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ENHANCING PATIENT EXPERIENCE IN RADIOLOGY: PREDICTIVE MODELING OF WAIT TIMES USING FEATURE SELECTION TECHNIQUES

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Abstract
The increasing patient flow and overcrowding in critical hospital departments have prompted the need for effective strategies to enhance patient satisfaction. This study focuses on machine learning algorithms to predict patient waiting times for X-ray services using the dataset from a high-volume radiology department. Three regression models, such as Linear Regression (LR), K-Nearest Neighbor (KNN), and Random Forest (RF) were proposed and integrated with the recursive feature elimination (RFE) algorithm to reduce the dimension of the dataset and to enhance the model's efficiency by selecting optimal features. The findings indicate that the LR-RFE model with 30 features predicted waiting time with a mean absolute error of 3.63 minutes as compared to the standard LR model with 63 features. Comparable results were observed with the RF and KNN models, which demonstrated mean absolute errors of 3.77 minutes and 3.81 minutes, respectively. Furthermore, the feature revealed key contributors to waiting times, such as the sum of patient queue wait times, the number of patients waiting in line, and the wait time for the most recent patient. This study underscores the potential of machine learning techniques combined with feature selection to offer actionable insights for better patient queue management.

Keywords:
Machine learning; feature selection, wait time, patient flow, regression

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1. Introduction

In most of the hospitals, dynamics of the patient queues critically shape the clinical workflow. As a result, predicting patient flow and wait times has become one of the most important clinical management techniques. The queuing is caused by variations in supply and demand, as well as a lack of resources at hand [1]. Implementing a tool for planning and control and using operational management techniques are the main goals to improve the operational efficiency in a sector. Radiology departments (RD) are the most important units in each hospital because they help in generating diagnostic information about a patient's condition. The problems of long waiting times among patients are faced due to crowd in the department. Most of the patients visiting RDs face long waiting times due to overcrowding which is a major concern across the hospitals in the United States. The patient flow should be improved by scaling up linked wards to achieve coordinated flow and by considering the total patient flow throughout the wards rather than concentrating on specific wards to prevent irregular flow [2].

When there are no slots available at the RD, the patient must wait in the preceding ward, which causes the queue to grow and seems to be problematic for patient flow. Therefore, the accurate prediction of radiology emergency patient flow is of great importance to optimize appointment scheduling decisions. This requires an accurate and efficient method to model the experienced waiting time for patients visiting an emergency medical services unit.

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The main causes for overcrowding at the RD are the excessive number of non-emergencies, unscheduled patients, and the socially recommended cases, in addition to the shortage of specialist radiology physicians. The majority of patients (74.1%) had examinations lasting between one and five minutes, particularly for X-rays, according to the distribution of patients based on examination time. The research shows that many models for estimating waiting time and utilization are available today but not adopted in our country [3]. Our main aim is to evaluate the applicability of machine learning models to predict patient wait time in walk in facility in RD. In this department even for high-priority cases, the hospital is facing a problem of long patient wait times. Due to the interconnectivity of the wards, any problem in the RD ward has a direct impact on the patient at the front of the line, resulting in the formation of a patient queues. There are many stages in healthcare system such as admission time, the in-patient period, and the discharge process. Not all phases of a patient's flow are carried out inside a single ward, and and a well-functioning infrastructure is necessary for the effective performance of these operations [4].

The patient flow is greater and has been worst during COVID 19 outbreaks. Considering the identified issue, the RD is the main area of attention since the flow needs to be changed without causing any harm to the Department. An overcrowded clinic is stressful, whereas an idle clinic wastes resources and is depressing. Realistic and timely prediction helps prevent congestion and idle time. It also helps load-balance by rerouting arriving patients to less-busy sections before it gets too packed. Modelling usually identifies waitline problems and proposes solutions (e.g., hiring more staff, implementing a ticketing system, using electronic patient records,polling patients for feedback) and uses discrete event simulation to prevent patient overcrowding.[5], [6] This study uses different ML models to predict waiting time of patients in walk-in RD for X-ray facility with consideration of different features related to patient queue, exam type and time related information. We constructed three linear and nonlinear models to predict wait times of patients at the time of arrival. The Linear regression, K-nearest neighbors, random forest models were applied on data and then evaluate the results for prediction of waiting time of patients wait for X ray exam.

2. Literature Review

The use of Machine learning techniques is increasingly applied in prediction of various time related aspects, such as patients waiting times for treatment, consultation durations with doctors, payment processing times at counters, delays in scheduled appointments and length of stay in inpatient departments. These applications are critical in optimizing hospital operations and improving the overall patient experience. Penn et al. [7] developed a logistic regression ML model to calculate the wait time from a primary care referral note. By connecting the specialist type from a primary care referral to a complete consultation visit conducted in Ontario, Canada, health administrative data was used to quantify the wait time. In order help future researchers, they also examine how note length (measured in tokens) and dataset size (measured in notes per target specialty) affect model performance. Alternatively, they suggested that electronic medical records (EMRs) can be used to arrive at wait time estimates. However, due to missing labels, target specialty physician labelling is presently a task requiring manual human labelling, something we wish to automate to increase the number of referrals labelled and decrease the cost and time associated with conducting such studies.

Silver et al. [3] investigated the reasons of increasing waiting times in a high-volume outpatient cancer clinic and use some quality improvement tools to reduce waiting time of patients. They analysed the patient flow and scheduling process in the department of head and neck surgery with the use of paired- t test. They found that average patient waiting time is 71 minutes and analysed that scheduling too many patients in a short time interval at the beginning of clinic hours exceeding the physician's patient capacity per hour. By implementing the rules of quality improvement (identifying best practices, standardizing appointment scheduling and load levelling), waiting time of patients significantly decreased. Accurate waiting time estimation was also expected to improve staffing decisions, leading to enhanced patient flow and satisfaction [8].

Susmitha et al. [9] analyse the patient waiting time at OPD, at various diagnostic services through a cross sectional observational study conducted in a tertiary care hospital for the period of 8 months. They found that average waiting time of patients for X-ray was 6.09 minutes and ultrasound 6.9 minutes. They concluded that patients satisfied with the activities of the hospital, but patients are not satisfied with the waiting time in hospital for consultation. Idigo [10] analysed that high patient load and ineffective appointment scheduling causes crowding in hospitals. They used the real time data of 768 patients conducted in a radiology department of tertiary hospital in Nigeria and analysed using MATLAB software. They find the scheduling method, arrival time, treatment time and waiting time of patients in radiology department for different examinations. The average patient arrival per hour (arrival rate) was 7 ± 5.4 patients per hour. Patient arrival rate distribution showed a pattern that resulted in the identification of three segments: 7:00–10:00, 10:00- 13:00 and 13:00-16:00 with arrival rates of 12, 6 and 2 patients per hour, respectively. The mean waiting time was 116.2 minutes.

Anusheel et al. [11] represented an analysis of waiting and treatment times for patients undergoing radiation therapy at a single institution over a 4-year period from Jan 2014 to Feb 2018. They collected a large dataset of patient related times, including waiting time before treatment and actual start treatment. They included many new modern therapy techniques in radiology oncology such as volumetric- modulated arc therapy, three-dimensional conformal radiotherapy etc. They obtained average wait time and average time spent in hospital is 12.1 ± 62.7 min and 52.4 ± 33.0 min respectively. They emphasize the importance of considering waiting times in modern-day radiation therapy and provides insights into the time requirements for different techniques in healthcare.

Goldovac et al . [12] concluded that wait times of more than 30 minutes are negatively associated to patient satisfaction in the orthopaedic department. Furthermore, appointment time, visit time, and whether the visit required an X-ray are the most effective predictors of longer wait time. Li et al. [13] predicted the outpatient waiting time in a Chinese paediatric hospital with the help of machine learning algorithms. They proposed a novel classification model based on statistical analysis and medical knowledge. Then applied four ML algorithms LR, KNN, RF, and GBDT to develop models for predicting waiting time of patients in four department categories. The best model for Internal medicine department was the RF model with MAE 5.03, while for other three departments was the GBDT model with lowest mean.

A study carried out in Northern India in 2020 found that 12% of patients spent more than 30 minutes in the laboratory and 29% of patients in the radiology department[14]. Goswami et al. [15] conducted an analysis on the wait times at a restaurant utilizing queuing theory. Employing Littles theorem and the M/M/1 model, they examined data obtained from Raipur restaurant. At the peak hours, the arrival rate at the restaurant was 3.244 customers per minute (cpm), while the service rate stood at 3.28 cpm. The restaurant typically accommodates an average of 104 customers with an average usage period of 0.989 minutes. This analysis aids in understanding the current scenario and offers insights for forecasting both customer arrivals and their wait times, thereby facilitating improvements for future operations. Grot et al. [16] analyse the dataset and found that random arrival of patients and random consultation times affect waiting time. This increased the average waiting time by up to 30 minutes compared to when patients arrived on scheduled time.

3. Proposed Methodology

This section describes the framework of proposed system to predict wait time. As Fig. 1 shows, the proposed system comprises three steps: Data understanding, Data Preprocessing, Features Selection, and Machine Learning algorithms. All preprocessing steps were performed using Jupyter notebook of Python. To predict the wait time, we used the dataset of a radiology department with walk in facility at Massachusetts General hospital. This dataset is taken from Kaggle to predict patients waiting time for their exam. In this study, one year data from Nov 2017 to dec 2018 including records for around 28870 patients. There are 61 features related to flow of patient such as arrival information of patient, resources used such as number of scanners used, queue information before and after arrival of patient as shown in Table 1.

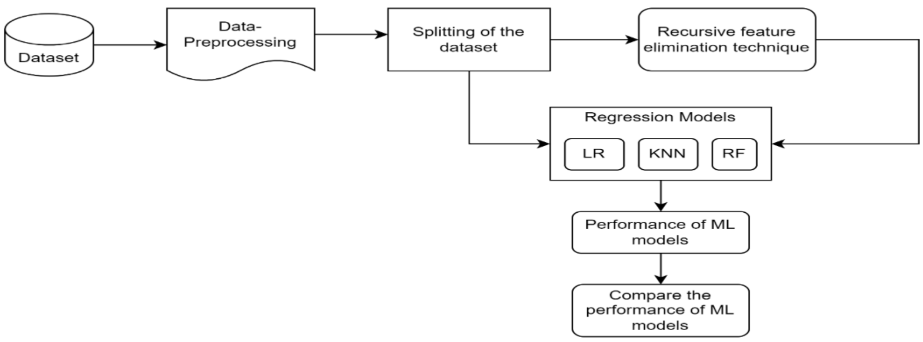

Figure 1: Flowchart of proposed machine learning model.

The patients waiting for different types of exams such as thoracic imaging which detects the diseases involving lungs and chest wall, paediatric imaging detects the diseases in children and musculoskeletal imaging detects conditions affecting the bones and muscle ligaments. The average waiting time of patients was 8 minutes and per hour of the day is shown in Fig 2. The average arrival rate of patients on each weekday with respect to each hour of the day shown in Fig 1. A very few patients with wait time greater than 70 minutes were removed from the dataset.

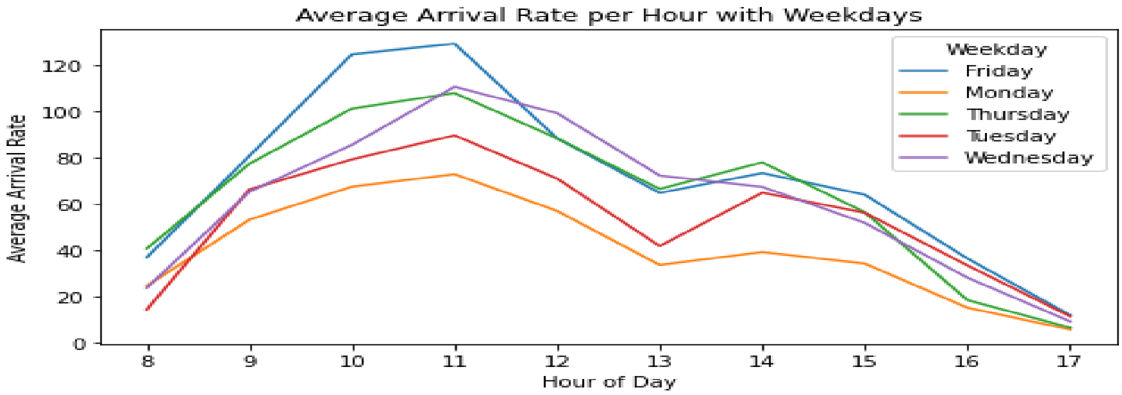

Figure 2: Distribution of average arrival rate per with each hour on each weekday**.**

To enhance the dataset understanding, we derived additional features from these datetime variables, such as arrival hour and arrival time shift, and subsequently removed the original features. The Pearson correlation coefficient was then employed to quantify the correlation between the target variable, wait time, and the independent variables [17].

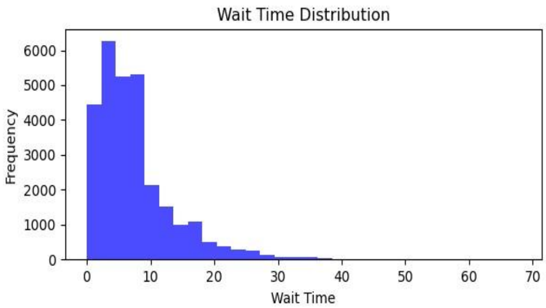

Figure 3: Distribution of patients with wait time.

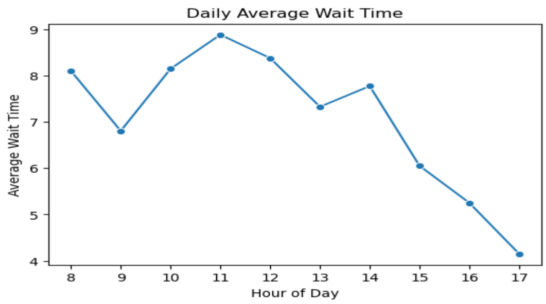

Figure 4 : Average wait time of patients per hour of the day.

A. Data Preprocessing

Data processing plays an important role in the learning process of machine learning models. It consists (1) cleaning of the dataset, (2) feature transformation, and (3)normalization of dataset. The following steps applied in the preprocessing phase, which aims to effectively prepare the data for analysis. There is no missing value in the dataset.

Categorical Encoding. Categorical transformation plays a crucial role in enhancing the learning capability of classifiers that are designed to process only numeric values. In our dataset, the features “Arrival weekday”, and “Time category” contain categorical data that has been encoded into numerical values. To carry out the encoding techniques, we have decided to use one hot encoder [18]. It is suitable with the dataset as it assigns a unique binary column to each unique categorical value. This transformation facilitates the interpretation and learning of encoded variables by the classifier. The “Arrival weekday” feature contains 5 categorical values, such as [‘Monday’, ‘Tuesday’, ‘Wednesday’, ’Thursday’, ’Friday’]. These categorical values have been encoded into five different binary columns. Similarly, the “Time category” feature contains two categorical values, namely [‘Morning’ and ‘Evening’], which are encoded into two variables.

Data Normalization. The presence of numerical values in different variables is on different scale, affects the learning process of ML algorithms such as LR, KNN, and RF. In this step, Min-Max scaling [19] technique is used to scale the features of the dataset using Equation (1).

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

This scaling technique helps in mapping the original values to a range between 0 and 1, maintaining the relative relationships among the data points. However, the datasets used to train and test the ML classifiers were scaled to get accurate and consistent model performance.

B. RFECV using RF for Feature Selection

The REFCV method is applied to carry out feature selection on the pre-processed dataset, resulting in the identification of the most significant features based on their importance scores. This is a wrapper-type feature selection technique that uses an ML algorithm to select the most relevant features from the dataset [20]. This method combines recursive feature elimination (RFE) and cross-validation (CV) to identify the optimal number of features, and it also maximizes the performance of the model. This algorithm effectively selects the features from the training dataset that are most significant in the prediction of the target variable. It operates by looking for a subset of features in the training dataset, starting with all features and recursively deleting them until the target number of variables. This algorithm employs backward selection for feature selection. It starts with the whole feature set and iteratively eliminates features that do not enhance classification accuracy. Eventually, it identifies the most optimal subset of features.

In this research work, the implementation of RFECV was conducted using the random forest regression model RF-RFECV as an estimator and five-fold cross-validation as a splitting strategy to preserve the percentage of samples for each class. However, the five-fold cross-validation divided the dataset into five folds of equal size. [21]. To assess feature selection performance, the RFECV method computes internal accuracy metrics for every cross-validation iteration.

This procedure builds a model with the predictors, and an importance score is computed for each predictor. The predictors with less significance were removed. Then, the model is built again, and the score is computed. Furthermore, the number of predictor subsets and their size were specified to evaluate a tuning parameter. The optimal subset of predictors obtained from this process can be used to train the model. Thus, the top-ranked features obtained from RFE algorithm can be considered as a group of selected features.

Algorithm 1 RFECV with RF

input: training dataset X, n number of desired features
output: feature set of tops- n most important features

for all features in X **do**
  Initialize an empty set Selected Features FS
  for $\boldsymbol{k = 1\ to\ 5}$ **do** ▹ k is the number of folds for cross validation
  X is randomly divided into five equal subsets using K-Fold cross validation method;
    One subset used as validation data, and
    the remaining four subsets are used as training data.
    Train a RF model using the training data.
    Calculate the prediction accuracy using the validation data.
    Obtain the importance of each feature produced by the RF model.
    Remove one least important feature in each step and update the training data.
  end for
    Obtain the featured subset FS with desired number of features.
    If number of features in FS is **n then**
    Selected features = FS;
    end if
  end for
Return list of top n most important feature.

C. Prediction Using Machine Learning Algorithms

Once the top features were selected, several ML regression models were trained using the training set. Then, the performances of the trained models were evaluated using the test dataset. This step demonstrates the wait time prediction model that performs the best. As stated initially, ML plays an important role in predicting wait time features and prediction, which is a main priority for hospital management and patient satisfaction. This subsection presents and describes three regressors utilized in our study.

Linear Regression: This is a supervised learning ML algorithm that predicts the target variable y using linear equation follows in Equation 1

$$\hat{y}(x) = w_0 + w_1 x_1 + \cdots . w_n x_n \tag{2}$$

where $x_1, x_2, \dots, x_n$ are n features, and $\hat{y}$ is the predicted value. The weight vectors $w_1, w_2, \dots, w_n$ are designated as an attribute co-efficient, and w_0 is defined as another attribute 'intercept' in the linear model of sklearn. Usually, there is no need of hyper-parameters tuned in this algorithm. The performance of a linear model's mainly depends on how well the problem follows a linear distribution.

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K Nearest Neighbors. KNN is the supervised ML algorithm used for both regression and classification task. In regression, KNN is used to predict continuous numerical value for given input. Assume that training dataset $T = \{(x_i, y_i)\}_{i=1}^{m}$ containing m observations with x_i feature vector and y_i represents numerical target variable. For any test instance x, the predicted value is calculated from Equation 3.

$$y = \frac{1}{k}\left(\sum_{x_i \epsilon N_k(x)} y_i\right) \tag{3}$$

Where, y_i is the target value of the ith nearest neighbors of x, k is the number of nearest neighbors and $N_k(x)$ is the set of k- nearest neighbors of x.

This approach assumes that instances with similar features have similar target values, making the average of their outputs a reasonable estimate for the target value of the test instance. In this algorithm, k is the most crucial hyper-parameter that is considered as number of nearest neighbors [22]. Moreover, the choice of the weighting function during prediction is an additional consideration. Two common options are 'uniform,' where all data points contribute equally to the prediction, and 'distance,' where points carry weight inversely proportional to their distance. The distance metric and the power parameter of the Euclidean metric or Minkowski metric can also be tuned as it can result in minor improvement.

Random Forest (RF). RF is an ensemble learning model consisting of a set of decision trees $\{ f_r(x, \theta_r) | r = 1,2,, \dots n\}$. The specific implementation process involves using a randomized with bootstrap method to extract the training set θ_r from the original dataset θ. Subsequently, this training set θ_r is used to train the decision tree regressor $f_r(x, \theta_r)$. When a new sample set x is given as input to the random forest then each decision trees f(x) predicts the target variable for the new sample and then final prediction determined by averaging the regression results:

$$Y = F(x) = \frac{1}{n}\left(\sum_{r=1}^{n} f_r(x)\right) \tag{4}$$

Where Y is the final result of regression model, $F(x)$ is regression model, $f_r(x)$ is a single decision tree regressor, and $f_r(x)$ is the average predicted value by each decision tree. Random Forest uses Gini importance to calculate the feature importance.

D. Evaluation Metrics

For the comparison of the predicting models, mean squared error (MSE), mean absolute error (MAE), and computation time were used.

Mean Squared Error. It measures of the errors that occurred between predicted values and actual values. The sum of the squares of each error is calculated and then divided by the total number of errors to find the average.

$$MSE = \frac{1}{n}\left(\sum_{i=1}^{n} (y_i - \hat{y}_i)^2\right) \tag{5}$$

Mean Absolute Error. It also measures the errors in a set of predictions. As it is absolute, so it disregards the positivity or negativity of the error and all distinct errors are equally weighted [23][24]. The formula to calculate MAE is shown in Equation 6.

$$MAE = \frac{1}{n}\left(\sum_{i=1}^{n} |y_i - \hat{y}_i|\right) \tag{6}$$

MSE was used to put more effort into outliers. While MAE indicates the average amount of error that may be expected from the prediction.

4. Result and Discussion

We developed three ML models by applying LR, KNN and RF algorithms on training dataset and then obtain the performance of all models on test dataset in terms of metrics MAE, MSE as shown in Table 1. The computational time of each model is also obtained.

In second experiment, REFCV algorithm is used to obtain the optimal number of features. We find 30 optimal features from the dataset and then applied all these algorithms on reduced dataset. Performance of all models with RFECV is shown in Table 1. LR model performed better among all models with and without using feature selection technique. The LR model with RFECV performs best with MAE 3.72 and least computational time with 30 features. KNN and KNN-RFE models performed with approximate same MAE. But computational time decreases with decreases features.

Table 1 Performance of all machine learning models with and without using Feature selection**.**

Models	MAE	MSE	Computational Time(s)
LR	3.823	28.15	0.05
KNN	3.929	31.70	0.03
RF	5.565	45.42	403
LR-RFE	3.717	28.41	0.01
KNN-RFE	3.961	32.07	0.003
RF- RFE	6.121	52.32	101.04

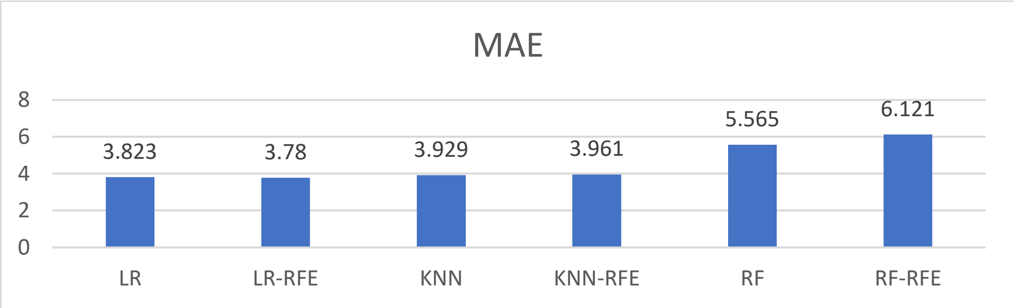

Figure: 5-Accuracy comparison of ML models on the dataset with and without RFE feature selection technique.

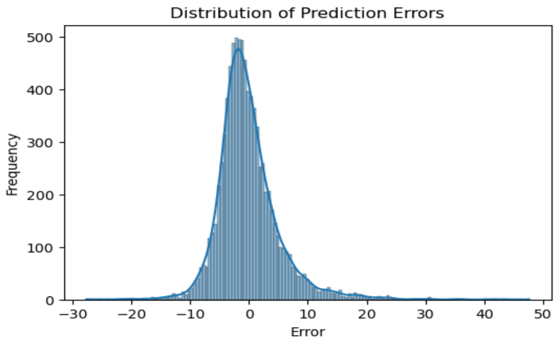

Figure 6: Distribution of prediction errors of best model (LR-RFE).

The actual and predicted values of 200 patients by LR-RFE is shown in Fig. The graph shows that there is in most of the cases, actual value is very close to predicted value which shows that model has good fit for those points.

Table 2 Mean Absolute error of LR model in different classes of waiting time

Classes of wait time	0-5	5-10	10-20	20-30	More than 30
MAE of Linear regression model	3.44	2.09	4.59	10.51	20.22
MAE of Linear regression model-RFE	4.04	2.06	4.12	10.22	20.39

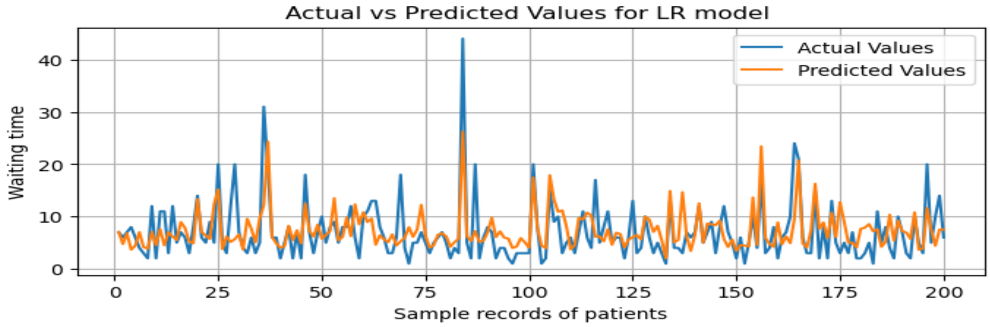

Figure 7: Waiting time predicted vs actual for the LR-RFE model for the sample test data

Table 2 shows that the accuracy of the LR model decreases as the wait time increases. The model is relatively more accurate for shorter wait times and less accurate for long wait times, accuracy indicated by MSE values. The peak of the distribution in Figure 5 shows that it is very close to zero and indicates that most of the predictions are quite accurate, with very less errors. The long tail on the right side of the distribution suggests there are a number of cases where the model has underestimated the target variable. While the short tail on left shows, there are a few instances of large overestimation.

5. Conclusion

This study aimed to demonstrate the ability of machine learning techniques to predict waiting times in hospital radiology departments, a critical issue in the face of increasing patient flow and departmental overcrowding. The integration of LR, KNN, and RF models with the RFE technique has proven not only to increase the predictive accuracy but also to optimize the feature selection process effectively.

Among the tested models, the LR-RFE model emerged as particularly effective, utilizing a reduced set of 30 features to obtain a lower mean absolute error compared to the standard LR model with 63 features. Additionally, the RF and KNN models also demonstrated robust performance, confirming the reliability of machine learning approaches in healthcare operational management. The important features such as patient queue lengths and recent wait times, highlight the areas where hospital administrations can target improvements to enhance patient Satisfaction and efficiency of departments. By applying these findings, healthcare facilities can better manage patient expectations, reduce wait times and optimize resource allocation.

Future research can explore the integration of real time data and the appli9cation of more complex machine learning models to further increase the predictive accuracy and operational responsiveness. This research also provides actionable strategies for healthcare management to increase service delivery in an increasing complex and demanding healthcare environment.

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