



AI-DRIVEN CLINICAL DECISION SUPPORT SYSTEM FOR INTELLIGENT MEDICAL REPORT ANALYSIS AND DISEASE PREDICTION

Sravanthi Duvvuri¹, Dr. G. Sharmila Sujatha²

Department of Computer Science and Systems Engineering (AI & ML), Andhra University¹

Associate Professor, Dept. of CS&SE, AUCE(A)²

Abstract: The AI-Driven Clinical Decision Support System for Intelligent Medical Report Analysis and Disease Prediction enhances healthcare decision-making by integrating Artificial Intelligence into clinical data processing. The system uses Natural Language Processing (NLP) to extract symptoms from patient complaints, suggests relevant medical tests, and applies machine learning algorithms to analyze laboratory reports and detect abnormal values. It predicts possible heart, liver, and kidney diseases with probability scores, identifies the key factors behind each prediction, and generates structured clinical summaries to assist doctors in faster evaluation. The heart disease module is built on the merged UCI Heart Disease dataset containing 920 records and 14 attributes. The prototype, developed in Python with spaCy, scikit-learn, SQLite, and Streamlit, demonstrates the complete workflow from patient registration to an explained prediction. Designed as a decision-support tool, the system reduces diagnostic workload, improves patient prioritization, and supports timely intervention while ensuring that final medical decisions remain under professional supervision.

Keywords: Clinical decision support system, electronic health records, natural language processing, machine learning, disease prediction, explainable AI, SHAP, clinical summary.

1. INTRODUCTION

The healthcare sector increasingly relies on Electronic Health Records (EHRs) to store patient data, yet most systems function only as digital repositories without analytical intelligence. Doctors must manually interpret patient complaints, laboratory reports, and medical history, which increases workload and consultation time. As patient volumes rise, this manual process can delay the identification of high-risk patients and the start of treatment. This highlights the need for intelligent systems that assist in structured medical data analysis.

This work proposes an AI-Driven Clinical Decision Support System (CDSS) that leverages NLP and machine learning to analyze symptoms, detect abnormal medical parameters, and predict possible illnesses. The system focuses on three major disease groups: heart, liver, and kidney diseases. It also generates structured clinical summaries to support efficient diagnosis, while ensuring that final medical decisions remain under professional medical supervision.

2. PROBLEM STATEMENT

Existing EHR systems store patient information but provide little support for interpreting it. Free-text complaints and structured laboratory values are reviewed separately and manually, rule-based alerts cannot estimate the likelihood of disease, and AI predictions that are offered are often difficult for doctors to verify. Therefore, a system is required that brings symptom analysis, laboratory analysis, and explainable disease prediction together in a single doctor-facing tool.

- Reduce the manual effort required to interpret patient complaints and lab reports.
- Combine symptom text and laboratory data into one clinical view.
- Provide probability-based disease prediction instead of simple rule-based alerts.
- Explain each prediction so that doctors can verify and trust the result.



3. OBJECTIVES

- Develop a patient registration module that generates a unique patient ID and stores records in a database.
- Extract key symptoms from free-text patient complaints using NLP.
- Suggest relevant medical tests based on the extracted symptoms.
- Analyze structured laboratory reports to detect abnormal medical parameters.
- Predict heart, liver, and kidney diseases with probability-based scores using machine learning models.
- Explain predictions using explainable AI (SHAP) and list the key contributing factors.
- Generate automated, structured clinical summary reports for doctors.

4. LITERATURE SURVEY AND TECHNICAL BACKGROUND

Health Level Seven International (HL7) standardizes EHR frameworks for interoperability and structured data exchange, but lacks integrated AI-based predictive analytics and automated summarization. IBM Watson Health provides AI-assisted clinical decision tools; however, these systems are proprietary and not modular for scalable hospital-level integration. The UCI Machine Learning Repository offers datasets for disease prediction research, but studies using it mainly focus on classification accuracy without integrated NLP and laboratory data analysis. The Ministry of Health and Family Welfare, through the National Digital Health Mission (NDHM), promotes healthcare digitization in India, primarily emphasizing record management rather than explainable AI-driven clinical decision support.

On the technical side, transformer-based language models such as BERT have improved the extraction of meaningful information from text, and NLP libraries such as spaCy make text-processing pipelines practical to deploy. SHapley Additive exPlanations (SHAP) provides a unified method to explain the output of a machine learning model by assigning each input feature a contribution to the prediction. Clinical decision support in the era of AI is expected to combine such predictive models with human oversight, which is also emphasized by WHO guidance on the ethics and governance of AI for health. These areas form the technical foundation of the proposed system.

5. EXISTING SYSTEM AND LIMITATIONS

- Primarily focus on structured patient data storage and retrieval, functioning mainly as digital repositories rather than intelligent analytical systems.
- Provide limited AI-based clinical decision support features, increasing doctor workload due to manual interpretation of medical data.
- Rely mainly on traditional rule-based alert mechanisms, lacking advanced predictive analytics for early disease identification.
- Do not integrate symptom text analysis with structured laboratory data evaluation, resulting in fragmented clinical insights.
- Lack automated and structured medical summary generation, delaying efficient patient review.
- Offer minimal disease prediction with probability-based scoring, reducing diagnostic support accuracy.

6. PROPOSED SYSTEM

The proposed system integrates AI-driven clinical decision support within a Smart EHR framework. A patient is registered and enters symptoms in free text; the NLP module extracts the symptoms and suggests tests; the laboratory values are analyzed for abnormalities; a disease-specific model predicts the probability of illness; the explainable AI module identifies the key factors; and a structured clinical summary is presented to the doctor.

- Integrates AI-driven clinical decision support within a Smart EHR framework.
- Uses NLP to extract key symptoms from patient complaints.
- Analyzes structured laboratory reports to detect abnormal medical parameters.
- Predicts possible illnesses with probability-based scoring using machine learning models.
- Generates automated, structured clinical summary reports for doctors.
- Incorporates explainable AI techniques to justify prediction results.
- Supports efficient clinical decision-making while ensuring doctor supervision.
-



7. SYSTEM ARCHITECTURE

The system architecture is organized into three layers. The Input Layer receives data from patients through the Patient Portal (symptom entry) and from the Laboratory System (lab reports). The Processing Layer contains the NLP Module for BERT-based symptom extraction; the Clinical Analysis Engine for symptom analysis, lab report analysis, and the illness prediction model; the Explainable AI Module that uses SHAP for result interpretability; and the Automated Report Generator that produces a structured clinical summary. The Output Layer presents the results to doctors through the Doctor Dashboard (CDSS interface), the Clinical Summary Report, and the Prediction Explainability view.

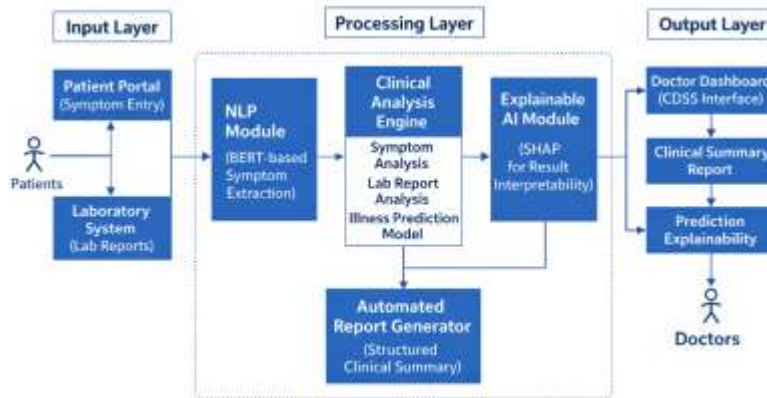


Fig. 1. System architecture of the AI-driven clinical decision support system showing the input, processing, and output layers.

8. DATASETS

The heart disease module uses the Heart Disease dataset from the UCI Machine Learning Repository. Four processed files are used: processed.cleveland.data, processed.hungarian.data, processed.switzerland.data, and processed.va.data. These files are merged into a single file (datasets/heart.csv) containing 920 records and 14 columns. The attributes and the number of missing values in each are listed below.

Attribute	Description	Missing Values
age	Age of the patient in years	0
sex	Sex (1 = male, 0 = female)	0
cp	Chest pain type	0
trestbps	Resting blood pressure (mm Hg)	59
chol	Serum cholesterol (mg/dl)	30
fbs	Fasting blood sugar > 120 mg/dl	90
restecg	Resting electrocardiographic result	2
thalach	Maximum heart rate achieved	55
exang	Exercise-induced angina	55
oldpeak	ST depression induced by exercise	62
slope	Slope of the peak exercise ST segment	309
ca	Number of major vessels colored by fluoroscopy	611
thal	Thallium stress test result	486
target	Presence of heart disease (0 = absent, 1 = present)	0

The attributes ca, thal, and slope have the largest number of missing values because these measurements were not recorded consistently across all four hospital sources. The missing values are therefore handled during preprocessing before the model is trained. Separate trained models are maintained for heart, liver, and kidney disease prediction.



9. SOFTWARE REQUIREMENTS AND TECHNOLOGIES

Component	Technology / Function
Programming Language	Python 3.12; used for data processing, model training, and the application.
ML Libraries	pandas, numpy, and joblib; used for data handling, numerical processing, and saving trained models.
NLP Libraries	spaCy and scikit-learn; used for symptom extraction and text processing.
Explainable AI	SHAP; used to identify the key factors behind each prediction.
Database	SQLite; stores patient details, patient IDs, and saved prediction results.
Frontend	Streamlit; provides the web interface for registration, symptom entry, and prediction.
Backend	Python; connects the interface, database, NLP module, and trained models.
Model Files	heart_model.pkl, liver_model.pkl, and kidney_model.pkl; trained disease prediction models.

10. PROJECT STRUCTURE

The project is organized into separate folders so that each part of the system can be developed, tested, and updated independently.

- datasets/: raw and merged datasets used for training.
- models/: trained disease prediction models.
- database/: SQLite database and database-access code.
- nlp/: symptom extraction and test suggestion logic.
- app/: Streamlit user interface pages.
- training/: scripts for data preparation and model training.
- utils: shared helper functions.
- main.py: entry point of the application.

11. NLP-BASED SYMPTOM ANALYSIS

The user enters the patient complaint in free text, for example "chest pain, shortness of breath, fatigue". The NLP module processes the text, identifies the symptoms it contains, and maps them to the related organ system. Based on the identified symptoms, the system suggests the medical tests needed for further evaluation. For cardiac symptoms, the suggested tests include ECG (electrocardiogram), blood pressure test, cholesterol test, fasting blood sugar, and echocardiogram. The flow is: Patient Complaint → NLP Module → Symptom Extraction → Suggested Medical Tests.

12. LABORATORY REPORT ANALYSIS

Laboratory values are received as structured data. Each parameter is compared with its normal reference range, and values outside the range are flagged as abnormal. The flagged parameters are highlighted in the clinical summary and are passed, together with the patient's demographic and clinical details, to the disease prediction model. This combines the symptom information and the laboratory evidence into one input for prediction.

13. DISEASE PREDICTION MODELS

Separate machine learning models are trained for heart, liver, and kidney diseases using scikit-learn, and the trained models are saved with joblib. When a prediction is requested, the corresponding model is loaded and the patient's data is passed to it. Instead of giving only a yes/no answer, the model returns the probability that the disease is present. This probability score helps the doctor judge the level of risk and prioritize patients who need urgent attention.

14. EXPLAINABLE AI MODULE

The Explainable AI module uses SHAP to explain each prediction. SHAP assigns every input feature a value that shows how much it pushed the prediction towards or away from the disease. The features with the highest positive contribution are shown to the doctor as the key factors. For example, in the demonstrated heart disease prediction, the key factors were a high



cholesterol level, elevated blood pressure, chest pain type (typical angina), and age above 50. This allows the doctor to check whether the prediction is clinically reasonable.

15. AUTOMATED CLINICAL SUMMARY

The Automated Report Generator combines the extracted symptoms, suggested tests, abnormal laboratory parameters, predicted disease, probability score, and key factors into a structured clinical summary. The summary is displayed on the doctor dashboard and can be saved to the patient record. A note on every result reminds the user that it is a predictive result based on the input data and that a medical professional must be consulted for an accurate diagnosis.

16. OVERALL WORKING

The complete workflow is: Patient Registration → Symptom Entry → NLP Symptom Extraction → Suggested Medical Tests → Lab Report Analysis → Disease Prediction → SHAP Explanation → Clinical Summary → Doctor Review. A patient is first registered with name, age, gender, height, and weight, and a unique patient ID is generated and saved in the database. The symptoms are entered and analyzed, the relevant tests are suggested, and the test results are evaluated. The selected disease prediction model then predicts the probability of illness, the key factors are identified, and the result is presented to the doctor, who can save the result or proceed to the next patient.

17. RESULTS AND DEMONSTRATION

The prototype was implemented and tested end to end. The heart datasets were merged successfully into a single file of 920 records and 14 columns. The home screen of the Disease Prediction System provides navigation to New Patient, Search Patient, Predict Disease, and About pages and supports heart, liver, and kidney disease prediction. The registration page generates a unique patient ID and saves it in the database. For the symptoms "chest pain, shortness of breath, fatigue", the system suggested ECG, blood pressure, cholesterol, fasting blood sugar, and echocardiogram tests. The prediction page reported heart disease with a probability of 82.5%, along with the key contributing factors and a note advising consultation with a medical professional.

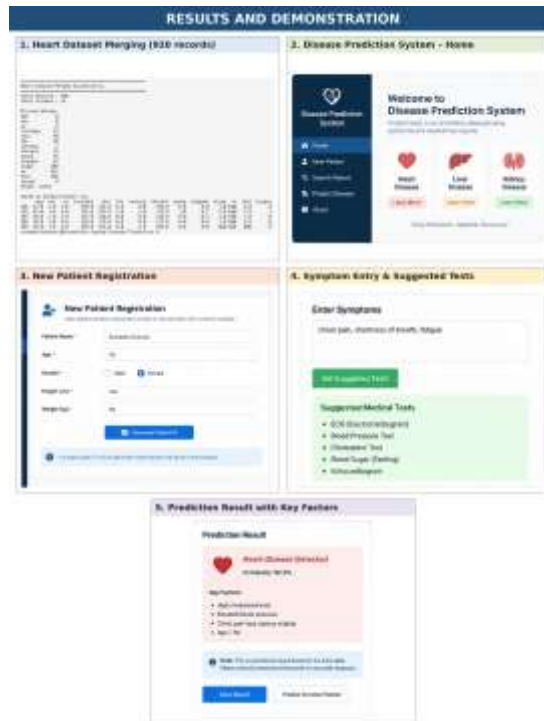


Fig. 2. Results and demonstration of the system: dataset merging, home screen, patient registration, symptom entry with suggested tests, and prediction result with key factors.

**18. FUNCTIONAL TEST RESULTS**

Test Case	Expected Outcome	Observed Result
Dataset merging	Four UCI files merged into one dataset	Success (920 records, 14 columns)
Home screen	Navigation and disease options displayed	Success
Patient registration	Unique patient ID generated and saved	Success
Symptom entry	Free-text symptoms accepted	Success
Test suggestion	Relevant medical tests suggested	Success
Heart disease prediction	Prediction with probability score	Success (82.5%)
Explainability	Key contributing factors displayed	Success
Clinical safety note	Advice to consult a medical professional shown	Success

The functional test table indicates successful completion of the listed test cases in the demonstrated workflow. The prototype therefore achieved the intended registration, symptom analysis, test suggestion, prediction, and explanation functions.

19. SAMPLE PREDICTION DEMONSTRATION

The sample case is performed in four stages: registering a 45-year-old patient, entering the symptoms “chest pain, shortness of breath, fatigue”, reviewing the suggested cardiac tests, and running the heart disease prediction. The system reported “Heart Disease Detected” with a probability of 82.5% and listed high cholesterol, elevated blood pressure, typical angina chest pain, and age as the key factors. The doctor can then save the result or predict for another patient. This sequence demonstrates how symptom analysis, test suggestion, prediction, and explanation work together in one system.

20. APPLICATIONS

- Hospitals and clinics: supporting doctors during outpatient consultation.
- Patient triage: prioritizing high-risk patients for early attention.
- Primary health centers: assisting where specialist doctors are not always available.
- Smart EHR systems: adding analytical intelligence to existing patient records.
- Preventive health check-ups: early screening for heart, liver, and kidney diseases.
- Medical education: demonstrating how symptoms and test results relate to disease risk.

21. ADVANTAGES

- Reduces doctor workload by automating symptom and report analysis.
- Combines symptom text and laboratory data in a single view.
- Provides probability-based risk scores instead of simple alerts.
- Explains every prediction through key contributing factors.
- Generates structured clinical summaries for faster patient review.
- Built with open-source tools, making it low-cost and modular.
- Keeps the doctor in control of the final medical decision.

22. FUTURE SCOPE

- Validation of the models using real hospital data and feedback from doctors.
- Extension of the system to additional diseases.
- Fine-tuned clinical language models for more accurate symptom extraction.
- Direct reading of lab reports from PDF or scanned documents.
- Integration with hospital information systems using HL7/FHIR standards.
- Secure cloud deployment with role-based access and data privacy controls.

These future directions are proposed extensions and are not claimed as implemented features of the present prototype.

**23. CONCLUSION**

The developed AI-Driven Clinical Decision Support System provides an intelligent layer on top of electronic health records for analyzing patient symptoms and medical reports. The system combines NLP-based symptom extraction, medical test suggestion, laboratory report analysis, probability-based prediction of heart, liver, and kidney diseases, SHAP-based explanation, and automated clinical summaries in a single application. The demonstrated results show successful patient registration, symptom analysis, test suggestion, and an explained heart disease prediction. The work demonstrates the practical use of AI to reduce diagnostic workload, improve patient prioritization, and support timely intervention, while ensuring that final medical decisions remain under professional supervision.

REFERENCES

- [1] J. Devlin, M. W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," *Proceedings of NAACL-HLT*, 2019.
- [2] E. H. Shortliffe and M. J. Sepúlveda, "Clinical Decision Support in the Era of Artificial Intelligence," *JAMA*, vol. 320, no. 21, pp. 2199–2200, 2018.
- [3] Health Level Seven International (HL7), "HL7 Standards Documentation for Electronic Health Records," 2023.
- [4] World Health Organization, "Ethics and Governance of Artificial Intelligence for Health," WHO Press, 2021.
- [5] S. M. Lundberg and S. I. Lee, "A Unified Approach to Interpreting Model Predictions," *Advances in Neural Information Processing Systems (NeurIPS)*, 2017.
- [6] A. Janosi, W. Steinbrunn, M. Pfisterer, and R. Detrano, "Heart Disease," *UCI Machine Learning Repository*, 1988.
- [7] Ministry of Health and Family Welfare, Government of India, "National Digital Health Blueprint," 2019.
- [8] F. Pedregosa et al., "Scikit-learn: Machine Learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.
- [9] R. T. Sutton et al., "An overview of clinical decision support systems: benefits, risks, and strategies for success," *npj Digital Medicine*, vol. 3, no. 17, 2020.
- [10] A. Rajkomar, J. Dean, and I. Kohane, "Machine Learning in Medicine," *New England Journal of Medicine*, vol. 380, no. 14, pp. 1347–1358, 2019.