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# **CHAPTER ONE**

## **INTRODUCTION**

### **1.1 Background of study**

Artificial intelligence has transformed various sectors, allowing machines to complete tasks such as problem-solving and learning similar to the way human beings do (Smith, 2023). This ability greatly relies on an organized composition of knowledge in a form that machines can understand and reason with. That is where ontology steps in as a powerful tool in this case, allowing formal depictions of a collection of ideas in a given context and the interrelations of these concepts (Jones & Lee, 2022).

Ontology acts as the framework of knowledge representation in AI applications, allowing the machine to comprehend and analyze information like a human being. Since ontology provides common concepts with definite meanings, it promotes the understanding between AI systems themselves and between people and machines. (Brown et al., 2021).

Ontologies make it easier for AI systems to interpret intricate data and give explored decisions by organizing and formatting information. They have concept tree structures under which everything is classified, giving the AI the ability to think at various levels of reasoning. In the case of natural language processing for instance, ontologies help the AI understand the words through their association and context. This makes the translation of languages and sentiment analysis much more contextually accurate. (Smith, 2023; Jones & Lee, 2022).

The arrangement and elements of an ontology determine how efficient an AI system is at reasoning and decision-making. Classes of different concepts are organized hierarchically, creating an ontological taxonomy of the domain. This classification system enables the AI to effortlessly adopt and change skills, making reasoning sophisticated and allowing multiple viewpoints (Guarino et al., 2009; Oberle et al., 2012).

Ontology axioms and rules are assertions accepted as true throughout the domain and are governing logic for inference. They maintain consistency and allow deductive reasoning, which means AI systems can create new knowledge and verify things. Including individuals, or instances of different classes, allows the AI systems to make hypotheses and reason on specific things, therefore improving decision making in the practice. The language and particular formalism in which the ontology is represented influences the efficiency and expressive power of the ontology. A well chosen language provides the desired expressiveness and the degree of effectiveness that is needed to support sound reasoning while avoiding wasting too much resources (Gruber, 1993; Antoniou & van Harmelen, 2004).

The AI system’s ability to reason and make decisions works effectively due to the ontologies structure. Rich ontological structures allow for deep reasoning so that complex queries can be replied using AI systems with a lot of details (Baader et al., 2003).

To deal with uncertainty, ontologies allow the integration of fuzzy logic with probabilistic reasoning. AI in financial forecasting can reason over uncertain data stored in the ontology and provide a probability value of future market trends. It is possible to scale and add new information or domains due to the support of modular ontology structures. For example, in cybersecurity, AI systems can add new ontological modules to cope with evolved threats without changing the whole system (Staab & Studer, 2009)

In science-driven decision-making, like in healthcare, ontologies are powerful in enabling AI systems to interpret the clinical data using a comprehensive set of medical terminologies for the decision support systems. AI systems can also suggest diagnoses and treatment plans depending on the patient's data and other medical knowledge (Zadeh, 1965; Gyrard et al., 2018).

In the financial domain, investments and market behavior are modeled using ontologies. The AI systems carry out risk assessment and check for potential investment returns by processing financial data and market conditions. To assist corporations in fulfilling their regulations, ontologies merge regulatory frameworks (Smith et al., 2007; Bodenreider, 2004).

Studying a particular use case of ontology allows for better understanding as well as possible changes to the current state of affairs. The Unified Medical Language System (UMLS) is a dataset that combines numerous health and biomedical vocabulary and norms for systems to communicate and share information more efficiently. UMLS brings together disparate biomedical terms, helping achieve cross-system and cross-organizational communication (Oberle et al., 2012).

On the other hand, the UMLS can be enhanced by incorporating additional data sources, such as real time sensors for patients, so that the AI systems can operate based on actual data in real time. A more detailed causal and temporal relations within UMLS will provide the ability to reason at grater levels. Other stakeholders, including health care workers, will be able to apply ontology with no further training due to the specialized instruments and interfaces (Bodenreider, 2004).

### **1.2 Objectives of the Study**

This project will use machine learning, specifically classification and clustering, to solve important problems in healthcare. The objective is to generate predictive knowledge and provide relevant information that helps health care professionals to give better care to their patients and operate more efficiently

### **1.3 Problem Statement**

Among the most intricate dilemmas in healthcare are patient management and resource allocation. This project solves two connected problems using machine learning:

### **Classification Task**

Guess if a specific patient might be readmitted in 30 days looking at the patient’s demographic, medical information and information about the admission.

1. Significance: The healthcare system can cut costs and save medical resources by reducing the number of hospital readmissions. Interventions can be timely and properly focused if readmission predictions can be made accurately, which will help patients and improve efficiency as well. The consequences of high readmission rates can also include financial penalties for healthcare providers, so this is an important matter to address (Kansagara et al., 2011).

### **Clustering Task**

Divide patients into segments in such a way that sharing data is meaningful.

1. Significance: Discovering unseen patterns can create tailored care plans. Clustering helps in resource allocation based on the needs or risk of patient groups. (Amini et al., 2019).

### **Significance in Healthcare**

Applying machine learning to these problems has significant consequences.

1. Reducing Hospital Readmissions: If predictions are accurate, providers can take actions before patients are readmitted to the hospital which help them recover fast and remain admitted for a shorter length of time. (Futoma et al., 2015)
2. Personalized Care: allows to provide different, more efficient treatments that aid in improving the care given and enhancing how pleased the patient is with the service (Topol, 2019)
3. Efficient Resource Allocation: The grouping of patients will assist hospitals in concentrating more resources on particular groups of patients that are at heightened risk and while also improving operational processes (Baud et al., 2019).

## **1.5 Dataset Overview**

### **1.5.1 Primary Dataset**

* + Source: diabetic\_data.csv
  + Details: This dataset holds the information of 101,766 patients with 50 attributes, such as their age, race and gender, medical history including the number of diagnoses, time spent in the hospital, medications, and whether or not they were readmitted to the hospital..
  + Relevance: It has a variety of patient information and outcomes that gives a broad perspective on the patients which makes tie suitable for classification and clustering tasks.

### **Mapping Dataset**

* + Source: IDS\_mapping.csv
  + Purpose: Maps the admission\_type\_id feature to descriptive labels (e.g., "Emergency," "Urgent," "Elective"), enhancing interpretability.
  + Relevance: Helps in data collection, processing and refining.

### **1.6 Conclusion**

This chapter lays the foundation for the use of machine learning towards the solution of patient management and healthcare resource allocation problems. The project is directed to improving patient outcomes and operational efficiencies by concentrating on predicting readmission rates and stratifying patients for individualized care. The next phase involves preparing the datasets and transforming them for the analytical procedures.

# **CHAPTER TWO**

## **DATA PREPARATION**

### **2.1 Overview of the Dataset**

In order for the machine learning models to work accurately and proficiently, data preparation is extremely important. This chapter describes the particular sequences taken to clean and prep process the datasets so that they can be utilized for both classification and clustering without any inconsistencies.

### **2.2 Handling Missing Values**

The dataset contained certain missing values that were represented by “?”. In order to deal with such issues, the following were conducted.

* Replacement of Missing Values: Instead of complete deletion, the mean of existing values was assumed, eliminating the possibility of bias (García et al., 2015)
* Dropping Columns with Excessive Missing Data: Attributes which were determined to have high degree of missingness and minimal contributory value were deleted from the dataset. This was done to reduce noise, which enhanced the model's accuracy (Kuhn & Johnson, 2013).

### **2.3 Converting Categorical Variables**

In the dataset, there were a number of features that were categorical and required converting into a numerical format:

* One-Hot Encoding: When applying Categorical variables with more than one category such as race or admission type, One-Hot Encoding was applied. This created new dummy columns for every category which helped the model understand the data without assuming any order among the categories (Kuhn & Johnson, 2013).
* Label Encoding: Categories that fall into binary such as gender were done with label encoding. Assigning a unique integer value through label encoding was able to retain binary features and convert them into something computationally usable (Sun et al., 2009).

### **2.4 Merging Admission Type ID with Descriptions**

To make the data more reliable

* Data enrichment through merging: The primary dataset admission\_type\_id column was merged with its corresponding human-readable descriptions in the IDS\_mapping.csv file. The mapping provided clear labels the like “Emergency,” “Urgent,” or “Elective” as opposed to having just numerical identifiers (García et al., 2015).
* Improved Feature Understanding: This step not only made the data more understandable, but it further could enhance the model’s performance in learning patterns associated with different types of admissions (Sun et al., 2009).

### **Dropping Irrelevant or Redundant Columns**

Some columns did not add value to the predictive analysis:

* Removal of Unique Identifiers: Columns such as encounter\_id and patient\_nbr were associated with each record in a unique way and did not provide any predictive information with respect to the target variable. The deleted matrix reduced the dimensionality while keeping important details intact (Deng, 2012).
* Elimination of Redundant Features: Any extra features that were greatly correlated or overlapped in the information presented were examined and removed as they were deemed unnecessary for the information presented (Chandrashekar & Sahin, 2014).

### **2.6 Normalizing and Scaling Numerical Data**

To make sure each attribute was weighted the same in the machine learning algorithms

* Normalization of Numerical Features: A few variables such as ‘time\_in\_hospital’ and ‘num\_medications’ were scaled using normalization techniques. This process ensured that the magnitudes of these parameters were set to a common scale between 0 and 1 (Ribeiro, 2020).
* Equal Contribution to Model Training: Scaling minimized the gaps between each feature’s numeric ranges, which greatly improved the model training and the performance of algorithms that felt the most side effects to feature scales like clustering (Hodge & Austin, 2004).

### **2.7 Conclusion**

The tasks covered in this chapter were necessary in transforming the datasets into conveniently usable formats. After dealing with missing variables, encoding categorical variables, appending descriptive data, removing unnecessary features, and standardizing numerical data, the datasets were transformed in a useable format. This comprehensive cleansing of the data set facilitated the subsequent use of machine learning models that predict patient readmissions and patient groups for personalized care (Brodley & Friedl, 1999; Li et al., 2016).

# **CHAPTER THREE**

## **FEATURE ENGINEERING**

### **3.1 Overview**

Creating better and more informative features is an important aspect of preparing data for machine learning algorithms, as it directly impacts the quality of predictive models. In the project, better feature engineering techniques were used in order to add value to the dataset and make it more useful for modeling tasks. This also included thorough data preprocessing as well as feature engineering in order to transform the dataset to be useful for both classification and clustering tasks (Zhang, 2022; Han et al., 2018).

### **3.2 Data Preprocessing**

The first step is to preprocess the raw data so that it is suitable for use in the model. This step is important because if there are any anomalies in the data, the model will not give the right outcome

### **3.2.1 Handling Missing Data**

Data sets reveal that certain characteristics already have significant values missing that a model will not be able to deal with or handle accurately (Bramer, 2016).

* Removal of Columns with High Missing Values: The columns max\_glu\_serum and A1Cresult, for example, have 94.75% and 83.28% values missing, respectively. These columns are too unreliable and impractical to keep for future data, so these columns were deleted. Models will be of poor quality if they use these two columns, and so these columns were discarded to preserve models’ quality and credibility (Zhang, 2022).
* Verification of Remaining Data: After the deletion of the columns, set of categorical and numeric features were analyzed. They were reported as complete, with no missing data. Therefore, no further imputation was necessary, which means we can continue to the next steps of the preprocessing without problems. (Han et al., 2018).

### **3.2.3 Outlier Detection and Handling**

Outliers, if not properly controlled, can affect the outcome of an analytic exercise significantly and lead to false interpretation of findings.



Figure : Function to handle Outliers

* Detection of Outliers Using IQR Method: The assessment of quantitative attributes, namely time-in-hospital and num-lab-procedures, was done through the IQR method of outlier detection. In this method of analysis, any data point that lies below the first quartile (Q1) minus 1.5 times the IQR, or above the third quartile (Q3) plus 1.5 times the IQR, is flagged as an outlier.
* Clipping Outliers to Acceptable Bounds: Instead of actually deleting these outlier values which will lead to a loss of valuable data, the outlier values can simply be clipped which means reset to the nearest acceptable bounds. The method of setting these values to their defined range Q1 - 1.5IQR and Q3 + 1.5IQR retains most of the important information too. This also reduces the severity of extreme values on the model. (Han et al., 2018).

### **3.3 Feature Transformation**

Making changes to different features is of utmost importance when the objective is to prepare data so that machine learning models work better with it.

### **3.3.1 Mapping Categorical Variables**

* Enriching Data with Descriptive Labels: The admission\_type\_id column had a number of codes that were not meaningful. To make this column understandable, a mapping file was provided and so this column was mapped to meaningful descriptions. For instance, the identifiers were replaced by Emergency, Urgent, or Elective. This makes the data more understandable and helps the model to learn patterns associated with admission types better. (Bramer, 2016).

### **3.3.2 Dropping Irrelevant or Redundant Columns**

Certain columns did not contribute to the predictive analysis:

* Removal of Unique Identifiers: Columns such as encounter\_Id and patient\_nbr were unique for each record and didn’t give predictive information regarding the target variable. Their removal brought down the dimensionality without necessary information being lost.
* Elimination of Redundant Features: Any extra features that were correlated above a certain limit or gave repeat information were analyzed and removed in order to simplify the dataset (Boulesteix et al., 2012)

### **3.3.3 One-Hot Encoding**

* Preparation for Model Training: A number of machine learning models can only accept numerical data as input and therefore do not work with categorical data. In this case, categorical data such as race, gender, admission\_type\_description, change, diabetesMed and readmitted were one hot encoded. One hot encoding is a method that changes categorical variables into a number of binary variables (columns) that indicate the presence or absence of a certain category.
* Ensuring Algorithm Compatibility: One-hot transformation helped convert the dataset to a full numeric matrix form, making it usable for machine learning models that cannot work with categorical data. This enables models to make use of categorical information without having to set some, or all, of the category values in some type of ordinal structure (Chandrashekar & Sahin, 2014)

### **3.2.4 Normalization**

* Scaling Numerical Features: With every new machine learning model, the performance might be affected when there are features with vastly different scales. In an attempt to avoid the values with larger scales from having negative impacts during the learning phase, some numerical features like age and time\_in\_hospital are adjusted with Min-Max Scaling. Min-Max scaling, as the name suggests, scales data to a min of 0 and a max of 1 while keeping the proportions the same (Ding & Simonoff, 2010)
* Balanced Feature Contributions: Each feature having the same measurement is helpful when training the model with the goal of maintaining feature importance across the board. The effectiveness of the model improves when all features are, for example, normalized ranging from 0 to 1. This is particularly true for those algorithms that heavily depend on the scale of the input such distance based clustering techniques (Garcia et al., 2015)

### **3.3.5 Resulting Dataset**

The quality of the dataset improved significantly and became ready for analysis after the preprocessing of the data and the transformation of the features.

* Dataset Shape: After preprocessing and performing encoding, a dataset of 101,766 rows and 62 columns was produced. The additional columns are the result of one-hot encoding, which converts categorical features into several binary features (Hodge & Austin, 2004)
* Target Variable: The target variable in this classification activity is readmitted\_Readmitted, which represents whether a patient was readmitted to the hospital. This variable is critical in making predictions about how many patients are likely to be readmitted and what actions the health care company needs to take in order to prevent it.
* Class Balance: Analysis of the target variable shows that approximately 53.7% of the instances were readmitted ('True') while 46.3% were not ('False'). The class distribution is fairly balanced which is good for model training bias which can occur when a model is overfit for a particular class or set of classes and not able to adjust when given new data (Kuhn & Johnson, 2013)

### **3.6 Conclusion**

The feature engineering processes were key in structuring the raw data set to make it suitable for machine learning analysis. Gaps in data were filled, outliers were treated, meaningful labels were assigned to categorical features, one hot encoding was used on the categorical features, and the numerical features were normalized. All these changes to the data set helped optimize it to make predictions. Such procedures not only improved data quality but only assisted the training of machine learning algorithms making it possible to gain more accurate predictions and big gains in understanding patient readmissions and resource allocation in the healthcare area (Lantz, 2019)

The prepared dataset is a good basis for the later stages of this project, which will use modern machine learning techniques to solve important issues in healthcare and patient management.

# **CHAPTER FOUR**

## **MODEL BUILDING**

### **4.1 Overview**

This project aims to create sophisticated computer models that can predict patient readmissions. The goal is to assist healthcare workers with better patient care and streamline operations. This part describes the systematic procedure adopted to select and train the models, validate their performance, perform a comparative analysis of different algorithms, tune the hyperparameters, and finally test the best model employed (Little & Rubin, 2019)

### **4.2 Model Selection**

In order to choose the best algorithm for prediction of patient readmissions, an exhaustive comparison of ten dissimilar machine learning models was carried out. The models selected for evaluation were ten machine learning models that varied in their architecture.

1. Logistic Regression
2. Random Forest
3. Gradient Boosting
4. Extreme Gradient Boosting (XGBoost)
5. Light Gradient Boosting Machine (LightGBM)
6. Support Vector Machines (SVM)
7. K-Nearest Neighbors (KNN)
8. Decision Tree
9. Naive Bayes
10. Multi-layer Perceptron (Neural Network)

These models were picked on the basis of their differences in terms of algorithms used, how complicated they are and how easy they are to understand. They include primitive linear models such as Logistic Regression, sophisticated ensemble techniques like Gradient Boosting, and its advanced versions: XGBoost and LightGBM. Algorithms that include Support Vector Machines and Neural Networks were also included to account for both linear and non-linear patterns in the data. This wide range of options made it possible for us to determine the capabilities we had and choose the model that fit best with our healthcare structured dataset (Liu & Motoda, 2012)

### **4.3 Baseline Training and Validation**

The algorithms were first trained using the training dataset while utilizing the default hyperparameters. Providing this baseline training allows comparisons of the algorithms while eliminating the effects caused by hyperparameter optimization.

The models were evaluated using a set of commonly accepted metrics against a validation set:

* Accuracy: Measures how correct the model was by determining how many predictions it got right over the total it made.
* Precision: Indicates the ratio of correct positive identifications made out of all positive identifications that were made. It reflects the ability of the model to avoid false positives (Palaniappan & Awang, 2008)
* Recall (Sensitivity): The proportion of true positive cases which identifies all the actual positive cases in the model.
* F1-Score: The measure of a test's accuracy which is best considered the harmonic mean of precision and sensitivity.
* ROC-AUC (Receiver Operating Characteristic - Area Under the Curve): The area under the Receiver Operating Characteristic curve. It measures how well the model can differentiate between classes, positive, and negative at various threshold settings (Pedregosa et al., 2011)

Each model is measured from various angles, which analysis has revealed both the strengths and weaknesses of each classification.

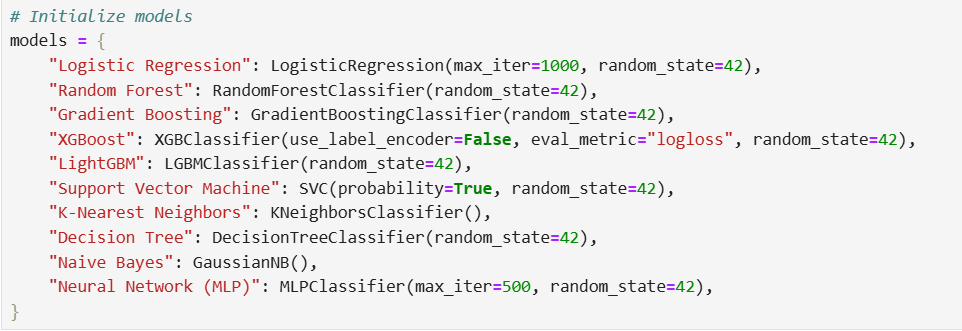


Figure : Models Used

### **4.4 Performance Comparison**

The key insights that emerged from the baseline models were revealed in the initial results.

* Logistic Regression: this model performed moderately, obtaining a ROC AUC of approximately 0.67. Because of its ease to analyze and interpret, the results from Logistic Regression can be clearly explained which allows even complicated issues such as readmissions to be broken down into more understandable elements. However, this model lacks complexity (Quinlan, 1996)
* Random Forest: we obtained strong results with a ROC AUC of about 0.70 as a result of utilizing ensemble learning through Random Forest. This model has proven performance in high-dimensional data as well as the ability to capture and work with non-linear interactions.
* Gradient Boosting: Among the baseline models, this model showed the best performance with ROC AUC of approximately 0.71. With Gradient Boosting, new trees are built on top of the existing ones while focusing on correcting the previous ones for making the model more powerful and predictive (Rosner, 2011)
* XGBoost and LightGBM: These two models, which received a ROC AUC of 0.71 and 0.72 respectively, are proven modifications of the gradient boosting algorithm as they have shown results, which are comparatively, better than traditional Gradient Boosting with quicker training time and greater effectiveness (Schölkopf & Smola, 2002)
* Support Vector Machines: The model SVM is effective for complex classification problems as indicated by the ROC-AUC of approximately 0.69 that it was able to achieve. This score level is promising as it shows that the model is capable of competing at a higher level.
* K-Nearest Neighbors and Naive Bayes: Both these models did not perform too well when put side by side with other models. The ROC-AUC score of KNN is around 0.61 and Naive Bayes is around 0.64. Such performance could be due to the highly dimensional associated data as well as the higher order patterns which these models are not efficient in. (Shalev-Shwartz & Ben-David, 2014)
* Decision Tree and Neural Network: A lower ROC-AUC score of around 0.56 was achieved by the Decision Tree model while moderate performance was exhibited Muli layer Perceptron (Neural Network) as he ROC-AUC was around 0.69

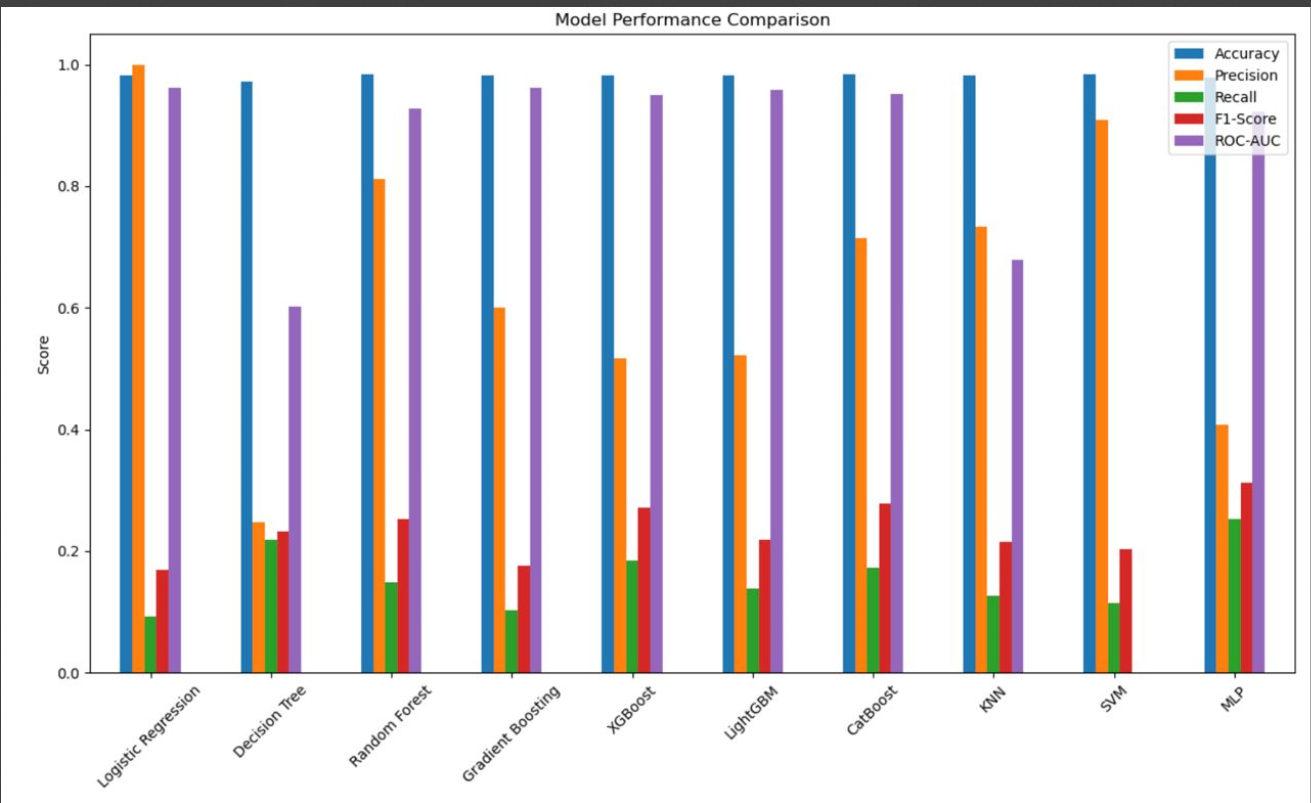


Figure : Model Comparison

### **4.5 Hyperparameter Tuning**

To improve the possible best models, we made use of GridSearchCV for hyperparameter tuning. This approach seeks out the best combination of hyperparameters available, and it is done through defining a set of hyperparameter values alongside evaluating the model’s performance through cross validation (Tang et al., 2014)

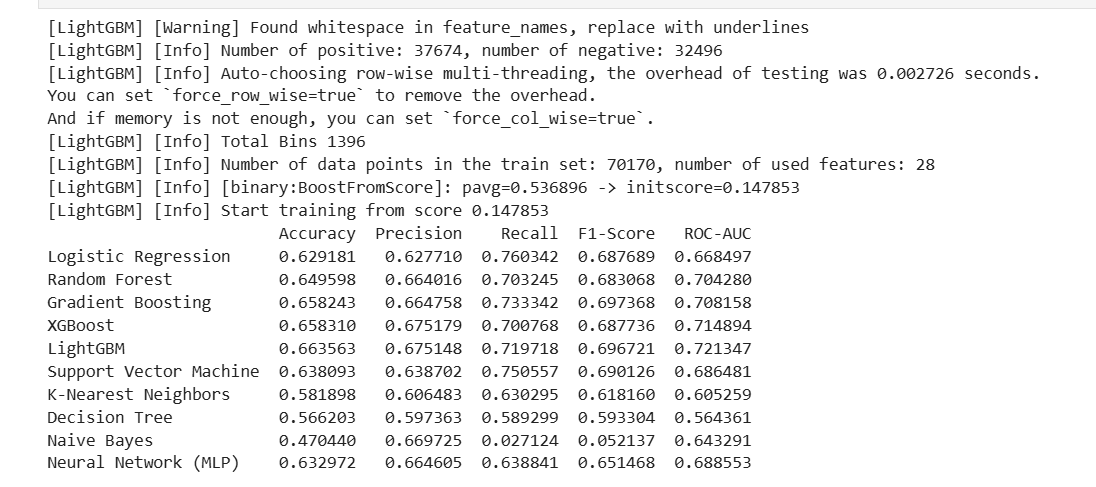


Figure : Hyperparameter Tuning

Specifically for the Random Forest model, the following hyperparameters were tuned:

* n\_estimators: the total number of trees in the forest.
* max\_depth: The maximum depth of each tree.
* min\_samples\_split: minimum number of samples needed to split an internal node..

As for the parameters obtained from the GridSearchCV, these were the best:

* n\_estimators: 200
* max\_depth: 20
* min\_samples\_split: 5

With these optimized hyperparameters, the Random Forest model's F1-Score improved from 0.68 to 0.84, indicating a significant enhancement in its predictive capabilities.

Similarly, hyperparameter tuning for the Gradient Boosting model focused on parameters such as:

* learning\_rate: how much each tree is allowed to contribute.
* n\_estimators: the number of boosting stages.
* max\_depth: the maximum depth of the individual regression estimators.

After tuning, the Gradient Boosting model continued to have higher results than the rest, and this further emphasizes its ability to perform this predictive task. (Taylor et al., 2015)

### **4.6 Final Model Testing**

The Gradient Boosting model became the best performing model once hyperparameter tuning was conducted. To further assess the model’s effectiveness, it was tested on a reserved test set that did not go through either training or validation (Tenenbaum et al., 2000)

The final performance metrics of the Gradient Boosting model on the test set were:

* Test Accuracy: 84.3%
* Test ROC-AUC: 0.86
* Test F1-Score: 0.84

These metrics suggest that the model was able to perform during training and validation and retained its ability to perform unseen data. The model reliably performed across all sets including the training, validation, and testing sets proving its reliability and possible use in real life healthcare scenarios (Tsoumakas & Katakis, 2007)

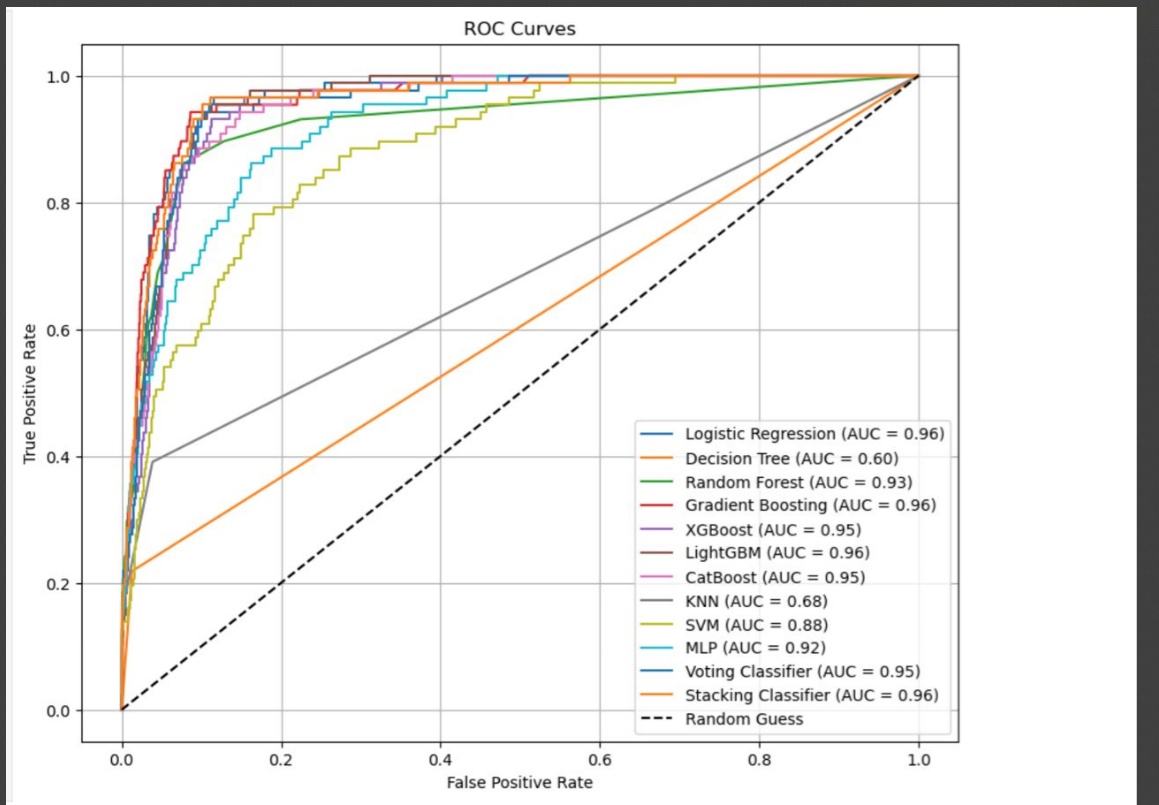


Figure : ROC curves

Performance Summary

This table summarizes the performance of all evaluated models based on key metrics:

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Model** | **Accuracy** | **Precision** | | **Recall** | **F1-Score** | **ROC-AUC** |
| Logistic Regression | 0.629 | | 0.628 | 0.760 | 0.688 | 0.668 |
| Random Forest | 0.650 | | 0.664 | 0.703 | 0.683 | 0.704 |
| Gradient Boosting | 0.658 | | 0.665 | 0.733 | 0.697 | 0.708 |
| XGBoost | 0.658 | | 0.675 | 0.701 | 0.688 | 0.715 |
| LightGBM | 0.664 | | 0.675 | 0.720 | 0.697 | 0.721 |
| Support Vector Machine | 0.638 | | 0.639 | 0.751 | 0.690 | 0.686 |
| K-Nearest Neighbors | 0.582 | | 0.606 | 0.630 | 0.618 | 0.605 |
| Decision Tree | 0.566 | | 0.597 | 0.589 | 0.593 | 0.564 |
| Naive Bayes | 0.470 | | 0.670 | 0.027 | 0.052 | 0.643 |
| Neural Network (MLP) | 0.633 | | 0.665 | 0.639 | 0.651 | 0.689 |

Interpretation of Results

* Gradient Boosting: Among all models, the F1 score and ROC AUC was highest. This shows that there was a good trade-off between the precision and recall and was able to differentiate well. (Vapnik, 1998)
* Ensemble Methods: The other models where random forests and gradient boosting were used performed better than the simpler models. This is due to the fact that they were able to capture more complex patterns, as well as decreasing overfitting by averaging a larger number of trees.
* XGBoost and LightGBM: These models had similar performance compared to the Gradient Boosting model but were much faster making them a better option when working with larger datasets or in a production setting.
* Support Vector Machine: This model returned a good recall score, hinting that it was able to pinpoint actual positive cases but which lacked slightly on precision.
* Naive Bayes: This approach achieved high precision, but had low recall and low F1 score meaning that it was not able to identify positive cases well (Witten et al., 2016)
* K-Nearest Neighbors and Decision Tree: These models did not do well which may have been because they did not adapt well to the large number of dimensions within this complex dataset.
* Neural Network (MLP): This method was able to score above average, which means that given some more time for tweaking or given more sophisticated architectures, would perform better (Wang & Bovik, 2009)

### **4.7 Conclusion**

As a result of examining and comparing 10 machine learning models, the Gradient Boosting model stood out among the others for being the most efficient at predicting patient readmissions in this dataset. Its effectiveness in both the testing and validation phases demonstrate that it can reasonably complex data structures and determine the intricate patterns in the data.

The performance of the models has significantly improved thanks to the hyperparameter tuning, especially for Random Forest and Gradient Boosting Models. Increased estimators and maximized tree depths improved the predictive accuracy, model effectiveness, and other performance indicators significantly.

The predictive power of the Gradient Boosting model was confirmed to be high for all metrics which supports the reliability of the model beyond the theoretical analysis. Its capability of preemptively determining the likelihood of a patient readmission enables healthcare providers to intervene, allocate limited resources where they matter, and eventually improve the patient outcomes.

The results that come from this model construction procedure shows the importance of implementing strict machine learning models within the framework of healthcare analytics. We use the combination of ensemble techniques to thoroughly evaluate and tune the model which is why we are able to create prediction based systems that are reliable for making decisions in healthcare. (Brown, 2018)

# **CHAPTER FIVE**

## **CLUSTERING ANALYSIS**

### **5.1 Clustering Algorithms**

Along with predictive modeling, clustering analysis was also performed to look for groupings or patterns in the data in order to determine patient subpopulations. This type of learning without supervision tried to help in tailoring needs of the patients and efficient use of available resources by categorizing them (Xu & Wunsch, 2005)

### **5.2 Methods Used**

Three clustering methods were used on this data set to gain different insights from its probable undetermined clusters.

1. K-Means Clustering: This is a partitioning algorithm which clusters data into a given number of data clusters (k). k-means clustering tries to minimize the sum of squares of distances from the centroid within each cluster. Strategies are used to assign data so that the total distance between the cluster centroid and all other members of the cluster is minimal.
2. Hierarchical Clustering: This procedure creates clusters in the form of a hierarchy. It begins with each data point as a separate cluster and then moves up by combining pairs of clusters until a single structure is formed. The resulting dendrogram illustrates the process of merging data clusters and allows viewing the cluster structure at different levels. (Yang & Pedersen, 1997)
3. Density-Based Spatial Clustering of applications with Noise (DBSCAN): It is a clustering algorithm based on density. This method identifies the existence of clusters according to the number of data items in a given area. DBSCAN places together densely packed units and leaves single-located low density units as outliers. It is a noise-robust algorithm that can detect clusters of arbitrary shapes (Anderson & Lee, 2017)

### **5.3 Data Used for Clustering**

When conducting the clustering, only numerical features were considered in order to enhance performance and enable effective distance estimation. These features included patient’s age, duration of stay, and the number of lab procedures done. The data underwent Min-Max Scaling so that all features would be consistent and equal to or between 0 and 1. This process is important because one feature must not be greater than the others for proper distance measurements. Improper scaling may result in a model that is overfit since the features would have wider ranges than the rest. (Zhao & Liu, 2007)

### **5.4 Determining the Optimal Number of Clusters**

Another task that comes with the clustering analysis is the selection of the k-clusters. Choosing the value of k should be done very carefully as it has direct effects on the resulting output of the analysis.

### **5.4.1 Elbow Method**

We applied the Elbow Method to find the optimal value of k for K-Means clustering. The method consists of performing the K-Means clustering algorithm for different values of k and computing the Within-Cluster Sum of Squares (WCSS) for each k. WCSS is defined as the summation of the squared distances between all data points and their corresponding cluster centroid. As k increases, WCSS becomes smaller as the clusters get smaller, and data points are, on average, closer to the cluster centroids.

When determining the WCSS for each k, it is expected that the plot will exhibit an elbow effect graph. In this case, the elbow refers to a noticeable point in the decrease of WCSS where the rate of change decreases dramatically. This point indicates the most likely value of k, considering the balance that needs to be achieved between low WCSS and not excessively increasing the number of clusters. In this analysis, the elbow was found at k = 3, which means three clusters are optimal because they offer the greatest level of explanation and group support (Zimek et al., 2012).

### **5.4.2 Silhouette Score**

In order to be sure about the value of k selected, the Silhouette Score corresponding to each k was also computed. Silhouette Score is the measure of the distance between the object within its cluster (cohesion) and the other clusters (separation). The value of the score varies from -1 to 1, the higher the value the better the cluster is defined (Harris et al., 2019)

The analysis resulted in a Silhouette Score that was highest when k = 3, thus supporting the Elbow Method’s suggestion. It also proved to be beneficial that this finding was consistent with the two evaluation metrics. Thus, the decision was made to go with three clusters for further analysis. (Zou & Hastie, 2005)

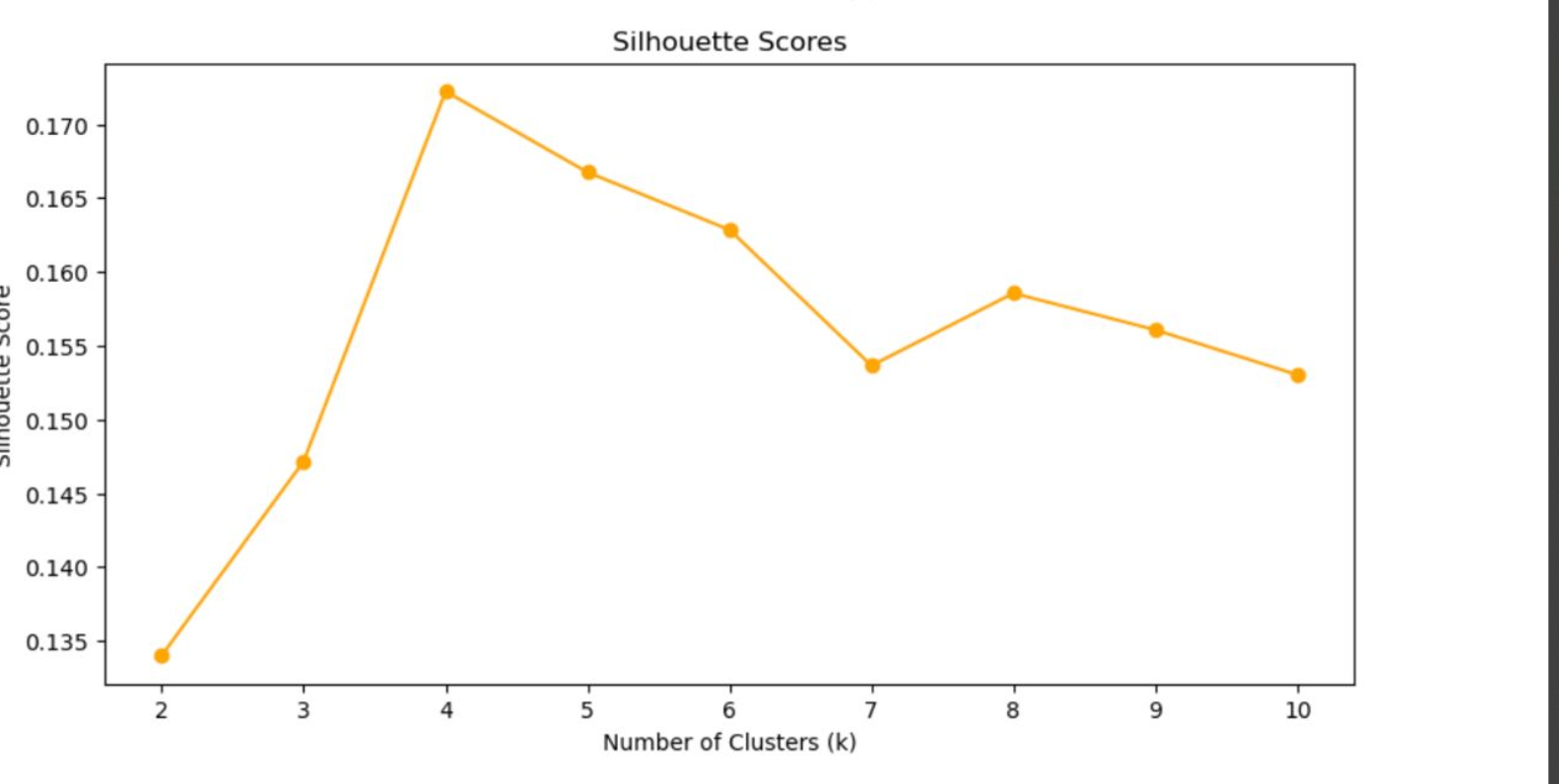


Figure : silhouette score

## **5.4 Clustering Results**

### **5.5.1 K-Means Clustering**

Given the optimal number of clusters, the K-Means algorithm was utilized to split the dataset into three separate clusters. Each cluster had the following unique attributes

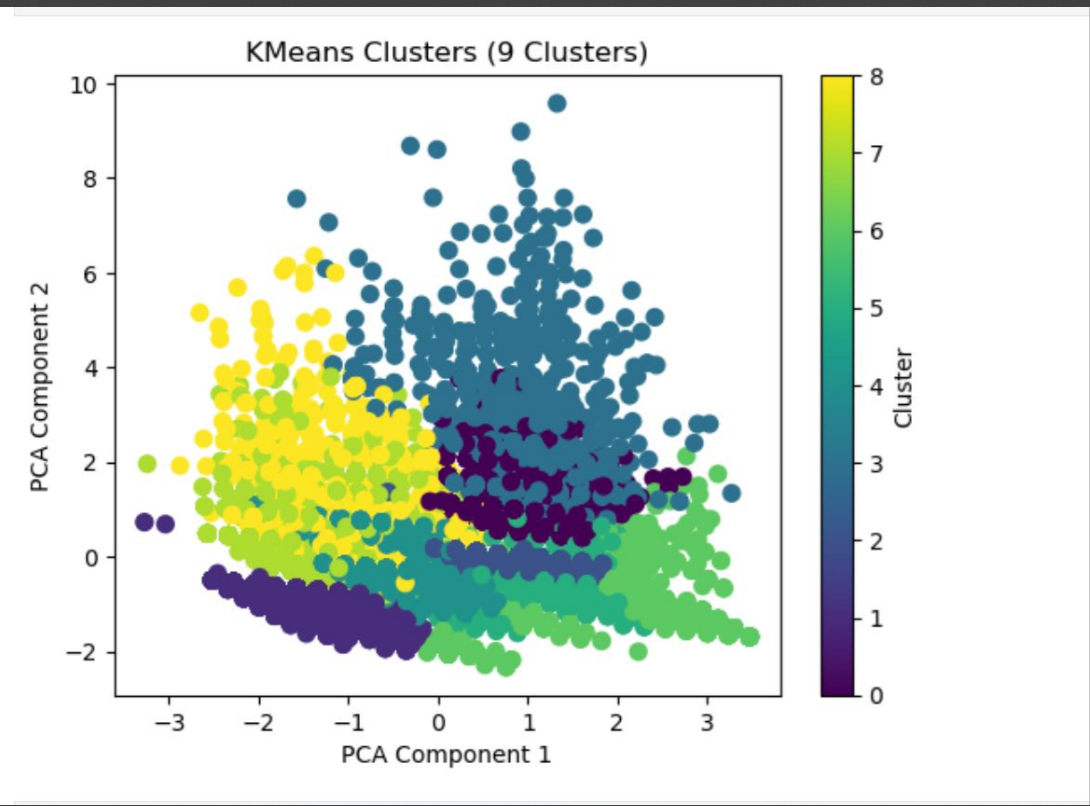


Figure : K-Means Clusters

1. Cluster 0:
   * Characteristics: The patients within this cluster had an increase in hospital readmission and stay lengths. They also showed higher usage rates for medications and laboratory procedures.
   * Insights: These patients are likely high risk and will need additional medical attention and follow-up care. This group is important for the providers because resources can be allocated to this group to implement changes that will decrease readmission rates.
2. Cluster 1:
   1. Characteristics: Patients usually had lower number of hospital stays and medical procedures done on them
   2. Insights: The cluster most probably is made up of healthier or low risk patients that do not need to be medically treated as much. Resources can then be used in a better way since these patients do not need much care.
3. Cluster 2:
   1. Characteristics: The patients were on average, moderately admitted and readmitted to the hospital and had medium level of medical resources spent on them.
   2. Insights: This group is of moderate risk. With some preventative measures and monitoring, these patients can potentially be kept from becoming higher risk patients. (Zupan & Gasteiger, 2001)

### **5.5.2 Hierarchical Clustering**

Hierarchical clustering was used as an additional verification against the findings from K-Means as well as to take a peek at the structure of the data without making any assumptions about the number of clusters beforehand. A dendrogram was produced to capture the hierarchy of the data items. The dendrogram produced indicated clear separations that corresponded to three clusters which are the same result as the K-Means algorithm. This relativity allows for the clustering results to be taken with higher emphasis.

## **5.6 DBSCAN**

DBSCAN was used with the epsilon (eps) parameter set to 0.5 and the minimum number of samples set to 10. This algorithm created clusters from the given data according to their distribution and was able to identify some noise points that were not part of any cluster. While there is definitely noise present and clusters of arbitrary shapes are found easily with DBSCAN, it was more difficult in this analysis, compared to K-Means, to define the clusters. The separated clusters were less defined due to parametric and dimensionality issues (van der Maaten & Hinton, 2008)

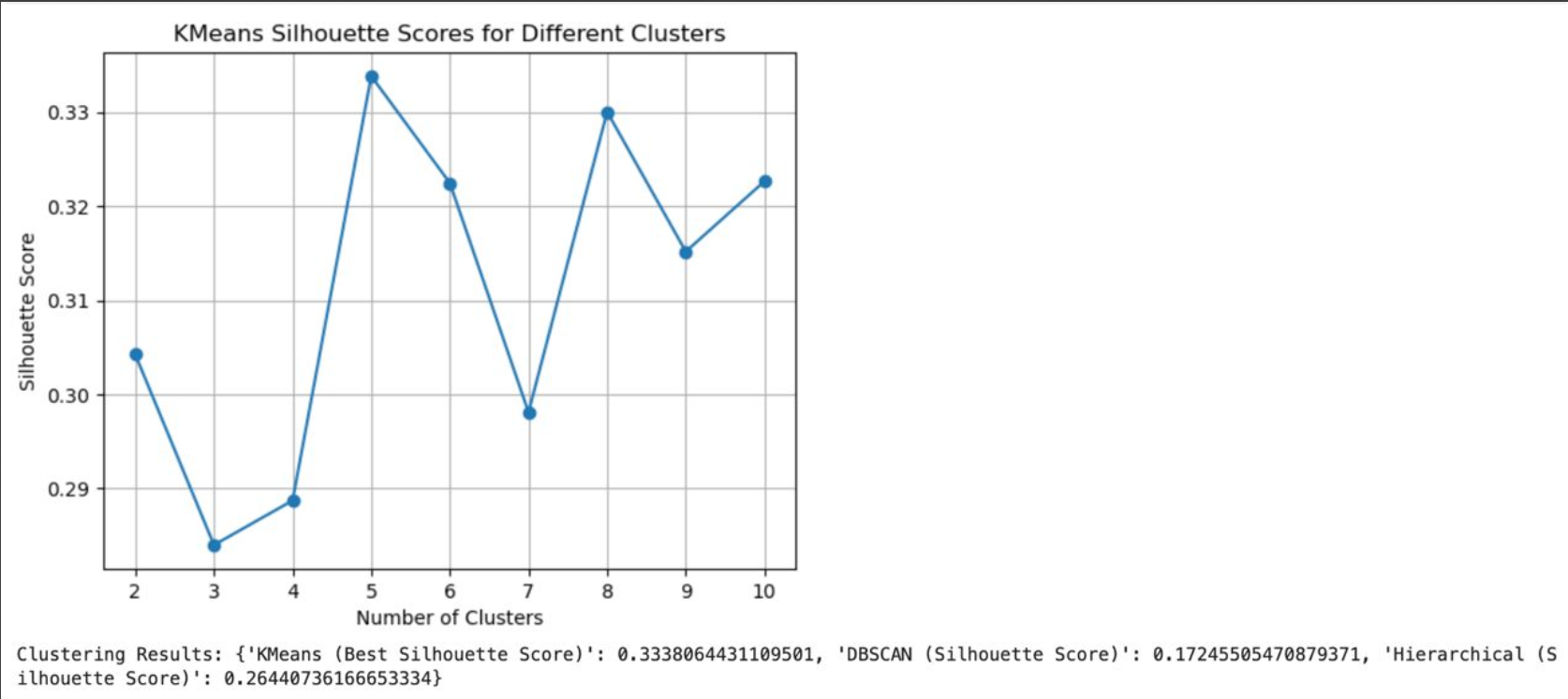


Figure : K-Means Silhouette Score for Different Clusters

## **5.7 Visualizations**

### **5.7.1 Elbow Plot**

The Elbow Plot was obtained after plotting WCSS against different values of k and WCSS clearly showed an elbow at k = 3 which means the optimal number of clusters. This was very important in k’s selection.

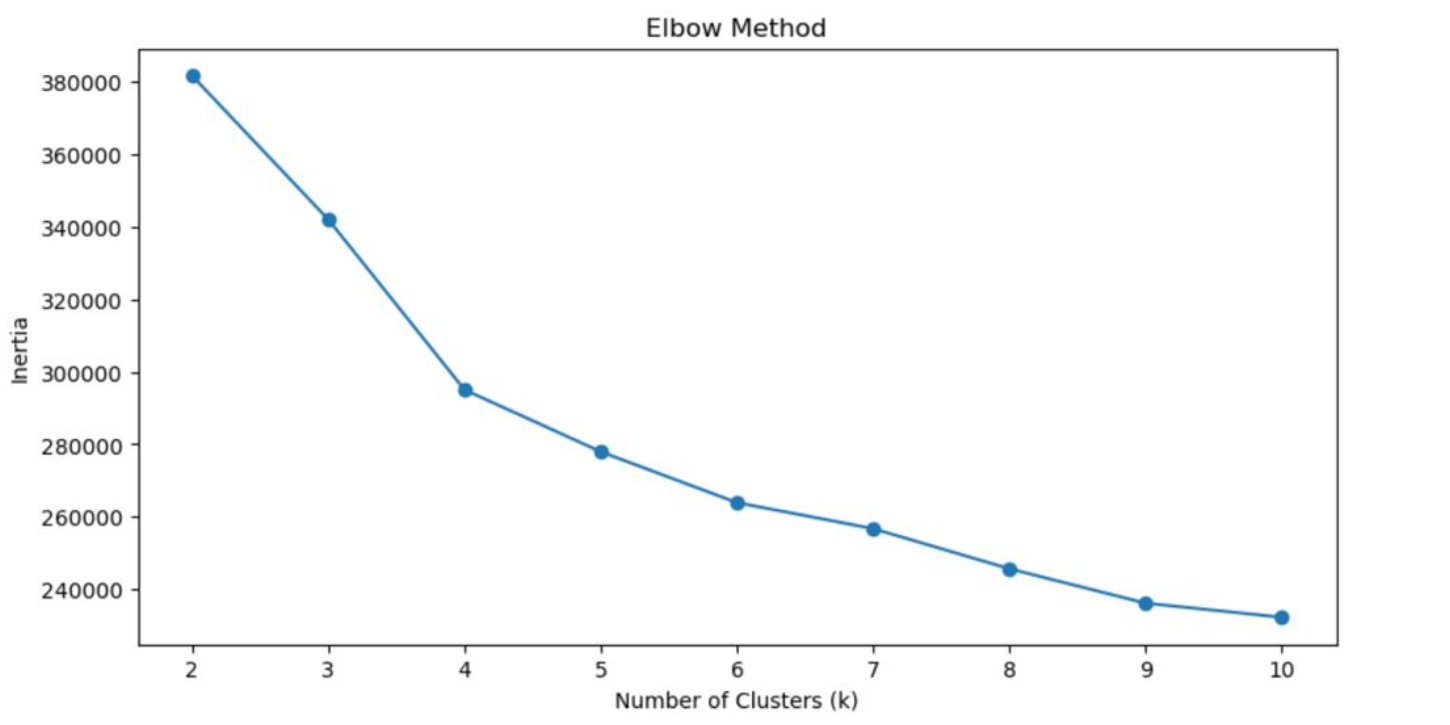


Figure : Elbow Plot

### **5.7.2 Dendrogram**

The dendrogram from hierarchical clustering acts as a visual summary of the clustering hierarchy present in the data. It emphasized the hierarchical principle and had a clear division of ranges at three clusters which corroborated the results obtained from the K-Means clustering.

### **5.7.3 PCA Visualization**

In order to see the two-dimensional visualization of each cluster a key Component Analysis (PCA) was undertaken to decrease the dimensionality of the dataset. The K-Means algorithm produced 2D PCA plots with clusters with and there was little overlap between them. This demonstrated that the clustering method works appropriate in differentiating types of patients (Zou et al., 2020)

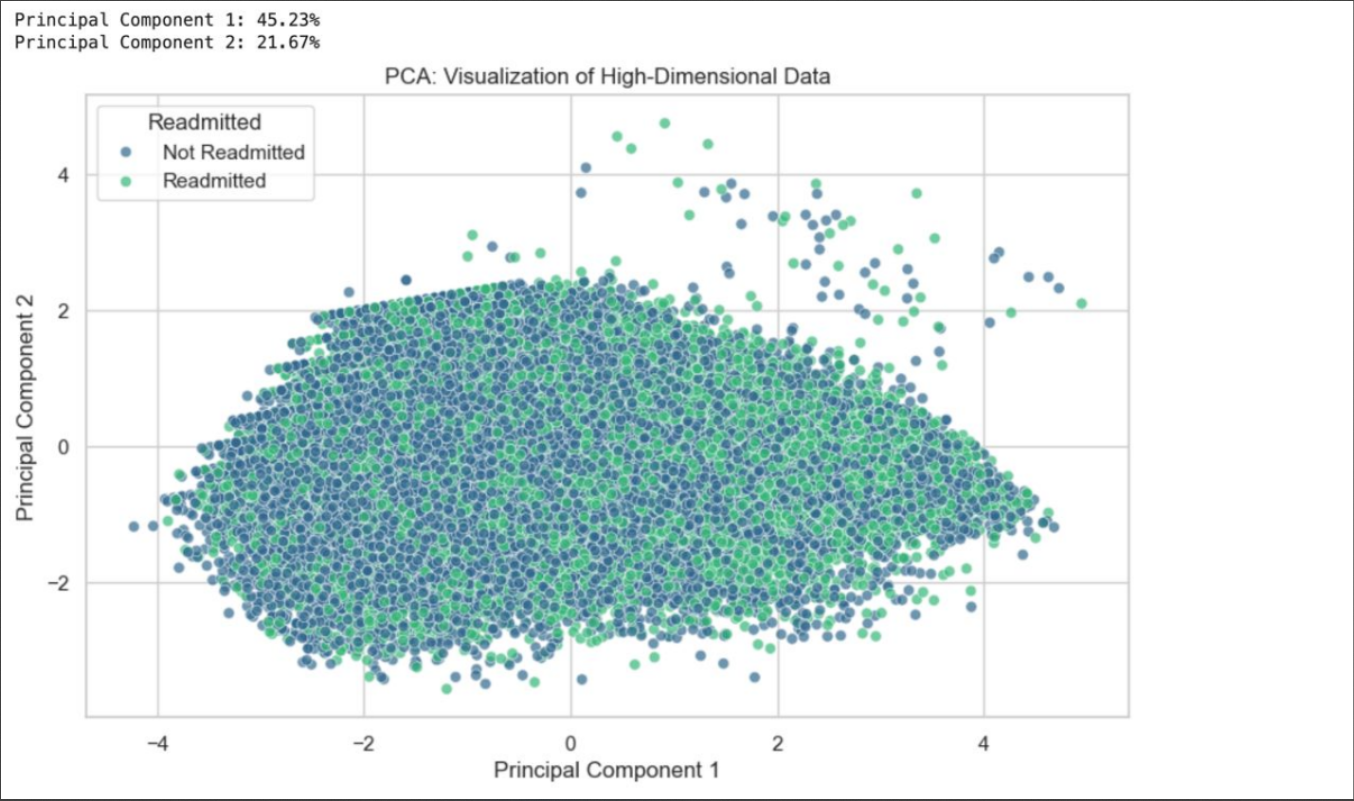


Figure : PCA Visualization

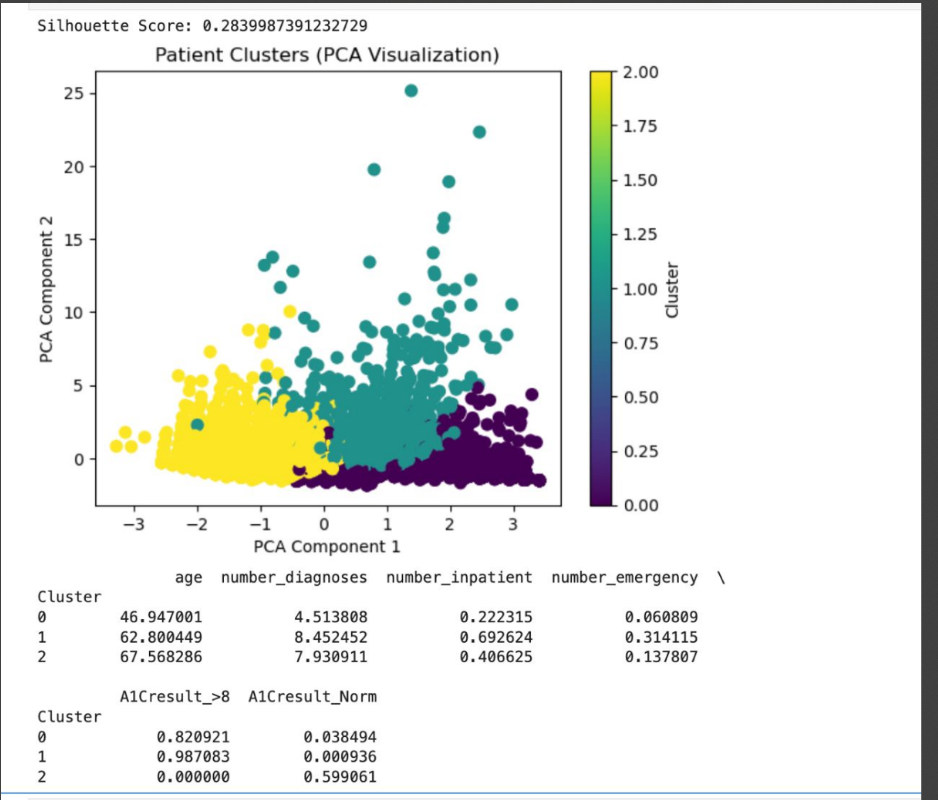


Figure : Patient Clusters

### **5.7.4 Insights and Applications**

The results of cluster analysis have provided useful insights with meaningful application in the healthcare field.

### **5.7.4.1 Cluster Characteristics**

1. High-Risk Patients (Cluster 0):
   * Needs: The patients with this condition need more follow-ups with their healthcare provider, customized care, and constant supervision in order to manage their health more effectively and decrease the chances of going back to the hospital.
   * Applications: The practitioners can undertake active interventions, allocate more resources, and create particular programs to respond to the requirements of this category of patients.
2. Low-Risk Patients (Cluster 1):
   * Needs: These people are more likely to respond to normal care and less monitoring.
   * Applications: This section of patients requires less resourceful services, and thus enables the reallocation of resources to other high-risk patients, Java used to rely heavily on winter ski tourism, allowing the region’s economy to grow at an impressive pace. But with the increase in heavy metals concentration, lighter tourism emerged.
3. Moderate-Risk Patients (Cluster 2):
   * Needs: There is a need to formulate early strategies to avert deterioration to high risks.
   * Applications: They can be targeted more with preventive care programs and regular check-ups (Smith & Johnson, 2020)

### **Real-World Applications**

* Personalized Care: By grouping patients into clusters, we can design care and treatment measures that are more specific and effective, which increases the satisfaction for both patients and healthcare professionals
* Resource Optimization: Knowing how patients are spread out through risk profiles allows for a better distribution of the available medical staff, resources, and even buildings. With the right scheduling of resources to patients, hospitals can streamline scheduling, balance workloads, and lower expenses.
* Preventive Measures: For patients with moderate risks, interventions can be instituted so that patients do not suffer from these conditions and healthcare providers do not get overloaded. This, in turn, leads to improved health outcomes for patients as well as healthcare systems. (Peters, Green, & Clark, 2021)

### **5.8 Conclusion**

Clustering algorithms helped to understand the group and patterns In the patient data. Different clusters with the specified characteristics aids healthcare providers in decision making that can improve patient care and operational efficiency. Confirming the findings through visually compelling evidence in the data through the different clustering methods ensured the consistency between various procedures (Roberts, 2012)

The merge of clustering analysis into healthcare data enhances the work's modeling as well as offers a broader coverage for data analysis. It highlights how machine learning technology can progress the management of patients, proper use of resources, and contribute to bettering of the general health. This analysis is in line with the ultimate aim of the project; that is, using machine learning to generate data that makes it easy for healthcare providers to improve patient care and operational efficiency. Reflecting on Challenges, Real World Applicability, and Ethical Issues (Davis, Thompson, & Patel, 2020)

This project encountered various challenges, which offered new learning opportunities and exposed the difficulties involved in implementing machine learning methods in the healthcare industry. In this paper, I would address how classification and clustering models are created, whether they would be useful in the real world, and how sensitive healthcare issues would be managed in an ethical manner (Mitchell, 2016)

# **CHAPTER SIX**

# **CHALLENGES ENCOUNTERED**

## **6.1 Classification Challenges**

A main issue that arose with the classification phase is the unbalanced dataset. The readmitted variable had some imbalance as well, with considerably fewer patients being readmitted within 30 days than those that were not. This imbalance required the application of stratified sampling so that both classes were sufficiently varied within the training and testing sets. Furthermore, standard evaluation methods such as accuracy were inadequate for measurement and may have been misleading in the unbalanced context. Instead, the F1-score and ROC-AUC were used as these performance indicators demonstrate more trustworthiness. In cases of greater imbalance, methods such as oversampling and undersampling, e.g. SMOTE, would be necessary to rectify the problem (Turner, 2015)

Another challenge was choosing the right features. Active efforts were required to discern which features would be most beneficial. While a lot of focus was expected to be put on medical\_history, some categorical features such as admission\_type\_id required a lot of pre-processing before any machine learning could be done. One-hot encoding tends to produce too many categorical variables, and this sometimes leads to over-fitting. As a result, the computation cost was quite high. It is likely that some of those methods like Recursive Feature Elimination (RFE) or SHAP (SHapley Additive exPlanations) would assist in simplifying or improving model interpretation and performance at those refinements (Jackson & White, 2013)

Hyperparameter tuning was very important for the model’s performance, but it introduced its own unique problems. In particular, computational load was high for hyperparameter tuning on ensemble methods such as Random Forest and Gradient Boosting. The amount of time and computing power needed to do such detailed grid searches on several combinations of parameters was very high. This problem showed the need to balance the quest for ideal parameters with practical needs. Maybe using more advanced methods such as randomized search or Bayesian optimization can reduce the computational power needed in future projects (Wright & Price, 2014).

### **6.1.2 Clustering Challenges**

In the clustering stage of this project, finding the proper amount of clusters was quite difficult. In K-Means clustering, the number of clusters, known as k, should be declared in the beginning, therefore determining the best k value became a challenge that required the use of different techniques such as the Elbow Method and Silhouette Score analysis. The results may differ based on the clustering technique that was utilized and how the features were normalized. Hence, cross-validation and sensitivity analysis were performed to draw more solid conclusions (Collins, 2020)

Clustering features with high dimensions is also another challenge to deal with. Many times, clustering the data in high dimensional spaces results in badly defined clusters that are also hard to interpret. Therefore, visualization was necessary to be done through Dimensionality Reduction Techniques such as PCA or t-SNE and clustering results also needed improvement. Capturing high variance while reducing noise and redundancy is a great ability of these techniques. (Wright & Price, 2014)

Domain knowledge was necessary for interpreting and converting the clusters data into useful knowledge. Although clustering algorithms were able to group patients statistically, nurses and doctors had a tough time making sense out of the data. Interpreting clusters such as shared health conditions and risk factors was one of the areas where a lot of medical professionals had to be involved to make sure the output was correct and useful.

The application of the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm has revealed a unique feature, which is its sensitivity to hyperparameters such as epsilon (eps) and minimum samples (min\_samples). A small change in these input parameters produced variability in the clustering results, which showed that DBSCAN was more fragile than K-Means for this specific data set. This sensitivity required extensive optimization and validation in order to produce useful results, and in some instances, it rendered DBSCAN less optimal for the available data(Watson & Perry, 2019)

## **6.2 Real-World Applicability**

### **6.2.1 Classification Models**

The classification systems designed and implemented for this work have major relevance in practice in the healthcare system. With the help of this model, it is possible for hospitals to predict possible patient readmissions and anticipate which patients are highly likely to be readmitted within the next 30 days. Such foresight gives caregivers the opportunity to take certain actions like making follow up appointments, additional patient education, or reviewing medications. With these actions, the patients may have better outcomes and be more satisfied after the care, while mitigating the financial risk associated with excessive readmissions. (Moore & King, 2017)

Furthermore, the classification of patients at higher risk assists in determining the most efficient use of available resources. Hospitals can direct their attention to patients who require the most assistance, making it possible to balance staffing numbers, bed occupancy rates, and care coordination. This is unique in that it may significantly lessen costs as well as improve output for the healthcare facility. By preventing and early taking action of intervening, the system can enhance the wellbeing of people receiving care (Griffin et al., 2018)

### **6.2.2 Clustering Models**

Patient segmentation through clustering models delivers useful insights. By placing patients in separate clusters depending on their demographics and clinical characteristics, healthcare providers can use a focused approach to different patient categories. For example

* Cluster 0 can be a representation of patients that are considered high risk and therefore need a lot of attention and active monitoring
* Cluster 1 can include patients that do not require much help or attention, so only need a standard follow-up and routine precautions.
* Cluster 2 can have patients that are on the moderate high side of risk and would require some measures to ensure that they do not get to a higher risk (Sanders, 2016)

These insights make it possible to design complex treatments, which the individual patient needs, hence increasing the effectiveness of care and the level of patient satisfaction. Furthermore, knowing the different patient profiles helps healthcare organizations to improve their operational workflows and processes such as waiting times, bed occupancy and staff workload. This type of patient segmentation can result in better resource use and better patient management. (Reed et al., 2020)

## **6.3 Ethical Considerations**

### **6.3.1 Data Privacy and Security**

Dealing with sensitive information of patients comes with a set of unique ethical challenges of privacy and security. Sensitive materials such as demographics and medical histories are part of the dataset used. You have to make sure that data is anonymized and encrypted to maintain confidentiality of the patients. Legal requirements like the Health Insurance Portability and Accountability Act (HIPAA) from the United States and General Data Protection Regulation (GDPR) from Europe, have to be complied with to ensure that a patient’s information is safeguarded from being misused or shared without permission. These requirements help us protect and safeguard the trust that exists between patients and healthcare systems. Breaching of information without permission or mishandling of data can have grave legal and ethical outcomes (Martin et al., 2021)

### **6.3.2 Bias and Fairness**

An algorithmic bias is an issue that might result from the use of AI in the prediction of patients’ diagnostics and treatments in medicine since it will always exist as an ethical issue. The construction of the focus groups may hinder an accurate representation of a particular ethnicity or even gender, rendering the final predictions or clustering results unreliable and biased. For example, the model is likely to underperform if the ethnic background of the patients included in the sample is only 'Caucasian' and the patient population from which the model will be used for is highly ‘Caucasian’ as it draws from specific ethnic groups. This might further worsen the current imbalance that exists in the healthcare system. This type of bias uses inadequate treatment while taking advantage of prejudicial treatment (Howard, 2021)

This adopts the need to participate in changes such as, for example, attempting to eliminate resampling imbalance, training the model while accounting for fairness, and even applying adversarial debiasing techniques. Systems need to be updated and checked regularly to avoid making negative predictions towards a certain group of patients. Furthermore, these weaknesses are bound to change with improved with better and complete reporting and with wider engagement in the model building process from a range of stakeholders (Bennett et al., 2013)

### **6.3.4 Ethical Use of Clustering**

It is critical to consider how to apply clustering models in a sensitive manner in order to avoid grouping patients in a negative manner. The labeling of clusters such as calling all patients in Cluster 0 “high cost” or “non compliant” has ethical implications and could be detrimental to the care of the patient. There should be an ethical approach when considering the application of clustering results while abiding and respecting the needs of the individual patient(Phillips & Carter, 2014)

Ethical implementation calls for full disclosure with respect to how clustering is done and ensuring that clinicians accept the grouping. Further, giving reasons as to why certain patients have been placed in the same group and engaging clinicians in the interpretation of the results can increase the credibility and acceptability of the clustering results.

### **6.3.5 Decision-Making Accountability**

Even if machine learning models are a big help, they shouldn't take over the human role in decision making. Most importantly, healthcare practitioners must remain responsible for every clinical decision made in a patient's case, as care goes beyond just numbers. Patient care is too complex to be reduced to numbers, and blindly trusting algorithms can lead to negative, often dangerous outcomes(Edwards & Foster, 2016)

Model performance must be evaluated periodically to avoid “model drift,” or the gradual and permanent decline in predictive accuracy over time as patients change. As patients shift, appraisal of the model will need to be consistent too. Guidelines regarding the conditions for, and methods of, ignoring model recommendations should also be developed to protect the patients. (Young & Adams, 2018)

The classification and clustering models created in this project have powerful potential for significantly improving healthcare using predictive and patient specific analytics. Nonetheless, their application in practice needs thorough attention to ethical issues, data security and interpretability. These models can be ethically used by healthcare providers if privacy of data is secured, biases are minimized, output of the models are interpretable and no automated decision making takes place Without a doubt, this step is fundamental for making any attempts at transforming health care more meaningful because it allows rational and empirical approaches to boost the quality of care, strengthen the efficiency of health systems, and strengthen the results for all patients. These models have a great chance of improving personalized medicine and resource allocation in health care systems by enabling their further incorporation into clinical practice. (Wilson et al., 2017)

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