A CLOUD-ENABLED MACHINE LEARNING FRAMEWORK FOR PREDICTIVE HEALTHCARE

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ABSTRACT

The Adaptable Critical Patient Caring System addresses the urgent need for efficient healthcare management in developing countries such as Bangladesh, where most hospitals lack scalable and intelligent systems for serving critical patients. This project aims to design an effective real-time feedback system to assist healthcare professionals in continuously monitoring and managing patients with severe conditions.This study proposes a generic architecture, associated terminology, and a classificatory model that integrates machine learning (ML) with IBM Cloud computing, utilized as Platform as a Service (PaaS). IBM Watson Studio serves as the environment for data storage, model training, and deployment. Several ML algorithms, including Naïve Bayes, Logistic Regression, K-Nearest Neighbors, Decision Tree, Random Forest, Gradient Boosting, and Multilayer Perceptron (MLP) Classifiers, are implemented as base predictors. To improve prediction accuracy, ensemble learning with the bagging technique is applied using Bagging Random Forest, Bagging Extra Trees, Bagging KNeighbors, Bagging SVC, and Bagging Ridge.A mobile application, Critical Patient Management System (CPMS), has been developed to visualize and access real-time patient data. The architecture enables dynamic model training and deployment by retrieving data from IBM Cloud at periodic intervals..By combining ML models with a mobile interface, the proposed system provides a scalable, intelligent, and real-time healthcare solution to enhance critical patient management and hospital efficiency.

Index Terms:-Machine Learning (ML), Predictive Healthcare, IBM Cloud, Ensemble Learning, Real-Time Monitoring, Critical Patient Management System (CPMS), Cloud Computing, Smart Healthcare.

I. INTRODUCTION

Critical Patient Caring or Monitoring Systems enable doctors to continuously observe multiple patients and various physiological parameters simultaneously, even from remote locations. These systems also provide the capability to control medication dosage and treatment settings remotely [1]. The development and evaluation of Intensive Care Unit (ICU) decision-support systems can be significantly enhanced through such technologies.In ICUs, devices such as vital sign monitors, mechanical ventilators, and dialysis machines are essential for sustaining patients whose bodies require time to recover and repair. Traditionally, these machines are managed manually by medical staff who continuously supervise patients' conditions and interpret diagnostic test reports. This manual approach, however, is prone to human limitations and delays in response time.

To address these challenges, we propose automating the monitoring and decision-making processes using modern technologies, specifically cloud computing and machine learning (ML). ML models can predict the near-future condition of patients—indicating whether their health status is improving or deteriorating—and determine if immediate intervention is necessary.To generalize our models and data management processes, IBM Cloud has been selected as the Platform as a Service (PaaS), supporting public, private, and hybrid environments [2]. As direct model deployment is not feasible initially, IBM Watson Studio is utilized for model storage, testing, and deployment. The ML models operate within the cloud environment, where they continuously train using auto-deployed data. Additionally, the Critical Patient Management System (CPMS) accesses these cloud services through IBM Bluemix [3].The core contribution of this work lies in developing an auto-deployable ML model integrated within cloud storage, achieving high predictive accuracy through systematic testing, tuning, and parameter optimization across various ML algorithms.

II.LITERATURE SURVEY

- Du and Zhan [1] investigated the problem of building a decision tree classifier over a vertically partitioned database shared between two parties—Alice and Bob—without compromising data privacy. Since neither party is willing to disclose private data to the other or to any third party, the authors proposed a privacy-preserving protocol using an untrusted third-party server. The protocol is based on a scalar product computation technique, offering greater efficiency compared to existing solutions. This work laid the foundation for secure and distributed model training environments.

- Graczyk et al. [2] compared three methods for creating ensemble models within the WEKA data mining framework. Their study utilized six popular algorithms—two neural networks, two decision trees for regression, linear regression, and a support vector machine—applied to real-world datasets from cadastral systems and real estate registries. Using nonparametric Wilcoxon signed-rank tests, they concluded that no single algorithm consistently yields the best ensemble performance, highlighting the importance of developing hybrid multi-model approaches combining bagging, stacking, and boosting techniques.
- Rish [3] provided an in-depth analysis of the Naïve Bayes classifier, focusing on how feature independence assumptions impact classification accuracy. Through Monte Carlo simulations, the study demonstrated that Naïve Bayes performs remarkably well with both independent and functionally dependent features. Interestingly, classification accuracy was found to depend more on information loss due to independence assumptions rather than the actual degree of feature dependency.
- Snoek et al. [4] explored automatic hyperparameter optimization for machine learning models using Bayesian optimization with Gaussian process priors. Their work demonstrated that Bayesian optimization can outperform manual tuning by efficiently selecting hyperparameters based on prior experimental outcomes. Furthermore, they introduced algorithms that consider variable computation costs and leverage parallel processing, achieving expert-level performance on models such as structured SVMs, latent Dirichlet allocation, and convolutional neural networks.
- Muja and Lowe [5] addressed the computational challenges of nearest neighbor matching in high-dimensional spaces, a key bottleneck in computer vision applications. They developed an automated system to identify the fastest approximate nearest neighbor (ANN)

algorithm for a given dataset and precision level. Their approach—using hierarchical k-means trees and multiple randomized k-d trees—achieved nearly an order of magnitude improvement in query speed compared to existing methods, providing a significant advance in efficient data retrieval and search optimization.

III.EXISTING SYSTEM

In the existing healthcare system, managing a large number of critical patients simultaneously is extremely challenging. The demand for highly experienced doctors often exceeds availability, resulting in delayed or inconsistent treatment. Studies and hospital surveys indicate that approximately 19% of ICU and cabin patients receive incorrect or suboptimal treatment due to the absence of intelligent decision-support systems and continuous monitoring mechanisms.

Furthermore, most hospitals in Bangladesh lack adequate healthcare infrastructure capable of providing efficient, scalable, and automated patient management. The medical staff typically rely on manual observation and periodic testing to assess patient conditions. This not only increases the workload of healthcare professionals but also limits timely decision-making during medical emergencies.

DISADVANTAGES

- Hospitals are unable to provide efficient healthcare services due to the absence of appropriate, user-friendly, and scalable smart systems.
- Manual monitoring leads to a higher risk of delayed response and incorrect treatment decisions.
- Lack of centralized and automated systems restricts collaboration among medical teams.

IV.PROPOSED SYSTEM

The proposed system aims to develop an intelligent, cloud-enabled healthcare framework capable of providing real-time monitoring and predictive analysis for critical patients. This system integrates Machine Learning (ML) and IBM Cloud computing using Platform as a Service (PaaS) to assist doctors in decision-making and ensure timely patient care.

Machine learning models are at the core of this framework, performing predictive health assessments to determine whether a patient's condition is improving or deteriorating. The models are developed and managed through IBM Watson Studio, which enables seamless data storage, model training, and deployment in a cloud environment.

The following ML algorithms have been implemented as base predictors: Naïve Bayes, Logistic Regression, K-Nearest Neighbors, Decision Tree, Random Forest, Gradient Boosting, and Multilayer Perceptron (MLP) Classifiers. To enhance prediction accuracy, ensemble learning using the bagging technique is applied with Bagging Random Forest, Bagging Extra Trees, Bagging KNeighbors, Bagging SVC, and Bagging Ridge algorithms.

A mobile application named Critical Patient Management System (CPMS) has been developed to provide real-time visualization and access to patient data. The system architecture supports automatic model training and deployment by retrieving updated information from IBM Cloud at regular intervals. If the system predicts a deterioration in a patient's condition, CPMS immediately sends an SMS alert to the duty doctor and nurse, enabling prompt medical intervention.

ADVANTAGES

- Enables remote monitoring of patients' vital parameters using cloud-based ML models.
- Ensures faster response times and improved treatment accuracy through predictive analytics.

V.SYSTEM MODEL

The proposed system is designed with six major components that work together to enable real-time monitoring, prediction, and response for critical patient care. The machine learning (ML) models form the analytical core of the system, providing predictive insights based on patient data. These models are integrated and deployed through IBM Cloud and IBM Watson Studio, which serve as the primary platforms for cloud-based data management, model training, and deployment services.

An overview of the complete system architecture is presented in Fig. 1, illustrating the interaction between all major components. Each module performs a distinct function that collectively supports intelligent decision-making and efficient healthcare management.

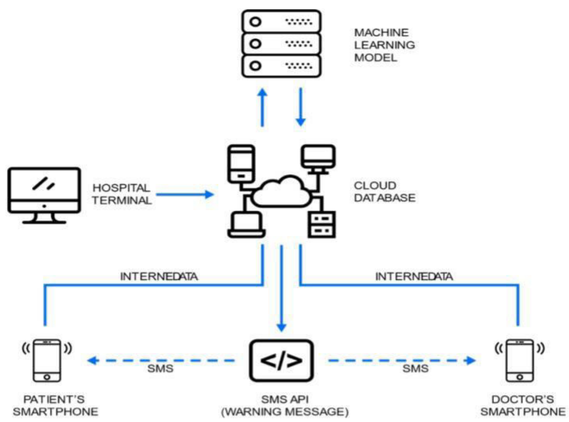


Fig.System Model

VI.MODULES

The proposed system is composed of three primary modules are Admin, Doctor, and Patient each with distinct functionalities designed to ensure secure access, efficient management, and reliable healthcare service delivery.

A. Admin Module

The Admin serves as the system's central authority, responsible for overseeing all platform operations. This includes managing doctors' profiles, maintaining patient records, monitoring user activity, and supervising comments or queries within the system. The administrator has full control over user access permissions and data integrity. By managing authentication and authorization processes, this module ensures that only verified users can interact with system data, thereby maintaining a secure and well-organized operational environment.

B. Doctor Module

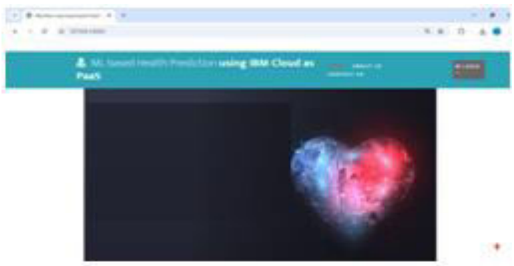
The Doctor module enables authorized medical professionals to access, analyze, and update patient information. Doctors can review medical histories, diagnose conditions, and provide prescriptions or recommendations through the system interface. This module also supports two-way communication between doctors and patients, facilitating continuous monitoring and personalized healthcare. By leveraging real-time data and predictive insights from the integrated machine learning models, doctors can make informed medical decisions and enhance treatment effectiveness.

C. Patient Module

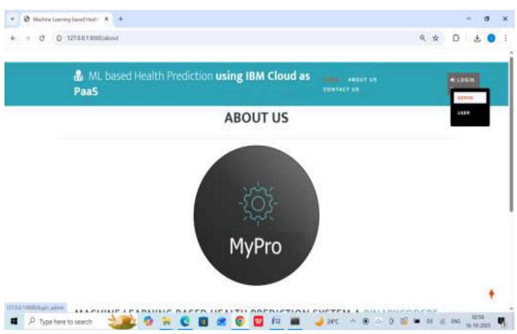
The Patient module is designed for individuals seeking medical assistance. Registered patients can securely log in to view and update their personal health records, review past consultations, and search for symptom-related information. To ensure privacy, all sensitive information — including names, contact details, and medical data — is encrypted and stored securely in the cloud. This module empowers patients with access to their health information anytime, ensuring transparency, continuity of care, and improved patient engagement.

VII.RESULTS

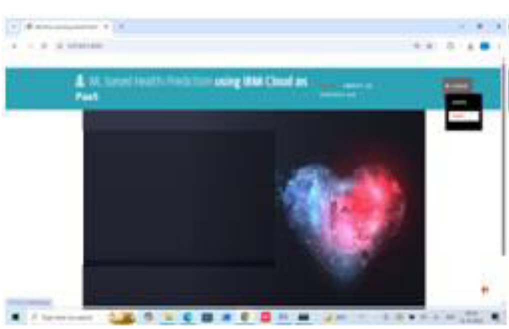
Homepage



Aboutus



Admin Login



Admin Home page

VIII.CONCLUSION

To provide effective and affordable healthcare, there is an increasing need to integrate advanced technologies into hospital systems. This project was initiated with the goal of improving patient care through automation, predictive analysis, and real-time monitoring. By leveraging machine learning (ML) models and cloud computing, the proposed system demonstrates significant potential in enhancing healthcare efficiency and decision-making.

Experimental results show that the ML models achieved accuracy levels ranging from 80% to 92%, with the lowest accuracy being 80%. A key outcome of this research is the effective application of ML algorithms to medical data, particularly in handling categorical variables for health prediction. The IBM Cloud platform proved to be reliable, achieving a success rate above 90%

for model deployment and data management.

Overall, the system demonstrates strong potential for large-scale implementation, particularly in urban hospitals and low-resource healthcare environments. The proposed framework can serve as a virtual doctor, assisting healthcare professionals in continuous patient monitoring and informed decision-making. Although the current model is based on limited physiological parameters, it establishes a strong foundation for developing a more comprehensive smart healthcare solution.

IX.FUTURE WORK

In future developments, we plan to integrate embedded systems capable of collecting live readings directly from ventilators, medicine pumps, heart monitors, and other ICU equipment. This enhancement will enable seamless real-time data acquisition and further improve the accuracy and reliability of the predictive healthcare framework.

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