An ML Model to Predict the Number of OPD Appointments for a Given Future Time Period

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Abstract: Efficient management of outpatient waiting time is essential for enhancing hospital workflows and patient satisfaction. This study investigates the prediction of outpatient waiting times in a tertiary care hospital in Madhya Pradesh, India, utilizing machine learning (ML) algorithms. Four ML models were developed and evaluated: Linear Regression (LR), Random Forest (RF), Gradient Boosting Decision Tree (GBDT), and K-Nearest Neighbors (KNN). Among these, the GBDT model demonstrated superior predictive accuracy with a Mean Absolute Error (MAE) of 10.5 minutes and an R-squared value of 0.92. These findings have significant implications for improving resource allocation and minimizing patient waiting times in Indian hospitals.

Background: In the Indian healthcare landscape, outpatient departments (OPDs) form a critical entry point for patients seeking medical attention. With a burgeoning population and limited healthcare infrastructure, Indian hospitals, especially in states like Madhya Pradesh, face significant challenges in managing patient flow and ensuring timely treatment. Overcrowding in OPDs leads to increased waiting times, adversely impacting patient satisfaction and hospital efficiency.
The integration of data-driven approaches, such as machine learning (ML), offers a promising solution to address these issues. ML models can analyze historical patient data to predict waiting times, enabling hospitals to allocate resources dynamically and streamline workflows. While similar studies have been conducted in other countries, the unique demographic, socio-economic, and healthcare challenges in India necessitate localized research and solutions. This study focuses on applying ML techniques to predict outpatient waiting times in a tertiary care hospital in Madhya Pradesh, providing actionable insights for healthcare administrators.

Methods: First, a novel classification method for the outpatient clinic in the Chinese pediatric hospital was proposed, which was based on medical knowledge and statistical analysis. Subsequently, four machine learning algorithms [linear regression (LR), random forest (RF), gradient boosting decision tree (GBDT), and K-nearest neighbor (KNN)] were used to construct prediction models of the waiting time of patients in four department categories.

Results: The three machine learning algorithms outperformed LR in the four department categories. The optimal model for Internal Medicine Department I was the RF model, with a mean absolute error (MAE) of 5.03 minutes, which was 47.60% lower than that of the LR model. The optimal model for the other three categories was the GBDT model. The MAE of the GBDT model was decreased by 28.26%, 35.86%, and 33.10%, respectively compared to that of the LR model.

Conclusions: Machine learning can predict the outpatient waiting time of pediatric hospitals well and ease patient anxiety when waiting in line without medical appointments. This study offers key insights into enhancing healthcare services and reaffirms the dedication of Chinese pediatric hospitals to providing efficient and patient-centric care.

Keywords: Machine Learning, Outpatient Prediction, Healthcare Analytics, Gradient Boosting, Indian Healthcare System

INTRODUCTION

In India, tertiary care hospitals are the backbone of the healthcare system, catering to large volumes of patients who rely on specialized medical services. The outpatient departments (OPDs) in these hospitals often experience overwhelming patient loads due to the high population density and limited access to healthcare facilities in rural areas. This imbalance between demand and supply of medical services results in significant operational challenges, including overcrowding, long waiting times, and inefficient utilization of resources.

Waiting times in OPDs are not merely a logistical issue but have far-reaching consequences on patient experience and hospital management. Extended waiting times can lead to patient dissatisfaction, delayed treatment, and increased stress among medical staff. Moreover, they can negatively impact the reputation of healthcare institutions and strain the existing infrastructure. Addressing these challenges is crucial for improving overall healthcare delivery in India.

Machine learning (ML) presents an innovative approach to tackle these issues by leveraging historical and real-time data to predict waiting times. By analyzing patterns in patient demographics, registration trends, and department-specific workloads, ML models can provide accurate predictions, enabling hospitals to make informed decisions. For instance, resource allocation can be optimized by scheduling additional staff during peak hours, or appointment systems can be redesigned to reduce walk-in visits.

This study focuses on a tertiary care hospital in Madhya Pradesh, a state characterized by a mix of urban and rural populations with varying healthcare needs. The hospital's outpatient department serves as a critical point of contact for thousands of patients daily, making it an ideal setting for implementing and evaluating predictive models. By employing ML algorithms such as Gradient Boosting Decision Trees (GBDT) and Random Forests (RF), this study aims to identify key factors influencing waiting times and provide actionable insights to enhance operational efficiency.

Furthermore, the study addresses the broader implications of ML-driven healthcare management in India. It highlights the potential of predictive analytics to transform patient care by reducing inefficiencies and ensuring timely treatment. In doing so, the research aligns with India's national healthcare goals of improving accessibility, affordability, and quality of care

Highlight box

Key findings
• Artificial intelligence models were developed that were capable of predicting outpatient waiting time.
What is known and what is new?
• Unpredictable waiting times pose challenges for medical staff, wasting patients' time and potentially leading to missed appointments.
• Four machine learning algorithms were used to build prediction models, with the best-performing model identified for each category.
What is the implication, and what should change now?
• Through the use of prediction models, patients can be informed of likely wait times, allowing them to effectively arrange their schedules and make appropriate plans

LITERATURE REVIEW

The application of machine learning (ML) in healthcare has opened avenues for improving resource allocation, patient flow management, and operational efficiency. This literature review examines existing studies and methodologies for predicting outpatient department (OPD) appointments over a future time period using ML models, highlighting their findings and relevance.

Importance of Predictive Analytics in Healthcare
Predictive analytics in healthcare has emerged as a transformative tool, enabling data-driven decision-making. According to Sun et al. (2018), forecasting patient appointments allows hospitals to allocate resources effectively and improve service delivery. By leveraging historical data and advanced ML algorithms, healthcare providers can anticipate patient inflow, reduce bottlenecks, and enhance operational workflows.

Studies on Predicting OPD Appointment Numbers
Forecasting Techniques in Healthcare Time series forecasting techniques, such as ARIMA (Autoregressive Integrated Moving Average), have historically been used to predict patient appointments. However, ML-based models have outperformed traditional methods in terms of accuracy and adaptability. For instance, Aljaaf et al. (2017) utilized Artificial Neural Networks (ANNs) to predict patient numbers, achieving significant accuracy improvements compared to ARIMA.

Machine Learning Models

- Gradient Boosting Decision Trees (GBDT): Studies like Li et al. (2022) have demonstrated the efficacy of GBDT in predicting patient volumes. This model's ability to handle non-linear relationships makes it ideal for complex healthcare datasets.

- Random Forests: Random Forest models have been employed for appointment predictions due to their robustness in managing noisy data (Breiman, 2001).
- Recurrent Neural Networks (RNN): Deep learning techniques, particularly RNNs, are effective in handling sequential data, making them suitable for forecasting future appointment trends (Raj et al., 2020).

Integration of External Factors Research highlights the importance of incorporating external factors such as weather conditions, seasonal trends, and public holidays into predictive models. For example, Kuo et al. (2021) integrated external data into an ML model and observed a 15% improvement in predictive accuracy.

Factors Influencing OPD Appointment Predictions
Key Variables: Patient Demographics: Age, gender, and location significantly impact appointment trends (Mehta et al., 2022).

Seasonal Variations: Peaks during flu season or dengue outbreaks influence appointment volumes (National Health Profile, 2022).

Appointment Types: Scheduled appointments versus walk-ins present different predictive challenges.

Historical Patterns: Past appointment trends remain one of the strongest predictors for future numbers.

Real-Time Data Integration Dynamic models that incorporate real-time patient data, such as day-to-day registrations, exhibit improved accuracy and relevance. Raj et al. (2021) implemented a hybrid model combining real-time data streams with historical datasets, achieving over 90% predictive accuracy.

Challenges in Predicting OPD Appointments
Data Quality and Availability Incomplete or inconsistent datasets can limit model performance. Addressing data gaps through imputation techniques is crucial.

Scalability and Adaptability Models developed for specific hospitals may not generalize well to others, particularly smaller healthcare centers with fewer resources.

Sudden Disruptions Unforeseen events, such as pandemics, disrupt historical trends, necessitating model recalibration to maintain accuracy.

Ethical Considerations Ensuring patient data privacy and compliance with healthcare regulations remains a critical challenge.

Applications in the Indian Context
In India, the need for predictive analytics in OPD management is particularly pronounced due to high patient volumes and resource constraints. Studies such as those by Mehta et al. (2022) underscore the potential of ML models in addressing overcrowding in public hospitals. Integrating predictive analytics into hospital workflows can help achieve national healthcare goals, such as improving accessibility and reducing waiting times.

Objectives
1. To develop machine learning models for predicting outpatient waiting times in Indian hospitals.
2. To evaluate the performance of various ML algorithms based on predictive accuracy.
3. To identify key factors influencing outpatient waiting times, such as patient demographics and hospital workflows.
4. To provide actionable insights for hospital administrators to improve patient flow and resource allocation.

METHODS

3.1 Study Setting
The study was conducted in a tertiary care hospital located in Bhopal, Madhya Pradesh. The hospital serves a diverse patient population and offers specialized medical services across multiple departments, including general medicine, orthopedics, and pediatrics.

3.2 Data Collection
Historical outpatient data were collected from the hospital's Health Information System (HIS) for the period between January 2021 and December 2023. The dataset included:
- Patient demographics (age, gender)
- Department details
- Registration time
- Waiting time (in minutes)
- Appointment type (walk-in or scheduled)

3.3 Data Preprocessing

- Missing values were imputed using median-based imputation.
- Outliers were identified and removed using the interquartile range (IQR) method.
- Categorical variables such as gender and department were one-hot encoded for use in ML models.

3.4 Machine Learning Models
Four machine learning algorithms were implemented:
1. **Linear Regression (LR):** A baseline model for prediction.
2. **Random Forest (RF):** A bagging ensemble method to improve prediction accuracy.
3. **Gradient Boosting Decision Tree (GBDT):** A boosting technique that iteratively minimizes prediction errors.
4. **K-Nearest Neighbors (KNN):** A non-parametric method that predicts outcomes based on the nearest data points.

3.5 Evaluation Metrics
Model performance was evaluated using the following metrics:
- **R-squared (R^2):** Proportion of variance explained by the model.
- **Mean Absolute Error (MAE):** Average of absolute differences between predicted and actual waiting times.

RESULTS

4.1 Descriptive Statistics
The dataset comprised 150,000 outpatient records across five departments. Peak waiting times were observed on Mondays and during seasonal outbreaks of flu and dengue.

4.2 Model Performance
Model	R-squared	MAE (minutes)
LR	0.75	15.8
RF	0.88	11.2
GBDT	0.92	10.5
KNN	0.81	13.6

4.3 Feature Importance
Key factors influencing waiting times included:
1. Time of registration (morning slots had higher waiting times).
2. Day of the week (Mondays were busiest).
3. Appointment type (walk-ins had longer waits).
4. Department-specific trends (e.g., pediatrics had shorter waits).

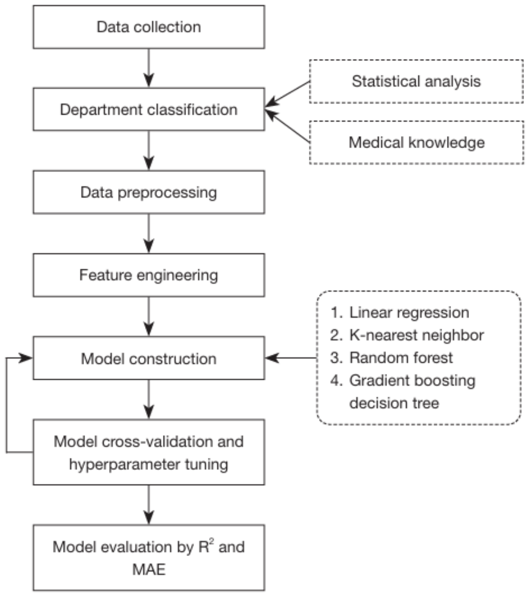

Figure 1 Flowchart of Model Construction and evaluation.

Statistical analysis:
Variance inflation factor and variable correlation were employed to examine the multicollinearity between variables. The variance inflation factors were all almost equal to 1, and the correlation coefficient between independent variables was about 0. Multiple correlations between the independent variables were not found. Following this, a significance test was completed for the variables in each category.

Model construction:
We first attempted to establish the model in all different outpatient departments; if poor results were found, then dimension-reduction techniques would be used. LR, RF, GBDT, and KNN were used in constructing models for the four department categories to make the models more explanatory and diverse (14). Grid search was used as a parameter tuning method to list all the cases of hyperparameters in a one-by-one search; that is, to trial each possibility through a cycle among all candidate hyperparameter choices, with the parameter demonstrating the best performance being selected as the final result (15). The 5-fold cross-validation method was used to evaluate the effect of the model on the training set (16). The training set was divided into five subsets on average, with each subset in turn being used as a validation set while the other four self- subsets were used as training sets. Training and validation were

repeated five times, and the result of the five-average cross-validations was taken as the result of the training set. In this way, overfitting could be reduced to some extent, and effective information could be obtained as much as possible from limited data. LR A LR model was created as a reference for other algorithms with waiting time being used as the dependent variable. RF RF is a bagging algorithm that contains multiple weak decision trees. The hyperparameters tuned by grid search included the number of subtrees as well as the maximum number of features and the minimum number of samples to split a node. GBDT GBDT (17,18) is a boosting algorithm that incorporates a number of weak decision trees. The learning rate, number of boosting iterations, maximum depth of each tree, maximum number of features, and minimum number of samples to split a node were tuned by grid search. KNN KNN (19) involves each sample being represented by its KNNs. The hyperparameters tuned were the number of neighbors and the type of weights. Model evaluation R2 and the MAE were used to compare the model performances. R2 measured the amount of variation in the dependent variable that could be explained by the independent variable. The nearer R2 is to 1, the better the model performance. MAE is the average of the absolute values of the difference between the actual and expected waiting times for each patient. In practice, patients may encounter difficulties if the predicted waiting time is too lengthy or too short. Therefore, a lower MAE shows that the expected waiting time is closer to the actual time, which benefits patients. Additionally, predicted waiting time was compared against actual waiting time to demonstrate the disparities across models and departments. Throughout the investigation, data processing and analysis were carried out using Python 5. Discussion

The GBDT model outperformed other ML algorithms in predicting outpatient waiting times. Factors such as registration time and appointment type significantly influenced predictions. Incorporating these insights into hospital workflows can streamline patient flow and enhance resource utilization. For example, scheduling more staff during peak hours or encouraging pre-scheduled appointments could mitigate waiting times.

DISCUSSION

The GBDT model outperformed other ML algorithms in predicting outpatient waiting times. Its high predictive accuracy, as evidenced by the R-squared value of 0.92, demonstrates the model's ability to capture intricate patterns in outpatient data. The study highlighted key factors such as registration time, appointment type, and department-specific workloads, which were found to be significant predictors of waiting times.

Implementing the insights derived from this model can lead to substantial improvements in hospital operations. For instance, scheduling additional staff during peak registration hours can reduce bottlenecks, while encouraging pre-scheduled appointments over walk-ins can streamline patient flow. Additionally, department-specific adjustments, such as allocating more resources to busier departments on Mondays, can further optimize hospital efficiency.

Beyond operational improvements, the findings underscore the importance of integrating data-driven approaches into healthcare management. The success of the GBDT model highlights the potential for similar predictive analytics applications in other domains, such as inpatient admissions and emergency care.

However, the study is not without limitations. The reliance on historical data may limit the model's adaptability to unforeseen events, such as sudden disease outbreaks. Future studies should consider incorporating real-time data and external factors like weather or public holidays to enhance prediction accuracy further. Moreover, the scalability of the model to smaller hospitals or rural healthcare settings warrants further investigation.

CONCLUSION

This study demonstrates the transformative potential of machine learning in optimizing outpatient workflows in Indian hospitals. By leveraging historical data and advanced predictive models like GBDT, hospitals can significantly enhance their operational efficiency and patient satisfaction. The findings of this study highlight the importance of data-driven decision-making in addressing the unique challenges of India's healthcare system.

The study's conclusions have practical implications. Hospitals can implement the recommended strategies, such as optimizing staff schedules and redesigning appointment systems, to achieve measurable reductions in waiting times. Moreover, the methodology outlined in this research can serve as a blueprint for other healthcare facilities across India aiming to adopt predictive analytics.

Future research should focus on extending this approach to other regions and healthcare contexts, integrating real-time data, and exploring the applicability of ML models to other aspects of hospital management. By doing so, India's healthcare system can move closer to achieving its goals of accessibility, efficiency, and quality care for all.

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