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Explainable AI for Hospitalization Duration Predictions

S Latha . V Hari Sai Praneeth . T Siddhartha . S Syed Moheed Nawaz . P Prasanthi

Department of AI and Data Science,
Annamacharya Institute of Technology and Sciences,
Kadapa, Andhra Pradesh, India.

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Abstract – Effective bed management is essential for reducing hospital expenses, improving operational efficiency, and enhancing patient care. This study introduces a predictive framework for ICU length of stay (LOS) at the time of admission, utilizing electronic health records (EHR). Our research applies supervised machine learning classification models to estimate ICU patients' LOS within hospital clinical information systems (CIS). Notably, this work represents the first known application of explainable artificial intelligence (xAI) to real-world hospital stay data for interpretable machine learning predictions. We assessed predictive classification models using various performance metrics, including Accuracy, AUC, Sensitivity, Specificity, F1-score, Precision, Recall, and others, to classify ICU stays as short or long upon admission. XGBoost demonstrated a 98% AUC in predicting LOS categories. This study highlights how hospitals and ICUs can integrate machine learning to forecast patient stays at admission. Additionally, our findings enhance clinical information systems by incorporating xAI to ensure robust and interpretable LOS prediction models.

Index Terms –Healthcare decision support systems, explainable artificial intelligence, machine learning, XGBOOST.

I. INTRODUCTION

The duration of hospitalization is widely recognized as a key measure of hospital efficiency [1]. It has a profound impact on resource management and healthcare costs [2]. According to a report by the Australian National Health Performance Authority, reducing hospital stays enhances efficiency by making beds available more quickly for new admissions. However, excessively short stays can compromise care quality and lead to negative health outcomes. Conversely, extended hospitalizations—often due to medical complications—increase the risk of adverse events. Additionally, delays in healthcare coordination, independent of a patient's medical condition, can unnecessarily prolong hospital stays. The report also emphasizes that longer stays may stem from inefficiencies in transitioning patients to alternative care settings, such as rehabilitation centers, community care, or aged care facilities [3].

Efficient ICU bed management is critical in addressing challenges such as overcrowding, infection risks, increased mortality rates, and medical complications. To mitigate these risks while optimizing resource utilization, reducing ICU stays without sacrificing care quality is essential, particularly during health crises such as pandemics [4]. This not only lowers hospital expenses but also improves patient outcomes. Ensuring adequate bed availability and prompt patient transfers plays a crucial role in maintaining healthcare quality. Effective ICU resource allocation is, therefore, fundamental to enhancing healthcare service delivery [5], [6], [7], [8]. AI-driven prediction models using electronic health records (EHRs) offer better accuracy in estimating ICU length of stay (LOS) compared to traditional scoring systems like APACHE, SAPS, and SOFA. Machine learning models, such as XGBoost, Random Forest, and Artificial Neural Networks, have shown promising results in predicting LOS. However, challenges remain, including data limitations, model interpretability, and the need for explainable AI approaches.

Several studies have explored different AI models for LOS prediction. Ma et al. used extreme learning machines (ELMs) for personalized ICU stay predictions. Su et al. found that Random Forest outperformed SOFA in predicting LOS for sepsis patients. Staziaki et al. showed that combining clinical and imaging data improved accuracy. Alghatani et al. tested various classifiers, with Random Forest and XGBoost performing best. Bayesian Networks also achieved high accuracy but lacked detailed parameter insights. Despite advancements, further research is needed to refine AI-driven ICU LOS prediction models, ensuring transparency, adaptability, and broader clinical application.

II. LITERATURE SURVEY

Machine learning ml has revolutionized the healthcare sector particularly in forecasting hospital length of stay los predicting los accurately is essential for optimizing hospital resources enhancing patient care and controlling costs traditional methods including logistic regression models and clinical scoring techniques such as apache saps and sofa have been utilized in this domain however these models rely on predefined assumptions and fail to capture complex non-linear patterns within patient data resulting in suboptimal predictive accuracy similarly conventional regression techniques like cox proportional hazards models and survival analysis have been explored for los prediction yet they exhibit challenges in handling large datasets and diverse patient demographics

The emergence of machine learning algorithms has significantly enhanced the accuracy of LOS forecasting by leveraging electronic health records (EHRs). Among supervised learning models, Decision Trees (DT) and Random Forests (RF) stand out for their interpretability and ability to rank key predictive features. However, these models are sometimes prone to overfitting, which limits their generalizability. Support Vector Machines (SVMs) have been effective in handling high-dimensional healthcare datasets, enabling the identification of intricate patterns in patient records. Additionally, boosting techniques such as XGBoost and Gradient Boosting Machines (GBM**)** have demonstrated superior performance by iteratively refining model predictions and managing missing data effectively. Deep learning techniques have further improved LOS estimations. Artificial Neural Networks (ANNs**)** have the capability to capture complex dependencies in structured and unstructured hospital data, while Recurrent Neural Networks

(RNNs) and Long Short-Term Memory (LSTM) networks are particularly effective in analyzing sequential patient data. Furthermore, Convolutional Neural Networks (CNNs) have been integrated into predictive models to incorporate imaging data, adding another dimension to LOS prediction.

Despite these improvements, several challenges continue to affect LOS prediction models. Imbalanced data distributions pose a significant issue, as shorter hospital stays are far more common than extended stays, leading to potential bias in model outcomes. Addressing this requires the use of oversampling methods and synthetic data augmentation techniques to ensure a balanced dataset for training. Generalizability is another major concern, as models trained on data from specific healthcare institutions may not perform effectively when applied to other hospitals with different patient populations. Additionally, there is often a trade-off between accuracy and explainability, where highly complex deep learning models provide high accuracy but lack transparency. Moreover, the integration of ML models into Clinical Decision Support Systems (CDSS) remains an underexplored area, preventing real-time implementation of predictive analytics in hospital workflows.

This study aims to overcome these challenges by developing an explainable ML framework for LOS prediction. The proposed approach utilizes real-world hospital datasets to create an effective and applicable model. Furthermore, SHAP-based interpretability methods are employed to provide insights into the model's decision-making process, ensuring that predictions remain transparent for healthcare professionals. Multiple ML techniques are evaluated to determine the most efficient approach, while strategies for seamless integration into hospital systems are explored. By balancing predictive performance with explainability, this study contributes to the development of AI-driven solutions that support informed decision-making in hospital management.

III. METHODOLOGY

This study presents a framework designed to predict the duration of hospital stays for patients specifically from their ICU admission to discharge machine learning techniques are utilized to estimate the length of stay lOS of inpatients based on real-world hospital data this process is crucial for evaluating and validating predictive models using actual hospitalization records in this section each phase of the proposed predictive framework fig 1 is explained in depth the following section provides a detailed discussion of every stage within the frame work.

Data description and features extraction

This study retrospectively analyzed electronic health record (EHR) data from Al-Ain Hospital, covering ICU admissions from December 31, 2017, to April 3, 2020. A de-identified dataset of 1,045 patients was used, ensuring compliance with UAE and Australia's data protection regulations. Ethical approval was obtained from Al-Ain Hospital, UAE University, and Western Sydney University. The study included all ICU hospitalizations, excluding cases with significant missing data or non-surviving patients. Disease classification followed the ICD-10 system, and 475 features were extracted from the hospital's medical records. Two experimental settings were used: one with all 1,045 patients and another dividing patients into three subsets. The inclusion criteria were developed collaboratively by medical and computer science experts.Participants engaged with the WUDI! app over six months, during which they earned rewards and incentives based on their engagement with physical activity, sleep, and dietary tracking. Parental involvement was also incorporated to track growth metrics and enhance adherence.

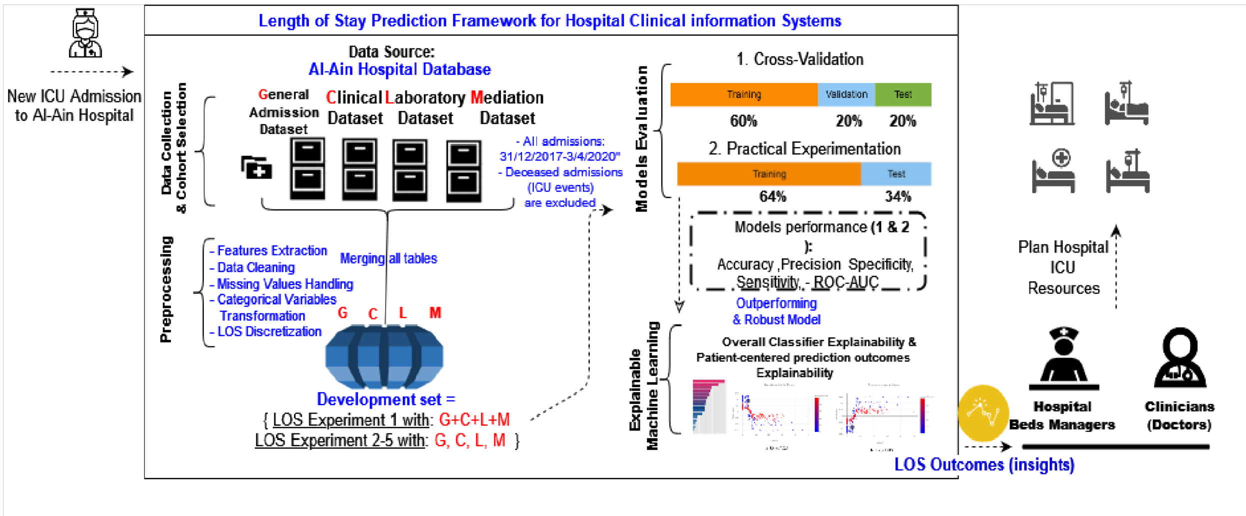

Fig 1: Predicting Hospital Stay Length Architecture

2. Data Pre-Processing And Discretisation

This study retrospectively analyzed electronic health record (EHR) data from Al-Ain Hospital, covering ICU admissions from December 31, 2017, to April 3, 2020. A de-identified dataset of 1,045 patients was used, ensuring compliance with UAE and Australia's data protection regulations. Ethical approval was obtained from Al-Ain Hospital, UAE University, and Western Sydney University. The study included all ICU hospitalizations, excluding cases with significant missing data or non-surviving patients. Disease classification followed the ICD-10 system, and 475 features were extracted from the hospital's medical records. Two experimental settings were used: one with all 1,045 patients and another dividing patients into three subsets. The inclusion criteria were developed collaboratively by medical and computer science experts.

TABLE 1. Hyperparameters of the predictive models.

Parameters	Description	Experiment setup All - G+C+L+M	G	C	L	M
	Logistic Regression (LR)					
C = 1	To control penalty strength (Inverse of regularization strength), and it must be a positive value.	1000	C=1	C=0.001	C=0.01	C=1
Solver = [liblinear, newton-cg]	for regularization (penalty) and optimization problem.	N/A	liblinear	newton-cg	liblinear	liblinear
	Multi-layer Perceptron (MLP)					
hidden_layer_sizes	Describes the ith element represents the number of neurons in the ith hidden layer.	10	50	50	N/A	10
activation	Refer to activation function for the hidden layer.	logistic	N/A	logistic	logistic	tanh
learning_rate	Learning rate schedule for weight updates.	0.01	0.01	0.01	0.01	0.01
	Random Forest (RF)					
n_estimators	Describes the number of trees in the forest.	50	250	5	250	50
max_depth	Describes the maximum depth of the tree.	None	8	4	8	8
max_features	Describes the number of features to consider when looking for the best split.	None	sqrt	log2	log2	sqrt
	Gradient Boosting (GB)					
n_estimators	Describes the number of boosting stages to perform.	500	50	5	50	500
max_depth	Refers to the maximum depth limits the number of nodes in the tree.	1	9	1	5	N/A
learning_rate	Learning rate shrinks the contribution of each tree	0.01	0.01	0.01	0.01	0.01
	eXtreme Gradient Boosting (XGBoost)					
n_estimators	Describes the number of gradients boosted trees (equivalent to the number of boosting rounds)	100	5	5	5	250
max_depth	Describes the maximum tree depth for base learners	None	3	1	5	3
learning_rate	Describes the Boosting learning rate	None	1	0.01	0.1	C=1

3. Models Selection And Performance Evaluation

This section examines the machine learning models employed to evaluate the predictive LOS framework for ICU hospitalizations based on real hospital datasets. The process involved model implementation, optimization, and performance assessment, utilizing Python along with the Sklearn library.

4. Model Training And Evaluation

- **Algorithms Used:** XGBoost, Random Forest (RF), Gradient Boosting Machines (GBM), Logistic Regression (LR), and Multi-Layer Perceptron (MLP).
- **Hyperparameter Tuning:** GridSearch with 5-fold cross-validation for optimization.
- **Dataset:** Electronic medical records from **Al-Ain Hospital**.
- **Evaluation Metrics:** Accuracy, Precision, Sensitivity, Specificity, F1-Score, AUC, PR-AUC.
- **Cross-Validation:** Ensured model robustness and generalization.
- **Confidence Intervals:** Used for performance validation.
- **Feature Selection:** Dataset subsets (All features, G, C, L, and M) tested for impact on predictions.

5. Ethical Consideration

The study ensures ethical compliance through approvals, patient data anonymization, and bias mitigation. It emphasizes transparency, responsible AI use, and human oversight in medical decision-making.

IV. RESULTS AND DISCUSSIONS

The study evaluated predictive models for ICU length of stay (LOS) using real hospital data. XGBoost demonstrated the highest predictive accuracy, outperforming other models like Random Forest, Gradient Boosting, MLP, and Logistic Regression. Cross-validation reduced bias and variance, ensuring robust model performance. The use of explainable AI (XAI) techniques, such as SHAP values, helped interpret predictions, making them transparent for healthcare professionals. The findings support AI-driven decision support systems for improving hospital resource management and patient care.

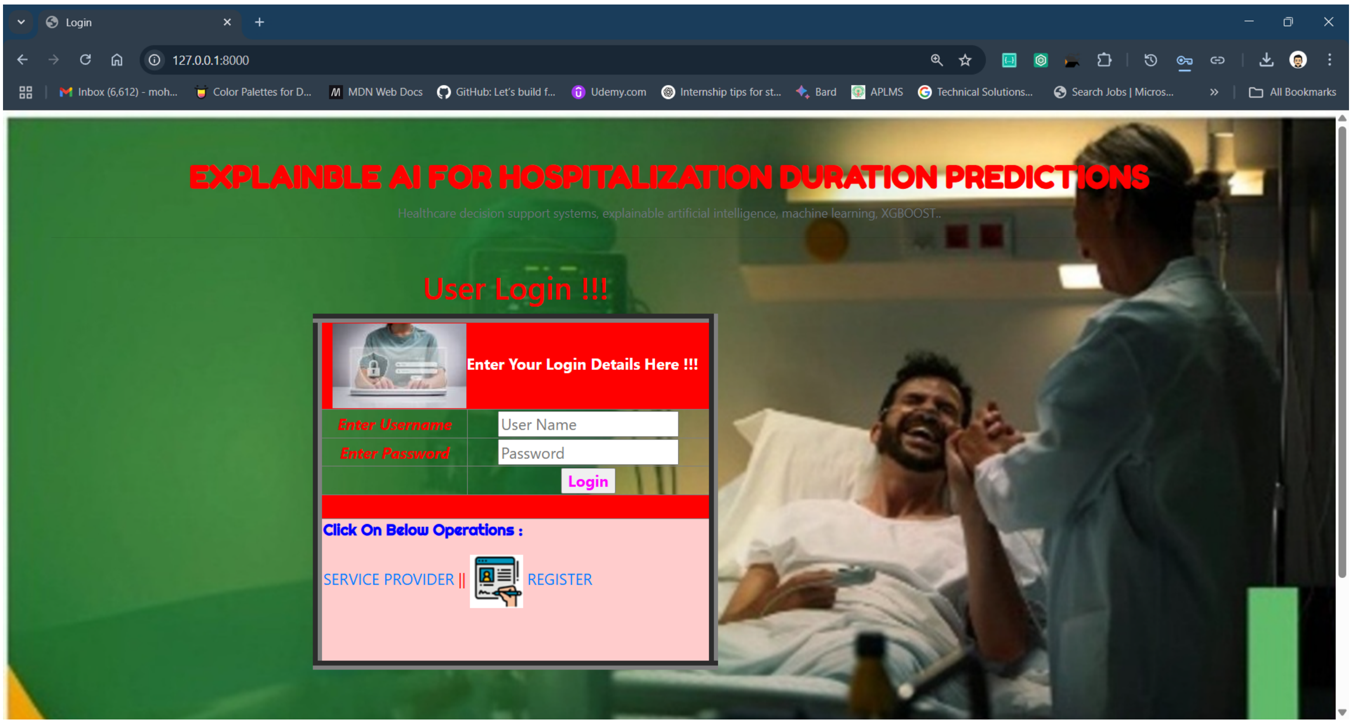

Fig 1: Home page

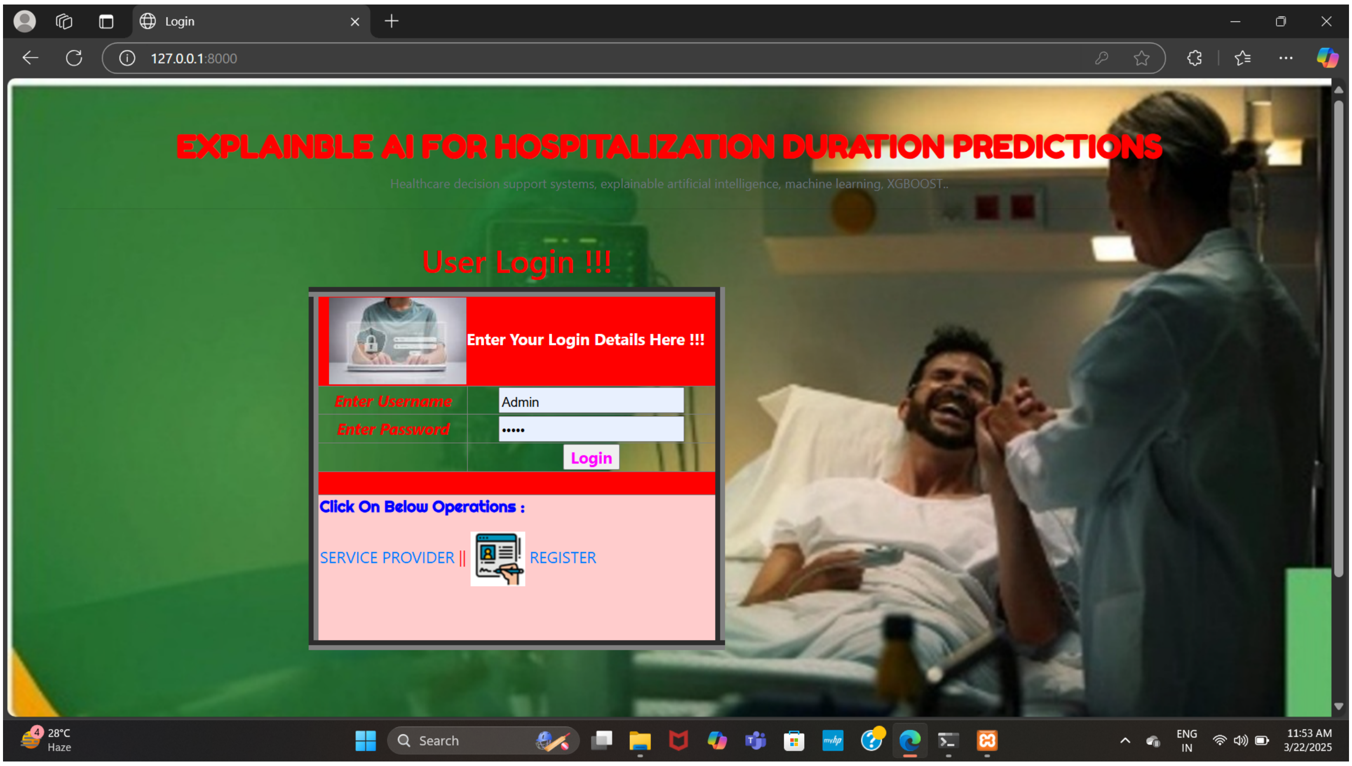

Fig 2: Register

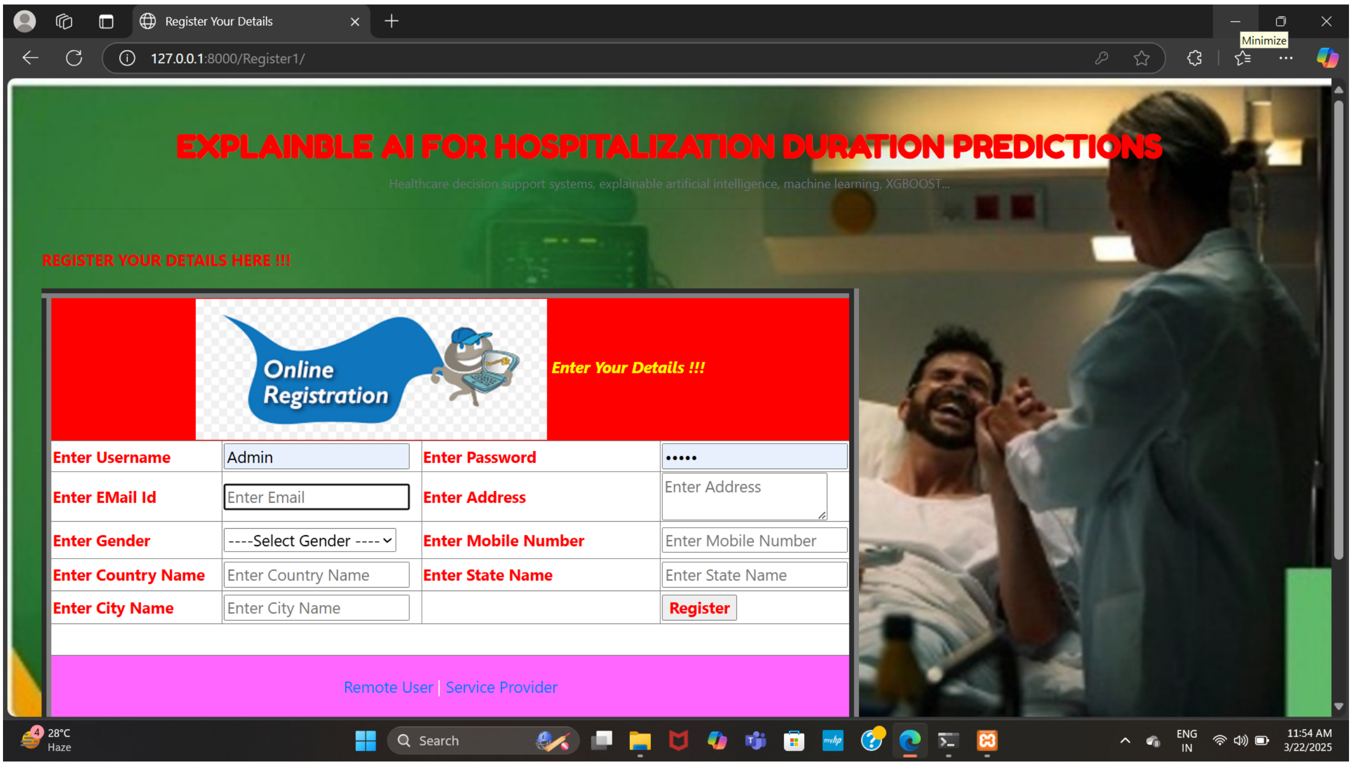

Fig 3:Registration details Here

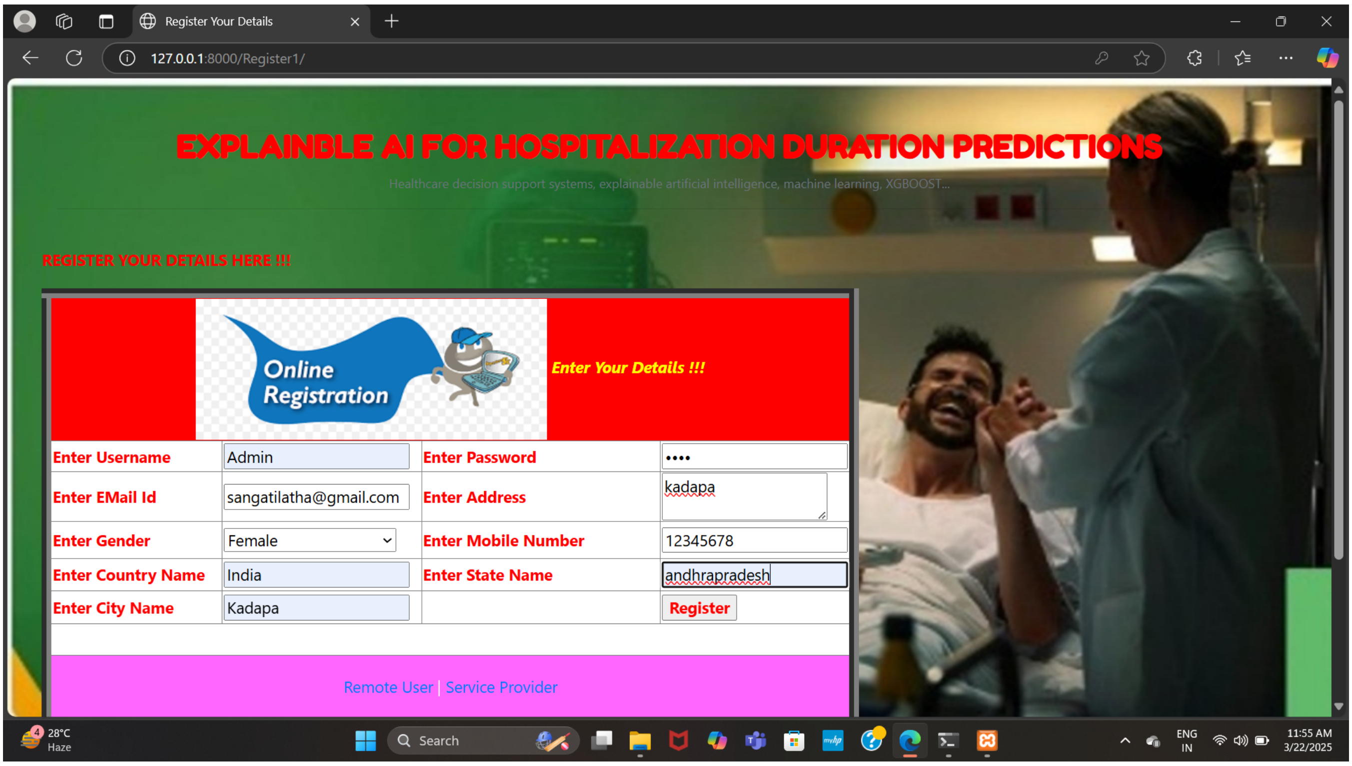

Fig 4: Registration details

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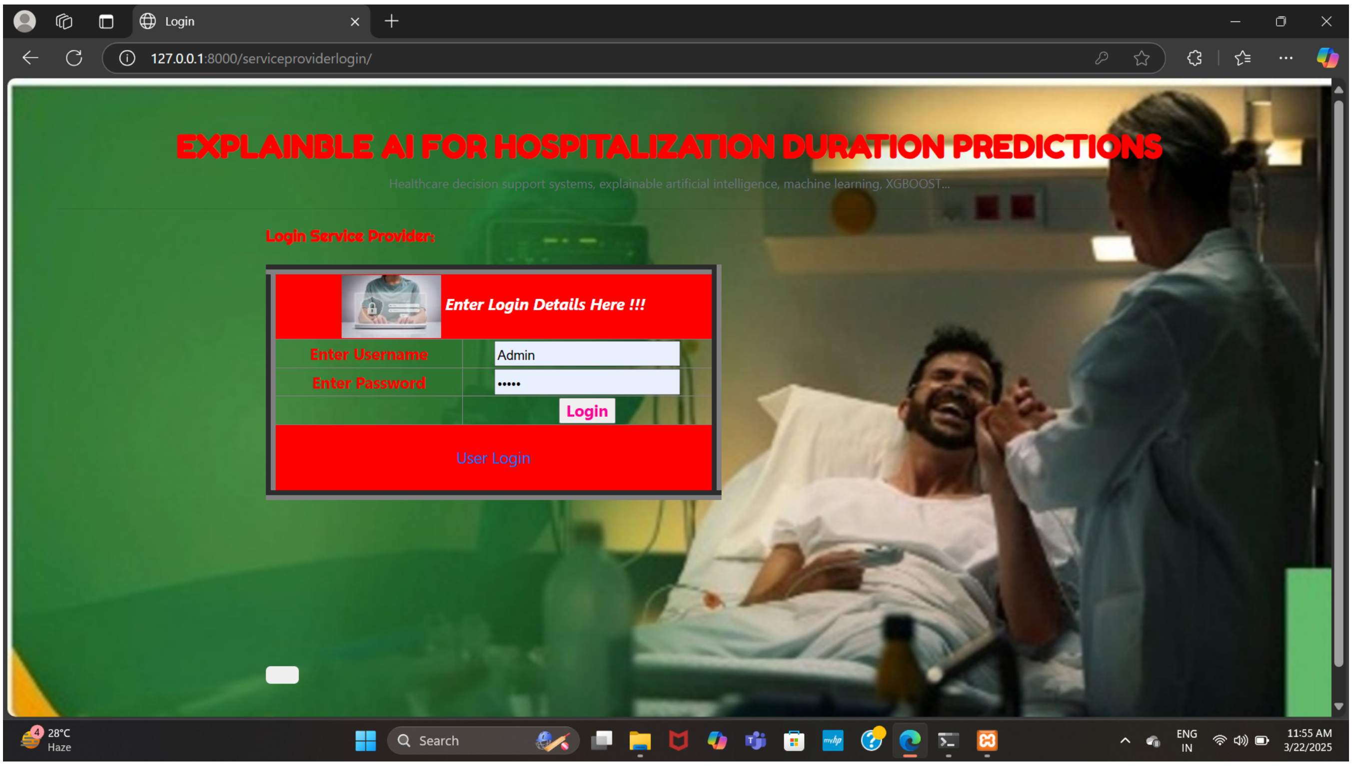


Fig 5: Login page

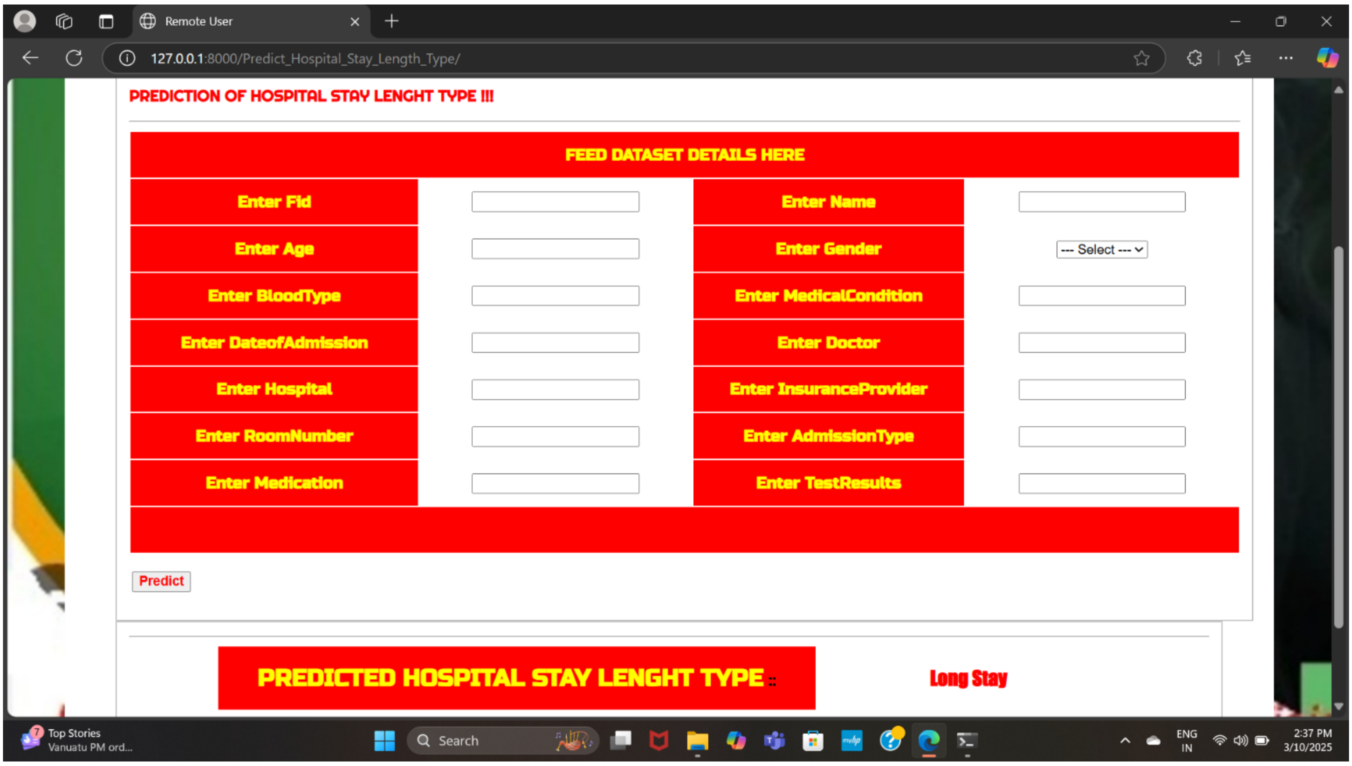


Fig 6:Prediction of hospital stay length type

Fig 6:Prediction of hospital stay length type dataset details here

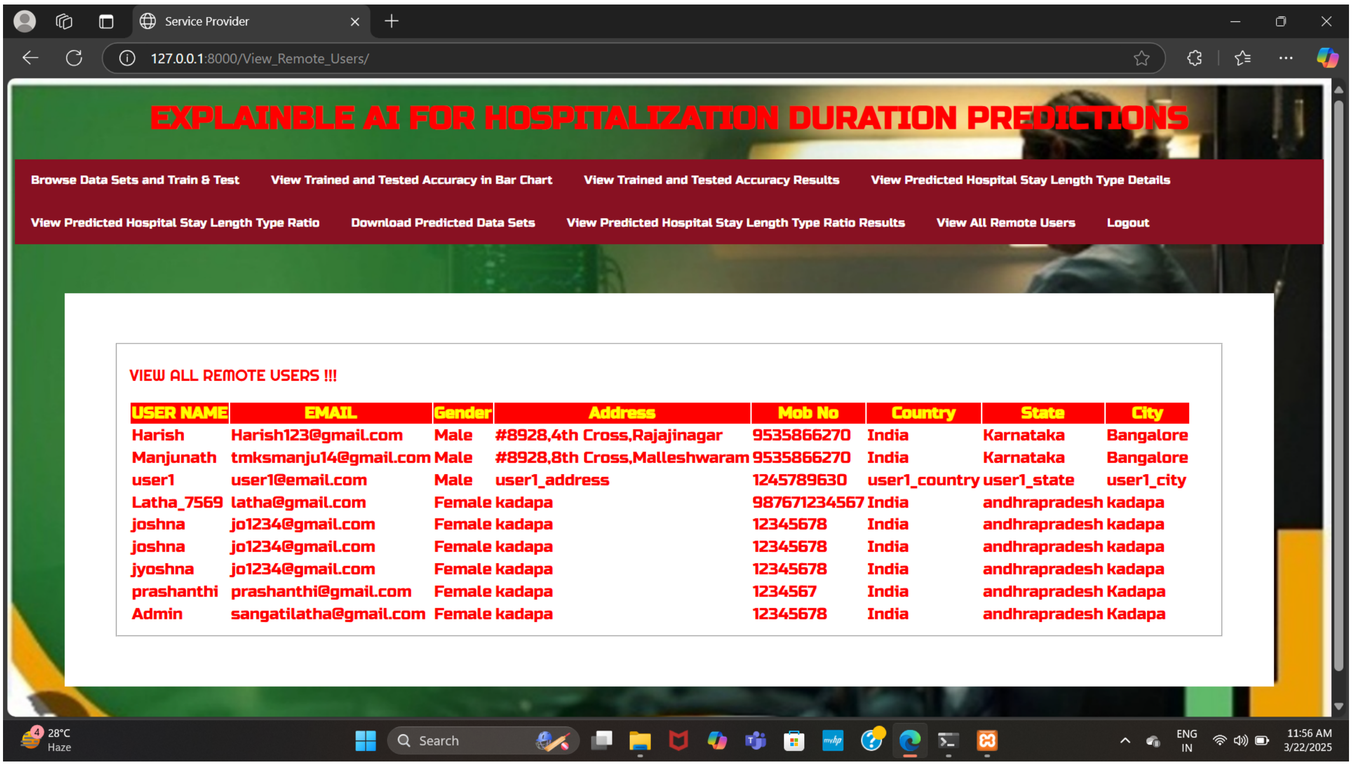
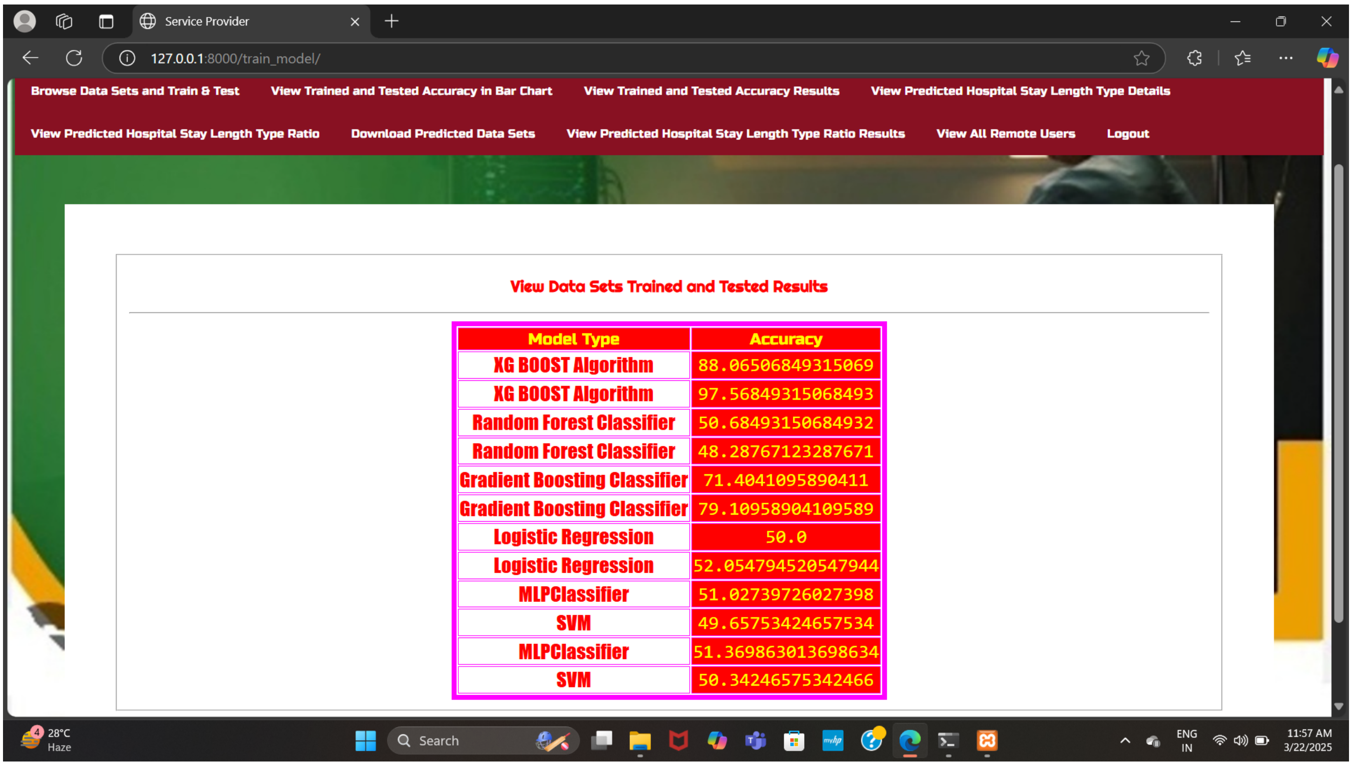


Fig 6: User login details



Model Type	Accuracy
XG BOOST Algorithm	88.06506849315069
XG BOOST Algorithm	97.56849315068493
Random Forest Classifier	50.68493150684932
Random Forest Classifier	48.28767123287671
Gradient Boosting Classifier	71.4041095890411
Gradient Boosting Classifier	79.10958904109589
Logistic Regression	50.0
Logistic Regression	52.054794520547944
MLPClassifier	51.02739726027398
SVM	49.65753424657534
MLPClassifier	51.369863013698634
SVM	50.3424657534246

Fig 7: Trained and Test results

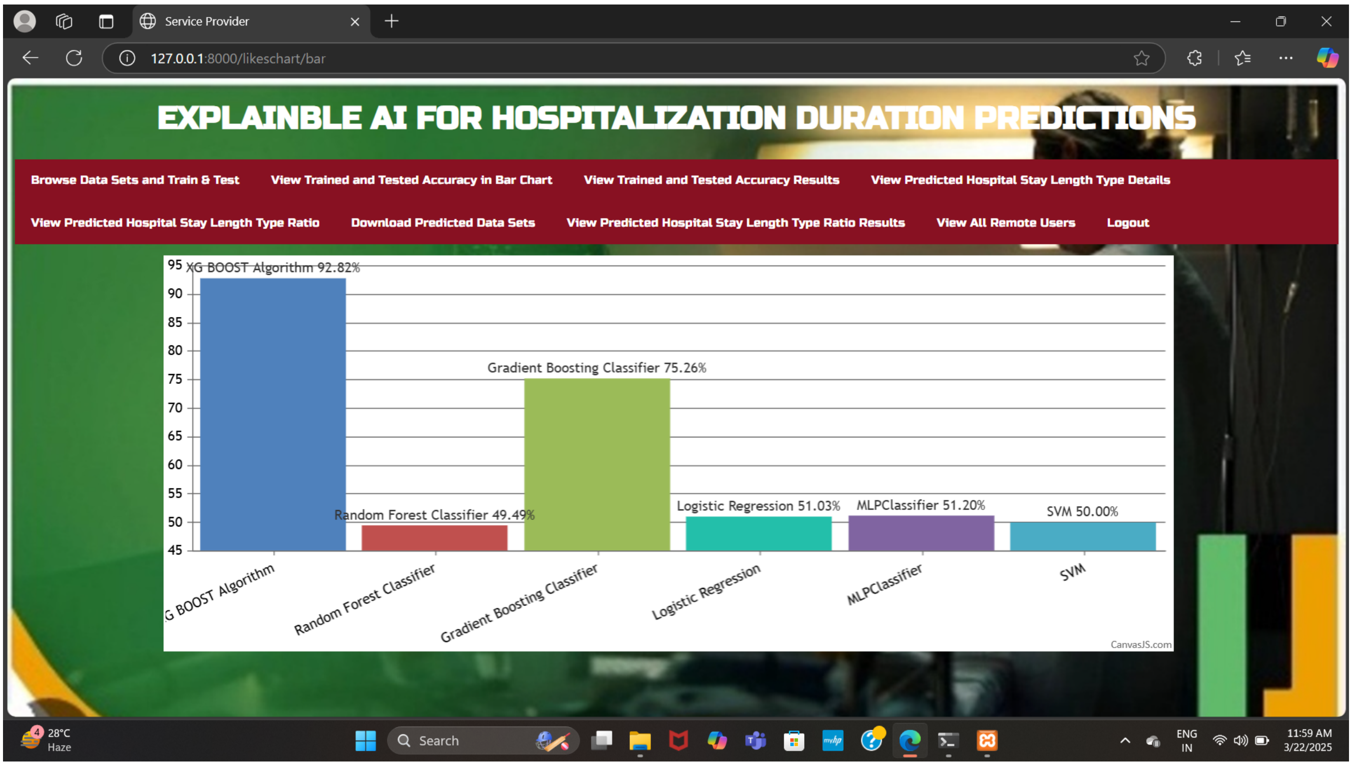


Fig 8: Trained and Test Results in bar chart

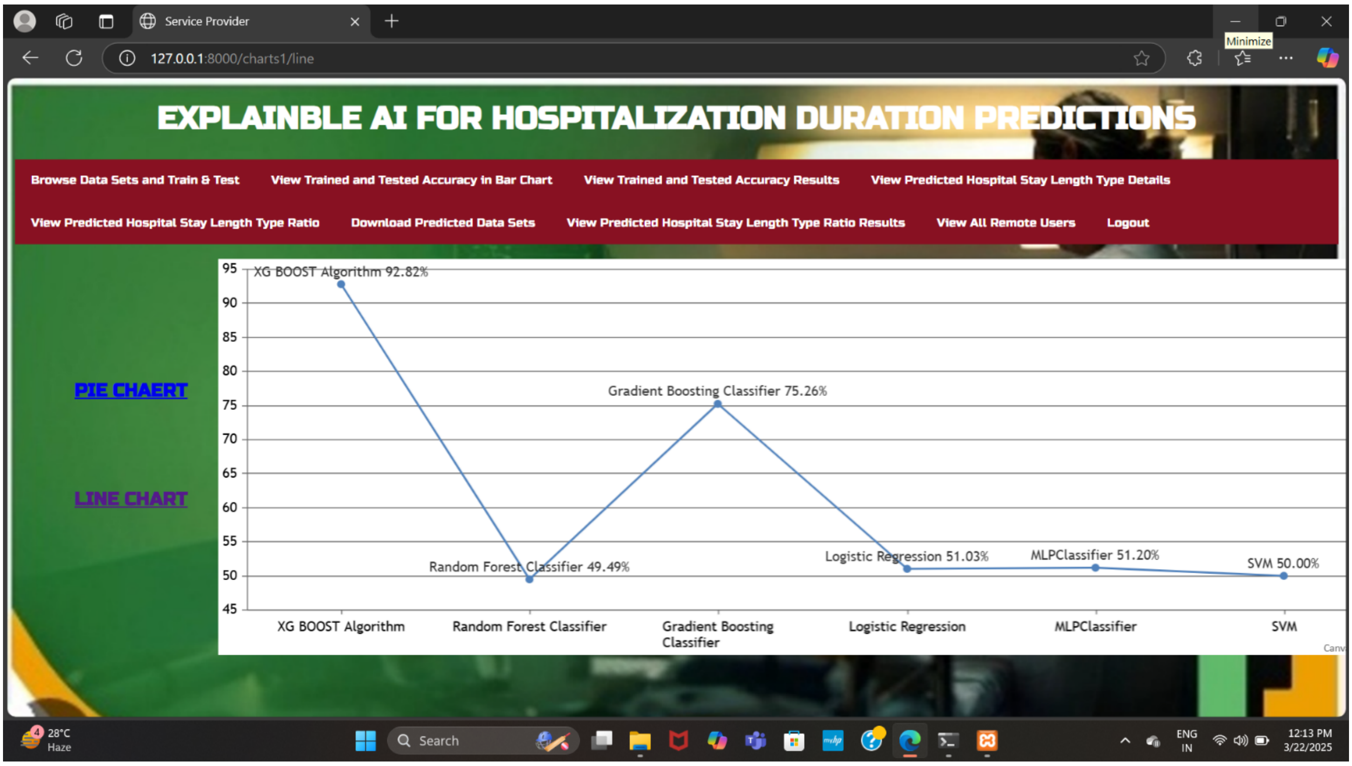


Fig 9: Trained and Test Results in Accuracy Results

Fig 10:Predicted Hospital Stay length Type details

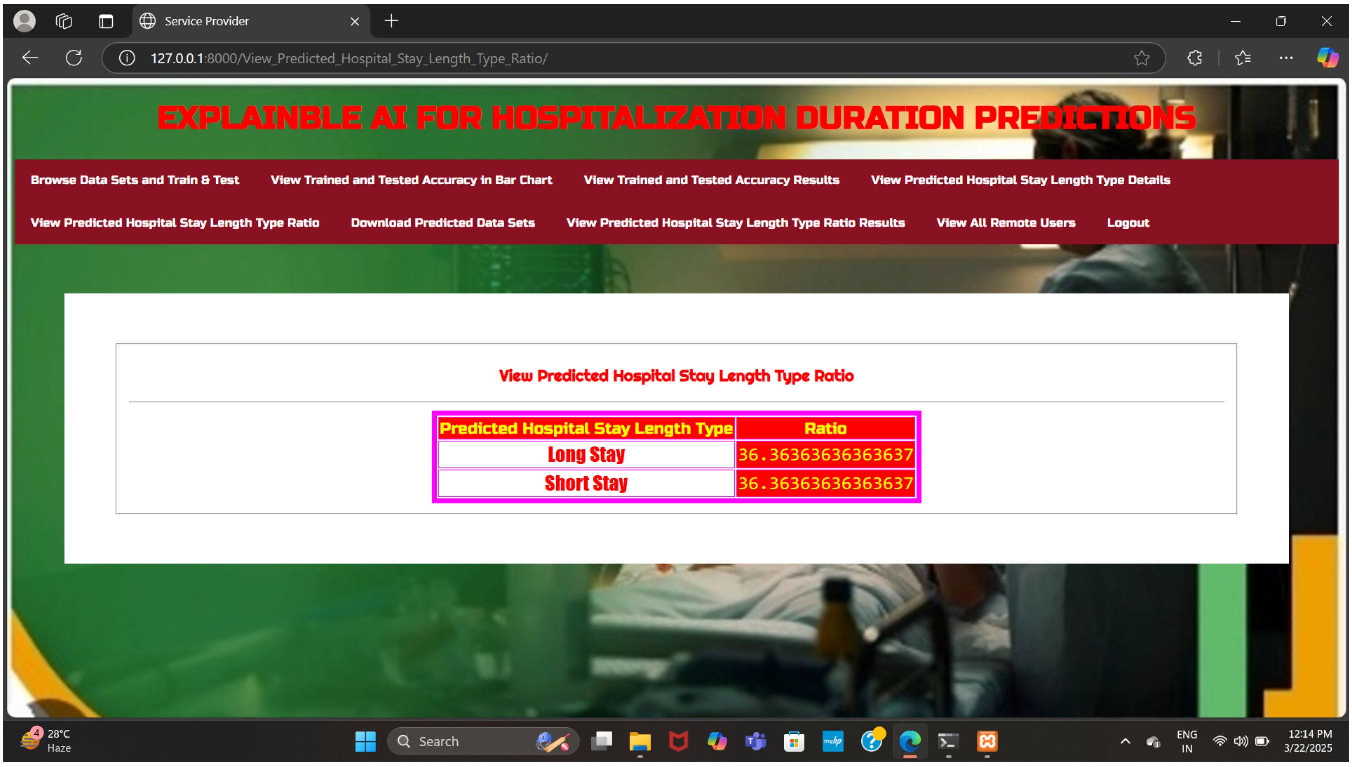


Fig 11: Predicted Hospital Stay Length Type ratio

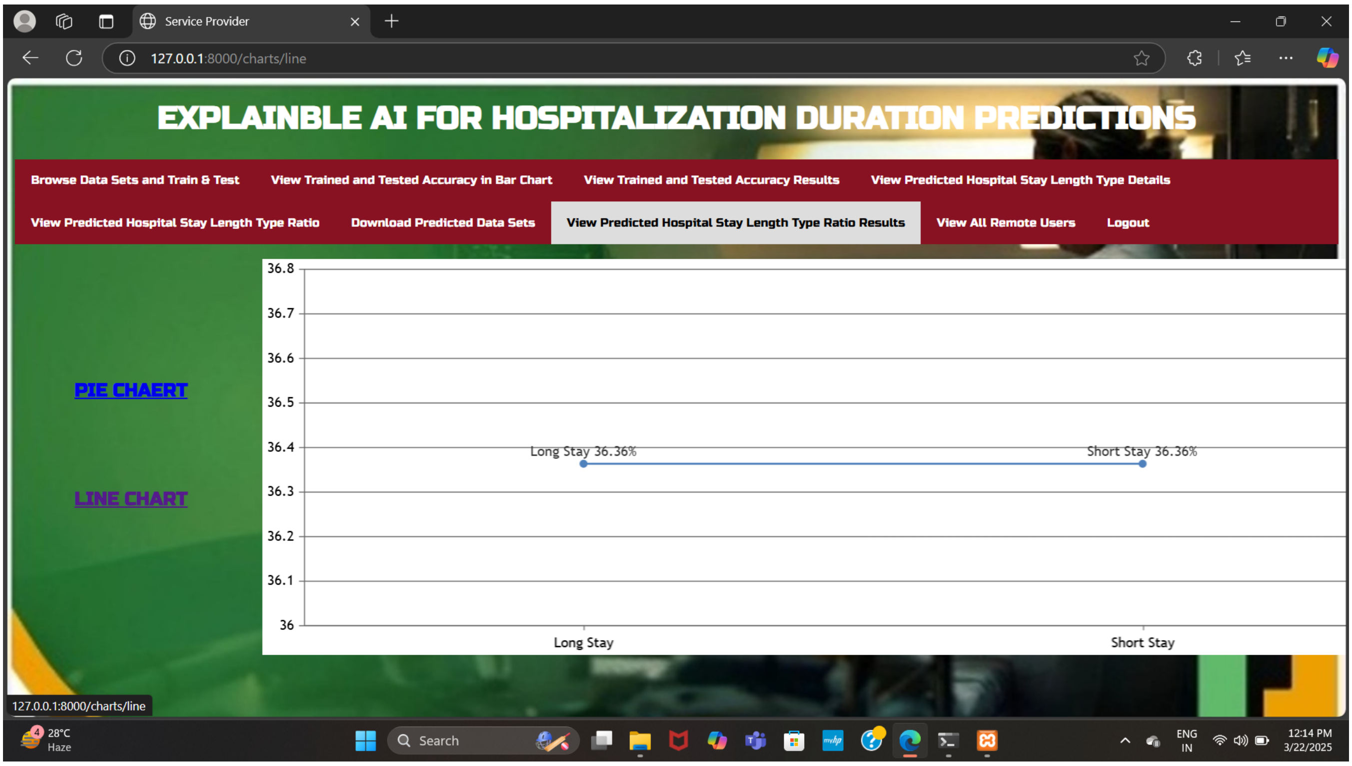


Fig 12: Predicted Hospital Stay Length type ratio results

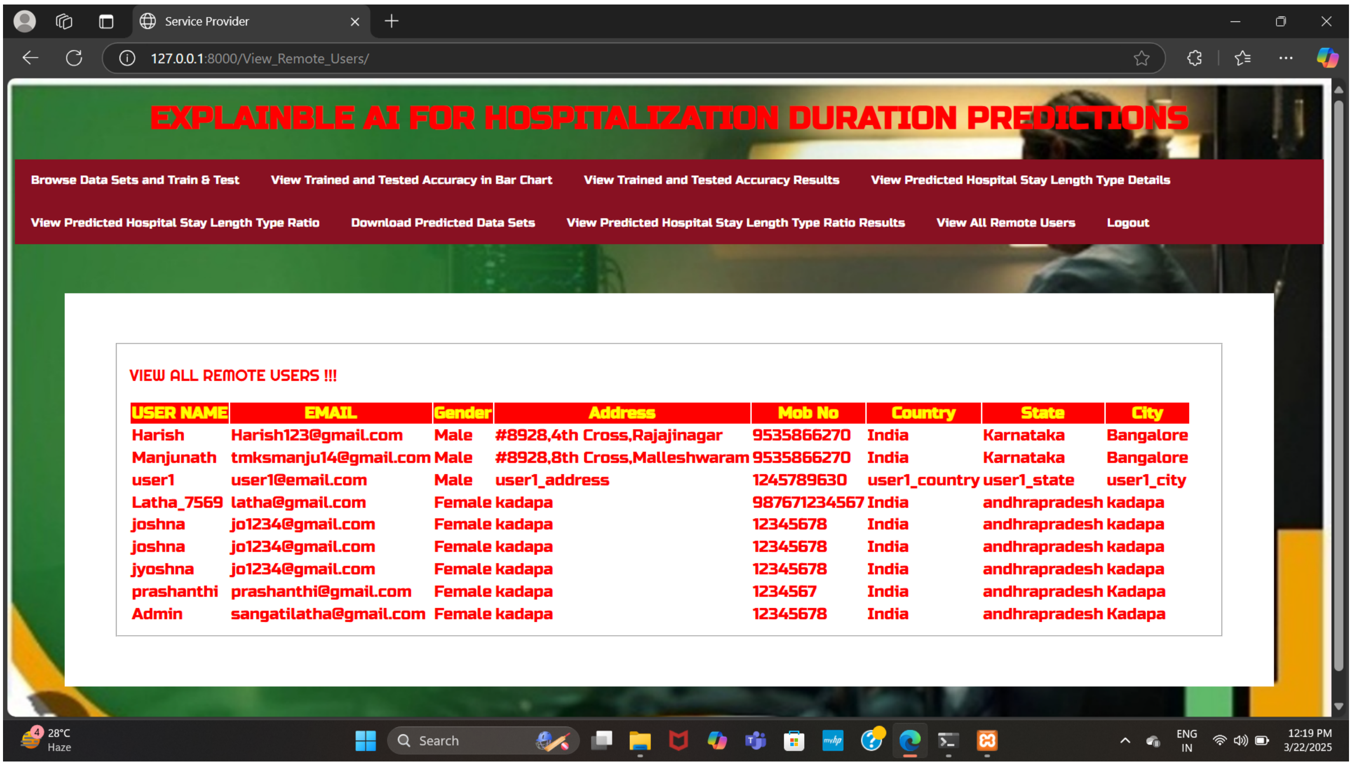


Fig 13: View all remote users

V. CONCLUSION AND FUTURE WORK

This study introduced a predictive ICU framework utilizing real hospital data to estimate patients' length of stay at ICU admission. This practical model carries significant implications for ICU bed management and resource optimization, delivering the expected predictive outcomes through its structured three-stage LOS prediction process. Among the different models evaluated, XGBoost demonstrated the highest performance due to its capacity to generate explainable results, making it accessible to non-AI experts. Importantly, this study is the first to propose an AI-driven explainable framework for forecasting ICU patients' length of stay using a data-driven methodology. The proposed framework is adaptable, applicable to various diseases and medical conditions, enhancing its value for clinical research and electronic health record applications. Additionally, it has the potential to advance predictive tasks such as identifying high-risk patients for mortality. Future research will prioritize incorporating user-centered clinical predictive systems into routine hospital operations while conducting an in-depth analysis of explainable AI applications in hospital, emergency department, and ICU environments. This effort will support the practical implementation of ML-xAI models and contribute to standardizing their integration into electronic health records and broader healthcare systems.

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