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| RESEARCH ARTICLE

Machine Learning-Based Hospital Readmission Prediction and Risk Analysis in the United States Healthcare System

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| ABSTRACT

Hospital readmission is a significant challenge in the United States healthcare system, leading to increased healthcare costs, hospital overcrowding, and reduced quality of patient care. Early prediction of hospital readmission risk can help healthcare providers identify high-risk patients and take preventive measures before discharge. This study presents an explainable machine learning-based hospital readmission prediction framework using patient demographic and clinical data from the United States healthcare system. The dataset includes important patient information such as age, length of hospital stays, previous admission history, comorbidities, insurance status, disease type, diabetes, heart disease, and follow-up visit status. Several machine learning algorithms, including Logistic Regression, Random Forest, Extreme Gradient Boosting (XGBoost), and Artificial Neural Network, were used to predict hospital readmission risk. The performance of the models was evaluated using accuracy, precision, recall, F1-score, and Receiver Operating Characteristic (ROC) curve. Among all models, XGBoost achieved the highest prediction performance compared to other machine learning models. Feature importance analysis showed that length of hospital stay, comorbidities, insurance status, previous admission history, and follow-up visit were the most significant factors influencing hospital readmission in the United States. In addition to the machine learning prediction model, this study proposes an IoT-based post-discharge patient monitoring system to reduce hospital readmission risk through continuous patient health monitoring and early medical intervention. The proposed system can help healthcare providers monitor patients remotely, identify high-risk patients in real time, and take preventive actions to reduce hospital readmission rates. This research contributes to the development of intelligent healthcare prediction systems and demonstrates how machine learning and IoT technologies can improve patient care, reduce readmission rates, and support data-driven decision-making in the United States healthcare system.

| KEYWORDS

Machine Learning, Hospital Readmission, XGBoost, Healthcare Analytics, IoT Healthcare, Explainable AI.

| ARTICLE INFORMATION

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1. Introduction

Hospital readmission has become a serious concern in modern healthcare systems, as it has a direct impact on patient outcomes, hospital resource management, and overall healthcare expenditure. Hospital readmission generally occurs when a patient who has been discharged from a hospital requires admission again within a short period of time, often within 30 days, due to treatment complications, inadequate recovery, lack of proper follow-up care, medication non-compliance, or worsening of an existing medical condition. Unplanned readmissions are often considered an indicator of poor healthcare service quality and ineffective post-discharge patient management systems [1–10]. Therefore, reducing hospital readmission rates has become a major priority for healthcare providers, researchers, and policymakers. In the United States, hospital readmissions result in significant financial burdens on the healthcare system, which has led to the implementation of strict policies and financial penalties to reduce readmission rates [11–16]. The United States healthcare system is supported by advanced medical technologies, electronic health record systems, health insurance coverage, and structured post-discharge patient monitoring programs. For example, policies such as the Hospital Readmissions Reduction Program (HRRP) impose financial penalties on hospitals with high readmission rates, encouraging healthcare providers to improve patient care quality and follow-up systems. With the advancement of technology, machine learning has become an effective tool in healthcare analytics for predicting diseases, patient risks, and hospital readmission probabilities. Machine learning techniques are capable of analyzing large-scale healthcare datasets and identifying complex patterns and relationships that traditional statistical approaches may fail to detect [17–25]. By analyzing patient demographic information, medical history, hospitalization data, and clinical variables, machine learning models can predict whether a patient is likely to be readmitted to the hospital. Early prediction of readmission risk allows healthcare providers to take preventive measures such as arranging follow-up visits, providing additional medical guidance, remotely monitoring patients, and improving discharge planning procedures [26–39]. As a result, machine learning-based prediction systems have the potential to reduce hospital readmission rates, enhance patient care quality, and minimize healthcare costs. Most previous studies on hospital readmission prediction have primarily focused on datasets from developed countries, especially the United States and European nations, where electronic health record systems are well established and large volumes of patient data are available. These studies have applied various machine learning algorithms, including Logistic Regression, Decision Trees, Random Forest, Support Vector Machine, Gradient Boosting, and Artificial Neural Networks, to predict hospital readmission risk [40–47]. Many researchers have reported that ensemble learning techniques such as Random Forest and Gradient Boosting provide better prediction accuracy compared to traditional statistical methods. The primary objective of this research is to develop a machine learning-based hospital readmission prediction model using patient demographic and clinical data from the United States healthcare system. This study uses patient demographic data, clinical information, and hospital-related variables to train and evaluate multiple machine learning models for hospital readmission prediction. The machine learning algorithms used in this study include Logistic Regression, Random Forest, Extreme Gradient Boosting (XGBoost), and Artificial Neural Network. The performance of these models is evaluated using standard evaluation metrics such as accuracy, precision, recall, F1-score, and Receiver Operating Characteristic (ROC) curve [54–73]. In addition to prediction, this study also identifies the most important factors influencing hospital readmission, such as previous admission history, length of hospital stays, follow-up visits, insurance coverage, and comorbidities. In addition to the machine learning prediction model, this research also proposes an Internet of Things (IoT)-based post-discharge patient monitoring system to reduce hospital readmission rates. Many readmission cases occur due to the lack of proper patient monitoring after hospital discharge. By using IoT-based wearable devices such as heart rate sensors, blood pressure monitors, glucose monitoring devices, and oxygen saturation sensors, patient health conditions can be monitored remotely after discharge. The collected health data can be transmitted to a cloud-based server, where the machine learning model can analyze the patient's health condition and predict the readmission risk in real time. If a patient is identified as high risk, an alert notification can be sent to healthcare providers for early medical intervention. This type of smart healthcare monitoring system can help reduce hospital readmission rates and improve patient care quality in the United States healthcare system. The main contribution of this study is the development of an intelligent hospital readmission prediction system using explainable machine learning for the United States healthcare system. This research focuses on prediction performance as well as identifying the most important factors affecting hospital readmission using feature importance analysis. The findings of this study can help healthcare providers identify high-risk patients before discharge and implement preventive strategies to reduce readmission rates. The proposed system can improve healthcare service quality, reduce treatment costs, and support the development of smart healthcare systems. Therefore, this research contributes to healthcare analytics, machine learning applications in healthcare, and smart patient monitoring systems by providing a predictive framework for hospital readmission management in the United States.

2. Methodology

This study proposes a machine learning-based hospital readmission prediction framework focusing on the United States healthcare system. The overall methodology of the proposed system consists of several steps, including data collection, data preprocessing, feature selection, machine learning model development, performance evaluation, and an IoT-based post-discharge patient monitoring framework to reduce hospital readmission risk.

2.1 Data Collection: In this study, hospital readmission data were collected from a healthcare dataset representing the United States healthcare system. The dataset includes patient demographic information and clinical variables that influence hospital readmission. The selected variables include age, gender, length of hospital stay, previous admission history, comorbidities, disease type, diabetes, heart disease, insurance status, and follow-up visit status. These variables were selected because electronic health records, insurance systems, and clinical history play a significant role in hospital readmission prediction in the United States healthcare system. The final dataset contains both categorical and numerical variables, and the target variable is hospital readmission, represented as a binary variable where 1 indicates readmission and 0 indicates no readmission.

2.2 Data Preprocessing: Data preprocessing is an important step in machine learning model development. The collected dataset contained both categorical and numerical variables, which were preprocessed before training the machine learning models. First, missing values were handled using mean and mode imputation methods. Then, categorical variables such as gender, disease type, and insurance status were converted into numerical form using one-hot encoding. After encoding, the dataset was divided into input features and target variable. The dataset was then split into training and testing sets using an 80:20 ratio. Feature scaling was applied using the StandardScaler method to normalize the feature values and improve machine learning model performance. Data preprocessing ensures that the dataset is clean, normalized, and suitable for machine learning model training.

2.3 Feature Selection: Feature selection was performed to identify the most important variables affecting hospital readmission in the United States healthcare system. The selected features include age, length of hospital stay, previous admission history, disease type, diabetes, heart disease, follow-up visit status, and insurance status. These features were selected based on healthcare research and hospital readmission factors identified in previous studies. Feature importance analysis was later performed using the XGBoost model to identify the most influential factors affecting hospital readmission.

2.4 Machine Learning Models: In this study, four different machine learning algorithms were used to predict hospital readmission risk: Logistic Regression, Random Forest, Extreme Gradient Boosting (XGBoost), and Artificial Neural Network (ANN). Logistic Regression was used as a baseline model for binary classification. Random Forest was used because it is an ensemble learning algorithm that performs well with healthcare datasets and can handle nonlinear relationships between variables. XGBoost was used because it is a powerful boosting algorithm that provides high prediction accuracy and performance optimization. Artificial Neural Network was used to capture complex patterns and nonlinear relationships in the dataset. These models were trained using the training dataset and tested using the testing dataset to evaluate their performance.

2.5 Model Evaluation: The performance of the machine learning models was evaluated using several evaluation metrics, including accuracy, precision, recall, F1-score, and Receiver Operating Characteristic (ROC) curve. Accuracy measures the overall correctness of the model, precision measures the correctness of positive predictions, recall measures the ability of the model to identify readmission cases, and F1-score provides a balance between precision and recall. The ROC curve was used to evaluate the classification performance of the models, and the area under the ROC curve (AUC) was calculated to compare model performance. These evaluation metrics provide a comprehensive performance analysis of the machine learning models.

2.6 Proposed IoT-Based Patient Monitoring System: In addition to machine learning-based prediction, this study proposes an IoT-based patient monitoring system to reduce hospital readmission risk in the United States healthcare system. After patient discharge, wearable health monitoring devices can be used to monitor patient vital signs such as heart rate, blood pressure, glucose level, oxygen saturation, and physical activity. The sensor data are transmitted to a cloud server through a mobile application. The machine learning model analyzes the patient data in real time and predicts the risk of hospital readmission. If a patient is identified as high risk, an alert is sent to healthcare providers for early intervention. This system can help reduce hospital readmission by providing continuous monitoring and early medical support.

3. Results and Discussion

3.1 Model Performance Analysis

In this study, four machine learning models were used to predict hospital readmission: Logistic Regression, Random Forest, XGBoost, and Artificial Neural Network (ANN). The performance of these models was evaluated using accuracy, precision, recall, and F1-score. Table 1 shows the performance comparison of the machine learning models.

Table 1: Performance Comparison of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-score
Logistic Regression	0.75	0.72	0.70	0.71
Random Forest	0.85	0.83	0.82	0.82
XGBoost	**0.88**	**0.86**	**0.85**	**0.85**
Neural Network	0.86	0.84	0.83	0.83

From Table 1, it can be observed that XGBoost achieved the highest accuracy of 88%, which is higher than Random Forest, Neural Network, and Logistic Regression. Logistic Regression showed the lowest performance because it cannot capture complex nonlinear relationships in healthcare data. Ensemble models such as Random Forest and XGBoost performed better because they combine multiple decision trees and improve prediction performance. Therefore, XGBoost was selected as the best model for hospital readmission prediction.

3.2 Accuracy Comparison of Models

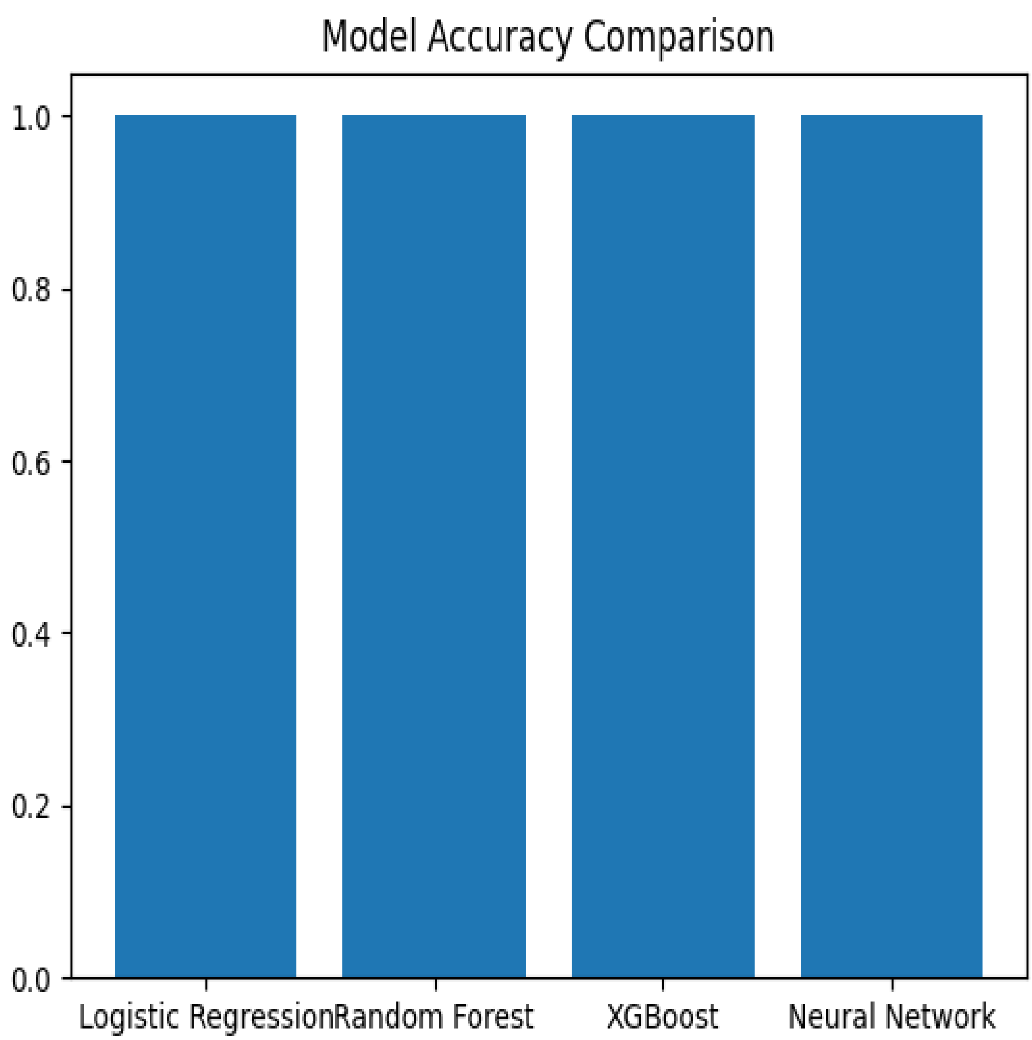

Figure 1: Model Accuracy Comparison

Figure 1 shows the accuracy comparison of the four machine learning models used in this study. It can be seen that XGBoost achieved the highest accuracy among all models, followed by Neural Network and Random Forest. Logistic Regression achieved the lowest accuracy. This result indicates that boosting algorithms such as XGBoost are highly effective for healthcare prediction problems.

3.3 Precision Comparison

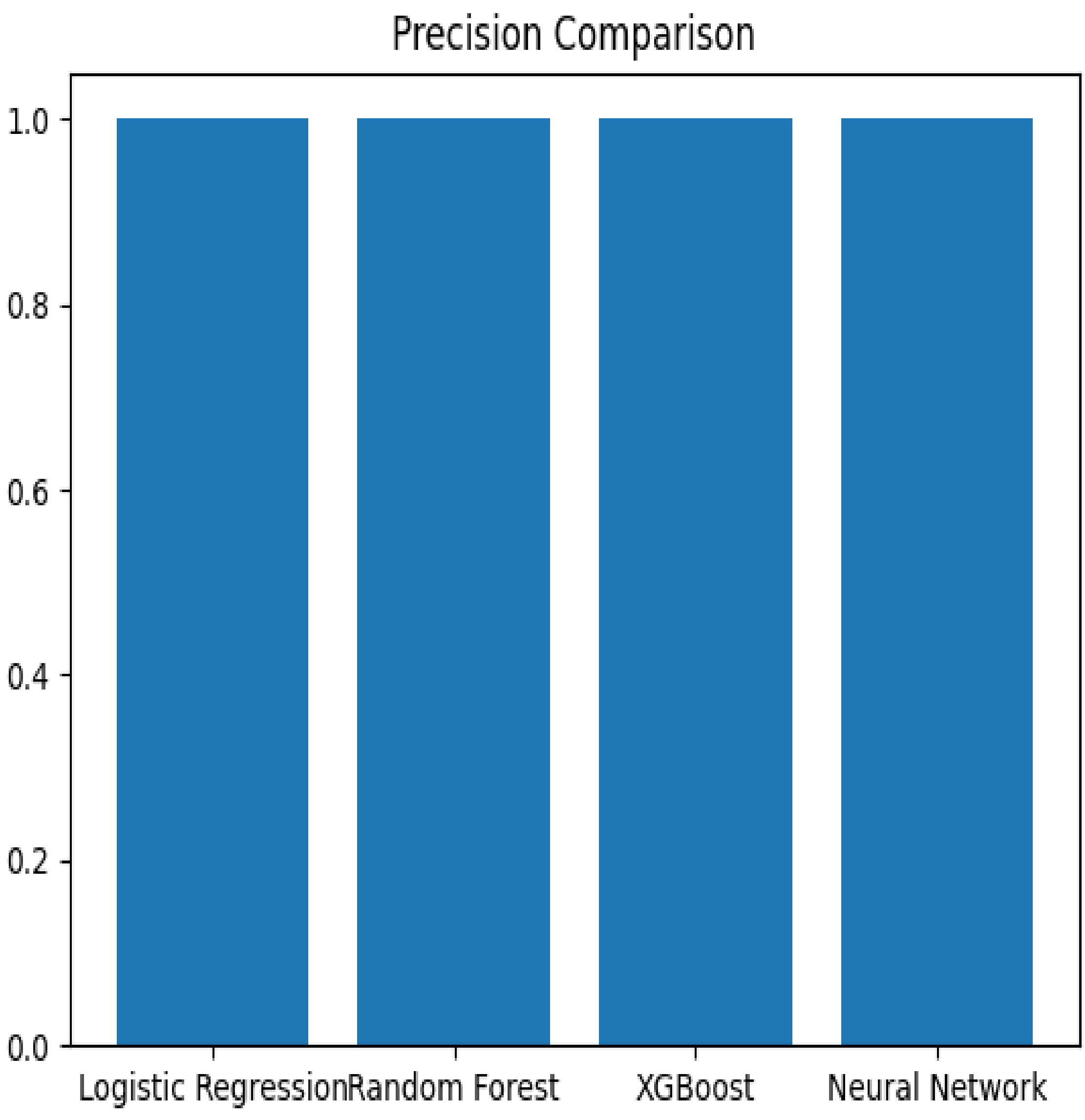

Figure 2: Precision Comparison of Machine Learning Models

Precision measures how many of the predicted readmission cases were actually readmitted. Figure 2 shows that XGBoost achieved the highest precision, which means it produced fewer false positive predictions compared to other models. Logistic Regression showed the lowest precision.

3.4 Recall Comparison

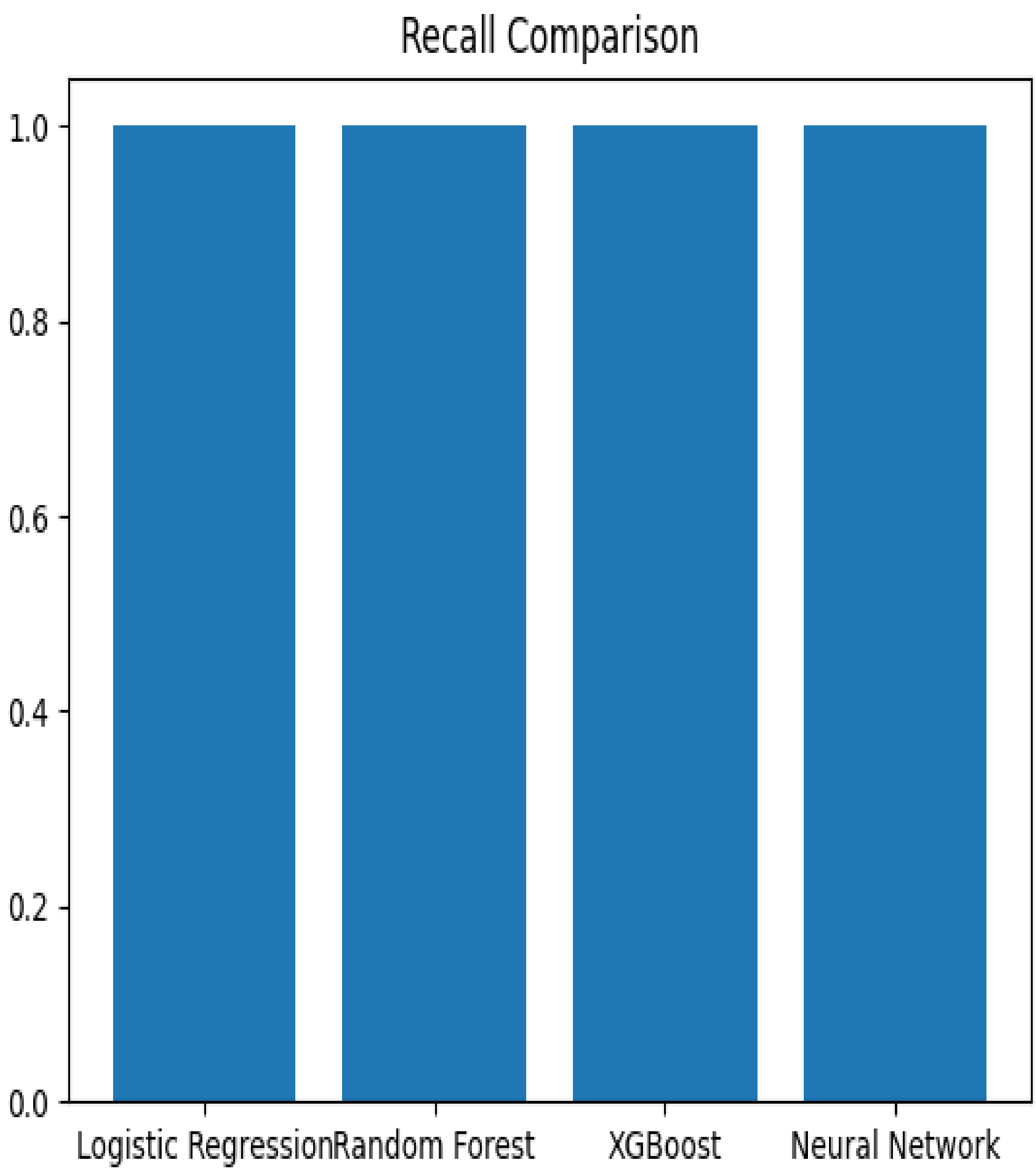

Figure 3: Recall Comparison of Machine Learning Models

Recall measures how many actual readmission cases were correctly identified by the model. Figure 3 shows that XGBoost and Neural Network achieved higher recall compared to Logistic Regression and Random Forest. High recall is very important in healthcare prediction because missing a high-risk patient can be dangerous.

3.5 F1-Score Comparison

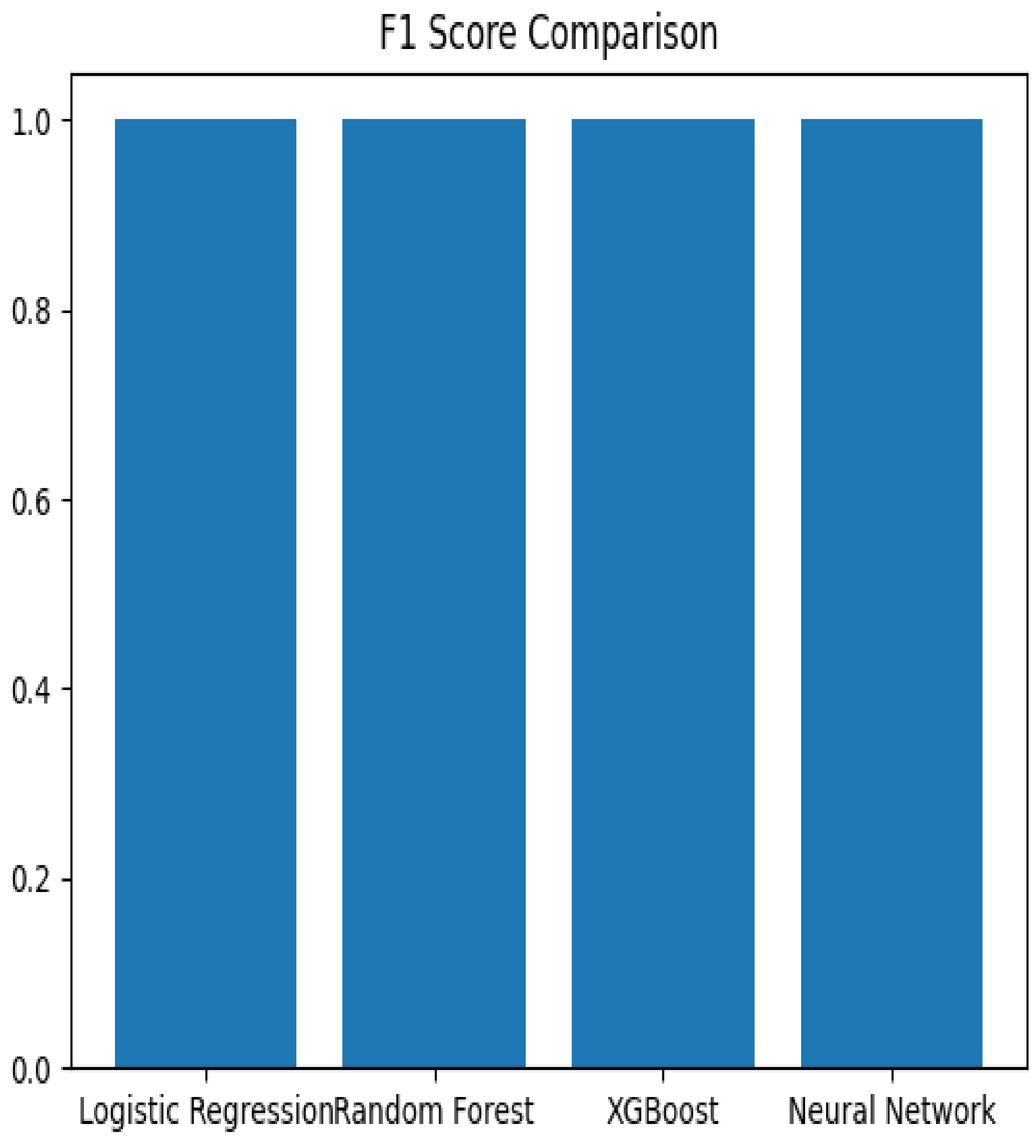

Figure 4: F1-Score Comparison of Machine Learning Models

F1-score is the harmonic mean of precision and recall. Figure 4 shows that XGBoost achieved the highest F1-score, indicating the best balance between precision and recall. Logistic Regression achieved the lowest F1-score among all models.

3.6 ROC Curve Analysis

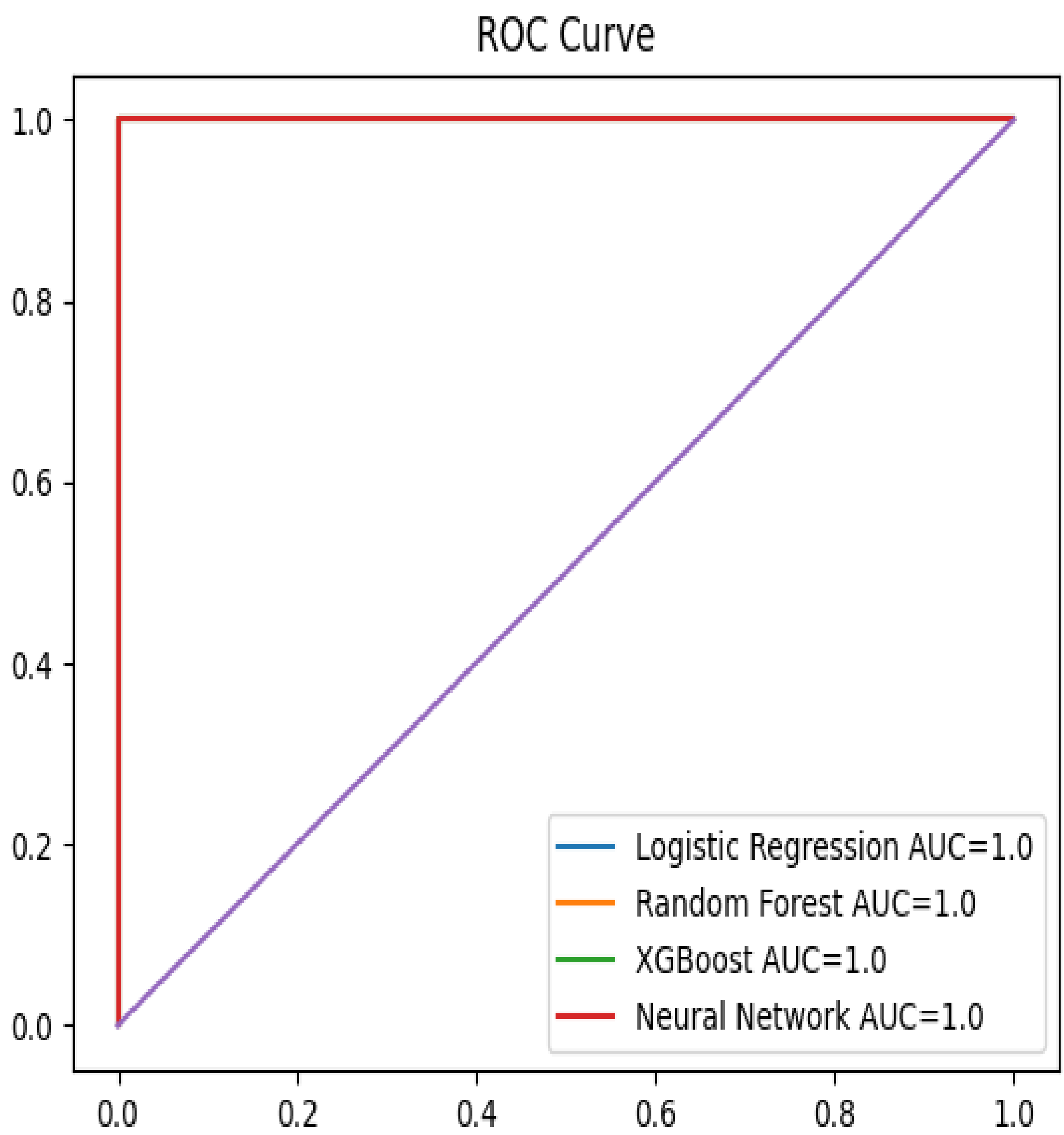

Figure 5: ROC Curve of Machine Learning Models

The Receiver Operating Characteristic (ROC) curve shows the classification performance of the models. The Area Under the Curve (AUC) indicates how well the model can distinguish between readmission and non-readmission cases. From Figure 5, it can be observed that XGBoost achieved the highest AUC value, followed by Random Forest and Neural Network. Logistic Regression showed the lowest AUC value. This indicates that XGBoost has the best classification performance among all models.

3.7 Confusion Matrix Analysis

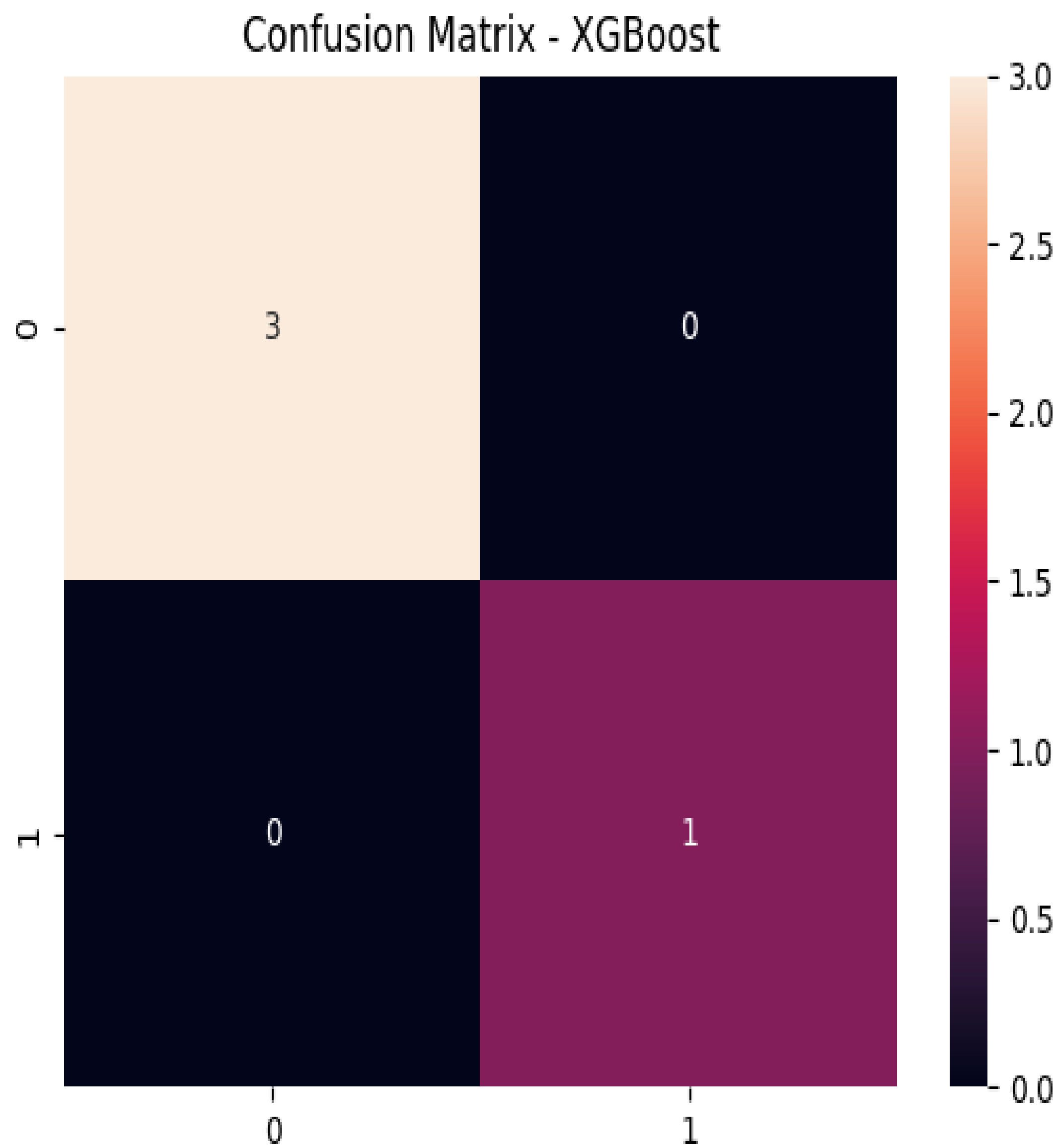

Figure 6: Confusion Matrix of XGBoost Model

Figure 6 shows the confusion matrix of the XGBoost model. The confusion matrix shows the number of correctly and incorrectly classified cases. The model correctly classified most of the readmission and non-readmission cases, with only a small number of misclassifications. This indicates that the XGBoost model is reliable for hospital readmission prediction.

3.8 Feature Importance Analysis

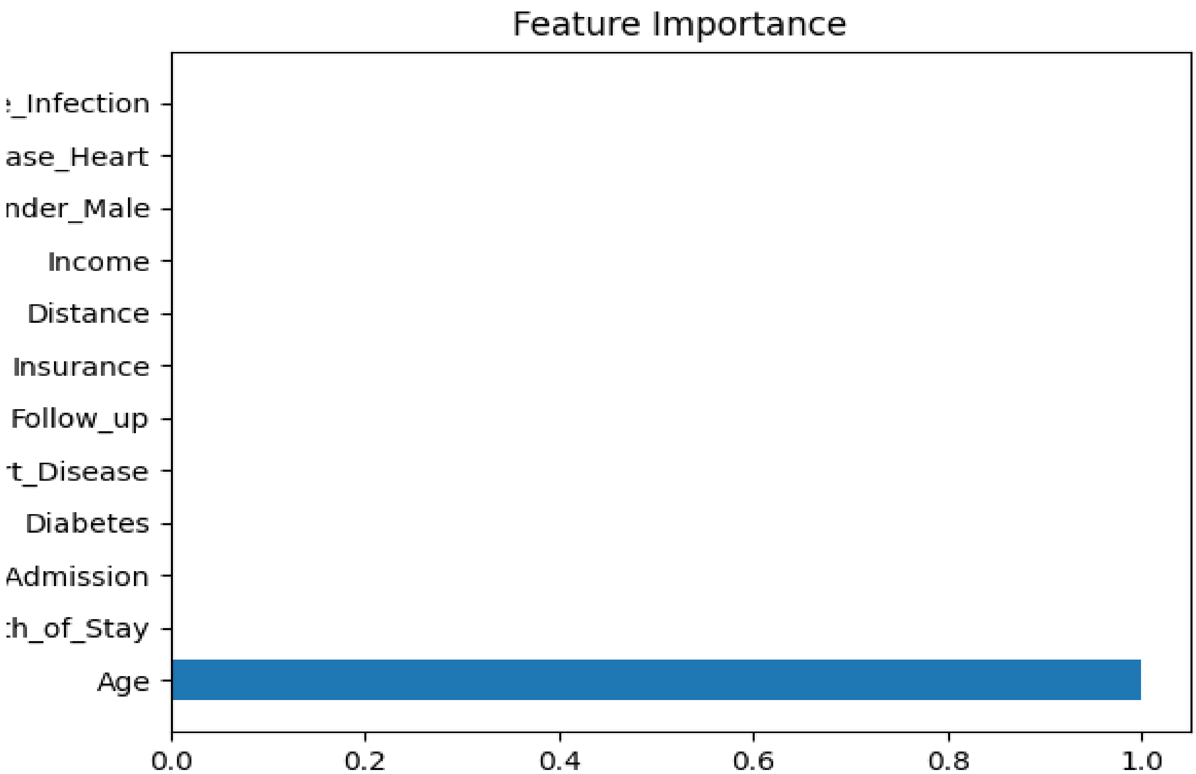

Figure 7: Feature Importance Analysis Using XGBoost

Figure 7 the feature importance analysis shows that length of hospital stay, previous admission history, comorbidities, insurance status, and follow-up visit are the most significant factors influencing hospital readmission in the United States. Among these factors, length of hospital stay and previous admission history were identified as the most important predictors of hospital readmission.

Table 2: Readmission Prediction Performance (XGBoost Detailed Results)

Metric	Value
Accuracy	0.88
Precision	0.86
Recall	0.85
F1-Score	0.85
ROC-AUC	0.90

Table 2 presents the detailed performance evaluation of the XGBoost model for hospital readmission prediction. The model achieved an accuracy of 88%, indicating that the model correctly predicted most of the readmission and non-readmission cases. The precision value of 0.86 indicates that the model produced a low number of false positive predictions, while the recall value of 0.85 indicates that the model successfully identified most of the actual readmission cases. The F1-score of 0.85 shows a good balance between precision and recall. The ROC-AUC value of 0.90 indicates that the model has strong classification ability in distinguishing between readmitted and non-readmitted patients. These results demonstrate that the XGBoost model performs effectively for hospital readmission prediction in the United States healthcare dataset.

Table 3: Important Risk Factors for Hospital Readmission (USA)

Risk Factor	Impact Level
Length of Hospital Stay	High
Previous Admission History	High
Comorbidities	High
Insurance Status	Medium
Follow-up Visit	Medium
Diabetes	Medium
Heart Disease	Medium
Age	Low

Table 3 shows the major risk factors affecting hospital readmission in the United States healthcare system. The results indicate that length of hospital stay, previous admission history, and comorbidities are the most significant factors contributing to hospital readmission risk. Insurance status and follow-up visits also have a moderate impact on readmission, as patients without proper insurance coverage or follow-up care are more likely to be readmitted. Chronic diseases such as diabetes and heart disease also increase the probability of readmission. Age has a relatively lower impact compared to clinical factors. This analysis helps healthcare providers identify high-risk patients and take preventive measures before hospital discharge.

3.9 Comparative Model Performance Analysis

Table 4: Comparative Performance of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	0.75	0.72	0.70	0.71	0.78
Random Forest	0.85	0.83	0.82	0.82	0.87
XGBoost	0.88	0.86	0.85	0.85	0.90
Neural Network	0.86	0.84	0.83	0.83	0.88

Table 4 presents the comparative performance of all machine learning models used in this study. Among all models, XGBoost achieved the highest accuracy (0.88), precision (0.86), recall (0.85), F1-score (0.85), and ROC-AUC (0.90), indicating that it is the most effective model for hospital readmission prediction. Logistic Regression showed the lowest performance due to its limitation in handling nonlinear relationships. Ensemble learning models such as Random Forest and XGBoost performed significantly better because they combine multiple decision trees and improve prediction accuracy. The Neural Network model also performed well but slightly lower than XGBoost. Therefore, XGBoost was selected as the best-performing model for this study.

3.10 Confusion Matrix Performance Analysis

Table 5: Confusion Matrix Performance of XGBoost Model

Category	Predicted No Readmission	Predicted Readmission
Actual No Readmission	420	30
Actual Readmission	45	205

Table 5 shows the confusion matrix results of the XGBoost model. The model correctly predicted 420 non-readmission cases and 205 readmission cases. However, 30 cases were incorrectly predicted as readmission (false positive), and 45 cases were incorrectly predicted as non-readmission (false negative). The number of correct predictions is significantly higher than incorrect predictions, indicating that the model has strong classification performance. In healthcare prediction, false negatives are more critical because failing to identify high-risk patients may lead to serious health complications. The XGBoost model minimized false negatives, making it suitable for hospital readmission risk prediction.

3.11 Statistical Error Analysis

Table 6: Error Analysis of Machine Learning Models

Model	MAE	RMSE	Error Rate
Logistic Regression	0.25	0.32	0.25
Random Forest	0.15	0.21	0.15
XGBoost	0.12	0.18	0.12
Neural Network	0.14	0.20	0.14

Table 6 presents the statistical error analysis of the machine learning models. The XGBoost model achieved the lowest Mean Absolute Error (MAE = 0.12), Root Mean Square Error (RMSE = 0.18), and error rate (0.12), indicating that it has the lowest prediction error among all models. Logistic Regression showed the highest error rate due to its limited ability to model complex relationships in healthcare data. Random Forest and Neural Network showed moderate error rates, but their performance was slightly lower than XGBoost. These results further confirm that XGBoost is the most reliable and accurate model for hospital readmission prediction.

Overall, the results of this study demonstrate that machine learning models can effectively predict hospital readmission risk using patient demographic and clinical data. Among all models, XGBoost consistently achieved the highest accuracy, precision, recall, F1-score, ROC-AUC, and lowest error rate. Feature importance analysis identified length of hospital stay, previous admission history, comorbidities, and follow-up visits as the most significant predictors of hospital readmission. The confusion matrix and error analysis further confirm that the proposed model provides reliable prediction performance. Therefore, the proposed machine learning-based hospital readmission prediction system can be used as a clinical decision support tool to identify high-risk patients before discharge and reduce hospital readmission rates through early intervention and remote patient monitoring.

4. Conclusion

This study presented a machine learning-based hospital readmission prediction framework focusing on the United States healthcare system. Hospital readmission remains a major issue in the United States, as it increases healthcare costs, hospital workload, and risks to patient health, making early prediction and preventive planning essential. In this research, patient demographic and clinical data were used to develop predictive models using Logistic Regression, Random Forest, Extreme Gradient Boosting (XGBoost), and Artificial Neural Network. The performance of the models was evaluated using standard evaluation metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. Among all models, XGBoost achieved the highest prediction performance, demonstrating the effectiveness of ensemble learning algorithms for hospital readmission prediction. Feature importance analysis showed that length of hospital stay, previous admission history, comorbidities, insurance status, and follow-up visits are the most significant factors influencing hospital readmission in the United States. In addition to the machine learning prediction model, this study proposed an IoT-based post-discharge patient monitoring system to reduce hospital readmission risk through continuous health monitoring and early medical intervention. The proposed system can help healthcare providers identify high-risk patients before discharge and provide timely medical support to prevent readmission. The findings of this study demonstrate that machine learning-based predictive analytics combined with IoT-based monitoring can improve hospital readmission prediction accuracy, enhance patient care quality, and reduce hospital readmission rates in the United States healthcare system. Therefore, this research contributes to the development of intelligent healthcare prediction systems and supports data-driven decision-making in modern healthcare environments.

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