

Predicting Hospital Re-Admissions from Clinical Narratives

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Abstract—In this era, hospital re-admissions have been a significant concern as the numbers of re-admissions are increasing at an alarming rate worldwide. The central idea of this paper is to predict unplanned patient re-admissions within 30 days of their discharge. When a patient is admitted to a health care center, there are high chances of re-admissions based on many healthcare parameters. This paper proposes a Machine Learning-based K-Nearest Neighbour model to predict 30-day unplanned hospital re-admission using clinical notes. The extracted dataset will undergo various text pre-processing stages to improve the overall accuracy of the model. To validate our proposed model, we have implemented many other Machine Learning models to compare different parameters obtained from each of the models. The hyperparameter tuning techniques and feature extraction techniques have been implemented to study the prediction results. According to our observations, the K-Nearest Neighbour model got the best accuracy of 85 percent, while Logistic Regression did not provide high accuracy. In this way, the clinicians can intervene in patients' conditions beforehand and predict possible re-admission chances and take various precautionary treatment steps to avoid unplanned re-admissions.

Index Terms—Hospital Re-admission, Machine Learning, Prediction System, Text Cleaning

I. INTRODUCTION

The purpose of digitizing personal medical history is to improve healthcare quality by analyzing medical data and providing patients with the best possible treatment. Today, health care data is so enormous and complex that it can be used in predictive models to improve healthcare delivery. Unfortunately, most of the information is not appropriate or suitable for our model predicting analysis. This is because the data is usually mishandled, or clinicians are restricted to share data due to the health sector's privacy or integrity norms. If the information is utilized efficiently, scientists predict that it would effectively help improve health care and provide patient's safety and quality, which would reduce the cost of health care all over the globe. Predicting a patient's re-admission in the hospital is a significant healthcare data application in predictive analytical modelling. Hospital re-admission refers to a patient's admission within 30 days of initial discharge, irrespective of any hospital. Multiple factors play an important role in hospital re-admissions, like premature discharge, insufficient care during initial admission, or unsuccessful treatment. The sole purpose of this paper is to

build a predictive classification model from clinical narratives to classify, which patients are likely to be re-admitted within 30 days. The idea of predicting unplanned re-admission of a hospitalized patient can be of great help as it saves many medical and financial resources. It is advantageous to patients and medical staff; hence it reduces the patient's exposure to the risk and well-being of their physical and mental status. The amalgamation of Natural Language Processing and Machine Learning techniques provide vast solutions to identify various patterns in complex, enormous, multi-dimensional datasets. And thus, it offers opportunities to develop an efficient decision-making support system for doctors while discharging a patient. According to the Canadian Institute of Health Information, re-admission to hospitals costs more than 2.1 billion dollars per year in Canada. As statistics illustrate, 1 in 11 patients has been re-admitted in Canada in the year 2018 [23]. To combat and reduce the patient's unplanned re-admission issue, the Hospital Re-admissions Reduction Program was created under the Affordable Care Act (ACA) to penalize the hospitals whose 30-day readmission rates are higher than expected value. According to the Centers for Medicare Services (CMS) statistics, after the program began, penalties worth 2.5 billion dollars were posed on hospitals for re-admissions, including 564 million dollars in 2018. Machine Learning has been tremendously used in multiple application areas, like education, health, finance, communications, etc. This is a rapid-growing research area, and cross-validation techniques like GridSearch and RandomSearch have been implemented to optimize the performance of our model.

Our objective is to analyze the model's predictive performance using different Machine Learning algorithms with the MIMIC-III (Medical Information Mart for Intensive Care III) database. MIMIC-III is a massive dataset that is widely used to derive predictive models for hospital re-admissions that hospitals can effectively implement. Section II describes MIMIC-III dataset. Section III narrates the related work. Section IV discusses the design and methodology used to develop the models and various Machine Learning algorithms. Section V discuss the results and implications. Section VI concludes the work.

II. DATASET

The predictive model is built using the MIMIC-III (Medical Information Mart for Intensive Care III) database [24] which is an enormous and free database for hospital records, containing identified data from about 50,000 patients admitted to Beth Israel Deaconess Medical Center in Boston, Massachusetts, from 2001 to 2012. This is an open-access, relational database of patients who stayed in ICU at the hospital. This database contains necessary information such as laboratory test results, medications, demographics, procedures, caregiver notes, imaging reports, fluid balance, procedure codes, diagnostic codes, imaging reports, hospital length of stay, and mortality (including post-hospital discharge). For building the predictive model, the work is done on two MIMIC datasets—firstly, the ADMISSIONS table containing necessary admission and discharge dates for prediction. Secondly, the NOTEVENTS table enlisting discharge summaries and notes specifying essential information regarding a patient's stay in the hospital. Both the tables have HADMID as the unique primary key for each admission. To access this project's data, you will need to request access at the Physionet access link [26]. Due to the sensitive nature of medical data and privacy permission, the raw data has not been publicly included in this paper.

III. RELATED WORK

In the study[1], "Analysis and prediction of unplanned intensive care unit re-admission using recurrent neural networks with long short-term memory," the author focuses on the unplanned re-admission prediction using chart events, demographics and ICD-9 embeddings features. In this paper, an LSTM-CNN based model was proposed to incorporate time-series data without losing any information. In the proposed study, an AUC score of 0.791 and a sensitivity of 0.742 was successfully achieved. These results were way better than the existing algorithms for the prediction of hospital re-admissions. However, since the model can have multiple operating points, its sensitivity and specificity can be tuned to match specific clinical settings requirements, such as high sensitivity for critical care. The proposed model mainly focused on input feature selection in the predictive model. The comparison was made with the logistic regression, where the author successfully demonstrated that the LSTM and CNN model proved to be accurate compared to that of the Logistic Regression model. Thus, the study proposes the proper use of supervised machine learning algorithms to predict hospital re-admissions. Various scenarios with varied combinations of Machine Learning algorithms have been implemented to achieve optimum results and better accuracy. An exemplary implementation of feature selection methodology has been depicted in the study. However, the model can be made better by co-operating Natural Language Processing tools for text. Clinical Narratives like TF-IDF, Sentence Tokenization, Word Tokenization, Text Lemmatization and Stemming, Stop Words, Regex, and Bag-of-Words.

In the paper [8], "Hospital Re-admission is Highly Predictable from Deep Learning," the author uses a supervised

learning approach to predict the re-admission. The author uses ten folds, cross-validation techniques to check the accuracy of the predictive model. Five different algorithms are compared - Logistic regression, Naive Bayes, Decision tree, Random forest, and Deep Learning. The output parameter for accuracy comparison used is AUC Score. After the score comparison, the author concluded that logistic regression provided relevant results, but all the attributes affecting re-admission could not be used for score derivation. Machine learning algorithms gave better prediction results while using more information. Deep Learning and Random Forest provided the best prediction results. However, there were few loopholes considered, which comes with the dataset model. First, after discharge, deaths after discharge outside the hospitals were not considered. Secondly, the Quebec dataset was not validated externally by hospitals for future analysis. After that, hospital-specific information was not included in the dataset, which might not give good analytical results. However, the author firmly states that it would be easier for clinicians to decide with such estimations while discharging them. Indeed, it would be beneficial to set up a system that will predict the patients' unplanned re-admission and provide an analytical report. Such a system would help improve health care as such information would help prepare patients who are prone to be re-admitted and help treat them accordingly. The doctors can also take aftercare on the patient's condition and make sure the patient is doing well outside the hospital. The main advantage is that this system can reduce many medical costs, and it is not expensive to deploy the system.

In the case study of CPD[7], "Predictive Modeling of the Hospital re-admission Risk from Patients' Claims Data Using Machine Learning", the author focuses on patients affected by Chronic Obstructive Pulmonary Disease (COPD) and conducts a systematic study on developing various types of predictive Machine Learning algorithms to predict the risk of unplanned re-admission of COPD patients. The author has considered a large real-world dataset from Geisinger Health System containing medical claims of 111992 patients from January 2004 to September 2015. The machine learning models are built using the patient's feature, from transfer learning when features are extracted from clinical knowledge regarding unplanned COPD re-admission. This mode is also called transfer learning. The author also tries to implement data-driven features that are extracted from the patient data themselves. As a result of analysis based on one year of claims history before discharge, the AUC score by combining the feature-driven and data-driven features is 0.653 compared to 0.60 using knowledge-driven features. In the article, the prediction performance is based on Area Under the receiver operating characteristic (ROC) Curve (AUC). The researcher also implemented deep learning models and got the AUC score of 0.65; thus, deep learning barely improves performance in this case. The author concludes by verifying the importance of medical knowledge in the predictive modelling process and demands better patient data.

The study [6], "Machine Learning-based Risk of Hos-

pital Re-admissions: Predicting Acute Re-admissions within 30 Days of Discharge,” proposed a predictive model using machine learning algorithms. The research’s primary purpose was to predict the unplanned re-admission of patients to the hospitals within 30 days of being discharged. There were several base learner model types used, such as Random Forest, XGBoost, Adaboost, to build the predictive model. This model was used after sufficient pre-processing and feature selection steps. LACE index and patient at-risk of hospital re-admission (PARR) models were used to validate the proposed predictive model. The significant attributes used for the predictive model includes the length of stay, emergency department visits in the last six months, understanding of admission and age, social support, living situation, socioeconomic status, insurance, behavioural and mental health data. The proposed model achieved an AUC score of 0.75. The author successfully obtained a higher F1- score than the LACE index models and PARR models by 12.5 percent and 30 percent, respectively. The proposed model’s mean sensitivity was 6.0 percent higher than LACE and 42 percent higher than PARR. The proposed model obtained the F1-score of 0.386, sensitivity 0.598, positive predictive value (PPV) 0.285 and negative predictive value (NPV) 0.932.

IV. METHODOLOGY

This section elaborates on various steps that are executed to get optimum prediction results. All the significant measures that are implemented in the research are shown in the figures below. Fig 1. depicts how to prepare data by dimension reduction, removing noise, and null values, changing data formats and merging datasets for other text pre-processing. Fig 2. provides significant steps implemented in this research to develop a machine learning model and prediction algorithms.

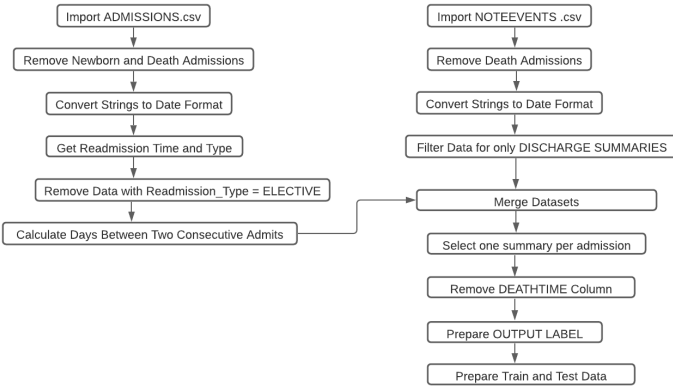


Fig. 1. Prepare Data.

A. Prepare Data

As mentioned above, we will be using ADMISSIONS and NOTEEVENTS datasets from the MIMIC-III database[27]. Thus, both datasets need to be pre-processed before it can be merged for predictive analysis.

Primarily, we will explore the ADMISSIONS table. The ADMISSIONS table has six significant attributes: SUBJECTID, HADMID, ADMITTIME, DISCHTIME, DEATHTIME, and ADMISSIONTYPE. Here, SUBJECTID represents a unique identifier for each subject and HADMID, for each hospitalization’s unique identifier. The ADMITTIME, DISCHTIME, and DEATHTIME represent the admission date, discharge date, and death time (if it exists), respectively, with YYYY-MM-DD hh:mm:ss string format. ADMISSIONTYPE is the primary type of admissions, which can be ELECTIVE, EMERGENCY, NEWBORN, or URGENT. Pre-processing stages were applied to the ADMISSIONS dataset. Firstly, the entries with ADMISSIONTYPE as NEWBORN and DEATHTIME column were removed. This is because our model predicts the chances of unplanned re-admissions within 30 days of getting discharged. There are obvious chances that patients with NEWBORNS and admissions with hospital deaths would never be re-admitted. Secondly, the date’s string format is converted to a Datetime format to pre-process the ADMISSIONS dataset. For the empty dates, errors = ‘coerce’ flag will depict the null values for missing dates. Lastly, to filter out the number of admissions of a particular SUBJECTID, we need to filter out each subject separately. This task is more comfortable if we sort the data using SUBJECTID and ADMITTIME. We will use the “group by” and “shift” operator to get the next admission date and time (if it exists) of each subject and the subsequent admission type. After executing group by and shift (-1) operator on ADMITTIME and SUBJECTID, two new columns would be termed as NEXTADMITTIME and NEXTADMISSIONTYPE. In the next admission, if the type is ELECTIVE then, it is not considered as unplanned re-admission. Thus, we can drop NEXTADMISSIONTYPE=ELECTIVE entries. Check the values by again sorting the data based on SUBJECTID and ADMITTIME and backfill the weights such that the entries are not null for further steps. We can calculate the difference between re-admission dates, which can exactly tell us after how many days the patient was re-admitted based on the pre-processed ADMISSIONS dataset.

Secondly, we can explore the NOTEEVENTS dataset for pre-processing purposes. The significant rows worth considering while working with the dataset include SUBJECTID, HADMID, CHART DATE that depicts the date at which the note was charted. CHART DATE will always have a time value of 00:00:00. The CATEGORY column represents the type of message recorded such as Nursing/other, Radiology, Nursing, ECG, Physician, Discharge summary, Echo, Respiratory, Nutrition, General, Rehab Services, Social Work, Case Management, Pharmacy and Consult. The attribute TEXT value contains the note text provided by Clinicians. Usually, there can be multiple notes per admission. It contains necessary patient information like name, doctor, location, and dates. This data has been successfully encrypted to maintain the confidentiality of the notes. For the data pre-processing in the NOTEEVENTS table, we must remove the death entries by comparing HADMID’s with that in the ADMISSIONS

table. If the HADMID is not there in the ADMISSIONS table, we can disregard the NOTEVENTS table's entry. We can now convert the CHARTDATE and CHARTTIME into the Datetime format from the string. Thereby, we will sort the entries based on SUBJECTID, CHARTDATE, and CHARTTIME. We will filter the data that are categorized as Discharge Summary. As already mentioned, there can be more than one note per admission; we will select only one summary for entries. After this step, we can successfully merge the datasets using the primary key "SUBJECTID" and "HADMID." The next section would briefly describe basic Natural Language Processing techniques used on the combined dataset.

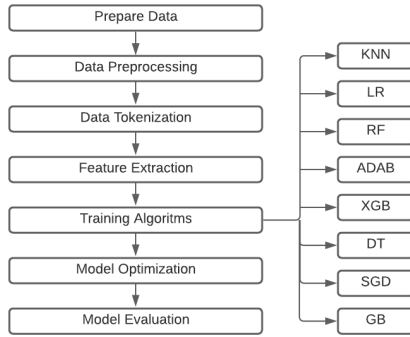


Fig. 2. Flowchart of Methodology.

B. Data Preprocessing

The problem of predicting re-admissions of patients from the clinical narratives includes studying the physicians' notes. For this, the system must be provided with Clinical Narratives in a similar format. It is also essential that the unnecessary words or items in the sentences must be removed to give the system a clear idea for easy and faster processing. This would also make the system learn quicker, and the prediction output is much more accurate and reliable. It is essential to carry out data pre-processing steps using NLP concepts in the text. This section consists of all the critical ideas implemented to prepare the NOTES field for the predictive model. We used the NLTK (Natural Language Toolkit) libraries in Python[15] to understand human language data. It is beneficial as it contains many text processing in-built libraries that help in the classification, tokenization, Lemmatization, POS tagging, parsing, and semantic reasoning.

In the pre-processing pipeline, performed the following necessary steps: Lowercase Text Conversion: This is done to solve the improper capitalization of texts. All the text in the NOTES field is converted to lowercase to ensure it does not misunderstand the input text. Punctuation Removal: This step ensures that the data is free of punctuation and provides a simple input.

Numerical Data Removal: Removing numbers would ensure that input text is a simple input text format which needs to be

analyzed to predict the re-admission based on clinical notes. Spaces can replace the numbers while pre-processing.

Stop Words Removal: This is a crucial step when the stop words such as are identified and removed. These words are meaningless and add a lot of noise while processing the data in the system. There is no confirmed list of the stop words, and they must be removed as they do not modify or change the meaning of sentences.

C. Tokenization

Tokenization is the splitting of longer texts into small fragments in sentences or words for a better readability score. We have used RegexTokenizer, which extracts tokens by using the provided regex pattern to split the text (default) or repeatedly matching the regex (if gaps are false).RegexTokenization is used to remove all the non-words characters in the Clinical Narratives. It can be efficiently removed using regex. Python provides a "re" module to replace regular expressions with the space character or replacement string. This is additional filtering and is optional to use. This step would make the input text easier to understand and evaluate.

D. Lemmatization

This is a form of normalization technique when text is converted into its meaningful root format. By doing Lemmatization, the feature space is reduced and thus makes the model more accurate.

E. Feature extraction

It is a dimensional reduction technique, where the text is reduced to a more understandable format. This reduces computation time, and the whole execution process is much more fast and efficient. We have used two primary feature extraction techniques - Count Vectorizer and Term Frequency-Inverse Document Frequency (TF-IDF). Both methods work similarly. These techniques quantify the words present in the document, which helps to weight the importance of words in the corpus. A Count vectorizer counts the occurrence of words and depicts them in vector format. It provides the count in "int" format. In TF-IDF, Term Frequency summarizes how often a word is used within a document, and Inverse Document Frequency down scales words with a lot of repetitions. TF-IDF would return a score in float format. Once these features are extracted using Count Vectorizer or TF-IDF from the dataset, we can only consider extracted features for further analysis. Thus, we can drop the text column from the dataset. This would efficiently reduce complexity from the clinical notes and save computation time, power, and space.

F. Bag-Of-Words (BOW) Technique

Machine Learning algorithms do not interpret raw text format directly. Thus, it is essential to convert the texts into vectors of numbers. This is also known as feature extraction. BOW is a simple feature extraction technique that works with a group of texts. It will count the occurrences of words in the document and represent text data in numerical form. Eventually, this data is fed into the respective Machine Learning

model. To implement the BOW approach, we need to design a vocabulary of known words or tokens. And then, choose the measure of the presence of new words. BOW does not bother about the order or structure in which the terms are arranged. Thus, the name Bag-Of-Words. This step's main motive is to understand if any known words occur in a document and learn more about its content.

G. Machine Learning Algorithms

This research includes the implementation of several Predictive algorithms to evaluate the accuracy of the output model. The prediction of unplanned re-admissions is a classification problem. Thus, various classification algorithms that are implemented are briefed in the section below.

- K-Nearest Neighbour (KNN)

KNN is a simple, easy to implement, and efficient supervised classification machine learning algorithm. It can be used to solve classification as well as regression problems. The basic idea of KNN is that the items that are similar to each other are nearer to each other. KNN classifier intends to classify unlabeled observations by assigning them to the most similar labelled data class. The characteristics of observations are collected for both training and test data. The appropriate choice of K has a significant impact on the evaluation performance of the KNN algorithm. A large K decreases the effects of variance caused by random error but runs the risk of ignoring a small but essential pattern [30].

- Logistic Regression (LR)

This algorithm is used to predict the probability of a categorical dependent variable. A dependent variable is a binary variable that contains data coded as 1 (positive) or 0 (negative). LR uses the Sigmoid function, which is a complex cost function. The hypothesis used in LR limits cost function between 0 and 1. Therefore, linear functions fail to represent it as it can have a value greater than one or less than 0, which is not possible as per LR's hypothesis. It is classified into binomial, multinomial and ordinal categories[28].

- Random Forest Classifier (RF)

RF classifier is an Ensemble learning technique that consists of a large number of individual decision trees. Each tree in the random forest spits out a class prediction, and the class with the most votes become the model's prediction. A large number of relatively uncorrelated models (trees) operating as a the committee will outperform any of the individual constituents models [29].

- Adaptive Boosting Algorithm (ADA)

The AdaBoost algorithm creates a set of poor learners by maintaining weights over training data and adjusting them after each weak learning cycle adaptively. The weights of the training samples, which are misclassified by the current weak learner, will be increased while the weights of the correctly classified samples will be decreased. AdaBoost is best used to improve decision trees' performance based on binary classification problems [33].

- Decision Tree (DT)

DT algorithm is non-parametric and can efficiently deal with large, complicated datasets [32]. It classifies data items by posing a series of questions about the features associated with the items. Each question is contained in a node, and every internal node points to one child node for each possible answer to its problem. The questions thereby form a hierarchy, encoded as a tree structure [31]. When the sample size is large enough, study data can be divided into training and validation datasets.

- Gradient Boosting Classifier (GBC)

GBC works on the algorithm to construct new base-learners to be maximally correlated with the loss function's negative gradient, associated with the whole ensemble. The learning procedure consecutively fits new models to provide a more accurate estimate of the response variable. The choice of the loss function is up to the researcher, with both a wide variety of loss functions derived so far and with the possibility of implementing one's task-specific loss [36].

- Stochastic Gradient Descent Classifier (SGDC)

SGDC implements regularized linear models with Stochastic Gradient Descent. SGDC considers only random points while changing weights, unlike gradient descent, which assumes all training data [35]. SGDC is much faster than gradient descent when dealing with large data sets. LR, by default, uses SGDC, but LR needs a dataset on RAM to work with it. In contrast, SGDC does not require a dataset on RAM to work with it.

- eXtreme Gradient Boosting (XGB)

XGBoost is a decision-tree-based ensemble Machine Learning algorithm that uses a GB framework. In prediction problems involving small-to-medium structured data, decision tree-based algorithms provide good results. XGB is scalable, which drives fast learning through parallel and distributed computing and offers efficient memory usage [34].

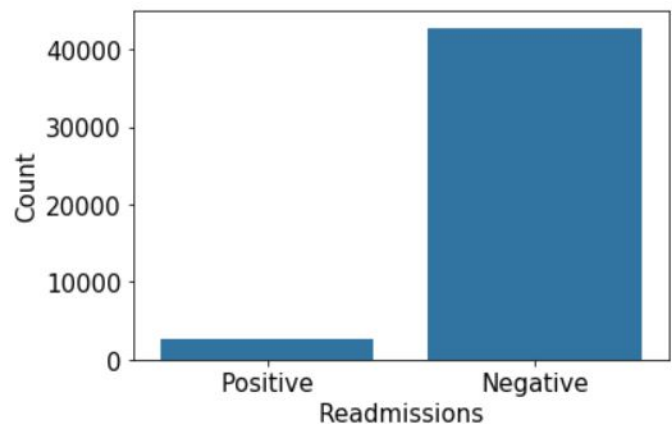


Fig. 3. Data Imbalance.

H. Training and Testing Model

Before splitting data into test and train, we have to check if the dataset has a class imbalance or not. Fig 3. provides the distribution of data for positive and negative samples. It is visible that the total number of unplanned re-admissions within 30 days, i.e. positive models, is less than negative samples. Thus, this is a clear case of class imbalance. This could create overfitting while executing the model. This problem is solved by downsampling the negative possibilities, such that the number of positive and negative samples is almost equal in training data. Overall, after down sampling, the data, totally positive and negative models were 1810, and 1805, respectively. After reshuffling and merging the dataset, it is broken down into training and testing data in the ratio of 70:30. Once the split is done and the algorithm is built, the data must undergo training to perform supervised learning. The algorithm uses trained data to learn features from the dataset. Later, testing is performed to evaluate our built model's performance using performance metrics like accuracy, precision, and f1 score. This is also called a confusion matrix. The evaluation metrics are also represented using a classification report.

I. Model Optimization

Once the base model is executed in any Machine Learning algorithm, there are several ways to optimize the model and increase the base accuracy. I have used the Random Search Cross-Validation and Grid Search Cross-Validation Technique for hyper-tuning estimators' parameters. The performance of both methods has been found consistent with all the models executed. GridsearchCV evaluates the algorithm using all possible combinations of specified hyper-parameters. Only the best variety of parameters is retained, and optimum accuracy is provided. RandomsearchCV is a technique where random combinations of the hyperparameters are used to find the built model's optimum result.

J. Model of Analysis

The predictive models can be successfully evaluated based on the parameters such as Accuracy, Precision, and F1-score. Accuracy is a critical metric for the evaluation classification model's performance. It represents the correctly predicted output while executing a model. True Positives and True negatives are crucial elements to evaluate the accuracy of a model. The precision represents the portions of the positive identifications that are correct. The F1-Score is the harmonic mean of precision and recall value. For F1-score False Positives and False Negatives are crucial while evaluating F1-score. For classification problems where data is imbalanced, F1-score is a better metric to evaluate a model.

V. RESULTS

We have performed an analysis on the MIMIC III dataset to predict hospital re-admissions within 30 days of discharge. While executing several models, the results provide broad insights into how our clinical data interact with different Machine Learning Algorithms. Our research started by extracting

the dataset from Physionet and preparing data. After that, pre-processing on data was done. We have also performed both the Feature Extraction Techniques - TF-IDF, and Count Vectorizer for better comparative results. Both the methods provided similar accuracy for almost all the Machine Learning algorithms. The features have importance as it contains valuable characteristics that define the dataset. As this is a supervised classification problem, labels were provided to data for further analysis.

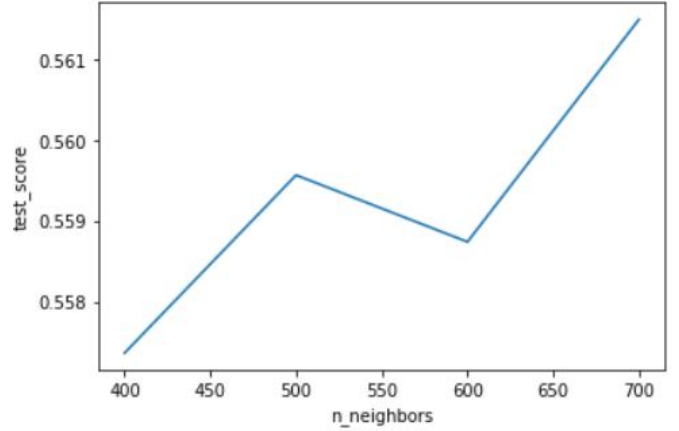


Fig. 4. Graph plotting KNN Score vs Neighbours .

The first algorithm performed on the dataset for analysis was Logistic Regression. All the previous researchers used LR as their base model to predict readmission accuracy. It is considered a baseline model for any machine learning analysis as it works well with large datasets and reduces the chances of overfitting.

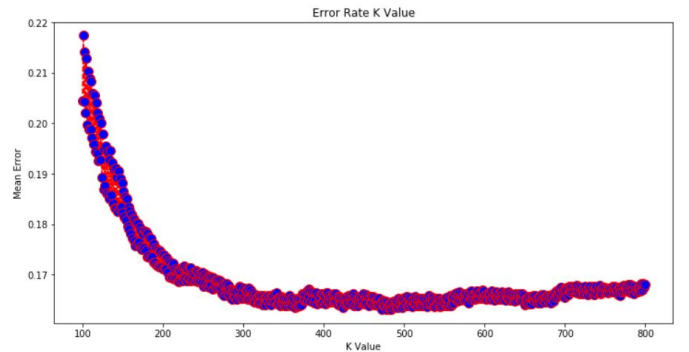


Fig. 5. Graph plotting KNN Score vs Neighbours .

However, LR did not perform well in accuracy with our dataset. LR algorithm achieved an accuracy of 66 percent on the base model and 69 percent accuracy on the optimized Grid Search Model. However, KNN model gave an accuracy of 85 percent for both the base model and the Grid Search Optimized model when performed with Count Vectorizer. Fig 4. depicts a graph showing the expected test score concerning the number of neighbours in the KNN model. It can be observed that, the

test scores increases as the number of neighbours increases. In the graph, for $n = 700$, maximum test score is attained. Fig 5. shows the error rate vs K value while executing the KNN model. Table 1 illustrates the evaluation metrics of our research. It can be concluded from the diagram that for K values between 300 to 600, there is least mean score error. Thus, these can be the most preferred K values for KNN model execution.

TABLE I
MODEL EVALUATION (IN FORM OF PERCENTAGE)

Algorithms	Accuracy	Precision	F1-score
KNN	85	91	87
LR	68	92	74
RF	64	92	74
ADAB	68	92	74
XGB	64	92	74
DT	72	92	80
SGDC	73	92	80
GB	62	92	72

The accuracy of all the base models executed in the research work is shown in a bar chart in Fig. 6. It can be clearly observed that the GB model achieves the lowest accuracy of 62 percent, followed by XGB and RF models, which attains a similar accuracy of 64 percent. ADAB and LR showcase the same accuracy of 68 percent. DT and SGDC show cases with almost equal accuracy of 72, and 73, respectively. KNN provides the best accuracy among all the machine learning models of 85 percent. Fig 7. provides a brief idea about the base as well as optimised accuracy scores of all the machine learning classification models implemented.

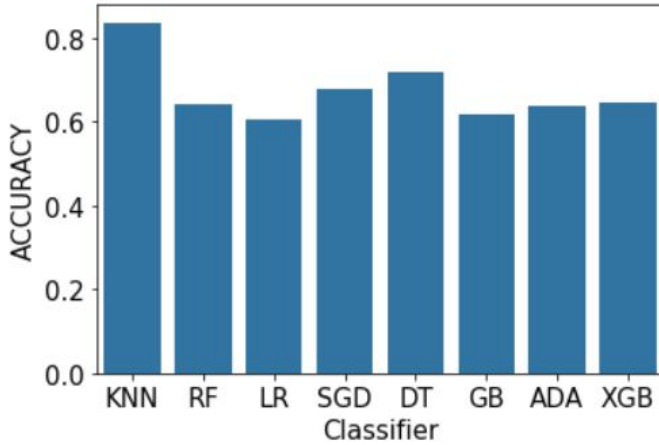


Fig. 6. Comparison of Base Models.

VI. CONCLUSION

Hospital re-admissions are expensive for both patients and the health care system. Many countries are sincerely working to reduce the chances of unplanned re-admissions. To tackle this issue, countries worldwide are spending a lot of man force on research and development in this sector. Governments

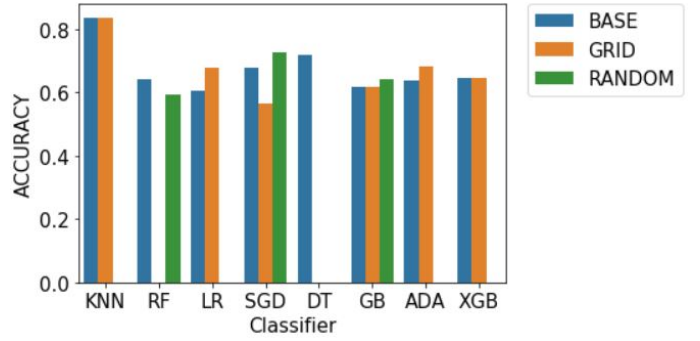


Fig. 7. Comparison of Executed Models with optimized version.

are posing strict fines and regulations on hospitals whose levels of re-admissions are higher than the permitted level. This increases the need to predict unplanned hospital re-admissions to multi-folds. Most of the research out there either does not provide good accuracy while predicting the re-admissions or only manual systems. This is tiresome and inefficient work in the modern world, and the chances of error increase significantly. However, in the health industry, we are dealing with human beings and their medical welfare, increasing the need for integrity and precision. Thus, research into analyzing clinical notes has become crucial to building a robust and highly efficient model. This research has attempted to study the clinical notes and prediction re-admissions rate on the MIMIC-III database. All the text pre-processing steps were followed thoroughly, and features were processed to extract essential characteristics. Eight types of Machine Learning algorithms were analyzed under multiple evaluation metrics. Hyper-parameter tuning helped to increase the prediction accuracy of our base models. For this predictive analysis, we can conclude that KNN outperformed all the other machine learning models acquiring accuracy of 85 percent. It has been analyzed that, due to less number of features, KNN provides better accuracy than other classification models [11]. Predicting hospital re-admissions is an actual application of Natural Language Processing, Machine Learning and Deep Learning techniques in the medical field. It is beneficial for both patients and medical staff. This would also cut down health expenses incurred by governments worldwide in the form of health insurance. With the availability of accurate information, computing power, memory, and high technology devices, these kinds of predictions would be easier to implement in the future. There are multiple government agencies, health care departments, and private companies intending to build stable, robust, more accurate, and reliable predictive algorithms for unplanned re-admissions predictions.

VII. FUTURE WORK

As the number of hospital re-admissions increases each year, there is a lot of scope for improvement in the proposed research. A more sophisticated and efficient model can be structured by considering multiple parameters while extracting

clinical notes. In the dataset, we can combine all textual data and improvise models for many clinical notes for a single patient. This would help the model to evaluate the patient's history while analyzing the patient's re-admissions. Due to limited memory, we could not evaluate the model by combining patients' medical records and thus filtered data based on discharge summaries. We want to extend our research to unstructured data like images of clinical information. Analyzing non-linear data allows research on Deep Learning algorithms as well.

REFERENCES

- [1] Lin, Y. W., Zhou, Y., Faghri, F., Shaw, M. J., Campbell, R. H. "Analysis and prediction of unplanned intensive care unit readmission using recurrent neural networks with long short-term memory." *PloS one*, 14(7), e0218942. <https://doi.org/10.1371/journal.pone.0218942>, 2019.
- [2] Z. Yu and W. B. Rouse, "A deeper look at the causes of hospital readmissions," 2017 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Singapore, 2017, pp. 919-923, doi: 10.1109/IEEM.2017.8290026.
- [3] H. Lai, P. Chan, H. Lin, Y. Chen, C. Lin and J. Hsu, "A Web-Based Decision Support System for Predicting Readmission of Pneumonia Patients after Discharge," 2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC), Miyazaki, Japan, 2018, pp. 2305-2310, doi: 10.1109/SMC.2018.00396.
- [4] S. Wang, M. E. Elkin and X. Zhu, "Imbalanced Learning for Hospital Readmission Prediction using National Readmission Database," 2020 IEEE International Conference on Knowledge Graph (ICKG), Nanjing, China, 2020, pp. 116-122, doi: 10.1109/ICKG50248.2020.00026.
- [5] X. Zhu, J. Hurtado and H. Tao, "Localized sampling for hospital readmission prediction with imbalanced sample distributions," 2017 International Joint Conference on Neural Networks (IJCNN), Anchorage, AK, 2017, pp. 4571-4578, doi: 10.1109/IJCNN.2017.7966436.
- [6] M. M. Baig et al., "Machine Learning-based Risk of Hospital Readmissions: Predicting Acute Readmissions within 30 Days of Discharge," 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Berlin, Germany, 2019, pp. 2178-2181, doi: 10.1109/EMBC.2019.8856646.
- [7] Min X, Yu B, Wang F. Predictive Modeling of the Hospital Readmission Risk from Patients' Claims Data Using Machine Learning: A Case Study on COPD. *Sci Rep*. 2019 Feb 20;9(1):2362. doi: 10.1038/s41598-019-39071-y. PMID: 30787351; PMCID: PMC6382784.
- [8] Échevin, Damien, Qing Li, and Marc-André Morin. Hospital Readmission is Highly Predictable from Deep Learning. *Chaire de recherche Industrielle Alliance sur les enjeux économiques des changements démographiques*, 2017.
- [9] Rajkomar, Alvin, Eyal Oren, Kai Chen, Andrew M. Dai, Nissan Hajaj, Michaela Hardt, Peter J. Liu et al. "Scalable and accurate deep learning with electronic health records." *NPJ Digital Medicine* 1, no. 1 (2018): 18.
- [10] Craig, Erin, Carlos Arias, and David Gillman. "Predicting readmission risk from doctors' notes." *arXiv preprint arXiv:1711.10663* (2017).
- [11] Jodha, Rajshree, B. C. Gaur Sanjay, K. R. Chowdhary, and Amit Mishra. "Text Classification using KNN with different Features Selection Methods." *Text Classification using KNN with different Features Selection Methods* 8, no. 1 (2018): 8-8.
- [12] Hosseinzadeh, Arian, Masoumeh T. Izadi, Aman Verma, Doina Precup, and David L. Buckeridge. "Assessing the Predictability of Hospital Readmission Using Machine Learning." In *IAAI*. 2013.
- [13] Jamei, Mehdi, Aleksandr Nisnevich, Everett Wetchler, Sylvia Sudat, Eric Liu, and Kirtan Upadhyaya. "Correction: Predicting all-cause risk of 30-day hospital readmission using artificial neural networks." *PloS one* 13, no. 5 (2018): e0197793.
- [14] Liu, Wenshuo, Cooper Stansbury, Karandeep Singh, Andrew M. Ryan, Devraj Sukul, Elham Mahmoudi, Akbar Waljee, Ji Zhu, and Brahmajee K. Nallamothu. "Predicting 30-day hospital readmissions using artificial neural networks with medical code embedding." *PloS one* 15, no. 4 (2020): e0221606.
- [15] Rajkomar, Alvin, Eyal Oren, Kai Chen, Andrew M. Dai, Nissan Hajaj, Michaela Hardt, Peter J. Liu et al. "Scalable and accurate deep learning with electronic health records." *NPJ Digital Medicine* 1, no. 1 (2018): 18.
- [16] Desautels T, Das R, Calvert J, et al Prediction of early unplanned intensive care unit readmission in a UK tertiary care hospital: a cross-sectional machine learning approach *BMJ Open* 2017;7:e017199. doi: 10.1136/bmjopen-2017-017199.
- [17] Nguyen, Dinh-Phong, Nicolas Paris, and Adrien Parrot. "Accurate and reproducible prediction of ICU readmissions." *medRxiv* (2019).
- [18] Craig, Erin, Carlos Arias, and David Gillman. "Predicting readmission risk from doctors' notes." *arXiv preprint arXiv:1711.10663* (2017).
- [19] Nwamaka Imasogie. "Predicting Hospital Readmission using NLP." Available: <https://medium.com/nwamaka-imasogie/predicting-hospital-readmission-using-nlp-5f0fe6f1a705> (Accessed October 09, 2020)[Online]
- [20] Andrew Long. "Introduction to Clinical Natural Language Processing: Predicting Hospital Readmission with Discharge Summaries." Available: <https://towardsdatascience.com/introduction-to-clinical-natural-language-processing-predicting-hospital-readmission-with-1736d52bc709> (Accessed October 09, 2020)[Online]
- [21] Ashok Chilakapati. "Predicting ICU Readmission from Discharge Notes: Significant Terms." Available: <https://towardsdatascience.com/predicting-icu-readmission-from-discharge-notes-significant-terms-270f6c6bb8f9> (Accessed October 09, 2020)[Online]
- [22] Ventsislav Yordanov. "Introduction to Natural Language Processing for Text." Available: <https://medium.com/nwamaka-imasogie/predicting-hospital-readmission-using-nlp-5f0fe6f1a705> (Accessed October 09, 2020)[Online]
- [23] Canadian Institute for Health Information. "All Patients Readmitted to Hospital." (Accessed October 09, 2020)[Online]
- [24] Goldberger, A., Amaral, L., Glass, L., Hausdorff, J., Ivanov, P. C., Mark, R., ... Stanley, H. E. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. *Circulation* [Online]. 101 (23), pp. e215-e220.
- [25] Johnson, A. E. W., Pollard, T. J., Shen, L., Lehman, L. H., Feng, M., Ghassemi, M., Moody, B., Szolovits, P., Celi, L. A., Mark, R. G. (2016). MIMIC-III, a freely accessible critical care database. *Scientific Data*, 3, 160035.
- [26] Johnson, A., Pollard, T., Mark, R. (2019). MIMIC-III Clinical Database Demo (version 1.4). PhysioNet. <https://doi.org/10.13026/C2HM2Q>.
- [27] Machine Learning Crash Course. Available: <https://developers.google.com/machine-learning/crash-course> (Accessed October 10, 2020) [Online].
- [28] O. Aborisade and M. Anwar, "Classification for Authorship of Tweets by Comparing Logistic Regression and Naive Bayes Classifiers," 2018 IEEE International Conference on Information Reuse and Integration (IRI), Salt Lake City, UT, 2018, pp. 269-276.
- [29] Tin Kam Ho. Random decision forests. *Proceedings of the International Conference on Document Analysis and Recognition, ICDAR*, 1:278-282, 1995.
- [30] Zhang, Zhongheng. "Introduction to machine learning: k-nearest neighbors." *Annals of translational medicine* 4, no. 11 (2016).
- [31] Song, Yan-Yan, and L. U. Ying. "Decision tree methods: applications for classification and prediction." *Shanghai archives of psychiatry* 27, no. 2 (2015): 130.
- [32] Kingsford, Carl, and Steven L. Salzberg. "What are decision trees?." *Nature biotechnology* 26, no. 9 (2008): 1011-1013.
- [33] Wang, Ruihu. "AdaBoost for feature selection, classification and its relation with SVM, a review." *Physics Procedia* 25 (2012): 800-807.
- [34] Chen, Tianqi, and Carlos Guestrin. "Xgboost: A scalable tree boosting system." In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining*, pp. 785-794. 2016.
- [35] Deepa, N., B. Prabadevi, Praveen Kumar Maddikunta, Thippa Reddy Gadekallu, Thar Baker, M. Ajmal Khan, and Usman Tariq. "An AI-based intelligent system for healthcare analysis using Ridge-Adaline Stochastic Gradient Descent Classifier." *Journal of Supercomputing* (2020).
- [36] Natekin, Alexey, and Alois Knoll. "Gradient boosting machines, a tutorial." *Frontiers in neuroinformatics* 7 (2013): 21.