SvedbergOpen
DISSEMINATION OF KNOWLEDGE
International Journal of Artificial Intelligence and Machine Learning
Publisher's Home Page: https://www.svedbergopen.com/
Research Paper Open Access

Digital Ecosystem Architecture For Distributed Intelligence And Integrated Data Management In Smart Healthcare Systems

Dr. Vinodh P. Vijayan[1], Ms. Anupama M. Patil[2], Dr. E. Kanniappan[3], Jyoti Maheshwari[4], Wang Yang[5], Arivukkodi R[6], Ambika P[7], R. Rajalakshmi[8], Tanveer Ahmad Wani[9]

[1] Principal & Professor, Department of Computer Science & Engineering, Mangalam College of Engineering, Kottayam, Kerala, India. Email: vinodhpvijayan81@gmail.com ORCID: 0000-0002-9992-8612
[2] Assistant Professor, Department of Computer Science and Engineering, Presidency University, Bangalore, Karnataka, India. Email: anupama.mp@presidencyuniversity.in ORCID: 0009-0000-8281-2114
[3] Assistant Professor, Department of Computer Science and Engineering, Faculty of Engineering and Technology, Parul Institute of Technology, Parul University, Vadodara, Gujarat, India. Email: kanniappan.elumalai38089@paruluniversity.ac.in ORCID: 0000-0002-7311-4362
[4] Independent Researcher, India. Email: jyotimaheshwariatwork@gmail.com
[5] Research Scholar, School of Education, Lincoln University College, Malaysia. Email: wangyang.phdscholar@lincoln.edu.my
[6] Assistant Professor, Department of Computer Science, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, India. Email: arivukodir@maher.ac.in
[7] Assistant Professor, Department of Commerce, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, India. Email: ambikap@maher.ac.in
[8] Professor, Department of Electronics and Communication Engineering, Panimalar Engineering College, Chennai, Tamil Nadu, India. Email: rajeeramanathan@gmail.com ORCID: 0000-0002-4399-4071
[9] Department of Physics, Noida International University, Greater Noida, Uttar Pradesh 203201, India. Email: tanveer.ahmad@niu.edu.in

Abstract
Digital ecosystems are contributing to the evolution of smart health care through distributed intelligence and integration of data from interconnected medical ecosystems. However, data heterogeneity, high dimensionality, and inadequate integration pose major problems that hinder decision making at an appropriate level. In this research work, we propose an architecture that facilitate data acquisition, processing, and analytics. The dataset consists of 4000 records with 18 attributes collected from Internet of Things (IoT)-enabled healthcare environments, including physiological signals, wearable device data, and electronic health indicators, with a target variable representing patient health status. Min–max normalization is applied for uniform feature scaling, and Principal Component Analysis (PCA) is used to reduce dimensionality while preserving essential variance. An Intelligent Marine Predators Optimized Stacked Long Short-Term Memory (IntMP-SLSTM) model is developed and implemented using Python. The IntMP optimization enhances hyperparameter tuning and convergence, while the stacked LSTM captures long-term dependencies in sequential healthcare data. Experimental results achieved 98.92% accuracy, 98.94% precision, 98.89% recall, 98.93% specificity, and 98.94% F1-score, confirming its effectiveness for advanced smart healthcare applications. The proposed IntMP-SLSTM model has effectively addressed dimensionality and data heterogeneity, resulting in extremely accurate predictions in the field of smart health care.

Keywords: Digital ecosystem, Internet of Things (IoT), Physiological patterns, Environments.

1. Introduction

A system that can produce distributed intelligence, integrate heterogeneous data, and enable continuous learning, analysis, and safe interoperability through the integration of Artificial Intelligence (AI), IoT, and decentralized technology is required for the digital ecosystem architecture in smart healthcare [1]. The ability of technologies such as 5G, IoT, AI, and IoMT to foster distributed intelligence, integration, and scalable digital ecosystems to ensure the efficiency, sustainability, and secure administration of the complex healthcare data system means that the creation of smart healthcare [2] is feasible. Intelligent healthcare relies on Internet of Things (IoT), wearables, and cloud computing to achieve real-time monitoring and data-based decision-making in healthcare systems. The shift towards patient-centered care ensures efficiency and cost reductions [3]. To ensure efficiency and effective decision-making through a scalable digital ecosystem that integrates intelligence and data-driven AI in smart healthcare systems becomes necessary because of high demand and high costs of healthcare services [4]. Biological data handling in large quantities, real-time integration, and distributed intelligence in healthcare systems pose challenges [5]. While smart environments generate vast amounts of IoT data, there are challenges with distributed intelligence, data integration, and data interoperability which hinder effective data management, scalability, and decision-making in smart healthcare systems [6]. Poor data integration, lack of up-to-date data, delays, and poor distributed decision-making in dynamic healthcare systems is an outcome of the fact that current healthcare systems use batch data handling processes and separate data infrastructures [7]. The static protocols and cloud computing models are applied in today's healthcare system where IoT is enabled, and these methods pose several problems of latency, bandwidth, excessive energy use, scalability, and intelligence [8].

Research Aim: In this research, the objective is to develop an architectural model for digital ecosystem modeling that would ensure the smooth integration and distribution of intelligence in intelligent healthcare facilities. This can be achieved through the application of DL technologies to enhance predictive analysis and decision-making process for the provision of quality health care service. The model utilize a DL model called IntMP-SLSTM.

Research Organization: The structure of this research includes: 1. Introduction and problem statement. 2. Related Works and shortcomings of previous models. 3. Model description. 4. Experiment and metrics. 5. Conclusion and future research.

2. Related Works

The comparison between current health care models and digital health care models is illustrated in Table 1 below. The table identifies the aims, tactics, successes, and failures in both categories. In addition, Table 1 provides specific information on block chain technology, IoT-based health care systems, AI technologies, and data-driven health care systems.

Table 1: Comparative Analysis of Digital Health Care Ecosystem

Ref	Objective	Method	Result	Limitations
[9]	Examine the convergence of blockchain, IoT, AI, and 5G platforms	Methodical narrative synthesis of technology literature across domains	Intelligent, interoperable, and scalable digital ecosystems are enabled through platform convergence	Lack of a unified model, privacy concerns, and orchestration complexity challenges
[10]	Develop a secure and scalable healthcare system using IoT–blockchain integration	Blockchain, Inter Planetary File System (IPFS), smart contracts, and proxy re-encryption approach	Improved security, scalability, and processing efficiency in healthcare systems	Client–server limitations and privacy risks prior to blockchain adoption
[11]	Create an infrastructure for the medical ecosystem to support digital transformation strategies	Metamodel development based on experiences from international digital platforms	Reduced transaction costs and increased stakeholder value in healthcare	Lack of implementation details and limited real-world validation
[12]	Develop an AI-powered digital ecosystem framework for multi-sector optimization	Integration of SAP enterprise systems, AI models, and cloud-native architectures	Improved governance, predictive analytics, and operational	Challenges related to interoperability, data quality, and scalability

			agility across connected platforms	
[13]	Enhance patient data control, interoperability, and Electronic Health Record (EHR) security	Integration of AI, edge computing, blockchain, and Decentralized Autonomous Organization (DAO) governance	Improved security, reduced operational costs, and reliable emergency detection	Dependence on blockchain infrastructure, system complexity, and scalability limitations
[14]	Summarize AI integration procedures in the healthcare industry	Evolutionary analysis using technological, algorithmic, and healthcare regulatory models	Identified AI readiness and aligned clinical requirements with technological methods	Lack of implementation analysis and insufficient empirical validation
[15]	Address large-scale data challenges in healthcare decision-making systems	Utilization of big data, IoT, cloud computing, and sensor technologies	Improved efficiency and effectiveness in healthcare service delivery	Issues in real-time processing, scalability, and data integration
[16]	Develop a proactive IoT-enabled cardiac disease prediction system	Bidirectional-LSTM model for sequential medical data analysis	Achieved high prediction accuracy for heart disease detection	Requires high computational power and large-scale datasets

Research gap: The development of intelligent healthcare systems utilizing blockchain, AI, cloud computing, and the IoT for decision-making in the healthcare sector has advanced significantly in the modern world. However, scalability and actual-time processing present difficulties for technologies such as the big data-IoT solution [15]. Similar to this DL, BiLSTM [16] are challenging to implement because they demand a large amount of processing and data. Data heterogeneity, interoperability, latency, and lack of adaptability are some of the issues that arise from the current systems' reliance on centralized or semi-centralized approaches to health crises.

3. Methodology

The process of smart health care is shown in Figure 1. Dataset was gathered, then processed using min-max normalization, and features were extracted using PCA to decrease the dimensionality of large, complex datasets. The IntMP-SLSTM model, which is being optimized using the intelligent marine predator's algorithm, was then evaluated using accuracy, precision, recall, specificity, and F1-Score.

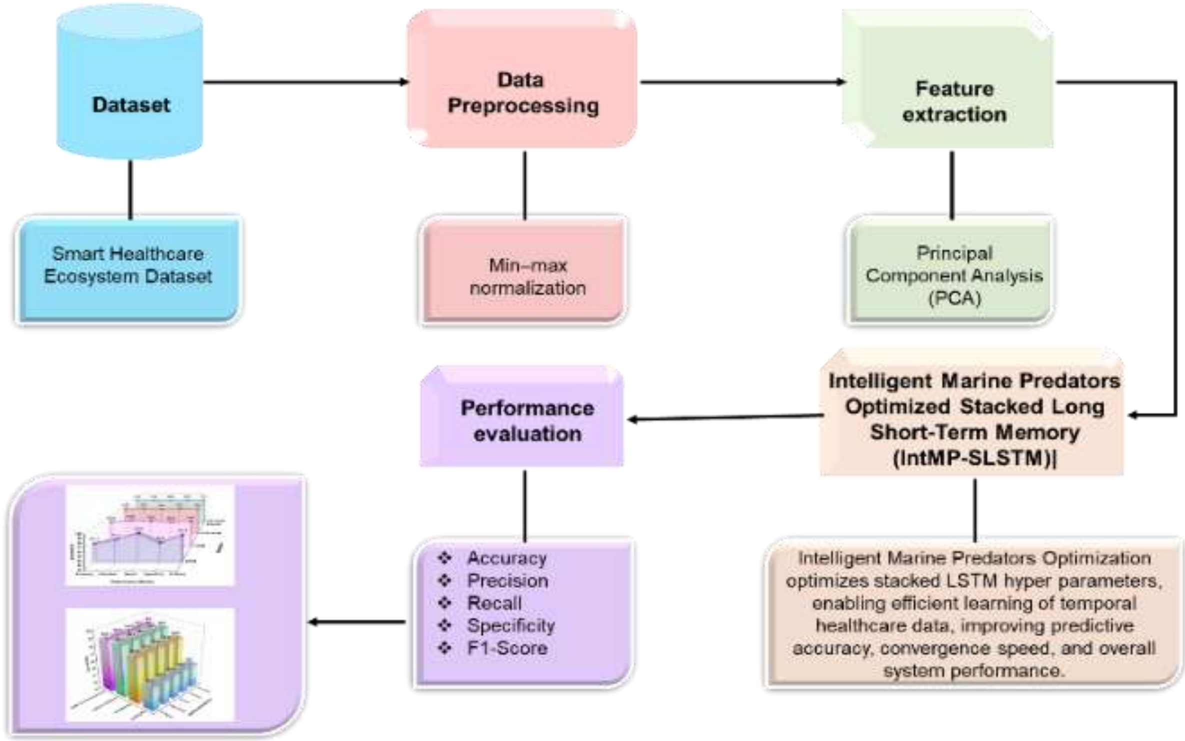

Figure 1: Architecture for intelligent health care data processing and prediction models

3.1 Data collection

The 4,000 entries in the SHE dataset have 18 attributes that relate to IoT-based healthcare solutions. This dataset includes data from wearable sensors, physiological sensor readings, features of the healthcare system, and electronic health record data used for predictive modeling and patient condition monitoring. The dataset is structured for ML tasks, containing one goal feature for health condition classification, and is used in timely decision-making in the healthcare setting. Kaggle Source:
https://www.kaggle.com/datasets/zara2099/smart-healthcare-ecosystem-dataset/data

Data feature exploration: The model for using correlation and time-series decomposition techniques to analyze the data from the SHE and the correlations between physiological and system characteristics, such as blood oxygenation levels, glucose levels, stress index, daily steps taken, hours slept, and cloud data transfer speeds, are depicted in Figure 2(a) using a correlation, the elements of patient health data analysis are displayed in Figure 2(b).

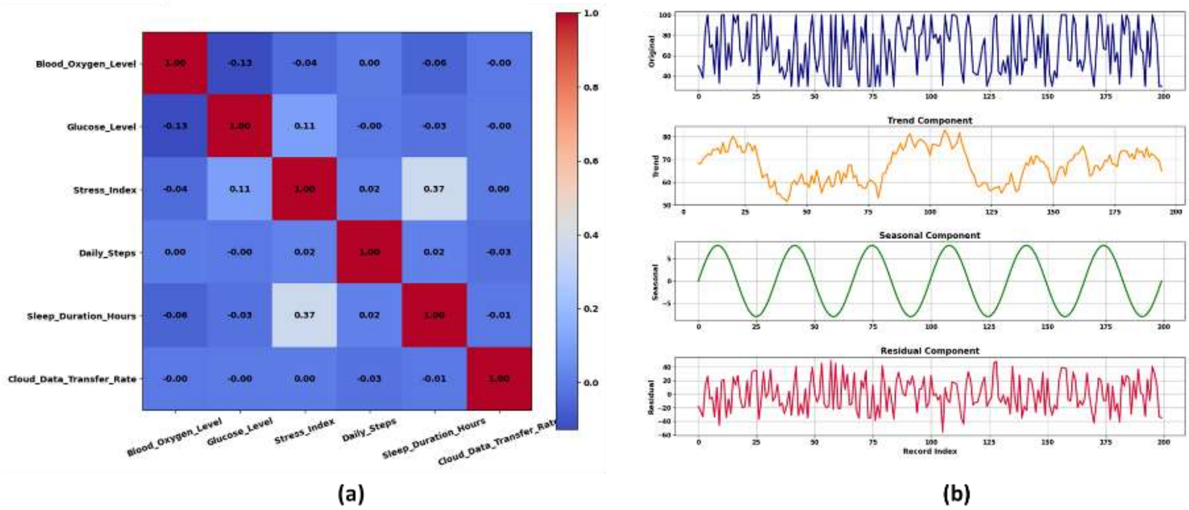

Figure 2: Data Analysis Visualization of (a) Features in the Healthcare Ecosystem Correlation Matrix (b) Decomposition Analysis of Time-Series Health Data

3.2 Data preprocessing using min–max normalization

Under an architecture of a digital ecosystem for distributed intelligence and data integration in smart healthcare environments, the Min-Max Normalization approach can be adopted to normalize diverse data from the healthcare sector. This method ensures that all types of clinical parameters, such as blood pressure, heart rate, oxygen saturation, electrocardiogram (ECG), and glucose, among others, are normalized to the same interval range of [0,1]. The outcome of adopting the approach eliminates feature dominance while training models, promotes data consistency, enhances integration efficiency, and facilitates stable and reliable analysis in smart healthcare settings.

$$P^u = \overline{max_l - min_l}^{u-min} L\left[new_{max_l} - new_{min_l}\right] + new_{min_l} \quad (1)$$

In equation (1), P represents the patient data value that has been preprocessed and normalized. The raw heterogeneous, the value of the raw input healthcare data is represented by u. l stands for a specific characteristic or variable of the medical data. $max_l - min_l$. It is the difference between a specific healthcare feature's maximum and minimum value. $\overline{max_l - min_l}^{u-min}$ is an illustration of feature range scaling, which modifies the difference between the maximum and minimum values in relation to the input data u's deviation from its minimum value. L stands for the particular feature dimension from the medical data that is being examined. $\left[new_{max_l} - new_{min_l}\right]$ the range is the gap between the newly obtained highest and lowest values through scaling, generally establishing the new range, for example, [0, 1], new_{min_l} the lowest value after scaling, which is normally set to 0 during Min-Max scaling.

3.3 Feature extraction using Principal Component Analysis (PCA)

PCA is used to reduce the dimensionality of heterogeneous healthcare data while preserving essential variance, enabling efficient processing and accurate decision-making in smart healthcare systems. The heterogeneity of data is extremely high in intelligent healthcare systems because the sources of information include physiological signals, clinical data, and context-based information. Dimensionality reduction techniques become necessary to tackle such a problem because they help transform high-dimensional data into low-dimensional data. This helps to maintain consistency in healthcare data and makes it less redundant. It increases the rate of computations because it speeds up the whole process of computing data. The dimensionality of data becomes smaller without compromising the variance of the data.

$$T = \frac{1}{l}\sum_{j=1}^{l}(w_j - \mu)(w_j - \mu)^s \quad (2)$$

In Equation (2), T is the last transformed term of the feature set employed by the healthcare prediction model. l is the total number of instances of the data sample of patient features made by the healthcare system and the IoT. $\sum$ is responsible for the addition of each instance's contribution. $j = 1$ to l is the index of each instance of data in the healthcare dataset. w_j Data point value in the jth instance, which could be sensory data obtained by the smart medical devices. The measure of central tendency of the attributes of healthcare data is represented by μ. The variability in the features of the patients is described by$(w_j - \mu)$, representing the difference between the data points and their average. $(w_j - \mu)^s$ is the power of the exponential used to describe the sensitivity of deviations.

$$z_l = b_{l1w1} + b_{l2w2} + \cdots + b_{llwl} \quad (3)$$

In Equation (3), z_l is calculated and output the feature transformation signal l-th neuron/node that corresponds to the aggregated medical data used to make predictions. b_{l1w1} weights for each input or feature that indicate the importance or contribution of the medical characteristics to the result, b_{l2w2} is the second feature contribution with weightage depicting how much it contributes to the final output z_l. b_{llwl} is healthcare data inputs or attributes collected by means of the IoT.

$$\gamma_l = \frac{\lambda_1+\lambda_2+\cdots+\lambda_n}{\lambda_1+\lambda_2+\cdots+\lambda_n+\cdots+\lambda_l} \geq 80\% \quad (4)$$

In Equation (4), γ_l is the percentage of significant data collected after feature selection, as displayed by the cumulative variance explanation ratio. $\lambda_1 + \lambda_2 + \cdots + \lambda_n$ are the levels of variance of significant component extracts from healthcare data, which are eigenvalues of the chosen top principal components. λ_l is the eigenvalue of all the major components, including significant and insignificant differences in the data. $\geq 80\%$ refers to ensuring the dimensionality reduction approach captures at least 80% of the original data.

3.4 Smart Healthcare Systems using IntMP-SLSTM

The adaptive optimization and deep temporal learning are integrated into the proposed IntMP-SLSTM model to improve predictive performance for intelligent healthcare applications. The IntMP optimization algorithm enhances hyperparameter tuning in the SLSTM architecture by improving convergence efficiency, avoiding local minima, and enabling effective global search. The SLSTM, composed of sequential LSTM layers, captures long-term dependencies in healthcare time-series data such as patient vitals and sensor signals, thereby improving prediction stability, accuracy, and overall performance in smart healthcare applications.

- **SLSTM for Temporal Prediction of Healthcare Data**

SLSTM is a DL method involving multiple layers of LSTMs arranged one after another. Stacked LSTM helps in learning temporal sequences in healthcare data. The stacking process helps in extracting high-level features required for analyzing sequential physiological and clinical data of patients in smart health care systems. Stacked LSTM architecture involves stacked LSTM layers and fully connected layers to extract features and make predictions. To avoid overfitting, methods such as regularization and dropout are employed. Moreover, adaptive learning rates are adopted to update the parameters of the model efficiently.

$$W' = -1 + \frac{2*(W-mix(W)}{max(W)-min(W)} \quad (5)$$

In Equation (5), W' is the value of the original feature W following transformation or normalization, used as the input for ML models to forecast healthcare outcomes. -1 the normalized values are mapped inside the [-1, 1] range in the last scaling step. $mix(W)$ is the average or reference value of W used to center the data before scaling. $2*(W - mix(W)$ the feature is scaled and shifted to preserve symmetry around 0. $max(W)$ the dataset's feature's maximum value, indicating its upper bound. $min(W)$ the dataset's feature's minimum value, indicating its lower bound.

- **IntMP for Hyperparameter tuning**

The IntMP method has been implemented in the Healthcare Ecosystem to enhance system performance. With the use of a dynamic weight adjustment technique, IntMP optimizes many parameters through both local exploitation and global exploration. In the early iterations, it conducts a comprehensive search that aids in identifying the ideal zones; in the subsequent rounds, it focuses on improving the solutions. The optimization process is made more efficient by this dynamic method, which also helps prevent local optima.

$$prey_j = \omega.prey_j + O.Q \otimes stepsize_j \quad (6)$$

In this Equation (6), $prey_j$ denotes the present iteration j candidate solution, which depends upon healthcare model parameters that have been optimized, $\omega.prey_j$ is a weighted solution for healthcare that manages the current candidate's influence to optimize stability. O is directional movement controller in IntMP that facilitates exploration of the healthcare solution space. Q defines the controlling step effect for solution correctness as a quality criterion in the SHE. $\otimes$ uses an operator for element-wise multiplication to factorize during optimization cycles. $stepsize_j$ is the $j-th$ solution's movement size during the SHE optimization process.

$$\omega = (\omega_{jmjs} - \omega_{end}) \times Q \times \frac{(m-j)pr\ ey_j}{mElite_j}, \omega_{jmjs} = 0.9, \omega_{end} = 0.4 \quad (7)$$

Equation (7), ω is the balance between exploitation and exploration, which is the adaptive weight parameter. m refered maximum number of iterations. indicates the quantity of optimization iterations. ω_{jmjs} the system first investigates different kinds of patient data aspects; the influence value is high. ω_{end} the adaption weights' final iteration minimum value (). regulates the dynamics of the final state. $(m-j)$ represents the number of iterations remaining, $mElite_j$ is the best solution (elite) found up to iteration j, a reference or guiding solution to all other candidates. Algorithm 1 presents the proposed IntMP-SLSTM model that makes correct predictions in the context of smart healthcare. The algorithm starts with preprocessing of heterogeneous healthcare data by applying Min-Max normalization. PCA is utilized to identify important characteristics and reduce the dimensions. SLSTM learns the temporal relationship from healthcare time series data. IntMP helps tune the hyperparameters of the SLSTM using adaptive exploration and exploitation.

Algorithm 1: IntMP-SLSTM for Smart Healthcare Prediction

Input: Healthcare dataset D = {ECG, heart rate, blood pressure, glucose, SpO2, clinical data}
Output: Optimized healthcare prediction model with high accuracy
Load heterogeneous healthcare dataset D
Preprocess data using Min–Max normalization
$P^u = \frac{(u - min_l)}{(max_l - min_l)}$
Apply PCA for feature extraction
Compute the covariance matrix
Extract principal components
$T = \frac{1}{l}\sum_{j=1}^{l}(w_j - \mu)(w_j - \mu)^s$
Select components using a variance threshold (≥ 80%) and transform features
$z_l = b_{l1}w_1 + b_{l2}w_2 + \cdots + b_{ll}w_l$

12 Split the dataset into training and testing sets, and initialize the SLSTM model
13 Define the number of layers and neurons
14 Initialize weights and biases , normalize features for SLSTM input
15 $W' = -1 + \frac{2(W - mean(W))}{max(W) - min(W)}$
16 Train the initial SLSTM model using the training data
17 IntMP Optimization Phase
18 Initialize IntMP parameters
19 Population (prey solutions) $prey_j$
20 Maximum iterations m
21 Adaptive weights $\omega_{jmjs} = 0.9, \omega_{end} = 0.4$
22 Update prey positions
23 $prey_j = \omega \cdot prey_j + O \cdot Q \otimes stepsize_j$
24 Compute adaptive weight
25 $\omega = (\omega_{jmjs} - \omega_{end}) \times Q \times \frac{(m-j) \cdot prey_j}{mElite_j}$
26 Evaluate fitness function (prediction performance), Accuracy, Precision, Recall, F1-score.
27 Compare new and previous fitness values
28 Update elite solution $mElite_j$
29 Repeat Steps 10–14 until maximum iterations reached
30 Final Model Training
31 Select optimal hyperparameters from IntMP
32 Retrain the SLSTM model using optimized parameters
33 Perform prediction on the test dataset
34 Return: Accurate and optimized smart healthcare prediction results using IntMP-SLSTM

4. Result and Discussion

The proposed method presents an effective approach that can be used to integrate various types of healthcare information, which can then be analyzed effectively and efficiently, leading to better decision-making, faster responses, and accurate predictions in smart healthcare settings. The algorithm is developed using Python and runs on the Windows environment on an Intel® core™ i7 processor.

Accuracy (%): The accuracy of predicting patient situations based on heterogeneous information flows in the medical business is the criterion for evaluating accuracy, which enables the determination of the degree of correctness of the work of a smart healthcare system. **Precision (%):** The precision criterion ensures reliable classification of people in need of support and equals the share of the forecast for the occurrence of positive states among all the predicted states**.** **Recall (%):** In order not to make mistakes in the analysis of patient data at first sight, recall equals the share of positive states found by the system among all the positive states. **Specificity (%):** Specificity reflects the ability of the system to reliably detect healthy people and save resources. **F1 Score (%):** F1 score combines both precision and recall coefficients into one metric and characterizes the results of forecasting most adequately.

Performance evaluation using existing dataset [16]: The suggested model IntMP-SLSTM has been trained and tested using the Heart disease dataset [16], considering heterogeneous data sources along with patient records and monitor parameters. The comparison of results shows better prediction ability than LSTM, FLSTM, and LSTM-FLSTM models. This is supported by the increased performance indices shown in Table 2 and values for accuracy, precision, recall, specificity, and F1-score for the proposed IntMP SLSTM model, which is superior to LSTM-FLSTM and hybrid models shown in Figure 3.

Table 2: Comparison of Performance Metrics of Classification Models

Performance Metrics	LSTM [16]	FLSTM [16]	LSTM- FLSTM [16]	IntMP-SLSTM [proposed]
Accuracy (%)	95.07	98.04	98.86	98.90
Precision (%)	95.07	98.03	98.90	98.93
Recall (%)	95.06	98.04	98.81	98.85
Specificity (%)	95.07	98.03	98.90	98.92
F1 Score (%)	95.07	98.03	98.86	98.91

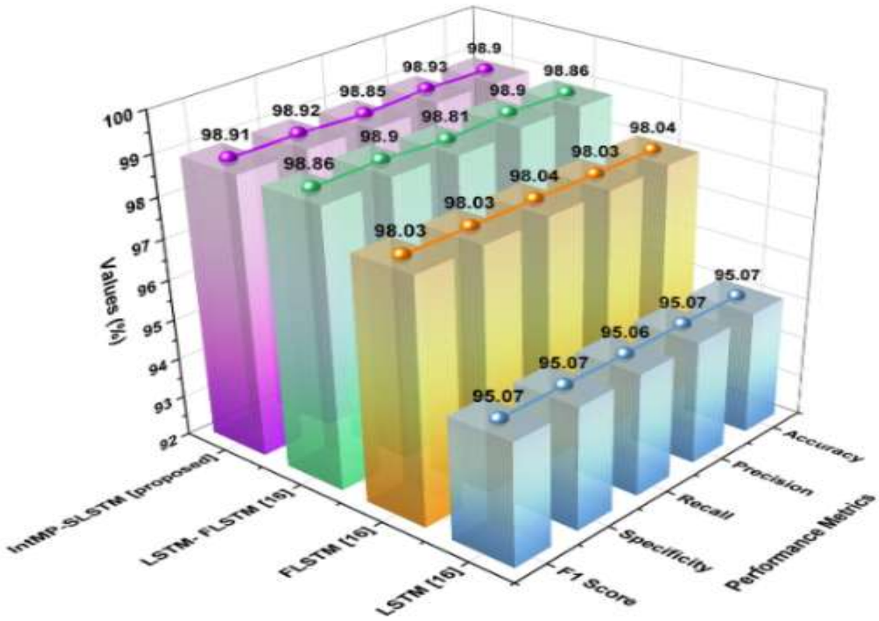

Figure 3: Performance Comparison of DL healthcare models

Performance evaluation using the proposed dataset: The existing models, including LSTM, FLSTM, and LSTM-FLSTM [16], were trained using the proposed smart healthcare dataset, which consists of heterogeneous clinical records, temporal patient data, and current time monitoring features. The proposed IntMP-SLSTM model achieves superior performance in terms of accuracy, precision, recall, specificity, and F1 score, demonstrating its enhanced prediction capability and computational efficiency. Table 3 shows that the proposed IntMP-SLSTM algorithm is more efficient than the other algorithms with an accuracy of 98.92, a precision of 98.94, a recall of 98.89, a specificity of 98.93, and an F1 score of 98.94. A performance comparison involving the accuracy, precision, recall, specificity, and F1 score values is provided in Figure 4.

Table 3: Comparison of Learning Algorithms Based on Metrics

Performance Metrics	LSTM	FLSTM	LSTM-FLSTM	IntMP-SLSTM (Proposed)
Accuracy (%)	96.12	98.12	98.89	98.92
Precision (%)	97.12	98.54	98.92	98.94
Recall (%)	98.54	98.45	98.83	98.89
Specificity (%)	96.34	98.15	98.93	98.93
F1 Score (%)	98.14	98.34	98.89	98.94

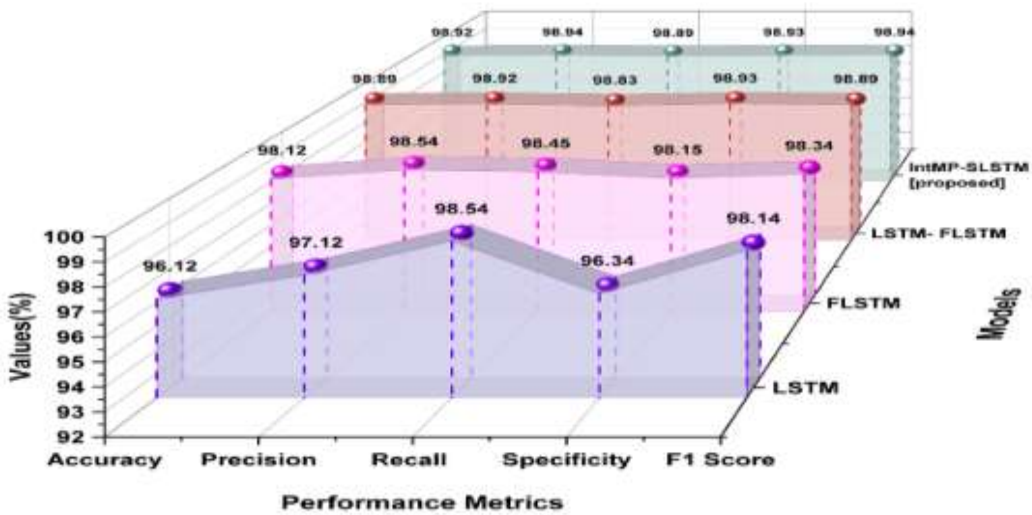

Figure 4: Assessment of ML Models for Predicting Healthcare Outcomes

For the cases where data involved is of high dimensionality and heterogeneity, the current methods like LSTM, FLSTM, and LSTM-FLSTM have inefficiencies and cannot model uncertainties and temporal dependencies at once. However, by including enhancements in feature interaction, adaptive learning procedures, and temporal analysis, the IntMP-SLSTM model overcomes all of these shortcomings and achieves higher accuracy.

5. Conclusion

The use of an integrated multi-phase feature extraction technique ensures that IntMP-SLSTM is able to mitigate the limits of both LSTM and FLSTM models. To begin with, Min-Max normalization is used for data preprocessing to ensure consistency in the scaling of data. The use of PCA to reduce dimensionality ensures that redundant data are excluded from the model so as to establish the most significant features. The LSTM network helps to stabilize the process of backpropagation and learn the temporal dependencies. Therefore, it achieves impressive accuracy when working on complicated medical datasets. The proposed algorithm achieves 98.92% accuracy, 98.94% precision, 98.89% recall, 98.93% specificity, and 98.94% F1-score across all performance metrics used in the experiments. Future research should focus on developing IoT-based intelligent health care apps employing continuous data streams and lightweight deep learning models that yield quicker insights. To reduce latency and expenses while maintaining accuracy, these solutions can be implemented on-device or on the edge.

References

1 Badr, N.G., Towards a Systemic Approach to Knowledge Integration in Learning Health Ecosystems: AI and DLT Perspectives. Proceedings Copyright, 332, p.339. https://doi.org/10.5220/0013657100004000
2 Harjula, E., Kumar, T., Islam, J., Ejaz, M. and Kovacevic, I., 2022. Distributed network and service architecture for future digital healthcare. Finnish Journal of eHealth and eWelfare, 14(1), pp.6-18. https://doi.org/10.23996/fjhw.111777
3 Almalawi, A., Khan, A.I., Alsolami, F., Abushark, Y.B. and Alfakeeh, A.S., 2023. Managing security of healthcare data for a modern healthcare system. Sensors, 23(7), p.3612. https://www.mdpi.com/1424-8220/23/7/3612#
4 Chow, W., Venkataraman, N., Oh, H.C., Ramanathan, S., Sridharan, S., Arish, S.M., Wong, K.C., Hay, K.K.X., Hoo, J.F., Tan, W.H.L. and Liew, C.J.Y., 2025. Building an artificial intelligence and digital ecosystem: a smart hospital's data-driven path to healthcare excellence. Singapore Medical Journal, 66(Suppl 1), pp.S75-S83. https://doi.org/10.4103/singaporemedj.SMJ-2025-066
5 Zeydan, E., Arslan, S.S. and Liyanage, M., 2024. Managing distributed machine learning lifecycle for healthcare data in the cloud. IEEe Access, 12, pp.115750-115774. https://doi.org/10.1109/ACCESS.2024.3443520
6 Adibi, S., Rajabifard, A., Shojaei, D. and Wickramasinghe, N., 2024. Enhancing healthcare through sensor-enabled digital twins in smart environments: A comprehensive analysis. Sensors, 24(9), p.2793. https://doi.org/10.3390/s24092793
7 Chen, Y., Lehmann, C.U. and Malin, B., 2024. Digital information ecosystems in modern care coordination and patient care pathways and the challenges and opportunities for AI solutions. Journal of medical Internet research, 26, p.e60258. https://doi.org/10.2196/60258
8 Ianculescu, M., Constantin, V.Ș., Gușatu, A.M., Petrache, M.C., Mihăescu, A.G., Bica, O. and Alexandru, A., 2025. Enhancing connected health ecosystems through IoT-enabled monitoring technologies: a case of the Monit4Healthy system. Sensors, 25(7), p.2292. https://www.mdpi.com/1424-8220/25/7/2292#
9 Mehmood, A., Arif, M. and Mehmood, F., 2025. Towards a Unified Digital Ecosystem: The Role of Platform Technology Convergence. Electronics, 14(24), p.4787. https://www.mdpi.com/2079-9292/14/24/4787#
10 Azbeg, K., Ouchetto, O. and Andaloussi, S.J., 2022. BlockMedCare: A healthcare system based on IoT, Blockchain and IPFS for data management security. Egyptian informatics journal, 23(2), pp.329-343. https://doi.org/10.1016/j.eij.2022.02.004
11 Voronova, O.V., Khnykina, T.S. and Karaptan, D.N., 2022. The digital ecosystem of a healthcare organisation. Technoeconomics, 2(2), pp.47-63. https://doi.org/10.57809/2022.2.2.5
12 Hampstead, P.J., 2024. Next-Generation Digital Ecosystems for AI Optimization Across Finance and Healthcare and Critical Infrastructure and Digital Marketing. International Journal of Research Publications in Engineering, Technology and Management (IJRPETM), 7(5), pp.11181-11188. https://doi.org/10.15662/IJRPETM.2024.0705007

13 Kumar A, H., Venkatram C, P., Daniel, D. and Joe IR, P., 2025. Decentralized digital health ecosystems: a unified architecture for AI-enhanced medical record management. Frontiers in Digital Health, 7, p.1685628. http://dx.doi.org/10.3389/fdgth.2025.1685628

14 Reali, G. and Femminella, M., 2024. Artificial Intelligence to Reshape the Healthcare Ecosystem. Future Internet, 16(9), p.343. https://www.mdpi.com/1999-5903/16/9/343#

15 Sakr, S. and Elgammal, A., 2016. Towards a comprehensive data analytics framework for smart healthcare services. Big Data Research, 4, pp.44-58. https://doi.org/10.1016/j.bdr.2016.05.002

16 Nancy, A.A., Ravindran, D., Raj Vincent, P.D., Srinivasan, K. and Gutierrez Reina, D., 2022. Iot-cloud-based smart healthcare monitoring system for heart disease prediction via deep learning. Electronics, 11(15), p.2292. https://doi.org/10.3390/electronics11152292