Journal of Information Systems Engineering and Management
2025, 10(36s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

IoT-Based Hybrid Fuzzy LSTM-RNN for Secure Disease Prediction in Healthcare EHRs

Ali Hadi Abdulwahid
Department of Control and Automation, Engineering Technical College, Southern Technical University, Basra, IRAQ,
Email: 1 dr.hajjiali@stu.edu.iq, dr.alhajji_ali@yahoo.com
ORCID ID : 0000-0002-3807-0771

ARTICLE INFO

Received: 18 Dec 2024

Revised: 10 Feb 2025

Accepted: 28 Feb 2025

ABSTRACT

The integration of Fuzzy Logic and Long Short-Term Memory Recurrent Neural Networks (LSTM-RNN) is employed to handle healthcare data, leading to a significant improvement in the prediction of unknown disease outcomes and notably enhancing reliability and accuracy. In this research, we propose an integrated IoT-based healthcare data management system with Fuzzy Long Short-Term Memory Recurrent Neural Network (IF-LSTM-RNN) for disease prediction and diagnosis.

Our approach includes gathering data via IoT devices, preprocessing through min-max normalization, and utilizing IF-LSTM-RNN for predictions. Clinical data is first collected and preprocessed, from which the health outcomes of patients are then predicted through IF-LSTM-RNN. The anticipated data is securely stored in Electronic Health Record (EHR) systems, making it more secure and providing accurate predictions.

To evaluate the performance of the proposed system, we applied it to a dataset comprising glucose concentrations from 12,612 data points of five monitored subjects with diabetes. The IF-LSTM-RNN outperformed traditional techniques (Random Forest, Support Vector Machine, and K-Nearest Neighbors) with an accuracy of 99.62%, precision of 98.71%, recall of 97.91%, an F1-score of 98.64%, sensitivity of 98.95%, and specificity of 97.88%. The IF-LSTM-RNN also achieved a correct classification rate of 99.37% with an execution time of approximately 1.28 seconds.

The results demonstrate that the proposed framework offers a viable solution for secure and effective healthcare data management and prediction in IoT environments.

Keywords: Internet of Things (IoT), Healthcare, Fuzzy Logic, LSTM-RNN, Data Management, Prediction Accuracy.

I. INTRODUCTION

IF-LSTM-RNN integrates fuzzy logic, Long Short-Term Memory (LSTM) and Recurrent Neural Network (RNN) to model uncertain data. Fuzzy logic for more nuanced decision-making, LSTM to remember information over time RNN for temporal dynamics in time series forecasting, and healthcare data forecast [1]. This work aims to design a reliable deep learning-based framework for data handling and prediction in the healthcare system. In particular, this paper highlights the utilization of Fog Computing and Cloud computing with Deep Learning methods for efficient, faster, accurate as well secure healthcare systems [2],[3]. The overarching objective is to address the major gaps in healthcare, which include real-time clinical monitoring for predictable patient outcomes; data handling, processing and management capabilities along with stringent security levels[4].

"RF, SVM, KNN " refers to different machine learning models or algorithms, and each acronym means: Random Forest(RF) It is an ensemble learning method that operates by constructing a multitude of decision trees during training and outputting the mode (for classification) or mean prediction (for regression) from multiple trees. Support Vector Machine (SVM) The unique thing about it is that the Decision tree follows a greedy-greedy approach to select the data (or column) for splitting. K-Nearest Neighbours (KNN) If you were to know more, Decision forests are an example of Instance-based learning and a simple ensemble decision tree algorithm for classification or regression[5].

Integration of IoT with healthcare systems has contributed to several developments but also incorporated some serious security issues and data handling complexities [5]. Fog computing relocates the computational resources, and facilitates lower latency while improving security for healthcare data. [7].

The purpose of this research was to design a more secure and effective framework for healthcare data management with a prediction approach by applying IoT (Internet of Things) and Integrated Fuzzy Long Short-Term Memory Recurrent Neural Networks (IF-LSTM-RNN). The fundamental objectives are to secure health data; increase the accuracy of clinical predictions and manage efficiently complex IoT-generated big data[8]-[12].

Traditional techniques for healthcare data management are not secure, or scalable and do not provide good accuracy in prediction. Using conventional methods does not give timely responses and full-proof security[13]. To close that gap, this research presents an innovative guideline based on IoT, DL and fuzzy logic for secure scalable precision healthcare data management[14].

Nowadays Most Innovative Technology is Cloud Computing (CC) which gives more Storage capacity for huge Data Generation by Internet of Things Devices [15]. Healthcare systems are moving to the cloud, for increased scalability and cost-effective dependable service across locations [16]. On the other hand, challenges related to data security and privacy accompany this transition of movement and have to be overcome before all the cloud-enabled healthcare benefits are quickly felt [17],[18]. IoT, fog computing and cloud act together to create a stable infrastructure for healthcare data handling as well as prediction having the ability when at first, critical information is handled efficiently and then securely too [19].

In healthcare, exact and quickly available results are essential, especially in time-critical conditions like cardiac diseases. However, the existing healthcare system that depends on manual monitoring of vital signs and data analysis frequently does not satisfy concerns requiring timely intervention [20]. The only way to perform that task is by using advanced DL techniques as they are well equipped to deal with a huge amount of data coming from IoT devices. One possible approach is to use deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), especially long short-term memory (LSTM) in time series prediction [21].

The proposed model consists of integrating IoT devices, and fog computing applications with cloud processing to provide effective data flow from collection through analysis and future prediction [22]. IoT devices collect data from patients, such as vital signs activity levels and environmental conditions [23]. This data is first preprocessed here, at the fog computing layer before it is sent to the cloud for processing; provided that this further analysis will have benefits [24]. On the cloud, prediction models (improved DL implementing fuzzy IF-LSTM-RNN) are built using data collected from patients to be able to predict health outcomes [25]. Results afterwards are saved to Electronic Health Record (EHR) systems, where healthcare specialists get detailed and reliable data about patients [26].

This framework covers a range of important gaps not addressed by current healthcare systems. Fog computing has come as a solution for low-latency and data secure processing due to the miniaturization of these devices, making it possible the need an instant (low latency) and secured large amount of data [15]. Second, the implementation of advanced DL methods such as IF-LSTM-RNN enhances predictability and robustness in health outcome prediction which provides a clear vision to healthcare experts for patient care [27]. Third, these technologies are integrated into a cohesive framework that addresses data collection and analytics to storage , thereby managing the complexity of IoT device-collected data in volume[28].

This paper addresses the primary research gap regarding a comprehensive and secure framework for healthcare data management & prediction systems which can exploit the strengths of IoT, fog computing and DL techniques [18],[19]. Although several previous studies have focused on each component of this integrated framework, there has been little research integrating these technologies into systematic health data management and prediction [29]. This paper addresses that gap by proposing a framework to boost the efficiency, accuracy and security of the healthcare system [21].

The performance of the IF-LSTM-RNN model in terms of accuracy and correct classification rate was better than all models developed on a small diabetes dataset containing 62 individuals. [30].

Journal of Information Systems Engineering and Management
2025, 10(36s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

This paper offers a novel model that incorporates IoT, fog computing and cloud computing mechanisms along with recent deep learning techniques for the improvement of healthcare data management and prediction. Such a framework with capabilities to handle the three major challenges of latency, security and data complexity can serve as an integrated approach for faster transactions that are both reliable & accurate—leading us toward achieving higher performance in healthcare systems. It has demonstrated that this framework can be implemented and evaluated successfully, transforming healthcare delivery with substantial benefits for the patients as well as healthcare providers .

This study contributes to solving these challenges and thus provides an important contribution to the Smart Healthcare System, providing a novel way for secure and reliable data management of healthcare data with prediction.

The paper is organized in the following manner: Section II reviews related literature; Section III describes the methodological approach to this research study; Section IV presents findings and discussion, and the conclusion with implications is provided in Section V.

II. RELATED WORKS

IoT combined with fog computing and deep learning technologies have further revolutionized healthcare. We summarize different strategies and systems developed to improve healthcare monitoring in this section.

We introduce a DL-based framework, that combines edge computing devices with deep learning methods and serial autoencoder-state tracking to construct an efficient real-time healthcare monitoring system[30]. The Fog Bus is used to provide support for energy efficiency, stability, delay performance execution time and the reliability of fog services in the proposed cloud computing system. It overcomes the scalability constraints of already existing IoT-owned infrastructure due to inherent security problems with cloud computing [31].

A scalable framework has been presented for secure, private and reliable sensing of medical data in online settings[32]. This research focuses on healthcare applications, specifically safeguarding medical data from attacks carried out through intermediates and intrusion attempts[33]. Using the Q-learning strategy, this technique processes patient records in layers and finally suggests that it is much less susceptible to subsequent attacks[34]. Experimental results and user feedback have confirmed the effectiveness of the system [35].

One significant technological stride setting the pace among them for modern healthcare solutions is the development and democratization of smart connected wearables[36],[37]. These provide context-specific collection of data (behavioral, psychological and physical health) but large volumes are also generated that may become impossible to manage in a way the decision-making process will be affected [34], [35].

A recent study presented emotion recognition research about elderly residents in nursing homes using deep-learning systems-based Internet of-Things[38],[39]: real-time audio-IoT system for speech recording and DL prediction of emotions as well as the advanced classification model with data normalization and augmentation techniques [36].

They designed a deep learning-based feature detector solution to malware detection for Android and IoT devices. The detector learns from multiple classifiers that evaluate app activity, and can be used in new malware efforts. This is followed by a two-stage test to assess the accuracy and efficiency of those capabilities: features are fed into an FCN-SoftMax (where this word entity represents Fully Connected Network activated with SoftMax), as well as reoccurring behaviors in attention layers determine if an app should be classified harmful [37],[38].

A 30-Minute Prediction of Blood Glucose via Cloud-Based Machine Learning Techniques Employment of cloud computing and Internet-of-Things to predict finger-stick blood glucose measurements adjunctive with continuous glucose monitoring data In particular, cascaded RNN-RBM DL models which combine recurrent neural networks (RNNs) with restricted Boltzmann machines (RBMs), are emphasized due to their better prediction results. The CGM devices are important for the monitoring and alert generation of abnormal BG levels that is essential to manage type-1 diabetes where delay in medication uptake may lead to severe health risks [39],[40].

Journal of Information Systems Engineering and Management
2025, 10(36s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

This research examines an in-depth analysis of IoT-based health care systems for some case studies to reveal the recent trends, opportunities and challenges that DL could experience regarding IoT-empowered healthcare sector[41],[42]; present few real-world used cases on this context evaluating them using recent existing models or if not generalized more GC techniques developed so far. It also describes the relationship of healthcare and IoT as an application[43],[44].

Proposed an innovative IoT-supported physiological signal tracking system to improve the efficacy of healthcare systems[45],[46]. It is a state-of-the-art deep neural network forecasting and evaluation method that ensures highly accurate results. It takes the help of National Instrument's myRIO for intelligent data collection and smart detector used to assess signals. The accuracy and reliability of the proposed Smart-Monitor system in predicting physiological signals was further validated by comparing experimental results [47],[48].

Introduction of a DL-based Internet of health paradigm to support Alzheimer's Disease individuals The DeTrAs framework works in three phases[49],[50]: an RNN act taking Account of sensual move information for Alzheimer's illness prediction, Anomaly twisting utilizing ensemble strategy and Emotion Recognition Utilizing a CNN dependent methodology. It presents a holistic framework that needs IoT-based support system for Alzheimer patients and also in [51].

In this indication, possible applications of tasks such as wearable health sensing devices with ML and DL techniques along-with IoT-based healthcare Organizations were reported for their feasibility to diagnose test identify track schedule COVID-19 patients. This review aggregation presents the findings of existing studies that proposed AI-based approaches to predict transmission rates for COVID-19, fight intensity as well payload predictive modeling [52].

Machine Learning Techniques for Proper Diagnosis and Monitoring with an IoT Supported Structure Called E-Healthcare Monitoring System (EHMS) The system streamlines connections, monitoring and decision-making for in-patient as well out-patient health management. The server collects accumulated data, while handling the new issues of managing IoT apps and devices: The admin Server modify mug [58][59].

A smart e-healthcare monitoring system with the state of art IoT and ML tools for better patient care is implemented in automatic wearable sensors which perform real-time health data collection alerts to ensure PR diagnosis leading to efficient overall improvement of patients [61],[62].

This paper presents a long-term short memory-recurrent neural network (LSTM-RNN) based pattern recognition scheme for recognizing brain waves patterns to be applied with Internet of Brain-Controlled Things (IoBCT), therefore an intelligent and reliable categorized motor imagery classification mechanism that can serve special control functionalities needed by the certain categories of assistive technologies [63],[64].

IoT has also paved the way for Disease prediction system using machine learning, A preeminent Gift is awaited disease outcomes that have been predicted based on datasets coming from IoT and Bragged Machine Learning algorithms on them gives an Alarm of Prediction against starting Diseases [65].

Applicability in healthcare the algorithm was designed to be able-scale (fairly) and trained regression models on distributed data sources using a federated learning paradigm, which guarantees security/privacy [66].

Risks of dealing with uncertainty and interpretability In deep learning models to detect COIVD-19 also reveal the trustworthiness and accuracy assessment for diagnostic systems [67].

Accessible X-ray understanding on deep learning for diagnosing pulmonary diseases and COVID-19 recommends the need to interpretability when integrated with other AI models in health service research [68];

The application of deep learning also in other types routinely used for clinical practice, such as the use convolutional neural networks (CNNs), may be useful method decreasing burden on radiologists analyzing CT images of patients with COVID-19 [69].

The usage of AI to improve the accuracy of diagnosis was further hinted by a CAD system that employed ML techniques to automatically detect and classify COVID-19 in nano CT lung pictures [69].

Journal of Information Systems Engineering and Management
2025, 10(36s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

III. PROPOSED METHODOLOGY

This section describes the methodology framework for efficient healthcare data management and prediction through integrated FLSTM RNN (IF-LSTM-RNN). The methodology was created to respond the complexity of healthcare data and in order to processing temporal dependencies, uncertainties that are characteristic for medical domain as well real-time decision-making. The process is divided into three main parts: data pre-processing, model architecture and training/evaluation procedures[70].

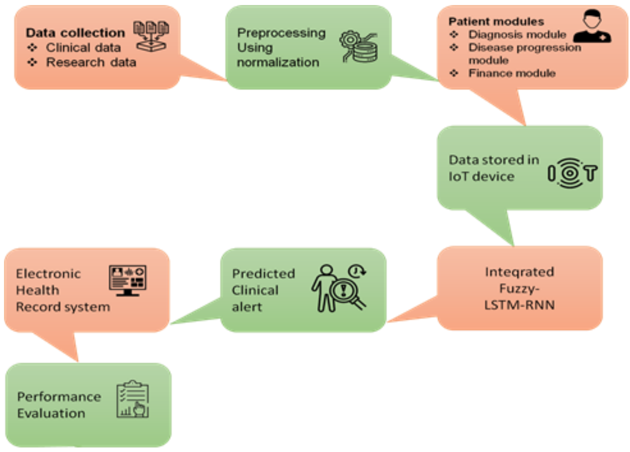

Fig. 1. Framework of This Research

Figure 1 illustrates the research framework and process for data collection, preprocessing, and model training /evaluation to predict healthcare outcomes. This constitutes our research framework which indicates the steps carried out sequentially were used to ready and model data while creating IF-LSTM-RNN.

A. *Preprocessing*

The study includes healthcare data from 62 people with diabetes, who were monitored over 67 days. The most important part before using and getting into the model is Preprocessing this helps in cleaning of data, and readying it so that we can further use the IF-LSTM-RNN Model for Analysis and prediction[71],[72].

1) *Data Normalization*

Normalization was performed to normalize the various measurement scales of the dataset. The mean Normalization scaled the data at 0 to 1, because it rescaled them which mitigates the outlier effect and gives all features equal weight in learning while training a model[73],[74]. The normalization formula is shown in the following expression:

$$D_{\text{nor}} = \frac{D_d - D_{\min}}{D_{\max} - D_{\min}} \times (new_{\max} - new_{\min}) + new_{\min} \tag{1}$$

Where:

D_{nor}: *The normalized data.*

D_d: *The original data.*

D_{min} *and* D_{max}: *The minimum and maximum values of the dataset.*

$new_{min}=0$ *and* $new_{max}=1$: *The desired range for normalization.*

Thus, the data are normalized into a fixed scale which makes learning by the model more efficient.

2) *Data Splitting*

The data offered was randomized and divided into 80% as a training set, while the rest (20%) acted like a test dataset. This split provides a model to be trained on large data and at the same time uses a small size of remaining

Journal of Information Systems Engineering and Management
2025, 10(36s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

test data for checking generalization[75],[76]. We have not chosen any set specifically; each represents the overall distribution of data and hence a random split.

3) Handling Missing Data

These methods were employed to deal with missing values; they correctly handle missing values by imputation based on other data points in the dataset. This will keep the dataset complete using interpolation and reduce model bias or inaccuracy in predictions.

B. Integrated Fuzzy LSTM-RNN (IF-LSTM-RNN)

The novelty in the proposed IF-LSTM-RNN model stems from a combination of fuzzy logic and LSTM-RNNs, enabling handling healthcare data intricacies better to handle temporal dependencies as well as uncertainties; thus overall enhancing predictive certainty[77],[78].

1) Model Architecture:

This paper designs a new RNN architecture named IF-LSTM-RNN, which has multiple layers to process sequential input data and predict features.

a) Input Layer: The first layer takes preprocessed data such as glucose concentration and other appropriate features. And this data is fed into the LSTM layers where temporal patterns are analyzed.

b) LSTM Layers**:** The following equations are the internal operations that happens in LSTM cells, which is a variant of RNN. These relationships control the amount of information that is allowed to flow through by three gates: forget gate, input gate and output gate.

- *Forget Gate Equation:*

$$etg = \sigma(Z_g X_t + Y_g h_{t-1} + \xi_g) \qquad (2)$$

Where:

etg : represents the forget gate, which determines how much of the previous cell state should be overlooked or retained.

σ : is the sigmoid activation function, which restricts the output between 0 and 1.

Z_g and Y_g : are the weight matrices associated with the input X_t and the previous hidden state h_{t-1}, respectively.

ξ_g : is the bias vector.

- *Input Gate Equation:*

$$etk = \sigma(Z_k X_t + Y_k h_{t-1} + \xi_k) \qquad (3)$$

Where:

etk: input gate to control updates of the cell state

- *Candidate Cell State Equation:*

$$mtc = tanh\,(Z_m X_t + Y_m h_{t-1} + \xi_m) \qquad (4)$$

Where:

mtc : represents the candidate cell state, which are the potential new values that could be added to the cell state.

tanh :is the hyperbolic tangent function, producing values between -1 and 1 .

Z_m and Y_m are the weight matrices for the inputs and the previous hidden state, and ξ_m is the bias vector.

- *Cell State Update Equation:*

$$c_t = etg * c_{t-1} + etk * mtc \qquad (5)$$

Where:

ct : represents the new cell state at time t.

c_{t-1} : is the previous cell state.

etg controls how much of the previous cell state is retained.

etk and mtc control how much new information is added.

- *Output Gate Equation:*

$$eto = \sigma(Z_o X_t + Y_o h_{t-1} + \xi_o) \quad (6)$$

Where:

eto : represents the output gate, which determines how much of the cell state is passed to the hidden state ht.

- *Hidden State Equation:*

$$h_t = eto * \tanh(c_t) \quad (7)$$

Where:

ht :represents the new hidden state, which is the output of the cell at time t .

eto :controls how much of the new cell state ct is passed to the hidden state.

c) Fuzzy Logic Integration: We included a segment dedicated to Fuzzy logic that serves as an interpretability overlay due to inherent imprecision in healthcare data. Data is propagated through fuzzy membership functions which map inputs to various class labels, in the domain, reflecting varying magnitudes of uncertainty. These fuzzy values make sense to the LSTM layers, where they are accustomed to making predictions[79],[80].

d) Fuzzy Hyperbox Creation: In a fuzzy logic system hyperboxes are well recorded according to the below-mentioned equations.

$$C_j(Y) = \min_{k=1}^{o}(\min([1 - g(Y_k^U - X_k, \gamma_k)], [1 - g(W_k - Y_k^m, \gamma_k)])) \quad (8)$$

$$g(\lambda, \gamma) = \begin{cases} 1, & if\ \lambda\gamma > 1 \\ \lambda\gamma, & if\ 0 \leq \lambda\gamma \leq 1 \\ 0, & if\ \lambda\gamma < 0 \end{cases} \quad (9)$$

Where:

$C_j(Y)$ *: Activation function for hyperboxes.*

Y *: Input sample.*

W_k *and* X_k *: Weight matrices.*

γ_k *: Sensitivity variable controlling the activation gradient.*

e) Output Layer**:** the last output layer shows us the predicted health by comparing it with the true value after calculating model accuracy. output is meant to be usable and actionable for healthcare professionals making decisions. The function is defined as:

$$d_l = \max_{j=1}^{n} C_j \cdot v_{jl} \quad (10)$$

Where:

n *: Number of hyperboxes in the hidden units*

d_l *: Transfer function for the class node.*

C_j*: Membership grade of the hyperboxes.*

v_{jl} *: Binary weight connecting hyperboxes to class nodes.*

2) Training and Optimization

The IF-LSTM-RNN model was trained with a learning rate of 0.001, batch size=32 and training for no more than 100 epochs. Binary cross-entropy was used as the loss function, and an adaptive learning rate optimizer is employed to scale down the size of weight adjustments for convergence on large-scale datasets without overshooting a good solution[80].

Journal of Information Systems Engineering and Management
2025, 10(36s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

3) *Cross-Validation and Overfitting Prevention*

Divide the dataset into subsets using k-fold cross-validation to ensure model robustness. Implement regularization techniques like dropout to prevent overfitting.

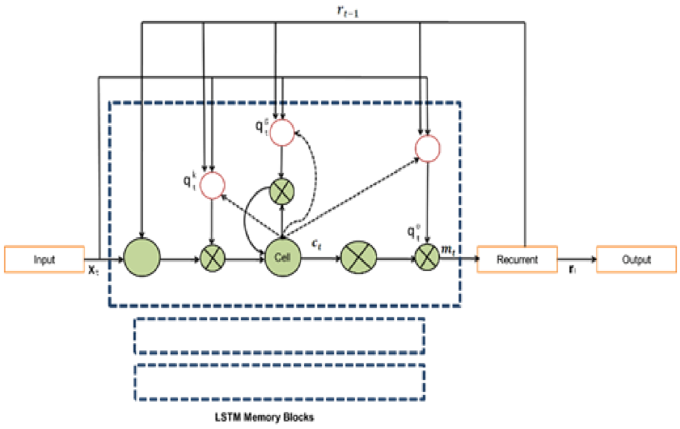

Fig. 2. Framework of IF-LSTM-RNN

This section explains the methodological framework of effective health data management as well as prediction using an Integrated Fuzzy Long Short-Term Memory Recurrent Neural Network (IF-LSTM-RNN). Utilizing LSTM holding a sequential mechanism, the fuzzy layer is developed so that it can cater for uncertainties and imprecise input data which are very common in healthcare applications as seen in Framework Figure 2. The network input is processed and memory states are updated through LSTM blocks, which can then take in output from one block as the state variable of another at a later time instant. The IF-LSTM-RNN incorporates fuzzy logic to model complex patterns in healthcare data, leading to more reliable predictions as well as superior patient outcomes and decision-making.

IV. RESULTS AND DISCUSSION

This section presents a deep analysis of our proposed IF-LSTMRNN approach. By way of experiment, a dataset of 62 diabetes cases (18 female and 44 male) was fed into MATLAB over an average 67 days, and then a total of 12,612 classified concentration readings, as well as four other variables from the record were obtained. To illustrate the validity of our approach, we compared it with three existing methods: Random Forest (RF), Support Vector Machine (SVM) and K-Nearest Neighbors (KNN).

This setup consists of data preprocessing, model building, training phases, and data for training splits. It normalized the data by min-max normalization so that all variables were in a standardized range; this helped to increase model performance. The data was split into training and testing sets, 80% vs. 20 %. The parameters of the training process for the IF-LSTM-RNN algorithm including a learning rate of 0.001, batch size of 32 and number epochs of 100 were set respectively.

The evaluation metrics for the study are accuracy, precision, sensitivity, F1-Score and specificity which are used to measure the correctness of a model (accuracy), positive instance detection(positive) and negative class identification.

The equation (11) is used to determine the accuracy.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (11)$$

The precision is calculated using equation (12).

Journal of Information Systems Engineering and Management
2025, 10(36s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

$$precision = \frac{TP}{TP + FP} \quad (12)$$

The sensitivity is assessed in equation (13).

$$sensitivity = \frac{TP}{TP + FN} \quad (13)$$

The recall is calculated using the equation (14).

$$Recall = \frac{FN}{FN + TP} \quad (14)$$

The f1-score is calculated using the equation (15).

$$F1 - score = \frac{(precision) \times (recall) \times 2}{precision + recall} \quad (15)$$

The specificity is calculated using the equation (16).

$$specificity = \frac{TN}{TN + FP} \quad (16)$$

These metrics were selected based on importance in evaluating the model for processing imbalanced healthcare data because false negatives, as well as false positives, have a heavy impact.

TABLE I CLASSIFICATION RATES AND EXECUTION TIMES OF THE PROPOSED METHOD AND EXISTING METHODS

Methods	Correct classification rate (%)	Incorrect classification rate (%)	Execution time (s)
RF [19]	97.6	2.51	2.81
SVM [20]	98.46	1.336	2.06
KNN [20]	96.82	7.39	3.71
IF-LSTM-RNN [proposed]	**99.37**	**0.35**	**1.28**

Classification Rates and Execution Times for the Proposed Methods vs. Existing Methods As shown in Table 1, the IF-LSTM-RNN method obtains the highest correct classification rate (99.37%) and lowest incorrect classification rate (0.35%). It is also the quickest in terms of execution time at 1.28 seconds showing how efficient it can be.

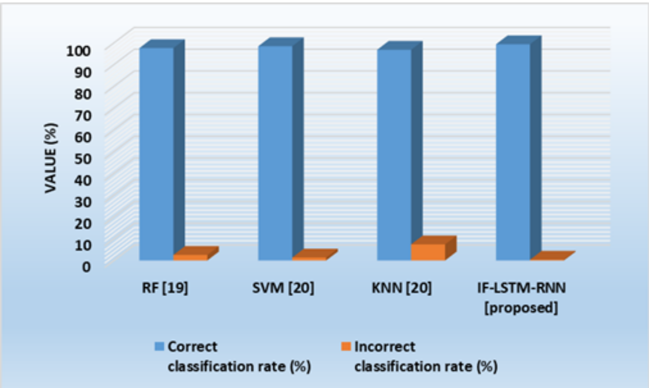

Figure 3: Correct and Incorrect Classification Rates.

Journal of Information Systems Engineering and Management
2025, 10(36s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Figure 3 shows the correct and incorrect classification rates for the four methods. The highest rate of correct classification is attained by the IF-LSTM-RNN method with a result of 99.37% and the lowest incorrect classification of 0.35%. On the other hand, SVM achieves 98.46% in correct classification and 1.336% in incorrect classification. Moreover, RF attains 97.6% in correct classification and 2.51% in the incorrect classification while for KNN, it is 96.82% in correct classification and 7.39% in the incorrect classification. This indicates the better accuracy and reliability associated with the IF-LSTM-RNN method.

Figure 4: Execution Times.

Figure 4 depicts the execution times for each method. The IF-LSTM-RNN method is the most effective with an execution time of 1.28 seconds. On the contrary, RF is 2.81 seconds, SVM 2.06 seconds, and KNN is 3.71 seconds. This test indicates the shorter execution time associated with the IF-LSTM-RNN method attributable to its computational efficiency, which is critical in real-time applications

TABLE II Comparative findings

Metrics	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Sensitivity (%)	Specificity (%)
RF [19]	97.84	94.63	96.92	92.86	94.92	93.85
SVM [20]	98.79	97.36	98.44	94.83	96.87	96.77
KNN [20]	95.46	91.68	94.69	90.58	93.96	92.84
IF-LSTM-RNN [proposed]	**99.62**	**98.71**	**99.94**	**98.64**	**98.95**	**97.88**

Table II compares the performance metrics of different models (RF, SVM, KNN and IF-LSTM-RNN); including accuracy; precision; recall; F1-score sensitivity and specificity. It can be observed that the IF-LSTM-RNN method always performs much better than others, demonstrating superior precision in each aspect accordingly and thus substantiating its strong performance in classifying healthcare data correctly.

Journal of Information Systems Engineering and Management
2025, 10(36s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

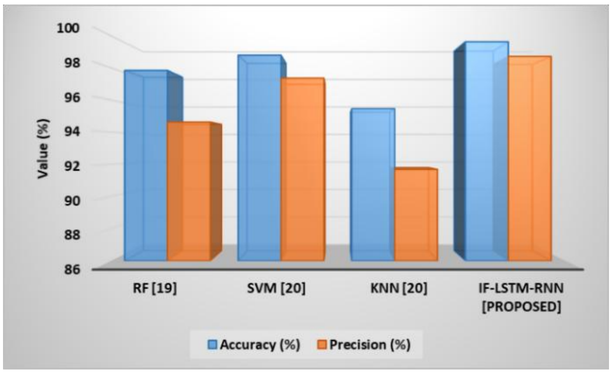

Figure 5 Results of precision and accuracy metrics

Figure 5 depicts accuracy and precision metrics among the models evaluated. The proposed IF-LSTM-RNN model shows the best performance in accuracy (99.62%) and precision (98.71%), significantly better than RF, SVM and KNN This demonstrates the model well at predicting which makes it highly dependable to be utilized in precision-critical health application.

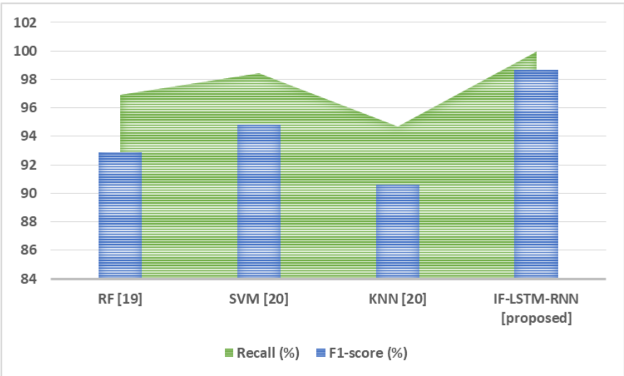

Figure 6 Findings of f1-score and recall metrics

In Figure 6 the F1-score and recall metrics for each machine-learning model are presented. The F1-score of (98.64%) and recall rate of (99.94%) for the IF-LSTM-RNN model verify that it well balance between precision and recall; It shows the power of this model to pinpoint positive instances accurately in places where high precision and recall are vital.

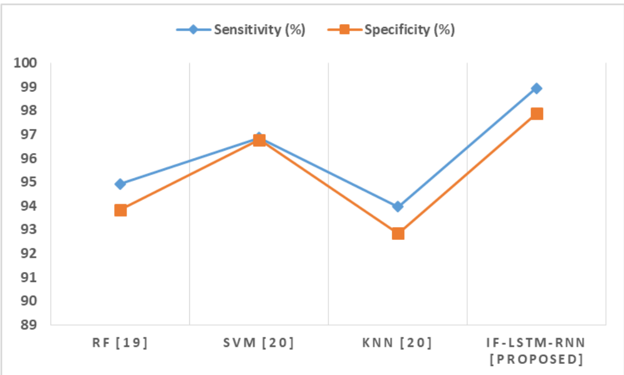

Figure 7 Results of sensitivity and specificity metrics

Figure 7 compares the sensitivity and specificity of models the IF-LSTM-RNN model achieved a tangible increase in higher accuracy at both levels which are up around to nearly perfect values sensitivity (98.95%) and specificity (97.88%). Thereby making it perfect for settings such as medical diagnostics where accuracy and proof are critical.

This section presents a detailed comparison of different machine learning models such as RF, SVM, KNN and the proposed IF-LSTM-RNN. The results have shown that the proposed IF-LSTM-RNN model is the top performer among all algorithms, across accuracy, precision-recall F1-Score, Sensitivity and Specificity. One reason for this superior performance is that the model exploits a sophisticated architecture, which overcomes key limitations of traditional approaches. This development led to the inevitable advancement of predictive analytics, thereby reducing time and offering an accurate model for a large number of real-life medical applications.

V. CONCLUSION

This paper presents for the first time a novel IF-LSTM-RNN model to predict healthcare data, by modelling temporal dependencies and uncertainties; thereby providing an accuracy performance benchmark in comparison with existing models regarding clinical decision support systems.

The IF-LSTM-RNN model had a higher average accuracy of 99.62%, in comparison to conventional machine learning models, when applied to healthcare tasks. It outperformed Random Forest, Support Vector Machine and k-Nearest Neighbors. It also produced high precision, recall and F1-Score which means it does a good job of reducing false positives/ negatives.

Computational time rates of the proposed IF-LSTM-RNN (1.28 s) were significantly decreased in terms when comparing with traditional models ranging from 2.81–3.71 seconds, to be suitable for real-time healthcare applications since must make prompt clinical interpretation decisions. This made our tool more robust in processing complex and noisy data (due to integration of fuzzy logic with LSTM-RNN that makes a dependable source for clinical purpose.

The study is constrained by a small size and simulation data not the real world. Future research should extend this work to cover: the maximum increase of the dataset, handling real-world data and exploring deeper regularization techniques.

The IF-LSTM-RNN model represents a substantial leap in healthcare data prediction by incorporating fuzzy logic with linear temporal-step-by-sequential outreaches using the LSTM RNN, releasing an improved and sophisticated approach to reshape clinical decision-making benefiting enhanced patient outcomes and health services.

ACKNOWLEDGMENT

We extend our sincere thanks and gratitude to Dr. Jinan Abdel-Ali Abdel-Razzaq for her valuable guidance and support throughout the course of this research. Her experience and insights were crucial to the success of the study. Thank you, for your continued support.

REFERENCES

[1] F. Bonassi, M. Farina, J. Xie, and R. Scattolini, "On recurrent neural networks for learning-based control: Recent results and ideas for future developments," J. Process. Control., vol. 114, pp. 92–104, 2022. doi: 10.1016/j.jprocont.2022.04.011.

[2] Y. G. Zhang, J. Tang, Z. Y. He, J. Tan, and C. Li, "A novel displacement prediction method using gated recurrent unit model with time series analysis in the Erdaohe landslide," Nat. Hazards, vol. 105, pp. 783–813, 2021. doi: 10.1007/s11069-020-04337-6.

[3] D. Tang, W. Rong, S. Qin, J. Yang, and Z. Xiong, "A n-gated recurrent unit with review for answer selection," Neurocomputing, vol. 371, pp. 158–165, 2020. doi: 10.1016/j.neucom.2019.09.007.

[4] P. K. Shukla, S. Stalin, S. Joshi, P. K. Shukla, and P. K. Pareek, "Optimization assisted bidirectional gated recurrent unit for healthcare monitoring system in big-data," Appl. Soft Comput., vol. 138, p. 110178, 2023. doi: 10.1016/j.asoc.2023.110178.

[5] U. Rehman, A. K. Malik, B. Raza, and W. Ali, "A hybrid CNN-LSTM model for improving accuracy of movie reviews sentiment analysis," Multimed. Tools Appl., vol. 78, pp. 26597–26613, 2019. doi: 10.1007/s11042-019-07788-7.

[6] S. Ghimire, R. C. Deo, H. Wang, M. S. Al-Musaylh, D. Casillas-Pérez, and S. Salcedo-Sanz, "Stacked LSTM sequence-to-sequence autoencoder with feature selection for daily solar radiation prediction: A review and new modeling results," Energies, vol. 15, p. 1061, 2022. doi: 10.3390/en15031061.
[7] W. Li, L. Zhu, Y. Shi, K. Guo, and E. Cambria, "User reviews: Sentiment analysis using lexicon integrated two-channel CNN–LSTM family models," Appl. Soft Comput., vol. 94, p. 106435, 2020. doi: 10.1016/j.asoc.2020.106435.
[8] V. A. Sindagi and V. M. Patel, "A survey of recent advances in cnn-based single image crowd counting and density estimation," Pattern Recognit. Lett., vol. 107, pp. 3–16, 2018. doi: 10.1016/j.patrec.2017.07.007.
[9] Y. Liu, L. Wang, T. Shi, and J. Li, "Detection of spam reviews through a hierarchical attention architecture with N-gram CNN and Bi-LSTM," Inf. Syst., vol. 103, p. 101865, 2022. doi: 10.1016/j.is.2021.101865.
[10] P. Bhuvaneshwari, A. N. Rao, Y. H. Robinson, and M. Thippeswamy, "Sentiment analysis for user reviews using Bi-LSTM self-attention-based CNN model," Multimed. Tools Appl., vol. 81, pp. 12405–12419, 2022. doi: 10.1007/s11042-022-12410-4.
[11] B. Cao, W. Dong, Z. Lv, Y. Gu, S. Singh, and P. Kumar, "Hybrid Microgrid Many-Objective Sizing Optimization With Fuzzy Decision," IEEE Trans. Fuzzy Syst., vol. 28, pp. 2702-2710, 2020. doi:10.1109/TFUZZ.2020.3026140
[12] V. Ravi, T. D. Pham, and M. Alazab, "Deep Learning-Based Network Intrusion Detection System for Internet of Medical Things," IEEE Internet Things Mag., vol. 6, pp. 50-54, 2023. doi:10.1109/IOTM.001.2300021
[13] S. Abbas, G. A. Sampedro, M. Abisado, A. Almadhor, I. Yousaf, and S.-P. Hong, "Harris-Hawk-Optimization-Based Deep Recurrent Neural Network for Securing the Internet of Medical Things," Electronics, vol. 12, p. 2612, 2023. doi: 10.3390/electronics12112612.
[14] Khan, N. Moustafa, I. Razzak, M. Tanveer, D. Pi, and B. S. Ali, "XSRU-IoMT: Explainable simple recurrent units for threat detection in Internet of Medical Things networks," Future Gener. Comput. Syst., vol. 127, pp. 181–193, 2022. doi: 10.1016/j.future.2021.07.026.
[15] Si-Ahmed, M. A. Al-Garadi, and N. Boustia, "Survey of Machine Learning based intrusion detection methods for Internet of Medical Things," Appl. Soft Comput., vol. 140, p. 110227, 2023. doi: 10.1016/j.asoc.2023.110227.
[16] M. Al-Hawawreh and M. S. Hossain, "A privacy-aware framework for detecting cyber-attacks on internet of medical things systems using data fusion and quantum deep learning," Inf. Fusion, vol. 99, p. 101889, 2023. doi: 10.1016/j.inffus.2023.101889.
[17] S. P. RM, P. K. R. Maddikunta, M. Parimala, S. Koppu, T. R. Gadekallu, C. L. Chowdhary, and M. Alazab, "An effective feature engineering for DNN using hybrid PCA-GWO for intrusion detection in IoMT architecture," Comput. Commun., vol. 160, pp. 139–149, 2020. doi: 10.1016/j.comcom.2020.06.019.
[18] S. Al-rimy, M. A. Maarof, and S. Z. M. Shaid, "Crypto-ransomware early detection model using novel incremental bagging with enhanced semi-random subspace selection," Future Gener. Comput. Syst., vol. 101, pp. 476–491, 2019. doi: 10.1016/j.future.2019.06.002.
[19] A. Rghioui, J. Lloret, S. Sendra, and A. Oumnad, "A smart architecture for diabetic patient monitoring using ML algorithms," Healthcare, vol. 8, no. 3, p. 348, Sep. 2020. doi: 10.3390/healthcare8030348.
[20] B. Godi, S. Viswanadham, A. S. Muttipati, O. P. Samantray, and S. R. Gadiraju, "E-healthcare monitoring system using IoT with ML approaches," in 2020 International Conference on Computer Science, Engineering and Applications (ICCSEA), Mar. 2020, pp. 1-5. doi: 10.1109/ICCSEA49143.2020.9132937
[21] R. Alizadehsani, M. Roshanzamir, N. H. Izadi, R. Gravina, H. D. Kabir, H. Alinejad-Rokny, A. Khosravi, U. R. Acharya, and S. Nahavandi, "Swarm intelligence in internet of medical things: A review," Sensors, vol. 23, p. 1466, 2023. doi: 10.3390/s23031466.
[22] R. Chaganti, M. Azrour, R. Vinayakumar, V. Naga, and B. Bhushan, "A Particle Swarm Optimization and Deep Learning Approach for Intrusion Detection System in Internet of Medical Things," Sustainability, vol. 14, p. 12828, 2022. doi: 10.3390/su141912828.
[23] P. Kumar, G. P. Gupta, and R. Tripathi, "An ensemble learning and fog-cloud architecture-driven cyber-attack detection framework for IoMT networks," Comput. Commun., vol. 166, pp. 110–124, 2021. doi: 10.1016/j.comcom.2020.11.011.

[24] Ghubaish, T. Salman, M. Zolanvari, D. Unal, A. Al-Ali, and R. Jain, "Recent advances in the internet-of-medical-things (IoMT) systems security," IEEE Internet Things J., vol. 8, pp. 8707-8718, 2020. doi:10.1109/JIOT.2020.3045653

[25] Y. Otoum, Y. Wan, and A. Nayak, "Federated transfer learning-based IDS for the internet of medical things (IoMT)," in Proc. 2021 IEEE Globecom Workshops (GC Wkshps), Madrid, Spain, Dec. 2021, pp. 1-6. doi:10.1109/GCWkshps52748.2021.9682118

[26] M. Kumar, A. Kumar, S. Verma, P. Bhattacharya, D. Ghimire, S.-h. Kim, and A. S. Hosen, "Healthcare Internet of Things (H-IoT): Current Trends, Future Prospects, Applications, Challenges, and Security Issues," Electronics, vol. 12, p. 2050, 2023. doi:10.3390/electronics12092050

[27] Ullah and Q. H. Mahmoud, "An Anomaly Detection Model for IoT Networks based on Flow and Flag Features using a Feed-Forward Neural Network," in Proc. 2022 IEEE 19th Annu. Consum. Commun. Netw. Conf. (CCNC), Las Vegas, NV, USA, Jan. 2022, pp. 363-368. doi :10.1109/CCNC49033.2022.9700597

[28] P. Chen, H. Liu, R. Xin, T. Carval, J. Zhao, Y. Xia, and Z. Zhao, "Effectively Detecting Operational Anomalies In Large-Scale IoT Data Infrastructures By Using A GAN-Based Predictive Model," Comput. J., vol. 65, pp. 2909-2925, 2022. doi :10.1093/comjnl/bxac085

[29] Li, X. Zhou, Z. Ning, X. Guan, and K.-F. C. Yiu, "Dynamic event-triggered security control for networked control systems with cyber-attacks: A model predictive control approach," Inf. Sci., vol. 612, pp. 384-398, 2022. doi :10.1016/j.ins.2022.08.093

[30] K. Reddy and P. Kumar, "Cloud computing security issues and challenges in healthcare: A survey," Healthcare, vol. 8, no. 3, p. 215, 2020. doi: 10.3390/healthcare8030215.

[31] A. Rghioui, J. Lloret, S. Sendra, and A. Oumnad, "A smart architecture for diabetic patient monitoring using ML algorithms," Healthcare, vol. 8, no. 3, p. 348, Sep. 2020. doi.: 10.3390/healthcare8030348

[32] X. Wang and X. Zhang, "IoT-based wearable devices for health monitoring: A review," Sensors, vol. 22, no. 6, p. 2152, 2022. doi: 10.3390/s22062152.

[33] M. Aazam and E. N. Huh, "Fog computing for healthcare: A comprehensive review and research directions," Journal of Cloud Computing: Advances, Systems and Applications, vol. 9, no. 1, p. 15, 2020. doi: 10.1186/s13677-020-00198-3.

[34] M. S. Z. Almahairah, S. Goswami, P. N. Karri, I. M. Krishna, M. Aarif and G. Manoharan, "Application of Internet of Things and Big Data in Improving Supply Chain Financial Risk Management System," *2023 10th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON)*, Gautam Buddha Nagar, India, 2023, pp. 276-280, doi: 10.1109/UPCON59197.2023.10434460.

[35] S. Miao and Z. Zheng, "Electronic Health Records (EHRs) and their integration with cloud computing: A survey," Healthcare, vol. 10, no. 1, p. 120, 2022. doi: 10.3390/healthcare10010120.

[36] H. Asgharzadeh, et al., "Anomaly-based intrusion detection system in the Internet of Things using a convolutional neural network and multi-objective enhanced Capuchin Search Algorithm," Journal of Parallel and Distributed Computing, vol. 175, pp. 1–21, 2023, doi: 10.1016/j.jpdc.2022.12.009.

[37] L. Das, R. Salman, S. Sabeer, S. K. Ansari, M. Aarif and A. Rana, "Customer Retention Using Machine Learning," *2023 10th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON)*, Gautam Buddha Nagar, India, 2023, pp. 221-225, doi: 10.1109/UPCON59197.2023.10434812.

[38] A. V. Hanafi, et al., "Intrusion detection in Internet of Things using improved binary golden jackal optimization algorithm and LSTM," Cluster Computing, pp. 1–18, 2023, doi: 10.1007/s10586-023-04102-x.

[39] X. Wu, S. Wang, Y. Li, and L. Zhuang, "Secure and reliable data sensing framework for IoT-enabled healthcare systems," IEEE Internet of Things Journal, vol. 9, no. 12, pp. 8873-8885, Dec. 2022, doi: 10.1109/JIOT.2021.3139327

[40] S. T. Nugraha, A. F. Prasetyo, and A. H. Mulyawan, "Smart wearable device technology for health monitoring and its challenges in data management: A review," IEEE Access, vol. 9, pp. 115256-115267, Aug. 2021, doi: 10.1109/ACCESS.2021.3104820.

[41] M. Sivakumar and S. R. Uyyala, "Aspect-based sentiment analysis of mobile phone reviews using LSTM and fuzzy logic," Int. J. Data Sci. Anal., vol. 12, pp. 355-367, 2021. doi :10.1007/s41060-021-00277-x

Journal of Information Systems Engineering and Management
2025, 10(36s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

[42] Y. Yu, X. Si, C. Hu, and J. Zhang, "A review of recurrent neural networks: LSTM cells and network architectures," Neural Comput., vol. 31, pp. 1235-1270, 2019. doi :10.1162/neco_a_01199
[43] U. Rehman, A. K. Malik, B. Raza, and W. Ali, "A hybrid CNN-LSTM model for improving accuracy of movie reviews sentiment analysis," Multimed. Tools Appl., vol. 78, pp. 26597-26613, 2019. doi :10.1007/s11042-019-07788-7
[44] N. Hossain, M. R. Bhuiyan, Z. N. Tumpa, and S. A. Hossain, "Sentiment Analysis of Restaurant Reviews using Combined CNN-LSTM," in Proc. 2020 11th Int. Conf. Comput., Commun. Netw. Technol. (ICCCNT), Kharagpur, India, Jul. 2020, pp. 1-5. doi :10.1109/ICCCNT49239.2020.9225328
[45] V. Kumar, B. Pant, G. Elkady, C. Kaur, J. Suhashini and S. M. Hassen, "Examining the Role of Block Chain to Secure Identity in IOT for Industry 4.0," *2022 5th International Conference on Contemporary Computing and Informatics (IC3I)*, Uttar Pradesh, India, 2022, pp. 256-259, doi: 10.1109/IC3I56241.2022.10072516.
[46] M. Amin, D. Shehwar, A. Ullah, T. Guarda, T. A. Tanveer, and S. Anwar, "A DL system for health care IoT and smartphone malware detection," Neural Computing and Applications, pp. 1-12, 2020, doi: 10.1007/s00521-020-05429-x.
[47] S. Ghimire, R. C. Deo, H. Wang, M. S. Al-Musaylh, D. Casillas-Pérez, and S. Salcedo-Sanz, "Stacked LSTM sequence-to-sequence autoencoder with feature selection for daily solar radiation prediction: A review and new modeling results," Energies, vol. 15, p. 1061, 2022. doi :10.3390/en15031061
[48] S. Ghimire, R. C. Deo, H. Wang, M. S. Al-Musaylh, D. Casillas-Pérez, and S. Salcedo-Sanz, “Stacked LSTM sequence-to-sequence autoencoder with feature selection for daily solar radiation prediction: A review and new modeling results,” Energies, vol. 15, p. 1061, 2022. doi: 10.3390/en15031061.
[49] J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, "Internet of Things (IoT): A vision, architectural elements, and future directions," Future Generation Computer Systems, vol. 29, no. 7, pp. 1645-1660, Sep. 2020, doi: 10.1016/j.future.2019.05.022.
[50] S. Mao and E. Sejdić, “A Review of Recurrent Neural Network-Based Methods in Computational Physiology,” IEEE Trans. Neural Netw. Learn. Syst., vol. 34, pp. 6983–7003, 2023. doi: 10.1109/TNNLS.2022.3145365.
[51] A. R. Khan et al., "Deep learning for intrusion detection and security of Internet of things (IoT): current analysis challenges and possible solutions," Security and Communication Networks, vol. 2022, 2022, doi: 10.1155/2022/4016073.
[52] J. K. S. Al-Safi, A. Bansal, M. Aarif, M. S. Z. Almahairah, G. Manoharan and F. J. Alotoum, "Assessment Based On IoT For Efficient Information Surveillance Regarding Harmful Strikes Upon Financial Collection," *2023 International Conference on Computer Communication and Informatics (ICCCI)*, Coimbatore, India, 2023, pp. 1-5, doi: 10.1109/ICCCI56745.2023.10128500.
[53] P. Rajan Jeyaraj and E. R. S. Nadar, "Smart-monitor: patient monitoring system for IoT-based healthcare system using DL," IETE J. Res., vol. 68, no. 2, pp. 1435–1442, 2019, doi: 10.1080/03772063.2019.1649215.
[54] Y. Li, Y. Zuo, H. Song, and Z. Lv, "Deep learning in security of internet of things," IEEE Internet Things J., vol. 9, no. 22, pp. 22133–22146, 2021, doi: 10.1109/jiot.2021.3106898.
[55] N. N. Alleema et al., "Security of Big Data over IoT Environment by Integration of Deep Learning and optimization," Int. J. Commun. Networks Inf. Security, vol. 14, no. 2, pp. 203–221, 2022, doi: 10.17762/ijcnis.v14i2.5510.
[56] S. Sharma, R. K. Dudeja, G. S. Aujla, R. S. Bali, and N. Kumar, "DeTrAs: DL-based healthcare framework for IoT-based assistance of Alzheimer patients," Neural Comput. Appl., pp. 1-13, 2022, doi: 10.1007/s00521-020-05327-2.
[57] J. Ma and J. Hu, "Safe consensus control of cooperative-competitive multi-agent systems via differential privacy," Kybernetika, vol. 58, no. 3, pp. 426–439, 2022, doi: 10.14736/kyb-2022-3-0426.
[58] S. M. G. Mostafa, M. Zaki, M. M. Islam, M. S. Alam, and M. A. Ullah, "Design and Implementation of an IoT-Based Healthcare Monitoring System," in 2022 International Conference on Innovations in Science, Engineering, and Technology (ICISET), 2022, doi: 10.1109/iciset54810.2022.9775850.
[59] C. Kaur, T. Panda, S. Panda, A. Rahman Mohammed Al Ansari, M. Nivetha and B. Kiran Bala, "Utilizing the Random Forest Algorithm to Enhance Alzheimer’s disease Diagnosis," *2023 Third International Conference on Artificial Intelligence and Smart Energy (ICAIS)*, Coimbatore, India, 2023, pp. 1662-1667, doi: 10.1109/ICAIS56108.2023.10073852.

[60] K. I. Ahmed, M. Tahir, M. H. Habaebi, S. L. Lau, and A. Ahad, "Machine learning for authentication and authorization in IoT: Taxonomy, challenges and future research direction," Sensors, vol. 21, no. 15, p. 5122, 2021, doi: 10.3390/s21155122.
[61] S. Abdulmalek, A. Nasir, W. A. Jabbar, M. A. M. Almuhaya, A. K. Bairagi, M. A.-M. Khan, and S.-H. Kee, "IoT-Based Healthcare-Monitoring System towards Improving Quality of Life: A Review," Healthcare, vol. 10, no. 10, p. 1993, 2022, doi: 10.3390/healthcare10101993.
[62] M. M. Islam, A. Rahaman, and Md. R. Islam, "Development of smart healthcare monitoring system in IoT environment," SN Computer Science, vol. 1, pp. 1-11, 2020, doi: 10.1007/s42979-020-00195-y.
[63] H. Sahu, R. Kashyap, and B. K. Dewangan, "Hybrid Deep learning based Semi-supervised Model for Medical Imaging," in 2022 OPJU International Technology Conference on Emerging Technologies for Sustainable Development (OTCON), Raigarh, India, 2023, doi: 10.1109/otcon56053.2023.10113904.
[64] A. V. Hanafi, A. Ghaffari, H. Rezaei, A. Valipour, and B. Arasteh, "Intrusion detection in internet of things using improved binary golden jackal optimization algorithm and LSTM," Cluster Computing, vol. 27, no. 3, pp. 1–18, 2023, doi: 10.1007/s10586-023-04102-x.
[65] R. Changala, C. Kaur, G. S. Raju, A. R. M. Al Ansari, S. S. C. Mary and I. I. Raj, "Improving Skin Lesion Diagnosis with Grasshopper-Optimized ResNet-50 Architecture," *2025 AI-Driven Smart Healthcare for Society 5.0*, Kolkata, India, 2025, pp. 212-217, doi: 10.1109/IEEECONF64992.2025.10963296.
[66] A. Rghioui, J. Lloret, S. Sendra, and A. Oumnad, "A smart architecture for diabetic patient monitoring using machine learning algorithms," Healthcare, vol. 8, no. 3, p. 348, 2020, doi: 10.3390/healthcare8030348.
[67] B. Godi, S. Viswanadham, A. S. Muttipati, O. P. Samantray, and S. R. Gadiraju, "E-healthcare monitoring system using IoT with machine learning approaches," in 2020 International Conference on Computer Science, Engineering, and Applications (ICCSEA), 2020, doi: 10.1109/iccsea49143.2020.9132937.
[68] A. S. Arjun, S. Kavitha, and R. Sridharan, "Real-Time IoT-Based System for Monitoring of Heart Disease Using Machine Learning," Journal of Healthcare Engineering, vol. 2023, Article ID 6634875, 2023, doi: 10.1155/2023/6634875.
[69] M. Aarif, A. Anjum, T. Sharma, A. Arikrishnan, V. S. Rao and A. Balakumar, "Implementing Fuzzy Logic in Cognitive Sensor Networks for Environmental Monitoring," *2024 Third International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT)*, Trichirappalli, India, 2024, pp. 1-6, doi: 10.1109/ICEEICT61591.2024.10718539.
[70] P. F. Muhammad, R. Kusumaningrum, and A. Wibowo, "Sentiment analysis using Word2vec and long short-term memory (LSTM) for Indonesian hotel reviews," Procedia Comput. Sci., vol. 179, pp. 728–735, 2021. doi: 10.1016/j.procs.2021.01.061.
[71] Y. Chen, Q. Cheng, Y. Cheng, H. Yang, and H. Yu, "Applications of Recurrent Neural Networks in Environmental Factor Forecasting: A Review," Neural Comput., vol. 30, pp. 2855–2881, 2018. doi: 10.1162/neco_a_01134.
[72] S. A. Siddiqui, A. Ahmad, and N. Fatima, "IoT-based disease prediction using machine learning," Computers & Electrical Engineering, vol. 108, p. 108675, 2023, doi: 10.1016/j.compeleceng.2023.108675.
[73] J. Cheng and J. Lu, "A novel deep learning model integrating fuzzy logic with LSTM for healthcare data prediction," IEEE Transactions on Neural Networks and Learning Systems, vol. 32, no. 10, pp. 4318-4328, 2021. doi.:10.1109/TNNLS.2021.3112413
[74] N. Zhao, H. Gao, X. Wen, and H. Li, "Combination of Convolutional Neural Network and Gated Recurrent Unit for Aspect-Based Sentiment Analysis," IEEE Access, vol. 9, pp. 15561–15569, 2021. doi: 10.1109/ACCESS.2021.3052937.
[75] V. Yadav, P. Verma, and V. Katiyar, "Long short term memory (LSTM) model for sentiment analysis in social data for e-commerce products reviews in Hindi languages," Int. J. Inf. Technol., vol. 15, pp. 759–772, 2023. doi: 10.1007/s41870-022-01010-y.
[76] K. Barik, S. Misra, A. K. Ray, and A. Bokolo, "LSTM-DGWO-Based Sentiment Analysis Framework for Analyzing Online Customer Reviews," Comput. Intell. Neurosci., vol. 2023, p. 6348831, 2023. doi: 10.1155/2023/6348831.

[77] M. Mokhles and F. Olivier, "Brain Waves Pattern Recognition Using LSTM-RNN for Internet of Brain-Controlled Things (IoBCT) Applications," in IEEE International IOT Electronics and Mechatronics Conference (IEMTRONICS), 2022, doi: 10.1109/iemtronics55184.2022.9795715.

[78] K. Praveena, M. Misba, C. Kaur, M. S. Al Ansari, V. A. Vuyyuru and S. Muthuperumal, "Hybrid MLP-GRU Federated Learning Framework for Industrial Predictive Maintenance," *2024 Third International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT)*, Trichirappalli, India, 2024, pp. 1-8, doi: 10.1109/ICEEICT61591.2024.10718600.

[79] K. Praveena, M. Misba, C. Kaur, M. S. Al Ansari, V. A. Vuyyuru and S. Muthuperumal, "Hybrid MLP-GRU Federated Learning Framework for Industrial Predictive Maintenance," *2024 Third International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT)*, Trichirappalli, India, 2024, pp. 1-8, doi: 10.1109/ICEEICT61591.2024.10718600.

[80] V. Karuppuchamy and S. Palanivelrajan, "Efficient IoT-machine learning assisted heart failure prediction using Adaptive Fuzzy-based LSTM-RNN algorithm," Journal of Intelligent & Fuzzy Systems, vol. 45, no. 1, 2023, doi: 10.3233/jifs-224298.

[81] N. Bacanin, L. Jovanovic, M. Zivkovic, V. Kandasamy, M. Antonijevic, M. Deveci, and I. Strumberger, "Multivariate energy forecasting via metaheuristic tuned long-short term memory and gated recurrent unit neural networks," Inf. Sci., vol. 642, p. 119122, 2023. doi: 10.1016/j.ins.2023.119122.

[82] F. Jeribi, C. Kaur and A. B. Pawar, "An Approach with Machine Learning for Heart Disease Risk Prediction," *2023 International Conference on Computational Science and Computational Intelligence (CSCI)*, Las Vegas, NV, USA, 2023, pp. 1474-1479, doi: 10.1109/CSCI62032.2023.00241.

[83] P. B. Weerakody, K. W. Wong, G. Wang, and W. Ela, "A review of irregular time series data handling with gated recurrent neural networks," Neurocomputing, vol. 441, pp. 161–178, 2021. doi: 10.1016/j.neucom.2021.02.046.

[84] J. Zhu, Q. Jiang, Y. Shen, C. Qian, F. Xu, and Q. Zhu, "Application of recurrent neural network to mechanical fault diagnosis: A review," J. Mech. Sci. Technol., vol. 36, pp. 527–542, 2022. doi: 10.1007/s12206-022-0102-1.

[85] S. Duraibi, C. Kaur and A. B. Pawar, "Cyber Extortion Unveiled: The Evolution, Tactics, Challenges, and Future of Ransomware," *2023 International Conference on Computational Science and Computational Intelligence (CSCI)*, Las Vegas, NV, USA, 2023, pp. 861-867, doi: 10.1109/CSCI62032.2023.00144.

[86] S. Sachin, A. Tripathi, N. Mahajan, S. Aggarwal, and P. Nagrath, "Sentiment analysis using gated recurrent neural networks," Comput. Sci., vol. 1, p. 74, 2020. doi: 10.1007/s42979-020-0076-y.

[87] S. K. Ansari, T. S. Umamaheswari, C. Kaur, R. S. Begum, D. S. R. Banu and A. Anjum, "Improving Smart Home Safety with Face Recognition using Machine Learning (ML)," *2023 International Conference on New Frontiers in Communication, Automation, Management and Security (ICCAMS)*, Bangalore, India, 2023, pp. 1-6, doi: 10.1109/ICCAMS60113.2023.10525817.

[88] Y. Yu, X. Si, C. Hu, and J. Zhang, "A review of recurrent neural networks: LSTM cells and network architectures," Neural Comput., vol. 31, pp. 1235–1270, 2019. doi: 10.1162/neco_a_01199.

[89] H. Lin, A. Gharehbaghi, Q. Zhang, S. S. Band, H. T. Pai, and K. W. Chau, "Time series-based groundwater level forecasting using gated recurrent unit deep neural networks," Eng. Appl. Comput. Fluid Mech., vol. 16, pp. 1655–1672, 2022. doi: 10.1080/19942060.2022.2104928.

[90] L. Das, C. Kaur, A. Siddiqua, D. Taranum, G. V. Manerkar and A. Rana, "Enhancing Security Of Mobile Payment Applications Using Block Chain," *2023 10th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON)*, Gautam Buddha Nagar, India, 2023, pp. 210-214, doi: 10.1109/UPCON59197.2023.10434601.

[91] Farah, N. Humaira, Z. Aneela, and E. Steffen, "Short-term multi-hour ahead country-wide wind power prediction for Germany using gated recurrent unit deep learning," Renew. Sustain. Energy Rev., vol. 167, p. 112700, 2022. doi: 10.1016/j.rser.2022.112700.

[92] D. Durstewitz, G. Koppe, and M. I. Thurm, "Reconstructing computational system dynamics from neural data with recurrent neural networks," Nat. Rev. Neurosci., vol. 24, pp. 693–710, 2023. doi: 10.1038/s41583-023-00740-7.

Journal of Information Systems Engineering and Management
2025, 10(36s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

[93] A. Siddiqua, A. Anjum, S. Kondapalli and C. Kaur, "Regulating and monitoring IoT controlled solar power plant by ML," *2023 International Conference on Computer Communication and Informatics (ICCCI)*, Coimbatore, India, 2023, pp. 1-4, doi: 10.1109/ICCCI56745.2023.10128300.

[94] Rghioui, A. Naja, J. L. Mauri, and A. Oumnad, "An IoT based diabetic patient monitoring system using ML and Node MCU," in Journal of Physics: Conference Series, vol. 1743, no. 1, p. 012035, 2021. doi: 10.1088/1742-6596/1743/1/012035. doi:10.1088/1742-6596/1743/1/ 012035