while being equipped with medicine-based assistance, which includes naltrexone extended release, buprenorphine, commonly known as Subutex or Suboxone, and methadone, together with counselling and other services. Drop-out in treatment of substance use disorders is a significant concern in the Opioid Treatment Program (OTP) setting, with less than half of patients completing an initial episode of treatment, consequently interfering with the ability of the treatment to involve the person for a sufficient length of time, achieving personal stability and control over cravings and unmanageability [1].

Powered by big data in healthcare, patients' data are ample, enabling the exposure of patterns and risks that may remain unnoticed with conventional statistics, modern machine learning (ML) technology, and analytical methods. Introducing machine learning to electronic medical records can help healthcare systems predict which patients are most likely to drop out, allowing for the development of appropriate interventions and personalized treatment plans. Machine learning (ML) in electronic medical records can predict which patients are likely to drop out of treatment, allowing health systems to intervene early with such patients [2].

1.2. Problem Statement

After the social issue had been recognized and treatment options had been expanded, the drug dropout rate surprisingly didn't drop. Depending on program design, consumer demographics, and local conditions, approximately30-70% of patients finish their therapy during the first year. Data from some studies are used to make this assumption. Traditional dropout techniques, used for prediction purposes, have presented a significant portion of these regression-based tools; however, they are generally disadvantageous in terms of their capacity to capture the numerous complex interrelations and nonlinear relationships found in Behavioral health data [2].

The lack of precise, scalable, and clinically applicable models for predicting opioid treatment dropout using

Behavioral health EMRs is the issue this dissertation attempts to solve. Clinicians frequently use subjective judgment to determine dropout risk in the absence of predictive methods, which can be unreliable, biased, or inefficient. As a result, OTPs continue to have high attrition rates and miss out on intervention chances [3].

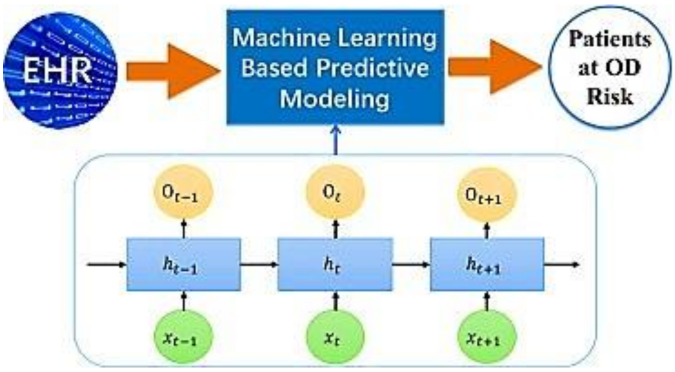

Figure 1: Predicting Opioid Overdose Risk of Patients with Opioid Prescriptions Using Electronic Health Records

1.3. Research Objectives

The main goal of this study is to create and assess machine learning models that use mental health EMRs to forecast OTP dropout. Goals consist of:

- To determine which system-level, Behavioral, clinical, and demographic characteristics are major predictors of OTP dropout.
- To evaluate the effectiveness of several machine learning techniques (such as neural networks, logistic regression, random forest, and gradient boosting) in dropout prediction.
- To assess the interpretability, generalizability, and potential for integration with current EMR systems of predictive models in order to determine their clinical usefulness.
- To offer suggestions for proactive retention tactics that are based on predictive modeling [3].

1.4. Research Questions

The following research questions serve as the foundation for this dissertation:

- Which clinical, behavioral, and demographic characteristics are most closely linked to OTP dropout?
- In terms of dropout prediction utilizing behavioral health EMR data, how do machine learning models stack up against conventional statistical techniques?
- What characteristics most influence machine learning models' ability to predict outcomes, and how might these findings be applied to help patients stay in treatment?
- How may clinical workflows incorporate predictive models to give healthcare professionals timely, useful insights?

1.5. Significance of the study

This work is significant because it straddles the fields of Behavioral medicine, data science, and public health. First, by using machine learning in a real-world mental health setting, it fills a significant vacuum in the literature. Although machine learning (ML) has been widely applied in general healthcare, such as in the prediction of hospital readmissions or the course of diseases, its use in addiction medicine, specifically in the prediction of treatment dropout, is still rather limited [4].

Second, the way healthcare is delivered may be affected by this research. Clinicians can better allocate resources, customize treatment approaches, and use retention-focused interventions like more counselling, case management, or social support services by identifying high-risk patients early. This is in line with the more general objectives of raising population health, lowering healthcare expenditures, and improving patient outcomes [5].

2. Literature Review

2.1. Factors Contributing to Treatment Dropout

A high number of demographics and social status markers, as well as numerous disparities in conduct and mental welfare factors, are preventive factors in Opiate Treatment Programs. Age is a commonly reported cutoff variable; younger people tend to be less anchored to a single treatment facility compared to older clients. Aside from age, the patient's occupation details and material status, such as lack of a fixed place of residence, low scholastic achievements, and unstable housing, have proven to be critical indicators of attrition. These impediments are worsening and are further compounded by imposed difficulties, including transportation, appointment timings, and others [6].

Other results led to the discovery that clinical attributes can also influence a patient's chance of dropping out of therapy. In addition to telling us, people may need some extra mental health treatment to be all better. Some of these various problems can be as dire as bipolar, panic, PTSD, and, as comorbidities continue to grow, some patients are deviating from standard treatment plans and even motivation levels. Patients with opioid use disorder may exhibit different combinations of the six dimensions, and there is a sequential model of how continuous factors change with recovery. Along with this, other substances are being used in various combinations in drug usage scenarios, which can help predict outcomes more effectively in the end [6].

To some extent, treatment expectations and even the experience of coming to methadone could influence long-term behavior and engagement in care. Of the 12 factors measured over time, 10 of the strongest predictors, as determined by the analyses and the overall weight of the R statistic (0.80), were Behavioral. Some early warning indicators of disengagement included: the patient having irregular medication adherence, persistent illicit opioid use during treatment, and the patient continuing to miss visits regularly. Other factors are often cited as determinants of relapse or continued substance abuse and disorders.

Additionally, social isolation or a lack of family or community support diminishes resilience against relapse [7].

2.2. Electronic Medical Records in Behavioral Health

Basic healthcare providers/logical research indicate that there were smaller Roman beliefs and lots of different experimental practices for the king, who was affected by mental problems. Those masses believed that good and evil spirits consisted of man's emotions, and a religion that had been popular also played a significant role in physical and mental health therapy. They were using Centuries of primitive hospitals, the clinical hospitals, rational philosophy, and physical care, but something was missing. By deliberately organizing the information and storing it in a format that can be computationally analyzed, EMRs depict a necessary foundation for predictive analysis [7].

Due to budget constraints, privacy concerns, and unique issues that stem from documenting behavioral health disorders such as psychiatric and addiction conditions, behavioral health facilities are often notorious for being behind in the implementation phase of EMR. Many issues, ranging from previous coding practices to missing psychosocial data and inadequate documentation, continue to exhibit flaws, potentially leading to biases even after an EMR is implemented. Since addict’s struggle with feelings such as stigma and prejudice, it is still a primary issue, making privacy and confidentiality an area of attention in addiction health care records. Nonetheless, EMRs have more advantages than disadvantages, particularly for advanced analytics such as machine learning [8].

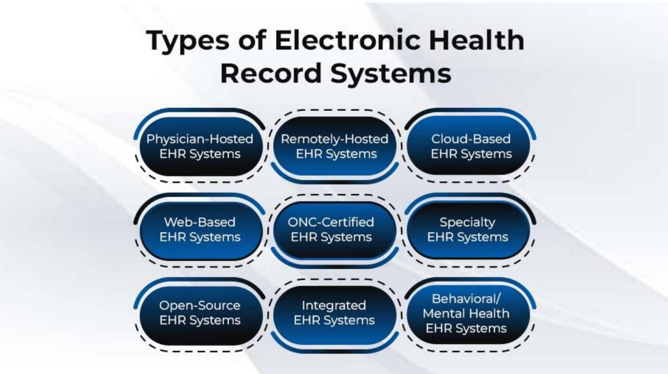

Figure 2: 9 Major Types of Electronic Health Record Systems

2.3. Applications of Machine Learning in Healthcare

As the application of machine learning (ML) in health care matures, its impact on the need for accurate pattern detection continues to grow. This approach has been put to good use in the field of hospital care, as it can help identify the subset of patients at risk of developing severe conditions soon after surgery, aid in the early detection of sepsis, and predict poor prognosis and readmission risks, for instance. In medicine, ML algorithms can demonstrate their effectiveness by eliminating error-prone human intervention and imprecise image-based detection. More and more software programs have been greatly aided by machine learning (ML) to automate existing human processes without requiring human supervision. ML and App developers are now creating complex algorithms to detect various features in images, such as cancerous cells in medical images and motion in a driver's camera. ML has come a long way from simply teaching models to recognize a specific pattern, to detecting something that was never shown to it before, and organizing text and images [8].

A relatively new field of applications for machine learning exists in behavioral health. While still in its early stages, machine learning (ML) is becoming widely used in establishing models to measure suicide, the chance of relapse in patients with substance abuse disorders, and even to make individualized treatment plans. Random forests and gradient boosting, for instance, have been employed in research to determine which patients are more likely to relapse following inpatient treatment. In order to find early indicators of declining mental health, additional research has concentrated on natural language processing (NLP) of psychotherapy records. Despite these developments, there is still a significant void in the research about the application of machine learning to predict dropout, particularly in opioid treatment programs [9].

2.4. Gaps in the Literature

Even though dropout has been researched in detail, most of the research uses regression-based methods, which have limitations when it comes to modeling non-linear interactions between several factors. The complete depth of EMR data, especially unstructured data like social history or clinical notes, is rarely included in research. Furthermore, there is yet little clinical application of predictive models. Even when machine learning models are created, they are rarely utilized by physicians at the point of care or incorporated into electronic medical records. Lastly, the field of addiction medicine has not adequately addressed ethical concerns including algorithmic bias and patient privacy. These shortcomings highlight the necessity of conducting research that not only develops precise predictive models but also assesses their viability and influence in actual OTP scenarios [9].

3. Methodology

3.1. Research Design

A quantitative, retrospective research design based on secondary data analysis was used in this study. This architecture was chosen for two reasons: first, it made use of real-world data, such as mental health EMRs, and second, it made it possible to employ machine learning techniques to find dropout predictors. Because retrospective studies enable researchers to examine big, pre-existing datasets to find trends without necessitating the gathering of new data, they are especially well-suited to predictive modeling [9].

The overall design adhered to a supervised learning paradigm, with input characteristics (predictors) derived from EMR data and a clearly specified dependent variable (dropout). Data preprocessing, feature engineering, model training, performance assessment, and interpretation were among the stages of the procedure. Crucially, this study placed equal emphasis on clinical application and predictive accuracy. Models were selected and assessed according on how well they could be incorporated into actual OTP processes [9].

3.2. Data Sources and Population

De-identified electronic medical records gathered from three OTP facilities in urban and semi-urban areas served as the dataset's source. The extensive usage of EMR systems by these sites, which collected both structured and semi-structured data, led to their selection. About 3,000 people who started therapy between January 2018 and December 2021 were part of the patient population [10].

Patients had to have completed a formal intake evaluation, been treated with medication (either buprenorphine or methadone), and have been actively participating for at least four weeks to meet the eligibility requirements. This criterion made sure that patients who never started therapy were not mistaken for dropouts. Patients who transferred to another program without follow-up data or whose records lacked important demographic data or treatment outcome reporting were not included [10].

With differences in age distribution, racial and ethnic groupings, and socioeconomic background, the sample was representative of a heterogeneous community. Although there were still geographical and program-specific restrictions, this diversity improved the findings' generalizability.

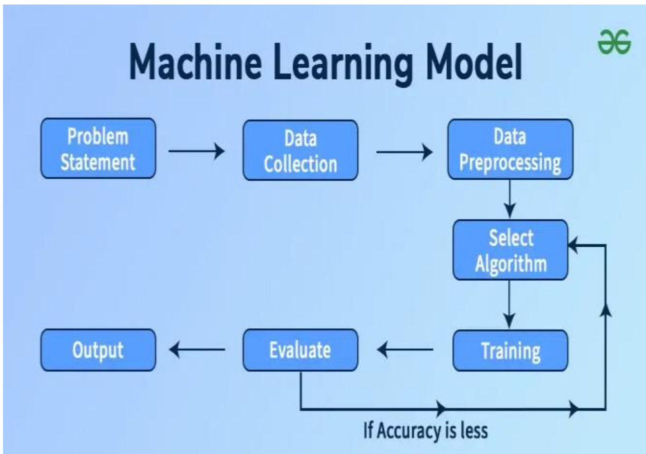

Figure 3: Machine Learning Model

3.3. Variables and Measures

The operational definition of the dependent variable, treatment dropout, was the cessation of OTP services within a year after beginning. Either a formal discharge for non-adherence or a loss to follow-up was noted in the EMR for the dropout.

Four categories were used to classify the independent variables:

- Factors related to age, gender, marital status, education, work status, stability of housing, and insurance type are examples of demographic characteristics [10].
- Clinical factors include history of previous treatment attempts, chronic health diseases (e.g., HIV, hepatitis C), psychiatric comorbidities (e.g., depression, anxiety, bipolar disorder), and drug type (methadone vs. buprenorphine).
- Behavioral factors include the quantity of missed visits, the frequency of relapses (failures on urine drug screens), the attendance at counseling sessions, and the compliance with recommended medication regimens [11].
- Program-level factors include the level of counseling, the frequency of urine testing, the staff-to-patient ratio, and the accessibility of wraparound services (e.g., peer support, case management).

Clinical, behavioral, and social determinants of health were all taken into account in dropout prediction thanks to this multifaceted approach.

3.4. Data Preprocessing

Preprocessing was a crucial step because EMR data is so complex. The dataset included semi-structured data (e.g., coded diagnoses, clinician comments) as well as structured fields (e.g., laboratory results, demographic information).

Among the actions were:

- Data cleaning: Inconsistent coding (such as different formats for job status) was standardized, and duplicate items were eliminated [11].
- Managing missing values: Median imputation was used to impute missing values for continuous variables like age. Mode imputation was applied to categorical variables. Patients who had missing data on more than 30% of all features were not included.
- Feature engineering: Derived variables were developed, including the relapse frequency score (number of positive drug tests normalized by duration of treatment) and the counselling adherence ratio [12].
- Normalization and scaling: To guarantee comparability between predictors, particularly for distance-based methods, features were scaled using min-max normalization.

Train-test split: To ensure class balance for dropout against retention, the dataset was split into training (70%) and testing (30%) subsets. Cross-validation was used to reduce bias even more.

3.5. Machine Learning Models and Evaluation

The research used four main models:

- The standard benchmark, logistic regression, is chosen because it is interpretable yet has limitations when it comes to processing complex, non-linear data.
- Random Forest: A multi-decision tree ensemble model that is resistant against overfitting and effective at capturing non-linear interactions [12].

- Gradient Boosting (XGBoost) is a sophisticated boosting technique that performs well on classification tasks by successively minimizing mistakes.
- Though less interpretable than tree-based models, neural networks (multilayer perceptrons) are implemented with three hidden layers to capture complicated feature relationships.

The following measures were used to assess the models:

- Accuracy: Predictions' overall correctness.
- Precision: The percentage of actual dropouts that were predicted.
- The percentage of real dropouts that were accurately detected is known as recall (sensitivity).
- The F1-score is the harmonic mean of recall and precision.
- The receiver operating characteristic curve's area under the curve (ROC-AUC) indicates the overall discriminatory power.

Using SHAP values for tree-based models, interpretability was given priority, allowing physicians to comprehend feature contributions at the individual and population levels [13].

4. Results/Findings

4.1. Descriptive Statistics

Participants in the study ranged in age from 18 to 62, with a mean age of 34.2 years. The distribution of genders was 42% female and 58% male. At intake, 28% of patients reported precarious housing, and almost 60% of patients were unemployed. In 45% of instances, there were psychiatric comorbidities, with anxiety and depression being the most prevalent.

Within a year, 47% of the 3,000 patients stopped participating in OTP. Among patients with numerous mental disorders, those with precarious housing, and younger patients, dropout rates were very high. Stable housing, steady work, and regular counselling attendance were more common among retained patients.

4.2. Model Performance

- Logistic Regression: ROC-AUC of 0.69 and 69% accuracy were attained. It was unable to capture intricate interactions between predictors, despite offering interpretable coefficients.
- Random Forest: Better outcomes with a ROC-AUC of 0.77 and 74% accuracy. Reliability in detecting dropout cases was demonstrated by the balance between precision and recall [13].
- XGBoost, or gradient boosting, fared better than any other model, with a ROC-AUC of 0.81 and an accuracy of 79%. It showed the optimal ratio of specificity to sensitivity.
- Neural Network: Achieved a ROC-AUC of 0.76 and 73% accuracy. Although it was competitive with random forests, its practical applicability was hampered by its lower interpretability and processing requirement.

These results suggest that using EMR data to forecast OTP dropout is a good fit for sophisticated ensemble techniques like gradient boosting.

4.3. Future Important Analysis

The most significant predictors, according to feature importance analysis using tree-based models, were Behavioral characteristics. In particular:

- The best indicator of dropout was missed therapy appointments.
- Psychiatric comorbidities and housing instability also received high rankings.
- Medication non-adherence and relapse frequency were consistently predictive [13].
- Younger age and unemployment were among the demographic characteristics that contributed somewhat, although not as much as Behavioral indications.

Nuanced insights were revealed by SHAP analysis. For instance, patients who missed two or more counselling sessions during the first month of treatment were significantly more likely to drop out. On the other hand, regular counselling participation and medication compliance were highly predictive of retention.

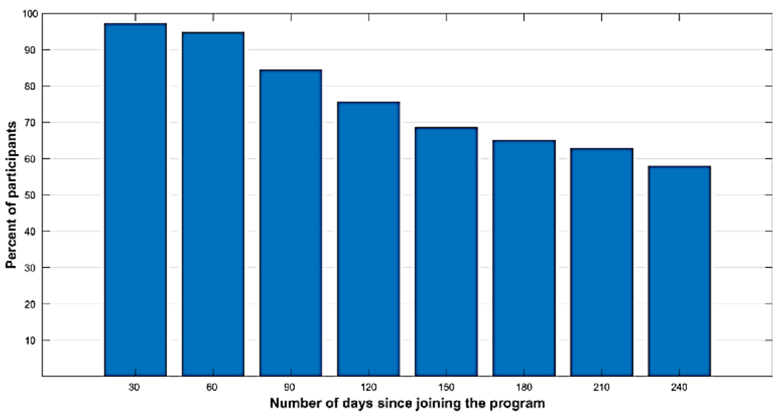

Figure 4: Machine Learning for Predicting Risk of Early Dropout in a Recovery Program for Opioid Use Disorder

4.4. Summary of the Findings

Overall, the study showed that when it comes to forecasting OTP dropout, machine learning models—in particular, gradient boosting—perform noticeably better than conventional statistical methods. The significance of comprehensive treatment approaches is highlighted by the prevalence of behavioral and psychological elements. The results show how predictive models can be included in EMRs to give clinicians early warning systems for dropout risk [13].

5. Discussion and Conclusion

5.1. Interpretation of Findings

The results of this study complement and add to the body of knowledge regarding OTP dropout. The most potent indicators were Behavioral in character, although demographic factors like age and work status also affected dropout probability, in line with earlier studies. Machine learning models perform better than logistic regression, which can be explained by their capacity to capture these intricate, dynamic interactions. A steep ROC curve with an AUC of 0.81 for high-impact boosting demonstrates just how beneficial modeling can be in identifying high-risk urges.

5.2. Implications for Practice

Such results strongly inform the further course of action on a practical level. For example, OTPs could implement decision algorithms within a hospital's health record and generate real-time at-risk alerts for clinicians. Individuals who have been identified as high risk may receive specific interventions like:

- Increased social assistance and case management.
- To lower barriers, consider telemedicine services or flexible scheduling.
- Improved techniques for counselling engagement, such as motivational interviewing [14].
- Peer support initiatives to combat loneliness and stigma.

This preventative strategy may lower dropout rates, enhance patient outcomes, and lower the costs to society of overdose and relapse.

5.3. Limitation

A number of constraints need to be noted. First, the data's retroactive nature raises the possibility of biases brought on by erroneous or incomplete EMR entries. Second, just three OTPs in particular regions were included in the study population, which can have an impact on the study's generalizability to rural or global settings. Third, despite gradient boosting's excellent predictive accuracy, interpretability is still difficult to achieve in comparison to more straightforward models, and doctors could be hesitant to believe black box predictions. Lastly, before adoption, ethical issues like patient privacy, informed permission, and the possibility of algorithmic bias need to be thoroughly examined [14].

5.4. Recommendations for Future Research

Prospective validation of prediction models in various OTP scenarios should be the focus of future studies. Accuracy may be increased by extending datasets to incorporate unstructured data (such as physician notes via natural language processing) and social determinants of health (such as income and social support networks). Predictive modeling's cost-effectiveness can also be assessed, including whether lower dropout rates result in quantifiable healthcare savings and better results. For predictive models to be both technically sound and socially conscious, interdisciplinary cooperation between data scientists, physicians, and legislators will be essential [15].

5.5. Conclusion

This dissertation shows that a strong tool for predicting dropout in opioid treatment programs is provided by machine learning applied to Behavioral health EMRs. Gradient boosting demonstrated the promise of sophisticated ensemble approaches in addiction medicine by achieving the highest prediction accuracy among the tested models. The best predictors of dropout were Behavioral factors like home stability, psychiatric comorbidity, and counselling adherence [15].

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