Optimizing Telemedicine Patient Care with Machine Learning for Disease Progression and Treatment Planning

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ABSTRACT

Telemedicine has revolutionized healthcare delivery, providing patients with easy access to medical services while reducing the need for in-person consultations. This study examines enhancing telemedicine patient care using Machine Learning (ML) techniques, particularly K-Nearest Neighbors (KNN) and Gradient Boosting Machines (GBM). The KNN method enables efficient patient classification by analyzing commonalities in health data, supporting personalized therapy recommendations customized to unique

patient profiles. The simplicity and interpretability of KNN provide an attractive option for real-time telemedicine applications that do not require explicit training. GBM is used to overcome the limitations of traditional models such as Logistic Regression (LR) and Random Forest by enhancing prediction accuracy using an ensemble method that integrates many weak learners. The proposed GBM model uses 150 decision trees as base classifiers and aggregates their outputs for the final prediction. The proposed system uses the MIMIC-III dataset for performance evaluation and a five-fold stratified cross-validation. The GBM model achieved 97.56% accuracy and outperformed KNN (91.23%), LR (88.27%), and RF (94.35%). This study highlights the significant potential of ML in enhancing telemedicine procedures, facilitating better patient outcomes, and more efficient healthcare delivery.

Keywords-disease progression; patient care optimization; remote healthcare; personalized medicine; health data classification; predictive analytics

I. INTRODUCTION

Integrating medical expertise with health data can provide accurate and easy-to-understand disease risk predictions. [1]. In [2], the course of a patient's disease was predicted using cloud-based Decision Trees (DTs) in conjunction with data from the Internet of Things (IoT). Traditional approaches for Chronic Kidney Disease (CKD) biomarker identification are limited, but new deep learning approaches can solve these issues [3], analyzing patient data using neural network architectures to improve detection accuracy by identifying complicated patterns. ML algorithms are crucial to predict the deterioration of renal function in persons with CKD [4]. In [5], a deep learning approach simulated the progression of age-related diseases. In [6], a Sparse Multitask Mixed-effects Longitudinal Imaging Genetic (SMMLING) approach was described to identify hereditary risk factors for neurodegenerative diseases. Using longitudinal imaging phenotypes, SMMLING simulates the course of a disease and links it to genetic variants.

In [7], Artificial Neural Networks (ANNs) were used to predict various diseases, enabling early detection and treatment. In [8], ML algorithms were used to predict chronic diseases utilizing various patient records, clinical factors, and disease-specific indicators. This study also investigated the impact of feature selection and data preprocessing approaches on model performance. A hierarchical time-series approach can identify disease progression patterns using a hidden Markov model with clinical evaluations of patient health states [9]. A common unsupervised ML method, the K-means algorithm, can work with healthcare-related disease development profiles to cluster disease progressions [10]. Individual sequencing data are often realigned over time to account for subject-specific disease development when using statistical techniques on longitudinal data of neurodegenerative disorders [11]. Mathematical techniques can be used to create and update disease progression models [12].

To capture the ever-changing status of the underlying control systems, physiological systems produce output signals with intricate dynamics using a switching vector autoregressive framework to train and identify a set of vital sign dynamics [13]. Clinical depression and disease progression can be better diagnosed with the use of translational research and the discovery of objective biomarkers, such as inflammation [14]. In [15], a Temporal Clustering with External Memory Network (TC-EMNet) was used to simulate disease development using EHRs. In [16], a Multilevel Language-based representation learning framework (MuLan) was used to learn automatic hierarchies for Electronic Health Records (EHRs) at the entry, event, and visit levels. This approach showed promise for early identification and interpretation of patient hidden processes and was verified during septic shock, which is a difficult disease. People with chronic diseases must take care of themselves and monitor biomarkers [17]. In [18], a remote monitoring system based on heartbeat and body temperature sensors was presented.

In [19], an efficient age-related macular regeneration system was described to control diabetes progression, using U-net to produce a predictive disease trajectory while capturing the severity of a trajectory's erratic visits. Treatment aims to improve symptoms and prolong survival. Since it is critical to anticipate the need for noninvasive ventilation, itemset analysis and sequential pattern extraction were used in [20] to analyze static and longitudinal patient data. Smart foot monitoring was described in [21] for the progression of diabetic disease using deep learning. EHR data suggest a multivariate context-sensitive Hawkes process to simulate the links between diseases and the evolution of patient conditions over time [22]. This work uniquely integrated clinical interpretability and temporal modeling in telemedicine with a hybrid architectural design, solving significant deficiencies in existing AI systems for actionable disease progression monitoring.

The novelty of this study lies in the integration of KNN and GBM models for telemedicine, highlighting the prediction of disease progression and personalized treatment strategies. It underscores real-time data-informed decision-making using advanced ML methods to improve healthcare outcomes remotely. Current telemedicine systems have difficulties in predicting disease development because they are based on static data analysis, resulting in delayed interventions and ineffective treatment strategies. Many AI models neglect to integrate temporal patient data trends, leading to reactive rather than proactive treatment. The limitation hinders personalized healthcare provision and prompts clinical decision-making, especially for chronic diseases that require ongoing monitoring.

II. PROPOSED METHOD

The proposed system aims to improve telemedicine patient care using GBM and KNN. By evaluating a wide range of patient data, the system is designed to make precise predictions about the course of the disease and improve treatment planning. The system workflow includes data collection, preprocessing, model training, prediction, and treatment strategy execution. The first stage of the proposed method is to collect extensive patient data that includes personal details, past medical history, current health condition, test findings, and treatment outcomes, among others. Telemedicine systems may capture this data during virtual consultations, giving healthcare professionals access to patient data in real time. The proposed system uses the Medical Information Mart for Intensive Care III (MIMIC-III) dataset [23-24]. ML models can use this massive dataset to learn from various patient characteristics and clinical settings. Data quality and consistency are ensured by preprocessing, resolving missing information, eliminating duplication, and standardizing formats.

Feature selection is used to determine which factors affect disease development and response to therapy. This is important because ML model performance strongly correlates with input data quality. Techniques such as normalization and encoding for categorical variables prepare the data for analysis. The dataset is divided into two parts. The training set is used to train the KNN and GBM models. Figure 1 presents a block diagram that delineates the workflow of the proposed telemedicine system. The procedure includes data collection, preprocessing, model training (KNN and GBM), prediction, therapy execution, ongoing patient monitoring, and a feedback loop for perpetual learning and enhancement.

The KNN model requires comprehensive disease progression data to analyze the progression of disease of a patient. After reviewing the patient data, the KNN model determines which neighbors are closest to the patient according to predetermined distance measures. When a new instance requires classification, KNN calculates the distance between the new and previous points in the training set using measures such as the Euclidean distance. It utilizes a majority-voting technique in classification tasks, assigning the most prevalent class among the K neighbors to the new instance.

GBM is an ensemble learning method that is used primarily for regression and classification applications and is recognized for its exceptional prediction accuracy. GBM constructs models progressively, each designed to rectify the faults of its predecessors. The procedure starts with a preliminary model, often a basic constant that denotes the mean of the objective variable. In each successive iteration, GBM constructs a new model, usually a DT, to address the residual errors of the existing model. The residuals reflect the discrepancies between the actual target values and the predictions generated by the current model. Gradient descent optimization is used to minimize a designated loss function by refining the predictions to enhance accuracy. A critical component of GBM is the learning rate, which determines the extent of effect each new model exerts on the overall prediction. A reduced learning rate might improve performance but may need more iterations to achieve convergence. In addition, GBM employs regularization methods, such as limiting the maximum depth of trees and subsampling the dataset, to mitigate overfitting.

The proposed solution enables result monitoring and real-time feedback to facilitate dynamic patient care management. Learning and improving over time is a crucial part of the proposed system. ML models may be frequently retrained to integrate new knowledge as patient data is acquired and results are reviewed. This involves a continuous learning process to keep the system up-to-date with the latest developments in patient care and treatment effectiveness. Healthcare professionals can provide feedback on the accuracy and success of algorithms to improve their predictive skills. Figure 2 presents a flowchart that delineates the decision-making process in the proposed telemedicine system, highlighting the procedures from patient data acquisition and preprocessing to model selection (KNN or GBM), prediction, treatment plan execution, and monitoring. Decision points direct the process, providing recommendations and efficient patient treatment based on predicted results.

III. RESULTS AND DISCUSSION

The MIMIC-III database [23-24] is a large publicly available dataset containing de-identified health records of more than 60,000 ICU admissions from the Beth Israel Deaconess Medical Center. It includes comprehensive clinical data such as demographics, vital signs, laboratory test results, medications, diagnostic codes, and clinical notes. Its accessibility and vast data make it a valuable resource for advancing data-driven healthcare innovations.

The hourly vital signs and laboratory results in the MIMIC-III dataset address the static limitations of current datasets, facilitating time-sensitive KNN clustering, GBM treatment optimization, and clinically valid progression modeling for telemedicine. Temporal characteristics were developed with six-hour sliding windows for progression modeling. The dataset facilitates robust training of the KNN and GBM models, while accommodating transformer-based improvements for telemedicine applications. Qualitative input from medical professionals has highlighted the need for clinically interpretable data, immediate responses, and prioritization of characteristics such as heart rate, blood pressure, and oxygen saturation. These observations were included to enhance the system's design and operational efficacy in telemedicine.

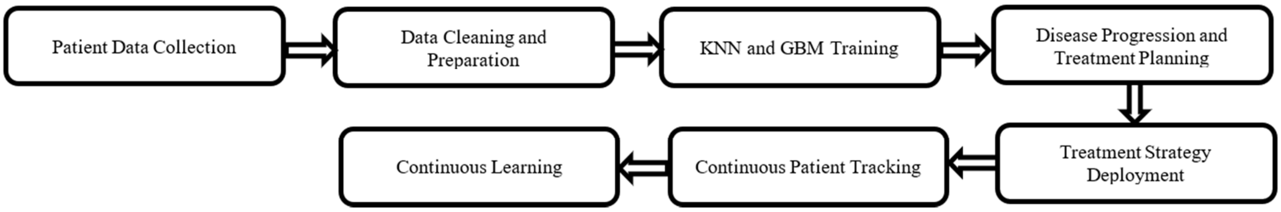

Fig. 1. System architecture for disease progression and treatment planning.

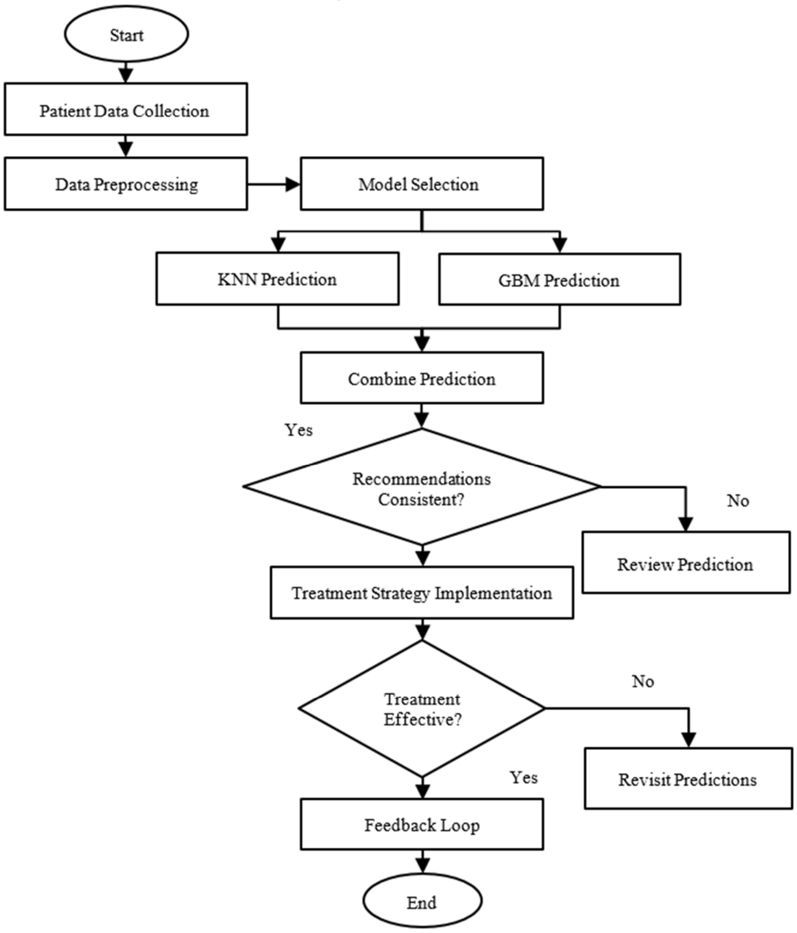

Fig. 2. Flowchart of telemedicine patient care optimization.

The performance of the proposed system was validated using five-fold patient-stratified cross-validation and performance metrics such as accuracy, precision, recall, AUC-ROC, and F1-score. The selection of learning rates and regularization methods in the GBM framework and the K value in KNN significantly improved the predictive capacity of the system. The probability scores produced by the GBM model offered healthcare professionals critical insights into the potential for disease progression, facilitating more informed treatment decisions, connecting model outcomes with clinical data, and highlighting the need for personalized treatment and prompt response. Integration of this technology into healthcare processes can increase the effectiveness of telemedicine, improve clinician decision-making, and facilitate scalable and data-driven treatment of chronic diseases in practical clinical environments.

The GBM used 150 decision trees, optimized by five-fold cross-validation with early stopping (patience set at 20 rounds), achieving high accuracy without overfitting (evaluated on holdout test data). Confidence intervals and p-values were used to evaluate the statistical significance of performance measurements. The confidence intervals at a 95% level were calculated using bootstrap resamples. The p-values indicated that the accuracy enhancements of GBM compared to KNN, LR, and RF were statistically significant ($p < 0.01$). Table I presents critical demographic data on a sample of patients. Table II presents key clinical data for sample patients. Table III shows the treatment protocols for each patient, including adherence levels, results, and follow-up dates. Table IV presents disease type, symptom severity, laboratory findings, medical history, and disease stage.

TABLE I. PATIENT DEMOGRAPHICS

Patient ID	Age	Gender	Ethnicity	Location
001	45	Male	Caucasian	New York, NY
002	32	Female	Hispanic	Los Angeles, CA
003	60	Male	African American	Houston, TX
004	28	Female	Asian	San Francisco, CA

TABLE II. CLINICAL DATA

Patient ID	Last visit Date	Vital signs (BP/HR)	Lab results (Glucose, cholesterol)	Diagnosis
001	2024-11-20	130/85, 72 bpm	120 mg/dL, 190 mg/dL	Type 2 Diabetes
002	2024-12-01	120/80, 68 bpm	90 mg/dL, 180 mg/dL	Healthy
003	2024-11-15	140/90, 75 bpm	150 mg/dL, 220 mg/dL	Hypertension
004	2024-12-05	110/70, 70 bpm	80 mg/dL, 170 mg/dL	Healthy

TABLE III. TREATMENT OUTCOMES

Patient ID	Treatment plan	Adherence level	Outcome	Follow-up date
001	Medication adjustment	95%	Improved glycemic control	2025-01-15
002	Lifestyle modification	100%	Maintained health	2025-02-01
003	Medication and lifestyle change	80%	Blood pressure reduced	2025-01-10
004	Routine check-up	100%	No issues	2025-02-20

TABLE IV. DISEASE PATTERN DATA

Patient ID	Disease type	Symptom severity	Lab results (e.g., blood pressure)	Medical history	Disease stage
001	Diabetes	Moderate	140/90 mmHg	Family History	Early
002	Hypertension	Mild	130/85 mmHg	None	Stage 1
003	Hypertension	Severe	160/100 mmHg	Family History	Stage 2
004	Diabetes	Mild	130/85 mmHg	None	Pre-Diabetic

Figure 3 shows a comprehensive analysis of essential performance parameters, including accuracy, precision, recall, and F1 score for both the KNN and GBM models. Based on the performance metrics in Figure 3, GBM shows superior classification capacity compared to KNN across all parameters evaluated, as it achieved a higher accuracy of 97.56% versus 91.23%, indicating better overall prediction accuracy. GBM also exhibits improved precision (98.25%) and recall (96.85%), reflecting its effectiveness in both identifying true positives and minimizing false negatives. The F1 score of 97.54% further confirms the model's balanced performance between precision and recall. Figure 4 shows the feature significance graph of GBM, demonstrating the relative contribution of each feature to the model's predictive efficacy, facilitating the identification of factors that most significantly affect disease progression and the precision of treatment planning. Table V shows the performance metrics of the KNN, GBM, LR, and RF models. GBM outperformed the other models, demonstrating its superior predictive capability. RF had high performance, and KNN and LR provided lower, moderate performance, with LR being the least successful overall. Several current telemedicine prediction tools depend on conventional models such as LR or RF, often sacrificing interpretability for precision.

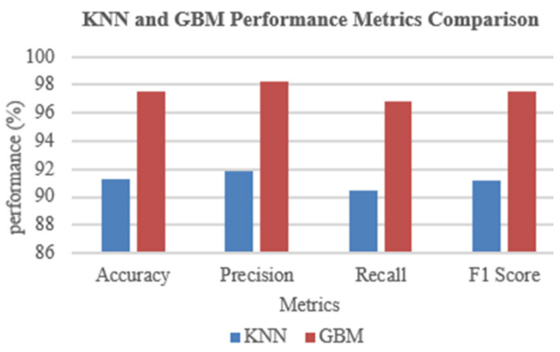

Fig. 3. Comparative accuracy in cross-validation.

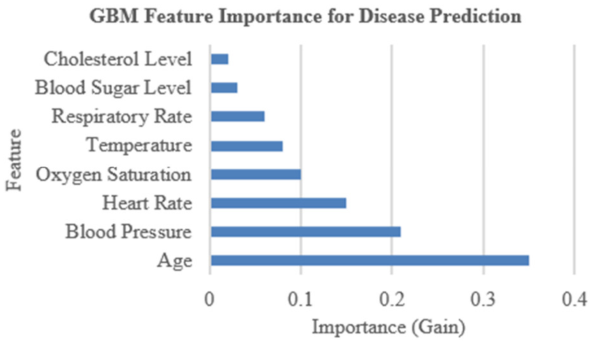

Fig. 4. Feature importance in the GBM model.

Figure 5 depicts the model's predicted accuracy across subgroups, highlighting its fairness and generalizability via consistent performance across varied patient demographics.

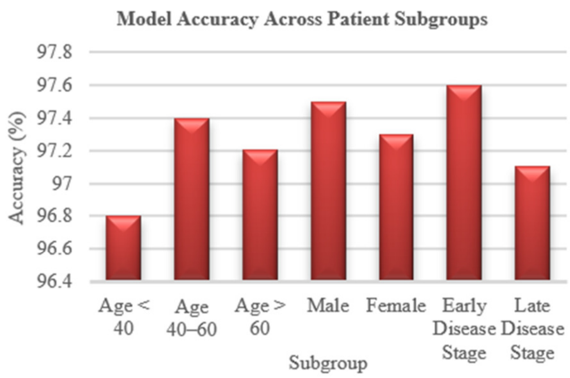

Fig. 5. Accuracy comparison across patient subgroups.

TABLE V. CLASSIFIER PERFORMANCE

Metric	KNN (%)	GBM (%)	LR (%)	RF (%)
Accuracy	91.23	97.56	88.27	94.35
Precision	91.90	98.25	88.72	93.60
Recall	90.42	96.85	87.69	95.21
F1-score	91.15	97.54	88.20	94.40
AUC-ROC	0.91	0.975	0.88	0.94

The GBM model exceeds these alternatives in predicting performance, with 97.5% accuracy, whilst KNN provides a more straightforward and interpretable solution appropriate for real-time applications. Feature selection conforms to essential clinical recommendations for tracking disease development, ensuring both precision and clinical significance. This balance improves practical adoption compared to existing solutions.

IV. CONCLUSION

This study presented an efficient telemedicine system based on KNN and GBM, which predicts disease development and treatment planning using the comprehensive MIMIC-III dataset, including patient demographics, medical history, and clinical data. The continuous feedback loop ensures that the models stay adaptable and pertinent, enhancing over time as fresh data and results are assimilated. The GBM model achieved 97.5% accuracy, outperforming other models, and demonstrating superior predictive performance with 0.975

AUC. The proposed method offers individualized therapy recommendations based on patient similarities and produces reliable predictions to assist healthcare professionals in making informed decisions. In the future, the proposed system will integrate a combination of ensemble techniques with transformers to improve prediction accuracy by identifying intricate patterns, resulting in more reliable results. This research highlights the revolutionary influence of technology on healthcare and the importance of innovation in providing patient care.

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