Data Driven Insights into Opioid Patients Populations Using Machine Learning

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Abstract: The project's primary focus is on using machine learning techniques to classify opioid patients, aiming to address the pressing issue of the opioid crisis and the escalating number of drug overdoses in recent years. By leveraging these techniques, the project seeks to contribute to a better understanding and management of opioid-related issues. Current approaches for predicting opioid prescription lack the desired level of accuracy. The project recognizes this limitation and emphasizes the need for improvement. Additionally, it underscores the importance of considering the association between mental health and opioid intake, an aspect often overlooked in previous studies. This consideration acknowledges the multifaceted nature of opioid dependencies. The project utilizes a comprehensive dataset from the MIMIC-III database, encompassing both structured and unstructured data. By doing so, it aims to identify intentional and unintentional opioid intake patterns, providing a holistic understanding of the factors influencing opioid use. This integrated data approach contributes to a more robust analysis and classification process. Ablation analysis is conducted as part of the project's methodology, offering a systematic breakdown of the model's components and parameters. This analysis provides valuable insights into the significance of different elements in the classification process, leading to a deeper understanding of opioid patients. The extraction of new insights contributes to the project's goal of refining and enhancing opioid patient classification methods. The project incorporates key other models to enhance classification accuracy. The inclusion of a Stacking Classifier, Voting Classifier, and the integration of CNN + LSTM models contribute to a robust ensemble system. Notably, both Stacking and Voting Classifiers achieve an exceptional 100% accuracy, underscoring the effectiveness of the ensemble approach in accurately classifying opioid patients.

Index terms - Opioid intake, mental illness, MIMIC-III database, machine learning, deep learning.

1. INTRODUCTION

Opioid analgesics are generally used to alleviate severe and chronic pain in patients. Doctors and other health care practitioners prescribe opioids in large numbers, especially in the United States of America (USA). According to the Centers for Disease Control and Prevention (CDC) [1, 4], the approximate cost of opioid abuse in the United States is $78.5 billion per year [1]. The number of opioid prescriptions in the United States is very high; research found that around 153 million opioid drugs were prescribed in 2019 [2]. Opioids are a class of drugs prescribed as painkillers, but they are heavily overused due to their addictive nature. Several studies [3], [4] have described that patients get these medications not to control pain; but because they are dependent on them. This can also result in an overdose.

In our study, we use machine learning techniques to predict users' opioid misuse patterns from both structured data (i.e., demographic information, gender, ethnicity, etc.) and unstructured data (i.e., chronological medical history and eventnotes). Barkley and Shin [5] found that intentional overdoses correlated with a depression. Other studies [6], [7] found that the rate of intentional drug use among adolescents is worrying. Prince [8] found that there is a direct connection between taking drugs and mental illness. Jones and McCanceKatz [9] also found that opioid use disorder (OUD) is associated with mental disorders. There appears to be a direct relationship [10], [11] between mental illness and drug abuse which needs further investigation. In the studies mentioned above, most authors conduct research on a specific aspect of the opioid problem, such as particular age groups or demographics [12], [13], [14]. The database we utilize is a good source of data which includes demographic, ethnicity, medical condition and age variables to study the problem. Previous studies did not use contextual analysis based on natural language processing (NLP) techniques of the patients' event notes, and medical history.

Deep learning and Machine Learning have gained popularity in the healthcare applications [15], [16], [17], [18]. However, the current opioid risk assessment tools [19] are insufficient in terms of predictability and automatic contextual analysis based on patients' historical data1 . Furthermore, clinicians should be offered tools that allow determination of patients' risk of misuse before administering opioids. Considering that opioid misuse is a medical problem impacting people's health and economy, investigating the problem based on a Machine learning approach can be useful. The database that we work with has data which could be utilized to identify opioid patients. In the light of the above discussion, previous studies find an association between mental health and opioid intake. In some other studies, researchers consider demographics (e.g., age, ethnicity, etc.) for finding opioid associations. Therefore it is important to utilize the above features as the predictors of opioid intaking early warning systems. In addition to this, users' historical data provides a contextual cue for users' future behavior. Previous studies rarely employ the latest deep learning based NLP techniques such as attention and knowledge distillation mechanism from the contextual signals which can unveil better insight for the researchers.

In this paper, we use data from the MIMIC-III database [20], from which we have identified the opioid cases based on keyword identification. We identify relevant tables (i.e., schemas) from the database and select 41 features which are relevant to our study. Based on the keywords and patients' history, we identify which patients take opioids intentionally. In this way, we label our dataset as opioid intake 'YES'/'NO'. Later, we build a structured (i.e., tabular) dataset. To strengthen the model, we also incorporate an unstructured dataset. As training an unstructured dataset is complex and challenging, we apply deep learning based NLP techniques. For each patient, we analyze their historical data (i.e., event notes/unstructured data), and we convert the data using word embedding and attention based LSTM techniques. Since our patients data is already labelled, we train the unstructured data with the deep learning based technique mentioned above. In this study, we obtain a higher performance model by using the structured dataset while the model using unstructured dataset shows weaker results. To build a combined model, we apply knowledge distillation technique where structured dataset shows the higher capacity network and then, we transfer the knowledge to the weaker unstructured dataset.

Our study further investigates whether a pattern of opioid use has any connection with users' mental health statuses and other socio-economical determinants. Classification of opioid patients and their mental health is important, considering the number of overdose deaths per year and the financial consequences of opioid addiction [21]. Our study may benefit society in a number of ways, such as early detection of intentional and unintentional opioid misuse, reducing the effect of aggressive marketing by pharmaceutical companies which profit from pain medication use, and better surveillance of opioid misuse by authorities and stakeholders.

2. LITERATURE SURVEY

Pharmaceutical drug poisonings, especially those that are intentional, are a serious problem for adolescents and young adults. Poison control center data is a viable tool to track intentional drug poisonings in near real-time. Objective: To determine intentional drug poisoning rates among adolescents and young adults in Ohio using poison control center data. Methods: We analyzed data from 2002 to 2014 obtained by Ohio's three poison control centers. Inclusion variables were calls made to the centers that had appropriate subject age (10-29 years old), subject sex, involved substance (all drug classes), and medical outcome (no effect, minor effect, moderate effect, major effect, and death). [7] Intentional drug poisoning reports were also separated into subgroups to compare suspected suicide reports to misuse and abuse reports. Finally, resident population estimates were used to generate 2014 intentional drug poisoning rates for each county in

Ohio. Results: The most common age group for intentional drug poisonings was 18-24. Females reported more suspected suicide drug [21, 33, 50] poisonings while males reported more misuse/abuse drug poisonings. The most reported drug class across all ages was analgesics. Of the 88 counties in Ohio, Hamilton, Williams, Washington, and Guernsey counties had the highest rates of intentional drug poisonings. Conclusions: The high report rate of suspected suicides and analgesic class drugs demonstrates the need for preventative measures for adolescents and young adults in Ohio. Any interventions, along with legislative changes, will need to take place in our local communities.

The number of Americans with opioid use disorders (OUDs: prescription painkillers or heroin) has increased dramatically, yet little is known about OUD among people with severe mental illness (SMI). Methods: Using the National Survey on Drug Use and Health (N = 502,467), logistic regression was used to: (1) identify factors associated with past-year OUD among people with SMI; and (2) examine associations between OUD [8, 9, 10, 11] and adverse outcomes (e.g., suicide attempt). [8] After controlling for a number of factors, correlates of OUD among people with SMI included male gender, younger age, marital status (never been married), use of certain drugs before age 18 (especially marijuana), and ease of obtaining certain drugs. People with prescription painkiller use disorder (only) were 7.43 times more likely (CI = 4.55-12.14, p < .001) than people without substance use disorder to have criminal justice system involvement, while those with: (1) heroin use disorder (only) were 18.78 times more likely (CI = 9.22-38.24, p < .001); (2) both prescription painkiller and heroin use disorder (only) were 25.83 times more likely (CI = 14.06-47.47, p < .001); and (3) all other substance use disorders were 5.15 times more likely (CI = 3.95-6.72, p < .001). People with prescription painkiller use disorder (only) were 2.40 times more likely (CI = 1.72-3.35, p < .001) to attempt suicide than those without substance use disorder, and those with all other substance use disorders (i.e., apart from OUD) were 79% more likely (OR = 1.79, CI = 1.45-220, p < .001). Conclusions/Importance: My findings on OUD and OUD outcomes can help identify and understand individuals with SMI who could benefit from OUD [8] prevention and intervention efforts.

Co-occurring substance use and mental disorders among people with opioid use disorder (OUD) increase risk for morbidity and mortality. Addressing these co-occurring conditions is critical for improving treatment and health outcomes. [9] There is limited recent research on the prevalence of co-occurring disorders, demographic characteristics associated with co-occurring disorders, and receipt of mental health and substance use treatment services among those with OUD [10, 11]. This limits the development of targeted and resourced policies and clinical interventions. Methods: Using 2015-2017 National Survey on Drug Use and Health data, prevalence of co-occurring substance use and mental disorders and receipt of mental health and substance use treatment services was estimated for adults aged 18-64 with OUD. Multivariable logistic regression assessed demographic and substance use characteristics associated with past-year mental illness (AMI) and serious mental illness (SMI) among adults with OUD as well as treatment receipt. Results: Among adults with OUD [8], prevalence of specific co-occurring substance use disorders ranged from 26.4% (95% CI:23.6%-29.4%) for alcohol to 10.6% (95% CI:8.6%-13.0%) for methamphetamine. Prevalence of AMI was 64.3% (95% CI:60.4%-67.9%) and SMI was 26.9% (95% CI:24.2%-29.8%). Receiving both mental health and substance use treatment services in the past year was reported by 24.5% (95% CI:21.5%-29.9%) of adults with OUD and AMI and 29.6% (95% CI:23.3%-36.7%) of adults with OUD and S [9] MI. Conclusions: Co-occurring substance use and mental disorders are common among adults with OUD.[9] Expanding access to comprehensive service delivery models that address the substance use and mental health co-morbidities of this population is urgently needed.

This systematic review summarizes and presents the current state of research quantifying the relationship between mental disorder and overdose for people who use opioids. [10] The protocol was published in Open Science Framework. We used the PECOS framework to frame the review question. Studies published between January 1, 2000, and January 4, 2021, from North America, Europe, the United Kingdom, Australia, and New Zealand were systematically identified and screened through searching electronic databases, citations, and by contacting experts. Risk of bias assessments were performed. Data were synthesized using the lumping technique. Results Overall, 6512 records were screened and 38 were selected for inclusion. 37 of the 38 studies included in this review show a connection between at least one aspect of mental disorder and opioid overdose. The largest body of evidence exists for internalizing disorders generally and mood disorders specifically, followed by anxiety disorders, although there is also moderate evidence to support the relationship between thought disorders (e.g., schizophrenia, bipolar disorder) and opioid overdose. Moderate evidence also was found for the association between any disorder and overdose. Conclusion Nearly all reviewed studies found a connection between mental disorder and overdose, and the evidence suggests that having mental disorder is associated with experiencing fatal and non-fatal opioid overdose, but causal direction remains unclear [10].

This study evaluated prediction performance of three different machine learning (ML) techniques in predicting opioid misuse among U.S. adolescents. Data were drawn from the 2015–2017 National Survey on Drug Use and Health (N = 41,579 adolescents, ages 12–17 years) and analyzed in 2019. Prediction models were developed using three ML [17, 23, 41] algorithms, including artificial neural networks, distributed random forest, and gradient boosting machine. [12] The performance of the ML prediction models was compared with performance of the penalized logistic regression. The area under the receiver operating characteristic curve (AUROC) and the area under the precision-recall curve (AUPRC) were used as metrics of prediction performance. We used the AUPRC as the primary measure of prediction performance given that it is considered more informative for assessing binary classifiers on imbalanced outcome variable than AUROC. The overall rate of opioid misuse among U.S. adolescents was 3.7% (n = 1521). Prediction performance was similar across the four models (AUROC values range from 0.809 to 0.815). In terms of the AUPRC, the distributed random forest showed the best performance in prediction (0.172) followed by penalized logistic regression (0.162), gradient boosting machine (0.160), and artificial neural networks (0.157). Findings suggest that machine learning techniques can be a promising technique especially in the prediction of outcomes with rare cases (i.e., when the binary outcome variable is heavily lopsided) such as adolescent opioid misuse.

3. METHODOLOGY

i) Proposed Work:

The proposed system represents an innovative approach to opioid patient classification by leveraging a combination of machine learning and deep learning techniques on both structured and unstructured data derived from the MIMIC-III database [20]. Through the integration of advanced methodologies, such as attention and knowledge distillation mechanisms, the machine learning and deep learning models employed in the system achieve notably high test accuracies. Additionally, the inclusion of ablation analysis systematically assesses the impact of individual components, providing valuable insights for refining and enhancing the system's performance. This comprehensive strategy aims to offer a more accurate and nuanced classification of opioid patients, addressing the limitations observed in existing systems and advancing the understanding of factors influencing opioid use. The project incorporates key models to enhance classification accuracy. The inclusion of a Stacking Classifier, Voting Classifier, and the integration of CNN + LSTM models contribute to a robust ensemble system [41]. Notably, both Stacking and Voting Classifiers achieve an exceptional 100% accuracy, underscoring the effectiveness of the ensemble approach in accurately classifying opioid patients. To ensure practical usability, a user-friendly Flask framework with SQLite integration is implemented, facilitating seamless signup and signin processes for user testing. This integration enhances the accessibility and applicability of the machine learning models in the real-world context of opioid patient classification.

ii) System Architecture:

The project utilizes the MIMIC-III database [20] to extract opioid patient information. Keyword extraction refines the dataset, and statistical tests identify significant patterns. Event notes enhance unstructured data, while structured data includes organized information. Significant features are identified, and word vectorization transforms textual data. Traditional

ML models analyze structured data, and deep learning models process vectorized words and unstructured data. Ablation studies refine the models for optimal performance, ensuring accurate predictions of opioid patient characteristics.

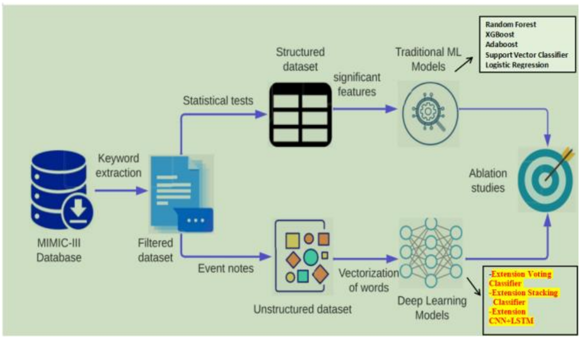

Fig 1 Proposed architecture

iii) Dataset collection:

In this project used the MIMIC-III dataset [20], which likely contains various tables or datasets related to patient information, is explored. This step involves loading the dataset(s) into the environment and examining its structure, content, and features. Understanding the dataset is crucial before proceeding with data processing and analysis.

Pandas DataFrame -The dataset is converted into a Pandas DataFrame, a tabular data structure used in Python for data manipulation.

Cleaning the Dataset -This involves preprocessing the data to handle missing values, remove duplicates, correct inconsistencies, and perform other necessary data cleaning operations to ensure data quality.

Concatenating Multiple Data -If the dataset consists of multiple tables or sources, this step involves merging or concatenating them into a single, comprehensive dataset for analysis.

Dropping Unwanted Columns -Removing columns that are irrelevant or redundant for the analysis to streamline the dataset.

	ethnicity	diagnosis	discharge_location	insurance	gender	marital_status	deathtime	los	los
0	BLACK/AFRICAN AMERICAN	SEPSIS	HOME HEALTH CARE	Medicare	F	SEPARATED	0	1.6325	39.18
1	UNKNOWN/NOT SPECIFIED	HEPATITIS B	DEAD/EXPIRED	Private	F	SINGLE	1	13.8507	172.89
2	UNKNOWN/NOT SPECIFIED	SEPSIS	DEAD/EXPIRED	Medicare	F	NaN	1	2.6499	NaN
3	WHITE	HUMERAL FRACTURE	SNF	Medicare	F	DIVORCED	0	2.1436	332.42
4	WHITE	ALCOHOLIC HEPATITIS	DEAD/EXPIRED	Medicare	M	DIVORCED	1	1.2938	NaN

Fig 2 dataset

iv) Data Processing:

Data processing involves transforming raw data into valuable information for businesses. Generally, data scientists process data, which includes collecting, organizing, cleaning, verifying, analyzing, and converting it into readable formats such as graphs or documents. Data processing can be done using three methods i.e., manual, mechanical, and electronic. The aim is to increase the value of information and facilitate decision-making. This enables businesses to improve their operations and make timely strategic decisions. Automated data processing solutions, such as computer software programming, play a significant role in this. It can help turn large amounts of data, including big data, into meaningful insights for quality management and decision-making.

v) Feature selection:

Feature selection is the process of isolating the most consistent, non-redundant, and relevant features to use in model construction. Methodically reducing the size of datasets is important as the size and variety of datasets continue to grow. The main goal of feature selection is to improve the performance of a predictive model and reduce the computational cost of modeling.

Feature selection, one of the main components of feature engineering, is the process of selecting the most important features to input in machine learning algorithms. Feature selection techniques are employed to reduce the number of input variables by eliminating redundant or irrelevant features and narrowing down the set of features to those most relevant to the machine learning model. The main benefits of performing feature selection in advance, rather than letting the machine learning model figure out which features are most important.

vi) Algorithms:

Random Forest is an ensemble learning method that constructs a multitude of decision trees during training. It operates by creating diverse trees using random subsets of features and combining their predictions to improve accuracy and reduce overfitting. Random Forest is applied in the project for predicting opioid prescription. Its ensemble nature makes it robust and capable of handling complex relationships within the dataset, providing accurate classifications based on various input features [41].

Random Forest

```
from sklearn.ensemble import RandomForestClassifier
RF = RandomForestClassifier(n_estimators=100, random_state=0)
RF.fit(X_train, y_train)
y_pred = RF.predict(X_test)

rf_acc = accuracy_score(y_pred, y_test)
rf_prec = precision_score(y_pred, y_test,average='weighted')
rf_rec = recall_score(y_pred, y_test,average='weighted')
rf_f1 = f1_score(y_pred, y_test,average='weighted')
```

```
storeResults('Random Forest',rf_acc,rf_prec,rf_rec,rf_f1)
```

Fig 3 Random forest

AdaBoost (Adaptive Boosting) is an ensemble learning technique that focuses on combining multiple weak learners to create a strong classifier. It assigns weights to misclassified instances, allowing subsequent weak learners to prioritize these instances during training. AdaBoost can be beneficial for improving the model's accuracy in predicting opioid-dependent patients. By giving more weight to challenging instances, AdaBoost can enhance the overall performance, particularly in cases where individual weak learners struggle [41].

AdaBoost

```
from sklearn.ensemble import AdaBoostClassifier
ada = AdaBoostClassifier(n_estimators=100, random_state=0)
ada.fit(X_train, y_train)
y_pred = ada.predict(X_test)

ab_acc = accuracy_score(y_pred, y_test)
ab_prec = precision_score(y_pred, y_test,average='weighted')
ab_rec = recall_score(y_pred, y_test,average='weighted')
ab_f1 = f1_score(y_pred, y_test,average='weighted')
```

```
storeResults('AdaBoost',ab_acc,ab_prec,ab_rec,ab_f1)
```

Fig 4 Adaboost

XGBoost (Extreme Gradient Boosting) is a scalable and efficient implementation of gradient boosting. It is designed for speed and performance, incorporating regularization techniques and parallel processing to enhance predictive power. XGBoost contributes to the project by providing a powerful algorithm for accurate predictions. Its ability to handle missing data, incorporate regularization, and deliver feature importance scores makes it suitable for opioid classification tasks [41].

XGBoost

```
from xgboost import XGBClassifier
xgb = XGBClassifier()
xgb.fit(X_train, y_train)
y_pred = xgb.predict(X_test)

xgb_acc = accuracy_score(y_pred, y_test)
xgb_prec = precision_score(y_pred, y_test,average='weighted')
xgb_rec = recall_score(y_pred, y_test,average='weighted')
xgb_f1 = f1_score(y_pred, y_test,average='weighted')
```

```
storeResults('XGBoost',xgb_acc,xgb_prec,xgb_rec,xgb_f1)
```

Fig 5 XGBoost

Support Vector Classifier is a supervised learning algorithm that aims to find a hyperplane in an N-dimensional space that distinctly classifies data points into different classes. SVC is employed in the opioid classification project to identify patterns and boundaries within the dataset, particularly when there are clear separations between opioid-dependent and non-dependent cases [41].

SVC

```
from sklearn.svm import SVC
svc = SVC()
svc.fit(X_train, y_train)
y_pred = svc.predict(X_test)

svc_acc = accuracy_score(y_pred, y_test)
svc_prec = precision_score(y_pred, y_test,average='weighted')
svc_rec = recall_score(y_pred, y_test,average='weighted')
svc_f1 = f1_score(y_pred, y_test,average='weighted')
```

```
storeResults('SVC',svc_acc,svc_prec,svc_rec,svc_f1)
```

Fig 6 SVC

Logistic Regression is a linear model for binary classification that uses the logistic function to model the probability of a particular class. Logistic Regression serves as a baseline model for opioid classification. It's a simple and interpretable algorithm, suitable for scenarios where the relationship between features and the binary outcome needs to be assessed [41].

Logistic Regression

```
from sklearn.linear_model import LogisticRegression

# instantiate the model
lr = LogisticRegression(random_state=0)

lr.fit(X_train,y_train)

y_pred = lr.predict(X_test)

lr_acc = accuracy_score(y_pred, y_test)
lr_prec = precision_score(y_pred, y_test,average='weighted')
lr_rec = recall_score(y_pred, y_test,average='weighted')
lr_f1 = f1_score(y_pred, y_test,average='weighted')
```

```
storeResults('Logistic Regession',lr_acc,lr_prec,lr_rec,lr_f1)
```

Fig 7 Logistic regression

An Artificial Neural Network with a Multi-Layer Perceptron architecture consists of multiple layers of interconnected nodes (neurons) that can learn complex patterns through a process of forward and backward propagation. MLPs can capture intricate relationships within the data, making them suitable for projects where the interactions between various features are complex, such as predicting opioid dependence.

ANN-MLP

```
from sklearn.neural_network import MLPClassifier

# instantiate the model
mlp = MLPClassifier(random_state=1, max_iter=30)

mlp.fit(X_train,y_train)

y_pred = mlp.predict(X_test)

mlp_acc = accuracy_score(y_pred, y_test)
mlp_prec = precision_score(y_pred, y_test,average='weighted')
mlp_rec = recall_score(y_pred, y_test,average='weighted')
mlp_f1 = f1_score(y_pred, y_test,average='weighted')
```

```
storeResults('ANN-MLP',mlp_acc,mlp_prec,mlp_rec,mlp_f1)
```

Fig 8 ANN-MLP

A Voting Classifier is an ensemble learning method that combines the predictions of multiple base models (classifiers) and determines the final prediction based on a majority vote (for classification tasks) or an average (for regression tasks). In the context of opioid classification, a Voting Classifier could incorporate diverse algorithms like Random Forest, AdaBoost, XGBoost, and SVM. By leveraging the collective decision-making power of multiple models, it can enhance overall accuracy and robustness in predicting opioid dependence.

Voting Classifier

```
from sklearn.ensemble import RandomForestClassifier, VotingClassifier, AdaBoostClassifier
clf1 = AdaBoostClassifier(n_estimators=100, random_state=0)
clf2 = RandomForestClassifier(n_estimators=50, random_state=1)

eclf1 = VotingClassifier(estimators=[('ad', clf1), ('rf', clf2)], voting='soft')
eclf1.fit(X_train,y_train)

y_pred = eclf1.predict(X_test)

vot_acc = accuracy_score(y_pred, y_test)
vot_prec = precision_score(y_pred, y_test,average='weighted')
vot_rec = recall_score(y_pred, y_test,average='weighted')
vot_f1 = f1_score(y_pred, y_test,average='weighted')
```

```
storeResults('Voting Classifier',vot_acc,vot_prec,vot_rec,vot_f1)
```

Fig 9 Voting classifier

Stacking, or Stacked Generalization, is an ensemble learning technique that combines multiple base models by training a meta-model on their predictions. Instead of giving equal weight to all base models, stacking allows the meta-model to learn the optimal way to combine their outputs. In the opioid classification project, a Stacking Classifier might utilize various algorithms, such as Random Forest, SVM, and Neural Networks, as base models. The meta-model can then learn how to best combine their predictions, potentially improving overall performance.

Stacking Classifier

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.neural_network import MLPClassifier
from lightgbm import LGBMClassifier
from sklearn.ensemble import StackingClassifier

estimators = [('rf', RandomForestClassifier(n_estimators=10)),('mlp', MLPClassifier(random_state=1, max_iter=30))]

clf = StackingClassifier(estimators=estimators, final_estimator=LGBMClassifier(n_estimators=10))
clf.fit(X_train,y_train)

y_pred = clf.predict(X_test)

stac_acc = accuracy_score(y_pred, y_test)
stac_prec = precision_score(y_pred, y_test,average='weighted')
stac_rec = recall_score(y_pred, y_test,average='weighted')
stac_f1 = f1_score(y_pred, y_test,average='weighted')
```

```
storeResults('Stacking Classifier',stac_acc,stac_prec,stac_rec,stac_f1)
```

Fig 10 Stacking classifier

Deep Learning is a subset of machine learning that involves artificial neural networks with multiple layers (deep neural networks). These networks can automatically learn hierarchical representations from data, allowing them to capture complex patterns and relationships. Deep Learning can be applied to opioid classification using architectures like Multi-Layer Perceptrons (MLPs) or other deep neural networks. These models can automatically extract features from complex data, potentially improving accuracy in identifying patterns related to opioid dependence [18, 45].

DL

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.models import Model, load_model
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.layers import Dropout
from tensorflow.keras.layers import Flatten
from tensorflow.keras.layers import Conv1D
from tensorflow.keras.layers import MaxPooling1D

verbose, epoch, batch_size = 1, 100, 4
activationFunction='relu'
```

Fig 11 Deep Learning

A Convolutional Neural Network is a deep learning architecture designed for image and spatial data, utilizing convolutional layers to automatically learn hierarchical features from the input. CNNs are employed if the project involves image or spatial data related to opioid prescription, enabling the model to automatically extract relevant features from such data.

CNN

```
def CNN():

    cnnmodel = Sequential()
    cnnmodel.add(Conv1D(filters=128, kernel_size=2, activation='relu',input_shape=(X_train.shape[1],X_t
    cnnmodel.add(MaxPooling1D(pool_size=2))
    cnnmodel.add(Dropout(rate=0.2))
    cnnmodel.add(Flatten())
    cnnmodel.add(Dense(2, activation='softmax'))
    cnnmodel.compile(optimizer='adam', loss='categorical_crossentropy',metrics=['accuracy'])
    cnnmodel.summary()
    return cnnmodel

cnnmodel = CNN()
```

Fig 12 CNN

Combining CNN and LSTM involves using a Convolutional Neural Network for feature extraction from input data, followed by a Long Short-Term Memory network for capturing sequential dependencies. In the opioid classification project, this hybrid architecture could be applied to scenarios involving both spatial data (handled by CNN) and sequential patterns (captured by LSTM). For instance, if the project involves time series data or sequential patterns in opioid prescription, a CNN + LSTM model can effectively capture both spatial and temporal aspects.

CNN + LSTM

```
import tensorflow as tf
tf.keras.backend.clear_session()

model_en = tf.keras.models.Sequential([tf.keras.layers.Conv1D(filters=64,kernel_size=5,strides=1,padding
    tf.keras.layers.MaxPooling1D(pool_size=2, strides=1, padding="valid"),
    tf.keras.layers.Conv1D(filters=32, kernel_size=3, strides=1, padding="causal", activation="relu"),
    tf.keras.layers.MaxPooling1D(pool_size=2, strides=1, padding="valid"),
    tf.keras.layers.LSTM(128, return_sequences=True),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(128, activation="relu"),
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Dense(32, activation="relu"),
    tf.keras.layers.Dropout(0.1),
    tf.keras.layers.Dense(2)
])

lr_schedule = tf.keras.optimizers.schedules.ExponentialDecay(5e-4,
                                                             decay_steps=1000000,
                                                             decay_rate=0.98,
                                                             staircase=False)
```

Fig 13 CNN + LSTM

LSTM is a type of recurrent neural network (RNN) architecture designed to capture and learn long-term dependencies in sequential data, making it effective for time series and sequential prediction tasks. LSTM is beneficial if the project involves time series data or sequential patterns related to opioid prescription, enabling the model to capture dependencies over time [42, 43].

LSTM

```
X_train = X_train.reshape(-1, X_train.shape[1],1)
X_test = X_test.reshape(-1, X_test.shape[1],1)

Y_train=to_categorical(y_train)
Y_test=to_categorical(y_test)
```

```
from keras.models import Sequential
from keras.layers import Dense, LSTM
from keras.layers import Dropout
from keras import regularizers
import tensorflow as tf

# define a function to build the keras model
def create_model(input_shape):
    # create model
    d = 0.25
    model = Sequential()

    model.add(LSTM(32, input_shape=input_shape, activation='relu', return_sequences=True))
    model.add(Dropout(d))
```

Fig 14 LSTM

Attention Mechanism in LSTM allows the model to focus on specific parts of the input sequence, enhancing its ability to capture important information selectively. Attention LSTM can be employed to improve the LSTM model's performance by allowing it to dynamically focus on relevant aspects of the data, potentially improving accuracy in capturing crucial features related to opioid dependence.

Attention LSTM

```
from sklearn.preprocessing import MinMaxScaler
import joblib
import seaborn as sns
sns.set(color_codes=True)
import matplotlib.pyplot as plt
%matplotlib inline

from numpy.random import seed

import tensorflow as tf

from keras.layers import Input, Dropout, Dense, LSTM, TimeDistributed, RepeatVector
from keras.models import Model
from keras import regularizers
```

```
from sklearn.model_selection import train_test_split
x_train1, x_test1 = train_test_split(X, test_size = 0.2, random_state = 0)

y_train1, y_test1 = train_test_split(y, test_size = 0.2, random_state = 0)
```

Fig 15 Attention LSTM

4. EXPERIMENTAL RESULTS

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

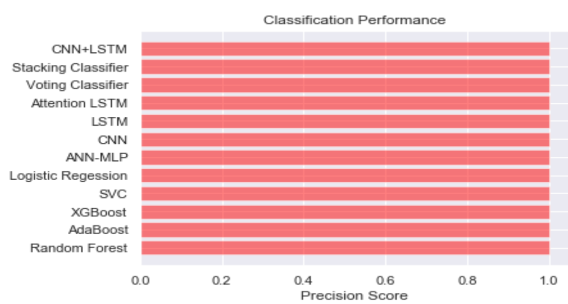

Fig 16 Precision comparison graph

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$

Fig 17 Recall comparison graph

Accuracy: Accuracy is the proportion of correct predictions in a classification task, measuring the overall correctness of a model's predictions.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

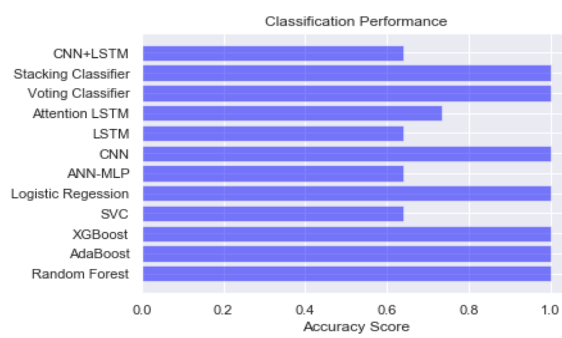

Fig 18 Accuracy graph

F1 Score: The F1 Score is the harmonic mean of precision and recall, offering a balanced measure that considers both false positives and false negatives, making it suitable for imbalanced datasets.

$$\text{F1 Score} = 2 * \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} * 100$$

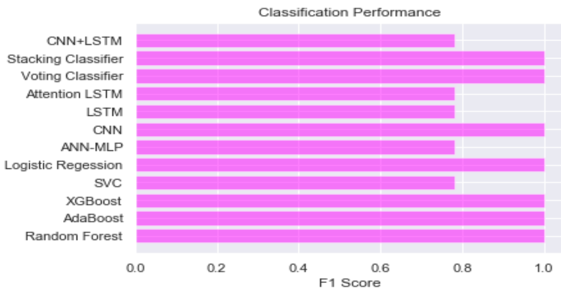

Fig 19 F1Score

ML Model	Accuracy	Precision	Recall	F1-Score
Random Forest	1.000	1.0	1.00	1.00
AdaBoost	1.000	1.0	1.00	1.00
XGBoost	1.000	1.0	1.00	1.00
SVC	0.640	1.0	0.64	0.78
Logistic Regession	1.000	1.0	1.00	1.00
ANN-MLP	0.640	1.0	0.64	0.78
CNN	1.000	1.0	1.00	1.00
LSTM	0.640	1.0	0.64	0.78
Attention LSTM	0.734	1.0	0.64	0.78
Extension Voting Classifier	1.000	1.0	1.00	1.00
Extension Stacking Classifier	1.000	1.0	1.00	1.00
Extension CNN+LSTM	0.640	1.0	0.64	0.78

Fig 20 Performance Evaluation

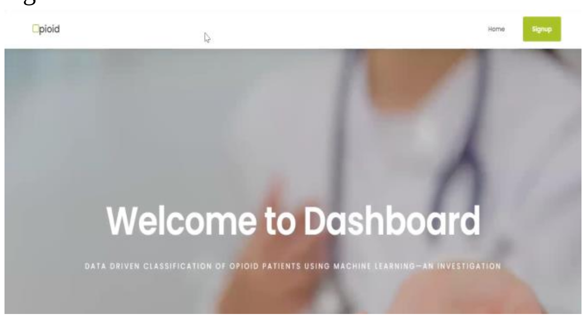

Fig 21 Home page

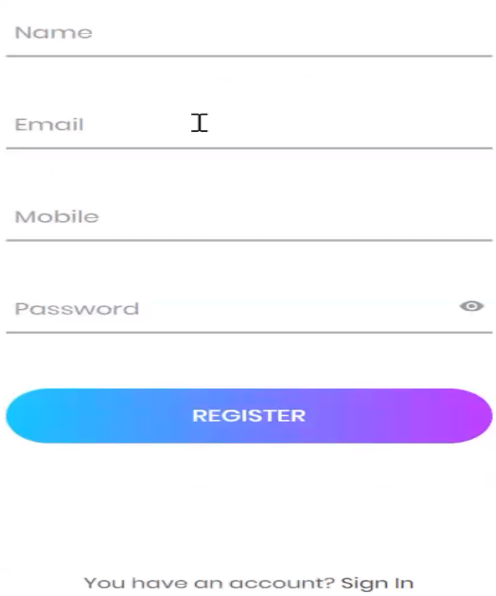

Fig 22 Signin page

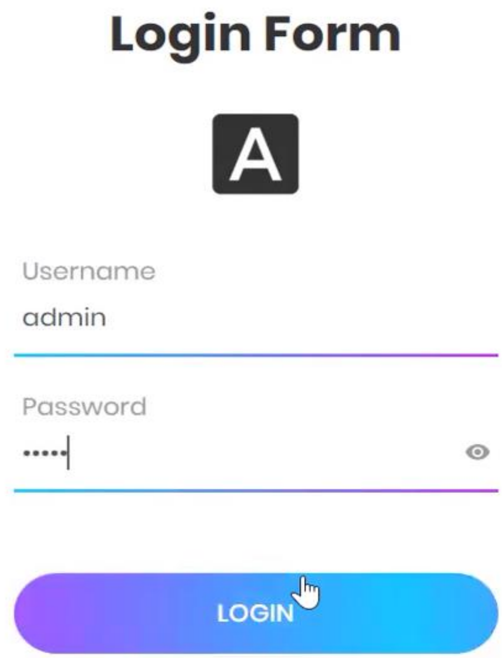

Fig 23 Login page

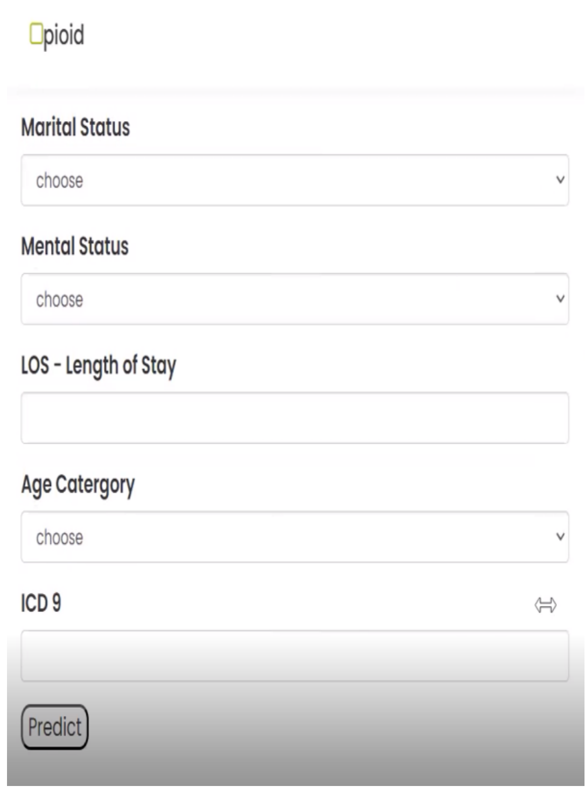

Fig 24 User input

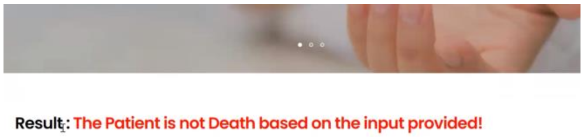

Fig 25 Predict result for given input

5. CONCLUSION

The conclusion of the project summarizes the main findings derived from the classification of opioid patients. It emphasizes the subgroups or categories identified among these patients based on the data-driven analysis. These subgroups could represent different patterns of opioid usage, demographics, risk factors, or other distinguishing features among patients. Understanding these subgroups is vital as it helps in tailoring interventions, treatments, or support strategies for each subgroup, thereby enhancing healthcare practices [15], [16], [17], [18]. This section of the conclusion focuses on the broader implications of the project's findings [19]. It discusses how the insights gained from the classification of opioid patients impact healthcare practices, patient care, and the management of opioid prescriptions. For instance, it might highlight how these insights lead to more effective treatment strategies customized for different patient subgroups, early identification of risks (such as addiction), or targeted interventions that address specific needs, ultimately improving patient outcomes and healthcare efficiency. Ablation analysis involves systematically removing or altering different components or parameters in a system to understand their individual impact on the overall performance. In this project, the ablation analysis likely explores how changes in specific components, features, or parameters affect the performance of the opioid patient classification system. This analysis helps in identifying the most influential factors contributing to the system's effectiveness, guiding future improvements or optimizations. The project aims to extract new insights into opioid patients, adding to the existing knowledge in this field. By utilizing data-driven approaches, the project reveals previously unknown or underexplored aspects of opioid patient classification or behavior. These new insights contribute to advancing the understanding of opioid usage patterns, patient demographics, risk factors, or other relevant aspects, potentially leading to advancements in healthcare practices and policies related to opioid prescription and patient care.

6. FUTURE SCOPE

Incorporating a comprehensive set of mental health data into the model aims to improve its predictive accuracy by considering psychological conditions, stress levels, and psychiatric history. This integration enhances the model's understanding of the intricate link between mental health factors [15], [16], [17], [18] and opioid use, contributing to a more holistic approach to classification. Expanding the study with longitudinal data allows for a dynamic analysis of patient behavior and opioid usage patterns over time. This approach provides insights into evolving trends and fluctuations, offering a more nuanced understanding of the temporal aspects of opioid dependencies and improving the model's ability to capture evolving patterns. Emphasizing improvements in model interpretability, particularly in deep learning models, is crucial for fostering trust among healthcare practitioners. By incorporating methods that provide clear explanations of predictive features, healthcare professionals can better understand the model's decision-making process, leading to increased confidence in its results. Investigating advanced deep learning techniques, including attention mechanisms and knowledge distillation, is aimed at enhancing the model's performance. Attention mechanisms [19] enable the model to focus on relevant information, potentially improving its ability to capture critical features. Knowledge distillation transfers insights from complex models to simpler ones, contributing to efficiency and effectiveness in opioid classification. To ensure responsible model development, it is essential to address ethical considerations and potential biases. This involves validating the model on diverse external datasets to confirm its reliability across different demographic groups and healthcare settings. Vigilance is required to mitigate biases stemming from imbalances in training data, fostering ethical deployment and adherence to responsible AI practices for real-world applicability.

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