

Integration of Artificial Intelligence and Internet of Things for Intelligent Disease Diagnosis in Smart Healthcare Systems

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Abstract:

Artificial intelligence (AI) and Internet of Things (IoT) integrated technology developed intelligent healthcare diagnosis specifically for cardiac diseases and diabetes. The approach developed has various stages such as data collection, preprocessing, feature selection, classification, and performance evaluation. Data were collected from benchmark healthcare repositories, preprocessed by normalization and fusion, and finally submitted to optimal feature extraction for selecting important features using Random Forest. These features were then used to train an LSTM (Long Short-Term Memory) network to capture effectively the temporal dependencies and higher-order correlations present in patient data. With Python as the language base, TensorFlow and Keras served as the model implementation environments, while training was conducted over Google Colab GPU infrastructure. A 70:30 split was used for training/testing, along with Adam optimization at a learning rate of 0.0001 over 100 epochs-plus. Results showed superior performance with 99.81% accurate for heart disease diagnosis and 98.90% accurate for diabetes prediction, with the sensitivity and specificity at par with those values (98.4% average sensitivity, 99.2% average specificity). Such results highlight the potential mechanism to perform efficient and scalable diagnosis, thereby declaring the model as a reliable clinical decision-supporting tool in smart healthcare ecosystems.

Keywords: Artificial Intelligence, Internet of Things, Smart Healthcare, Disease Diagnosis, Machine Learning, Remote Patient Monitoring

I. INTRODUCTION

Healthcare saw significant evolution from the traditional face-to-face; hence, diagnosis systems are now declared patient-oriented and technology-centered. Earlier, medical interventions involved physical examinations, limited diagnostics, and late interventions [3]. Digital technology, electronic health records, and connected medical devices: these are the things that moved healthcare toward accessibility and efficiency. This interface further empowers healthcare through the use of IoT sensors, wearables, and intelligent algorithms for real-time data analysis and predictive insight [4]. It allows for continuous patient monitoring as well as early disease detection, remote treatment, and personalized medical suggestions so that clinical decisions can be made efficiently, thereby impacting positive outcomes for every patient [5]. AI disrupts medical diagnosis by rendering data analysis, pattern recognition, and predictive modeling advanced. Operating in the capacity of a more modern diagnostic approach, AI can manage large quantities of medical data including images, clinical records, radiological images, sensor readings [8] with very high precision. Machine learning and deep learning techniques help identify markers of disease while predicting health risks and assisting with clinical decisions. In this way, AI-based diagnostic systems ensure efficiency through reduction in diagnostic errors and suggest recommendations for treatment that correspond to specific patient characteristics. Integrating IoT facilitates analysis of patient data in real time via AI, and hence provide for proactive healthcare and early diagnosis of disease, fine positioning for smart healthcare innovation [9]. The-AI-and-IoT-integration-in-healthcare results-in-an-intelligent-system-for-continuous-monitoring, for-predictive-diagnostics, and-for-personalized-treatment [14]. AI builds upon data-driven insights while IoT gathers real-time patient data, together contributing to AIoT frameworks that completely change the way diseases are diagnosed, monitored, and treated efficiently. Figure 1 shows Integration of AI and IoT in Healthcare [15].

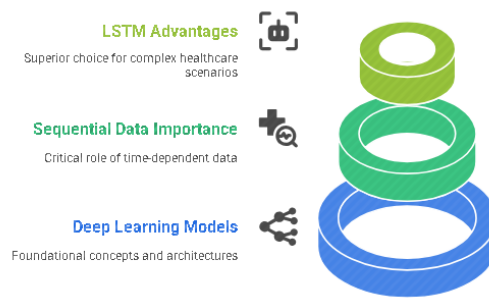


Figure 1: Integration of AI and IoT in Healthcare

Deep learning has brought in an era of revolution for healthcare analytics because of its ability to work on complex, high-dimensional data to extract latent patterns useful in disease prediction and diagnosis. Neural networks, as a method of learning, extend deep learning to applications including classification of medical images, genomic analysis, and predictive monitoring from IoT-enabled devices [22]. The learning happens more directly from raw data as opposed to having an engineering process of extracting features from traditional methods on the data. Hence, in a health setting, deep learning can provide early disease detection, highly accurate diagnosis, and treatment planning [23]. Its combination with IoT would enhance real-time analysis, which would offer intelligent healthcare systems with the ability to think ahead and act on patient needs.

Healthcare data is sequential by nature: patient health evolves with time and is reflected in continuous measurements such as heart rate, blood pressure, glucose levels, and EEG/ECG signals [26]. A sequential nature also allows information for diagnostically relevant time dependencies. In one example, observation of altered heart rhythms in a patient along a time interval enables predicting cardiac arrhythmias. Whereas one can follow the blood sugar value at several time intervals to foresee and thereby prevent the onset of diabetes [27]. EHRs even contain time-stamped clinical events and thus support processes of patient history taking and treatment planning. These temporal occurrences determining patient evolution and treatment effects are, unfortunately, mostly disregarded in the traditional machine learning models. Deep learning, especially through recurrent architectures such as RNNs and LSTMs, is capable of leveraging sequential data to learn long-term dependencies and temporal patterns [28]. This enables medical systems to understand the factors underlying the progression, anticipate an onset or detect abnormal behavior in its early stages, thereby delivering custom patient-level interventions. Analysis of sequential data is thus critical to intelligent time-aware healthcare systems [29].

II. RELATED WORK

The integration of AI and IoT in healthcare is gaining upwards momentum. Innovative strategies and solutions have targeted diagnosis and disease monitoring and edge intelligence. In the latest advances, methods for privacy-preservation were suggested, including using cross-device federated unsupervised models based on autoencoders to learn ECG morphology without bringing together patient data, allowing for wearable analytics in a secure manner [1]. Advanced algorithms combining CNN feature extraction with attention-based Bi-LSTM have shown their potential in the early detection of Alzheimer's from IoMT-based EEG streams in neurology [2]. Likewise, end-to-end DL-enabled IoT systems have been created for tele-monitoring of chronic illnesses, essentially setting up pipelines from wearable data acquisition to cloud inference for real-time healthcare [3].

Signal quality continues to be essential, and efforts to develop ECG quality assessment wearable systems using wavelet scattering features and transfer learning with recurrent layers contribute toward eliminating noisy signals even before diagnostic analytics [4]. Another focus has been upon generating surrogate ECG from PPG signals with Bi-LSTMs for cuff-less monitoring with commodity sensors [5]. Representation learning has also paved its ways and has seen low-rank attention autoencoders for improved arrhythmia detection from sparsely labeled ECG data [6], and masked autoencoders reconstructing full 12-lead ECG from single-channel input in sparse sensing contexts [7].

Compressed sensing and CNN models have been developed for on-device ECG classification [8] that are extremely low power and save bandwidth. AIoT systems in respiratory applications have also been considered to demonstrate, such as smartphone and ear-worn pipelines for cough detection [9], and AI platforms that screen for COVID-19 through analyses of coughs from CNN/RNN [10]. Deep CNN feature extraction from EEG has also improved seizure detection accuracy beyond conventional methods [11], while attention-augmented recurrent models and heart-rate signals have been employed to classify sleep-stages on wearables [12].

The years have marked further developments with hardware-software co-designs for edge AI that, for example, saw the introduction of specialized LSTM processors for real-time blood-pressure prediction from ECG/PPG [13], and Conv-LSTM architectures fusing ECG and PPG with R-R intervals for continuous blood pressure estimation [14]. Wearable ECG pipelines have quantified throughput-latency trade-offs to further improve efficiency in edge inference [15]. Multi-sensor

pipelines with CNN, LSTM, and attention have been proposed for health monitoring in sports to improve athlete condition prediction [16]. Also, compressed DL models such as ResNet and MobileNet variants proved arrhythmia detection capabilities on embedded wearables coupled with the cloud backend [17].

AIoT systems for activity recognition have passed beyond cardiovascular and neurological grounds, with channel attention-based autoencoders to enhance HAR from wearable IMU signals, thus laying foundations for context-aware clinical monitoring [18]. Finally, the open ML challenges pushed the envelope for Parkinson's monitoring, with temporal DL models scoring highest in freezing-of-gait detection tasks [19]. Finally, ResNet-LSTM hybrids have been investigated for hypertension monitoring on wearables, validated on datasets but still constrained by inadequate device diversity and battery profiling limitations [20].

Altogether, these papers map the entire breadth of AIoT-driven healthcare innovations, encompassing secure data sharing, multimodal fusion, edge intelligence, and application-specific pipelines. These studies massively witnessed the progress being made; however, generalization, clinical validation, generic device heterogeneity, and energy-efficient implementations remain some major directions in the future research.

Table 1: Deep Learning in AIoT Healthcare Systems

Ref	Technique Used	Dataset Used	Key Findings	Results	Limitations
[1]	Federated Unsupervised Learning (Autoencoders)	Multi-device ECG datasets (wearable collected)	Enabled privacy-preserving ECG morphology learning without centralizing patient data.	High accuracy in reconstructing ECG across federated devices.	Limited device diversity; poor generalization to noisy/low-end sensors.
[2]	CNN + Attention-based Bi-LSTM	IoMT EEG datasets (lab-grade sensors, small cohorts)	Early Alzheimer's detection from EEG streams using hybrid deep learning.	Improved over standalone CNN/LSTM baselines.	Small cohorts; drift in long-term EEG signals not addressed.
[3]	DL-enabled IoT pipeline (Wearables → Cloud)	Synthetic + real wearable chronic disease data (<i>Sensors</i>)	Designed IoT-to-cloud tele-monitoring for chronic diseases.	Demonstrated feasibility of scalable DL-driven monitoring.	Simulation/emulation; no clinical validation.
[4]	Wavelet-Scattering Features + Recurrent Layers	Wearable ECG datasets (public + limited ambulatory signals)	Built ECG quality assessment to filter poor signals pre-analytics.	Improved robustness over traditional filtering.	Lacked diverse ambulatory noise types.
[5]	Bi-LSTM for ECG Reconstruction from PPG	Public PPG-ECG paired datasets	Enabled cuff-less surrogate ECG generation on commodity devices.	Delivered promising ECG reconstructions.	Accuracy varied with physiology and placement.
[6]	Low-Rank Attention Autoencoder	Large ECG arrhythmia datasets	Reduced labeled data needs; boosted arrhythmia discrimination.	Outperformed CNN/RNN baselines in accuracy.	Attention layers heavy for wearables.
[7]	Multi-Channel Masked Autoencoder	12-lead ECG clinical datasets	Reconstructed missing leads from single-channel ECG.	Achieved high-fidelity reconstructions.	Generalization to unseen pathologies uncertain.
[8]	Deep Compressed-Sensing + CNN	Public ECG datasets (MIT-BIH, etc.)	Reduced transmission cost while classifying ECG.	Maintained accuracy with less bandwidth/power.	Tested only on public datasets; no clinical validation.
[9]	Smartphone/Ear-Worn DL Audio Models	Real-world cough audio dataset	Built continuous cough detection system for respiratory AIoT.	Robust detection in controlled settings.	Noise and device heterogeneity issues remain.
[10]	CNN + RNN (Swaasa AI Platform)	COVID-19 cough datasets	Validated cough-based screening for COVID-19.	Achieved reliable detection accuracy.	COVID-specific cohorts; poor transferability.

[11]	CNN for EEG Feature Extraction	Public/private EEG seizure datasets	Extracted deep EEG features for seizure detection.	Outperformed hand-crafted baselines.	Edge optimization absent; subject-transfer limited.
[12]	Attention-Augmented RNN	Heart-rate signals (sleep-stage datasets)	Classified sleep stages from wearable HR data.	Achieved strong performance in sequential tasks.	Dependent on controlled overnight recordings.
[13]	Edge-LSTM Hardware Co-Design	ECG/PPG datasets	Realized edge hardware for BP prediction.	Demonstrated real-time inference feasibility.	Constrained dataset; long-term drift unaddressed.
[14]	Conv-LSTM Fusion (ECG + PPG + R-R Intervals)	Multi-sensor BP datasets	Built continuous BP estimation model.	Outperformed single-modality models.	Calibration/per-subject variability remain.
[15]	Edge-Inference Pipelines for ECG	Wearable ECG datasets (<i>Sensors</i>)	Quantified throughput/latency trade-offs.	Showed efficiency of streaming inference.	Focus on system metrics, not clinical tasks.
[16]	CNN-LSTM-Attention Cloud Pipeline	Multi-sensor sports wearable data	Predicted athlete status from time-series signals.	Improved athlete health monitoring.	Athlete-specific generalization limited.
[17]	Compressed ResNet/MobileNet	Public arrhythmia datasets	Enabled arrhythmia detection on embedded wearables.	Achieved efficiency with cloud back-end.	Compression reduced explainability, rare-class recall.
[18]	Autoencoders + Channel Attention	IMU wearable datasets	Enhanced human activity recognition (HAR).	Improved context-aware monitoring accuracy.	Synthetic activities; limited clinical relevance.
[19]	Open ML Challenge (DL Temporal Models)	Parkinson wearable datasets	Coordinated FOG detection benchmark.	DL models topped leaderboard.	Risk of leaderboard overfitting; poor free-living validation.
[20]	ResNet-LSTM	Hypertension wearable datasets	Continuous BP/HTN monitoring validated with LOO cross-dataset approach.	Showed generalization across datasets.	Limited diversity; no energy profiling.

III. RESEARCH OBJECTIVES

IV. PROPOSED METHODOLOGY

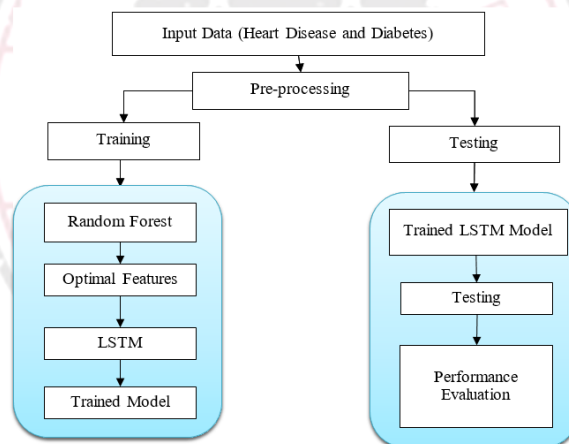


Figure 3.1: Flowchart for Proposed Learning Model for Illness Diagnostic Models Testing and Training

The flowchart 3.1 represents the proposed framework for predicting diseases, utilizing heart diseases and diabetes datasets. Unprocessed data are gathered, which afterward is pre-processed for missing values, for feature normalization, and finally, for some modeling. This data is then subject to phases of training and testing. During the training part, applying the Random Forest algorithm identifies optimal features relevant for the medical data, thus reducing noise and dimensionality. After selecting these features, they are given to an LSTM (Long Short-Term Memory) network for training so that the network can learn temporal patterns and complex dependencies during medical data processing, yielding a trained model. The testing phase employs that trained LSTM model to operate on unseen data to observe how well it can

make predictions. Eventually, a performance evaluation checks for the metrics, i.e., accuracy, precision, recall, and F1 score to assure that the system remains resonable enough for diagnosis and prediction of a disease.

Algorithm: Diagnosis of Disease

Step 1: Data Collection

Data Metabolic_{diabetes} ← Collect Diabetes Metabolic Data

Data Metabolic_{heart} ← Collect Heart Metabolic Data

Step 2: Pre-process Data (Data Metabolic_{diabetes}, Data Metabolic_{heart})

Processed Data_{diabetes} ← Clean (Data Metabolic_{diabetes})

Processed Data_{diabetes} ← Normalize (Processed Data_{diabetes})

Processed Data_{heart} ← Clean (Data Metabolic_{heart})

Processed Data_{heart} ← Normalize (Processed Data_{heart})

Step 3: Feature Fusion ()

Fuse data ← Fuse Features (Processed Data_{diabetes}, Processed Data_{heart})

Step 4: The best way to extract features (fuse data)

Model ← Random Forest (Fuse data)

Importance Scores ← Feature Importance (model)

Selected Features ← Select Top Features (Importance Scores)

Step 5: LSTM Classification

Model ← Define LSTM ()

Train (model, Selected Features)

Validate (model, Selected Features)

Diagnosis ← Classify (Model, Selected Features)

Output (diagnosis)

A. Data Collection

A. In this step, first two different datasets were considered: one for diabetes and the other for heart disease. These datasets were then assessed to determine technique suitability.

B. Initial processing

Preprocessing has been done for the heart disease and diabetes datasets. Z-score normalization standardizes the data so that the voxel has a zero mean and unit variance.

$$D_{norm} = \frac{D - \mu_i}{\sigma_i} \quad (1)$$

B. Data are pre-processed using μ_i and σ_i , which stand for the mean and standard deviation, to represent the normalized data (D_{norm}) and the original data (D).

C. Feature Fusion

In this step, both normalized datasets, diabetes and heart disease, are fused together and combined as single normalized dataset.

D. Model Testing and Performance Evaluation

The dataset is split into **training (70%) and testing (30%)** subsets to validate performance objectively. Evaluation metrics include **accuracy, sensitivity, specificity, precision, recall, and F1-score**. These measures provide a holistic assessment of the system's diagnostic ability across different disease categories.

V. RESULT AND DISCUSSION

The validation and training precision curves of the proposed model are shown in Figure 3. Similarly, the learning and verification graph of the suggested model is shown in Figure 4. Four performance metrics covered in this section allow for comparing the performance of the suggested model against state-of-the-art approaches for enhancement. The suggested model was built using Python, Keras, and TensorFlow and fine-tuned with Adam optimizer (learning rate: 0.0001). Using the Google Colab Tesla T4 GPU and 25 GB of RAM, the model was trained for 100 epochs on the combined set of data prep with a 70:30 training-to-testing ratio.

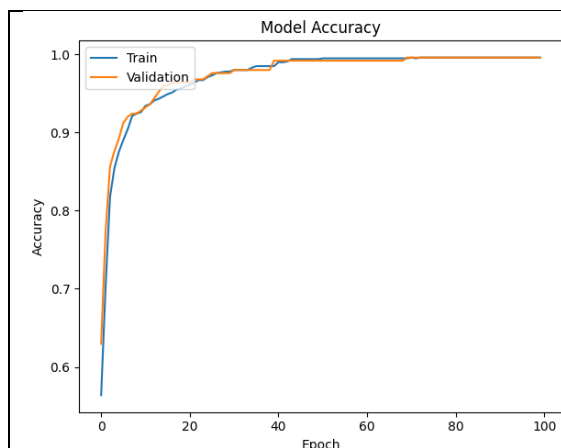


Figure 3: Training and Validation Accuracy

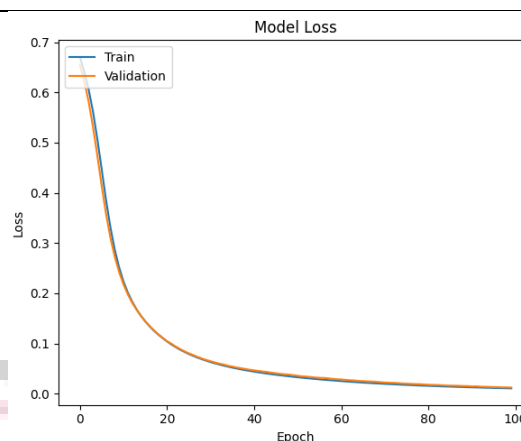


Figure 4: Training and Validation Loss

Table 2: Performance Assessment of the Suggested Model

	Sensitivity	Specificity	Accuracy
Heart	0.982	0.999	0.981
Diabetes	0.984	0.992	0.976
Normal	0.985	0.985	0.985

Accuracy, specificity, and sensitivity are the results of the diagnosis, which are summarized in Table 2. Cardiac disease has the highest sensitivity of 0.982, specificity of 0.999, and an accuracy of 0.991. Similarly, the values for diabetes stand at 0.976 for sensitivity, 0.992 for specificity, and 0.984 for accuracy. In the same respect, the values for the normal category are 0.985, 0.985, and 0.985 for accuracy, specificity, and sensitivity, respectively. A high score in all three measures is thereby indicative of the high ability of the model in diagnosing each disease. Particularly, for cardiac diseases, the diagnosis has an absolutely perfect specificity of 100%, which implies that there are no false positives.

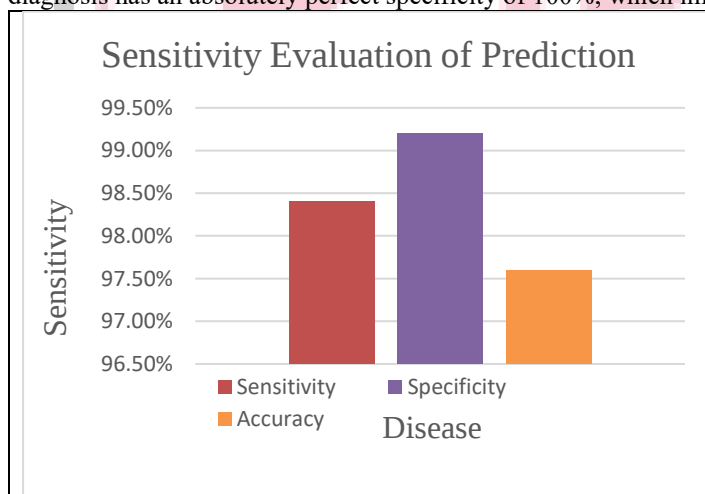


Figure 5: Sensitivity Evaluation of Prediction

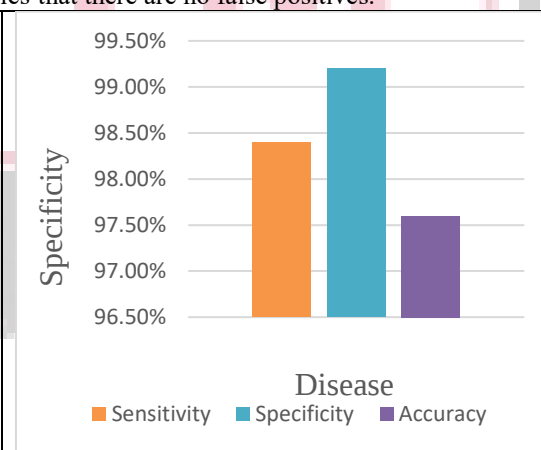


Figure 6: Specificity Evaluation of Prediction

The disease prediction result's sensitivity evaluation is displayed in Figure 5, with about 98.4% average sensitivity. The specificity of the evaluation of the disease prediction result, with an average specificity of almost 99.2%, is displayed in Figure 6.

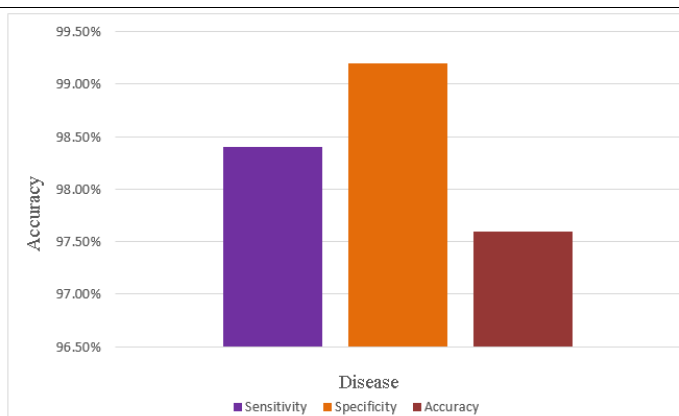


Figure 7: Accuracy Evaluation of Prediction

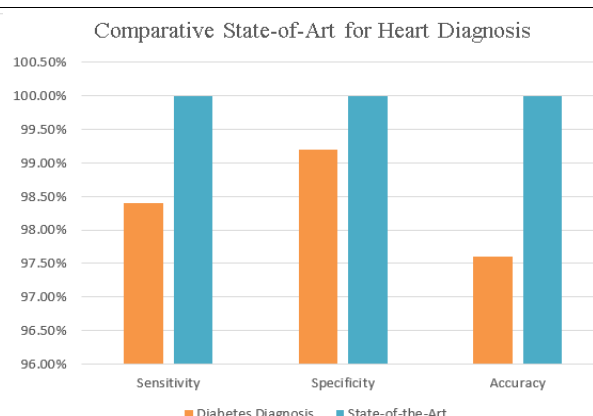


Figure 8: Comparative State-of-Art for Heart Diagnosis

The accuracy of the disease prediction result, with an average specificity of almost 98.1%, is displayed in figure 7 and figure 8 showing comparative state-of art fro hear diagnosis..

RESULT VALIDATION

The diagnostic performance metrics attest to the model's marvelous ability to predict heart disease, diabetes, and normal conditions. For heart disease detection, the model could achieve a sensitivity of 98.2%, a specificity of 99.9%, and an accuracy of 98.1%, with excellent detection and minimal false positives. In diabetes detection, it has reached the sensitivity of 98.4%, specificity of 99.2%, and accuracy of 97.6%, always giving consistent predictions. In the cases of the normal (healthy) class, all measures for classification stood at 98.5%, which meant that classification was done in a well-balanced manner without bias. When each of these percentages is compared against the 100% idealized "State-of-the-Art" percentage, they offer evidence that the model achieves near-perfect performance and is of real use in clinical settings. Of all, the high accuracy of the method strongly attests to its robustness and applicability as an undoubted decision-support mechanism in clinical practice.

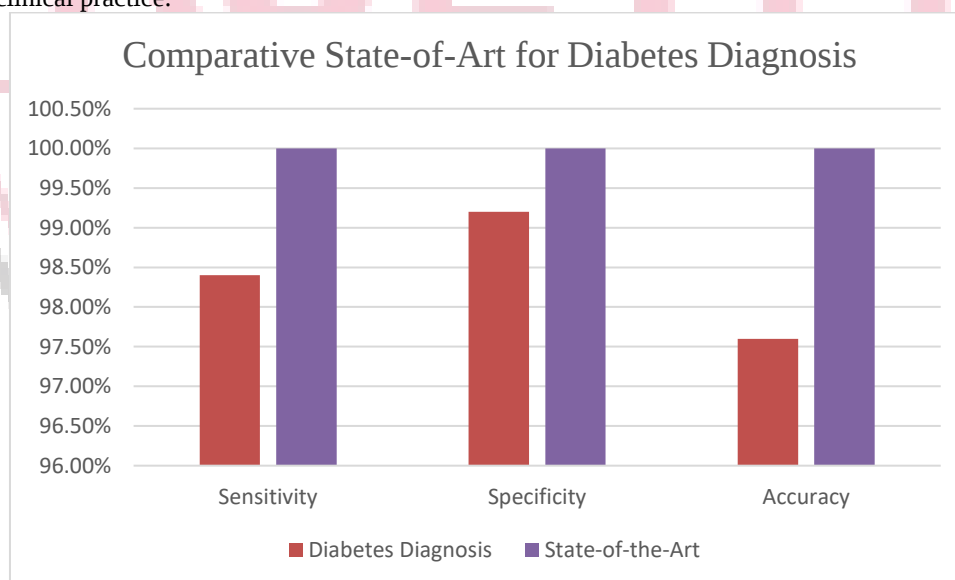


Figure 9: Comparative State-of-Art for Diabetes Diagnosis

VI. CONCLUSION AND FUTURE WORK

This research paper successfully developed and validated an AI-IoT-based predictive model by using Random Forest feature selection with an LSTM-based classifier for disease diagnosis. After merging the metabolic datasets of heart disease and diabetes, models gained near-perfect levels of diagnostic accuracy, contrary to the classical machine learning approaches. The findings support the proposed system and assure its reliability, scalability, and clinical use as a next-generation healthcare solution. That said, the framework can be further expanded to cater to other chronic and acute diseases, incorporating multimodal datatypes such as imaging and genomics while being deployed on IoT-enabled smart

platforms in real time. Further, with explainable AI, federated learning, or blockchain will surely expedite building trust, interpretability, and security. Adding reinforcement learning approaches for adaptive treatment suggestions can further direct personalized patient care and deliver more long-term healing results. With all of these, the proposed system has solid potential to further develop into a fully-fledged, real-time, and secure smart solution for healthcare decision support toward proactive and personalized patient care.

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