International Journal of Scientific Research and Engineering Development-– Volume 9 Issue 2, Mar-Apr 2026
Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

# Smart Healthcare Decision Making Using Artificial Intelligence

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***Abstract:*** This paper presents a smart healthcare decision-making system using Artificial Intelligence (AI) to analyze patient data—including medical history, laboratory reports, and real-time health parameters—for early-stage disease prediction. Leveraging Long Short-Term Memory (LSTM) for cardiovascular disorder detection and Deep Neural Networks (DNN) for diabetes prediction, the system integrates IoT devices for continuous patient monitoring. The proposed architecture provides real-time alerts, reduces diagnostic errors, and supports clinicians in time-sensitive decision-making. Experimental results demonstrate high prediction accuracy, underscoring the potential of AI-driven tools to improve healthcare efficiency and outcomes.

***Keywords*** — Artificial Intelligence, Machine Learning, LSTM, DNN, IoT, Disease Prediction, Healthcare Decision Support.

## I. INTRODUCTION

Healthcare systems worldwide face persistent challenges including delayed diagnosis, escalating costs, and human errors in clinical decision-making. With the rapid growth of digital health records and sensor-driven data, Artificial Intelligence offers a transformative path to intelligent, data-driven diagnostics.

This paper presents an AI-based smart healthcare system capable of predicting diseases such as cardiovascular disorders and diabetes at early stages, integrating IoT-based real-time monitoring with machine learning and deep learning models. The system aims to reduce physician workload, minimize diagnostic errors, and deliver timely clinical insights.

## II. LITERATURE SURVEY

Significant research has been conducted on AI-based healthcare systems. Support Vector Machines (SVM), Random Forests, and Artificial Neural Networks have been widely applied for disease classification tasks [1]. Deep learning approaches, particularly Recurrent Neural Networks (RNN) and LSTM, have demonstrated superior performance on sequential clinical data such as ECG readings and time-series vitals [2].

IoT-integrated systems have emerged as a leading paradigm for continuous remote patient monitoring, enabling proactive intervention before clinical deterioration occurs [3]. Recent work by Esteva et al. demonstrated that DNN models can match or exceed specialist-level performance in dermatology diagnosis [4]. These advances motivate the hybrid architecture proposed in this work.

## III. SYSTEM IMPLEMENTATION

### *A. Existing System*

Traditional healthcare diagnosis relies heavily on manual evaluation by clinicians, which introduces several limitations:

## V. ALGORITHMS

### *A. LSTM for Cardiovascular Prediction*

Long Short-Term Memory (LSTM) is a specialized Recurrent Neural Network architecture designed to model long-range temporal dependencies in sequential data. It is particularly suited to ECG signal analysis and multi-day vital sign trends.

The LSTM cell state is governed by forget, input, and output gates, allowing the model to selectively retain or discard information across time steps. This property is critical for detecting subtle early-warning patterns in cardiovascular data such as arrhythmia onset or gradual ST-segment changes.

Input features include heart rate, systolic and diastolic blood pressure, SpO2, and historical ECG waveform segments. The model outputs a cardiovascular risk probability score along with a classification label (Normal / At-Risk / Critical).

### *B. DNN for Diabetes Prediction*

A Deep Neural Network with fully connected layers is employed for diabetes prediction from structured patient data. The network architecture consists of an input layer, three hidden layers with ReLU activation and dropout regularization, and a sigmoid output layer for binary classification.

Input features include glucose level, BMI, age, HbA1c, blood pressure, insulin level, and family history. Dropout (rate = 0.3) is applied to prevent overfitting, and the model is trained using the Adam optimizer with binary cross-entropy loss.

## VI. RESULTS

Both models were evaluated on publicly available datasets: the PTB-XL ECG dataset for cardiovascular prediction and the Pima Indians Diabetes Dataset for diabetes classification.

  

- Diagnosis depends on individual physician expertise and may be inconsistent
- No mechanism for continuous real-time monitoring of patient vitals
- Limited capacity to process large multi-modal datasets simultaneously
- High probability of human error under time-pressured clinical settings

*B. Proposed System*

The proposed system addresses these limitations through a fully integrated AI-IoT pipeline:

- AI-driven disease prediction with high accuracy
- Continuous real-time health monitoring via IoT sensors
- Early-stage detection of cardiovascular disorders and diabetes
- Graphical User Interface (GUI) for clinician-friendly result visualization
- Automated alerts for critical health thresholds

## IV. SYSTEM ARCHITECTURE

The system architecture comprises five functional layers:

- Data Collection: Patient records, laboratory results, and IoT sensor streams (ECG, blood glucose, blood pressure, SpO2)
- Preprocessing: Data cleaning, normalization, feature extraction, and handling of missing values
- Model Training: LSTM network for cardiovascular time-series analysis; DNN for structured diabetic feature classification
- Prediction Engine: Ensemble decision logic combining model outputs with rule-based clinical thresholds
- Output Layer: GUI dashboard displaying predictions, confidence scores, and real-time alerts

**TABLE I**
Performance Metrics of Proposed Models

| Model | Accuracy | F1-Score |
|---|---|---|
| LSTM (Cardio) | 94.7% | 0.93 |
| DNN (Diabetes) | 91.3% | 0.90 |

The LSTM model achieved 94.7% accuracy for cardiovascular prediction while the DNN achieved 91.3% for diabetes classification. Real-time alert response latency averaged 1.2 seconds from sensor data acquisition to GUI notification.

## VII. ADVANTAGES

- Early detection of life-threatening diseases reduces mortality risk
- Minimizes human diagnostic error through automated AI inference
- Cost-effective deployment suitable for rural or low-resource healthcare settings
- Continuous IoT monitoring eliminates dependency on scheduled check-ups
- Scalable architecture supports future expansion to additional disease categories
- Telemedicine-ready interface enables remote clinical consultation

## VIII. CONCLUSION

This paper demonstrates an effective AI-based smart healthcare decision-making system integrating LSTM and DNN models with IoT-based continuous monitoring. The system achieves high predictive accuracy for cardiovascular disorders and diabetes, provides real-time clinical alerts, and offers a user-friendly interface for healthcare practitioners.

Future work will extend the system to detect additional conditions such as chronic kidney disease and Alzheimer's, incorporate federated learning for privacy-preserving distributed training, and validate the system through clinical trials in partner hospitals.

## ACKNOWLEDGMENT

The authors express sincere gratitude to Mrs. S. Lurdhu Jayasree, M.E., Assistant Professor, Department of Information Technology, Institute of Technology and Science, Thovalai, for her invaluable guidance and continuous support throughout this research.

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