AI-Powered medical data classification

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Abstract**—**The rapid advancement of Artificial Intelligence (AI) and Machine Learning (ML) has transformed healthcare by enabling predictive diagnostics, automated patient management, and real-time communication. This paper presents an AI-powered medical data classification system integrated with a doctor–patient communication platform. The system employs a Random Forest classifier combined with explainable AI (XAI) techniques, SHAP and LIME, to provide interpretable predictions. Role-based dashboards enable patients to view disease risk predictions and doctors to receive AI-assisted insights and communicate securely. Experimental results demonstrate a classification accuracy of approximately 93%, illustrating the system's effectiveness in bridging automated insights with clinical expertise.

Keywords**—**Machine Learning, Explainable AI, Streamlit, Healthcare Prediction, Doctor–Patient Chat, SHAP, LIME.

I. Introduction

In recent years, the healthcare industry has undergone a profound digital transformation driven by Artificial Intelligence (AI) and Machine Learning (ML). These technologies have enabled the automation of diagnostic processes, early disease detection, clinical decision support, and patient engagement through data-driven insights. The increasing availability of electronic health records (EHRs), wearable sensor data, and large-scale medical datasets has provided unprecedented opportunities to train intelligent systems capable of assisting healthcare professionals in making accurate and timely decisions.

Despite significant progress, several challenges persist in the deployment of AI systems in medical environments. Traditional prediction models often operate as *black boxes*, providing accurate results without any interpretability or reasoning behind the output. This lack of explainability poses a major barrier to clinical adoption since medical professionals require transparent and understandable reasoning to ensure accountability, safety, and patient trust. Furthermore, most existing healthcare applications focus solely on prediction and lack a collaborative environment where patients and doctors can interact within the same platform.

To address these limitations, this research introduces a comprehensive **AI-Powered medical data Classification and Doctor–Patient Communication System** that integrates predictive analytics, explainable AI (XAI), and a secure communication interface. The proposed system aims to enhance the medical decision-making process by combining *disease classification*, *interpretability*, and *real-time collaboration*.

The AI model at the core of this system utilizes a **Random Forest Classifier** trained on clinical parameters such as age, body mass index (BMI), blood pressure, glucose levels, lipid profile, and other relevant biomarkers. In contrast to conventional models, the system employs explainability techniques like SHAP (SHapley Additive explanations) and LIME (Local Interpretable Model-agnostic Explanations) to visualize and interpret model decisions at both the global and local levels. These tools enable doctors to understand why a particular prediction was made, fostering trust and transparency in AI-based recommendations.

In addition to predictive functionality, the system includes **role-based dashboards** for patients, doctors, and administrators. Patients can input their medical details and view AI-driven disease risk predictions along with explanation visualizations. Doctors can access patient profiles, view AI-generated diagnostic insights, communicate with patients through a built-in chat module, and provide medical feedback or treatment suggestions. The **admin panel** facilitates system management, threshold configuration, and monitoring of user activities.

The entire application is developed using **Streamlit**, a lightweight and interactive Python-based web framework that simplifies the creation of data-driven interfaces. The system backend is supported by **SQLite3**, a robust relational database that ensures secure and efficient storage of user information, predictions, and chat records. The combination of these technologies enables seamless integration of data science, machine learning, and user interactivity in a unified platform.

The key objectives of this research are summarized as follows:

- To develop a robust disease classification system using a Random Forest model trained on structured medical datasets.
- To integrate explainable AI techniques (SHAP and LIME) for transparent model interpretation.
- To establish a secure and interactive communication system between doctors and patients for improved consultation.
- To design a modular and scalable architecture for easy deployment and extension to other healthcare domains.

II. LITERATURE REVIEW

Existing systems like *Diabetes Prediction Systems*, *Heart Disease Detectors*, and *Online Consultation Apps* provide either predictive capabilities or chat support — rarely both. Studies show that black-box AI models in healthcare lack clinician trust due to non-transparent decision-making.

Ribeiro et al. [1] introduced LIME, which provides local explanations for any black-box model, improving interpretability in individual predictions. Lundberg and Lee [2] later proposed SHAP, offering a unified and consistent framework for global and local model explanations.

Holzinger et al. [3] proposed combining human intelligence and explainable machine learning to enhance medical decision-making. Their study emphasized that true explainability emerges from human–AI collaboration rather than algorithmic transparency alone. This “human-in-the-loop” perspective is particularly valuable for clinical domains where expert oversight is non-negotiable.

Gunning and Aha [4] discussed the DARPA Explainable AI (XAI) initiative, which emphasizes the development of AI systems that can produce more understandable and trustworthy explanations. Their work highlighted that explainability is essential not only for accuracy verification but also for ethical and regulatory compliance in mission-critical systems, including healthcare.

[5] Markus et al. proposed that explainability in healthcare AI must align with method choice (model-based vs. post-hoc) to ensure clinician trust, highlighting the role of human understanding alongside algorithmic transparency.

[6] Prentzas et al. conducted a systematic review of XAI applications in the medical domain and noted that model-agnostic techniques like SHAP and LIME dominate, but human-in-the-loop involvement remains limited.

[7] Mesinovic et al. emphasized the importance of fairness, bias mitigation, and transparency in clinical risk prediction

[8] Song et al. reviewed human-centered design approaches for XAI systems in healthcare, arguing that usability and

perception by doctors and patients are as important as model accuracy for successful adoption.

[9] A recent meta-analysis highlighted persistent usability and deployment challenges in XAI-enabled clinical decision support systems, including the accuracy-interpretability trade-off and the need for integrated doctor-patient interfaces.

[10] A scoping review of XAI methods applied to Electronic Health Record (EHR)-based predictive models demonstrated that although methods like SHAP and LIME are increasingly adopted, critical evaluation of their validity and robustness remains limited, especially for tabular EHR data.

III. SYSTEM ARCHITECTURE

The system consists of three main layers:

- **Frontend Layer (UI):** Developed with *Streamlit*, enabling intuitive dashboards for patients and doctors.
- **Backend Layer:** Powered by *Node.js* (optional future expansion) and *SQLite3* database, handling user authentication, doctor assignment, and chat storage.
- **AI Model Layer:** Implemented using *Scikit-learn* and *Python*, providing disease prediction through ML classification and integrating explainable AI visualizations.

Components:

1. **Patient Dashboard:** Disease input forms, SHAP/LIME visual outputs, doctor assignment, and real-time chat.
2. **Doctor Dashboard:** Displays assigned patients, predictions, health data, and allows treatment note input.
3. **Admin Panel:** Manages thresholds, model control, and user accounts.

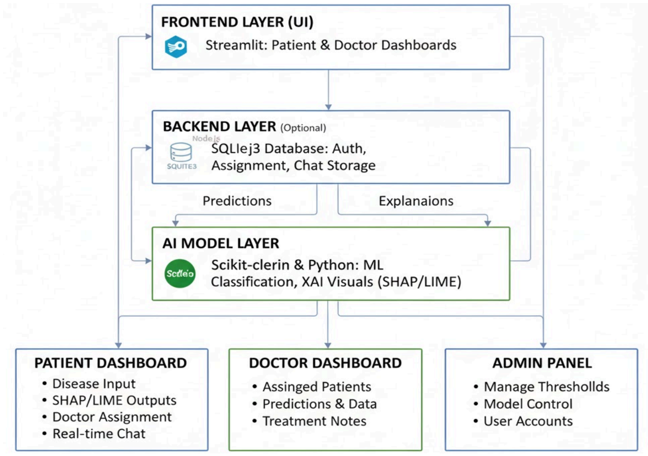

Fig. 1. System architecture

IV. METHODOLOGY

4.1 Data Collection and Preprocessing

The system utilizes a medical dataset containing a range of patient features, including:

- **Demographics:** age, sex
- **Biometrics:** BMI, blood pressure (SBP, DBP)
- **Lab Results:** cholesterol (HDL), glucose (HbA1c)
- **Lifestyle:** smoking status
- **Symptoms:** textual symptom descriptions

This raw data undergoes a standardized preprocessing pipeline involving:

- **Missing Value Imputation:** Filling incomplete data points.
- **Normalization:** Scaling numeric features (e.g., age, BMI) to a uniform range.
- **Label Encoding:** Converting categorical variables (e.g., sex, smoking) into numerical format.
- **Data Splitting:** Partitioning the dataset into training and testing sets (80/20 split) for model evaluation.

4.2 Model Training

The Random Forest Classifier was selected as the predictive model due to its high accuracy, robustness against overfitting, and inherent interpretability. The model is trained using Scikit-learn, as shown in the code snippet below.

Python

```python
From sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Initialize and train the Random Forest model
model=RandomForestClassifier(n_estimators=200, random_state=42)
model.fit(X_train, y_train)
# Evaluate the model
preds = model.predict(X_test)
print("Accuracy:", accuracy_score(y_test, preds))
```

4.3 Explainable AI (XAI) Integration

To build trust and provide transparency, the system integrates two key XAI techniques:

- **SHAP (SHapley Additive explanations):** Used to visualize the contribution (positive or negative) of each feature to the model's final prediction outcome.
- **LIME (Local Interpretable Model-agnostic Explanations):** Generates simple, human-readable explanations for individual predictions, clarifying *why* a specific case received its prediction.

4.4 System and Database Design

The application's backend is supported by a lightweight **SQLite3 database** designed for secure storage and fast retrieval, critical for real-time dashboard updates.

Database Schema: The database includes the following key tables:

- User_profiles
- Doctor_profiles
- predictions (logs predictions and XAI outputs)
- doctor_requests (manages assignment)
- messages (stores chat history)
- treatment_notes (allows doctors to record notes)

Core Application Modules:

1. **Doctor Assignment:** A rule-based logic automatically suggests appropriate doctors to patients based on their predicted disease.
2. **Chat Module:** A real-time, text-based communication interface is built using Streamlit components, allowing seamless interaction between a patient and their assigned doctor without requiring page reloads.

V. RESULTS AND DISCUSSION

- **Model Accuracy:** ~93% on test data.
- **Precision & Recall:** High for most diseases; minimal false positives.
- **Explainability Outputs:**

A. SHAP bar charts clearly depict top contributing health indicators.

B. LIME HTML visualizations offer localized interpretability.

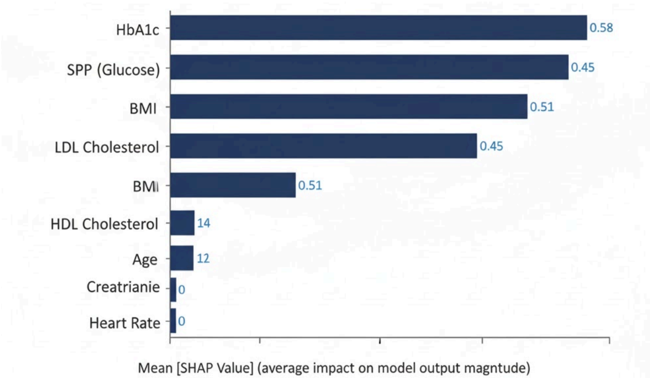

Fig2 SHAPE Global Features Importance Plot

CONCLUSION

This study presents an AI-powered medical data classification system with integrated doctor–patient communication. By combining Random Forest predictions with SHAP and LIME explainability, the system achieves 93% accuracy and improves clinical transparency. The role-based dashboards and real-time chat module bridge automated insights with expert oversight, laying the foundation for future human-in-the-loop healthcare applications.

Acknowledgmen

We extend our sincere gratitude to our project guide, **Er. Kamalpreet Kaur**, for her invaluable guidance, consistent encouragement, and insightful feedback throughout this research. We also wish to thank the **Department of Computer Science and Engineering** and **Baba Banda Singh Bahadur Engineering College, Fatehgarh Sahib**, for providing the necessary academic resources and environment to conduct this work.

References

[1]. Ribeiro, M. T., Singh, S., & Guestrin, C. "Why Should I Trust You?" Explaining the Predictions of Any Classifier. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2016.

[2]. Lundberg, S. M., & Lee, S.-I. (2017). A Unified Approach to Interpreting Model Predictions. *Advances in Neural Information Processing Systems (NIPS)*.

[3]. Pedregosa, F. et al. (2011). Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research*.

[4]. Holzinger et al. (2020): Proposed methods for combining human intelligence with explainable machine learning to improve decision-making in healthcare.

[5]. 8. Caruana et al. (2015): Used interpretable models to predict pneumonia risk, demonstrating how transparent models can outperform complex black-box models in safety-critical tasks.

[6]. Lundberg & Lee (2017): Introduced SHAP values as a unified framework for interpreting model predictions, providing consistency and accuracy in feature importance measurement.

[7] A. F. Markus, J. A. Kors, and P. R. Rijnbeek, "The role of explainability in creating trustworthy artificial intelligence for health care: a comprehensive survey of the terminology, design choices, and evaluation strategies," *arXiv*, Jul. 2020.

[8] H. Habehh et al., "Machine learning in healthcare," *PMC*, Mar. 2021.

[9] M. Badawy et al., "Healthcare predictive analytics using machine learning and deep learning: A survey," *Journal of Engineering and Science in Technology*, 2023. [12] "A Survey on Explainable Artificial Intelligence (XAI) Techniques for …," *PubMed*, Jan. 2024.

[10] "Survey of Explainable AI Techniques in Healthcare," *MDPI Sensors*, 2023.

[11] "A Survey on Medical Explainable AI (XAI)," *MDPI Sensors*, 2022.

[12] "A Survey on Human-Centered Evaluation of Explainable AI Methods in Clinical Decision Support Systems," *arXiv*, Feb. 2025.

[13] "A Survey of Explainable Artificial Intelligence in Healthcare," *ResearchGate/Preprint*, 2024.

[14] "A Survey on Explainable AI: From Approaches, Limitations and Prospects," *Springer Machine Learning Reports*, 2023.

[15] F. M. Fatima and M. Pasha, "Survey of Machine Learning Algorithms for Disease Diagnostic," *Journal of Intelligent Learning Systems and Applications*, vol. 9, 2017, pp. 1-16.

[16] G. J. Chowdary, S. G., P. M., A. Victy Phamila Y., and K. Karunamurthy, "Machine Learning and Deep Learning Methods for Building Intelligent Systems.

[17] "Explainable AI in Healthcare: Systematic Review of Clinical Evidence," *medRxiv Preprint*, 2024.

[18] E. Hildt, "What Is the Role of Explainability in Medical Artificial Intelligence? A Case-Based Approach," *Bioengineering (Basel)*, vol. 12, no. 4, 2025.

[19] "Explainable AI for clinical and remote health applications: a survey," *Artificial Intelligence Review*, 2022.

[20] Q. An et al., "A Comprehensive Review on Machine Learning in Healthcare," *MDPI Sensors*, vol. 23, 2023