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Research Article

FedDeepRiskNet: A Federated Learning Framework for Secure and Efficient Multi-Hospital Management

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ARTICLE INFO	ABSTRACT

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Existing multi-hospital management frameworks, especially those that combine vital sign IoT data with elasticity approaches, often have data storage, poor predictive skills, and poor human-centered design. This study tackles these issues and provide safe and private data exchange, by proposing a novel framework that works with a federated learning technique. Federated learning is a decentralized machine learning (ML) method that enables several hospitals to work together on model training without compromising the privacy of their patient data. The proposed approach directly addresses the issue of data storage by integrating the work with a deep learning (DL) algorithm. The aim of this research is to improve resources allocation, improve patient outcomes, and find diseases earlier. The DL method employed is a more sophisticated and more effective method of patient risk categorization. This framework greatly contributes to the development of healthcare 4.0 by allowing more effective, equitable, and patient-centered care across multi-hospital networks by solving the issues of data interoperability, improving prediction accuracy, and placing a priority on user experience.

Keywords: Federated Learning; Multi-Hospital Management; Healthcare 4.0; IoT; Patient Data Privacy

1. INTRODUCTION

Integrating physical infrastructure, IT, social services, and corporate resources allows "smart cities" to optimise decision-making and improve municipal operations. Optimising urban operations and services, enhance the effectiveness of resource utilisation, and enhance the quality of life for citizens. It is essential to improve people's lives via the use of concepts and information technology, such as the Wireless Sensor Networks (WSNs), Internet of Things (IoT) as well as Cyber-Physical Systems (CPS) [1]. Studies that used natural language processing (NLP) to automate fall detection and prediction in healthcare settings is reviewed. Between 2012 and April 2023, researchers combed through the following databases such as the Ovid Embase, Ei Compendex, PubMed, CINAHL, IEEE Xplore, Ovid Emcare as well as Ovid Medline [2].

The variety as well as depth of data saved at each patient visit have grown as medical services transition to electronic health record (EHR) systems. It is arguable that the increasing data riches and investment in healthcare systems have placed a heavier burden on services, as frontline workers are encouraged to spend more time on computers rather than with patients. As a means to minimize their reliance on EHR systems, physicians often resort to free-text data entry, which avoids the structured input fields altogether [3]. Hospitals have used numerous organizational models to provide high-quality healthcare at affordable prices. Among the many possible structures and methods of providing medical care, chain hospitals stand out. This research is an effort to clarify the components and ideas behind chain hospitals in light of the variety, complexity, and ambiguity of such ideas [4].

Research suggests that internal or external validation should handle missing data by relying only on the data used for model development. This approach ensures its relevance when making predictions for new individual patients, as existing guidance on the topic often fails to align with clinical prediction goals [5]. The COVID-19 pandemic has greatly challenged global healthcare systems. It made to realize how important it is to have strong prediction models that are easy to use to help find differences in how diseases progress, make decisions, and decide which treatments are best. This research gave a modified SuStaIn, which is an unsupervised data-driven model, and this include 11 routinely reported clinical parameters for short-term viral diseases like COVID-19 [6].

Examining the evolution of IT in the context of eHealth was the goal of a qualitative case study. As a result, there is a tremendous deal of space for more study into the ways in which cutting-edge eHealth systems are built via the use of IT strategy and execution. These ideas, if put into action, have the potential to provide efficient services to clients and patients in an instant. Through the use of state-of-the-art web/mobile-based and big data technologies, e-health unifies medical information, public health, healthcare services, data delivery, and data security measures online. This approach enables easy and instantaneous access to patient and client records [7]. Another research uses a random consideration sets model of hospital demand to look at how the market works. It is based on the idea that patients should look at all of their options within their loosely connected networks of providers [8]. Based on the existing work limitations this research provides the following contributions:

- This research introduces a novel federated learning architecture that lets different hospitals work together securely and in a decentralized manner. This framework gets rid of data storage and makes sure that patient privacy is protected when model training data is shared.
- This framework uses a hybrid Convolutional Neural Network (CNN) with Long Short-Term Memory (LSTM) architecture. This hybrid algorithm helps healthcare professionals make better decisions, figure out which patients are at higher risk, and find diseases earlier.
- This research enhances hospital administration and patient outcomes by proposing a system for better healthcare resource allocation through the use of predictive analytics.
- By enabling greater coordination and information flow across healthcare systems this work tackles the issue of data interoperability and assuring seamless integration of multi-hospital data.
- The proposed model is termed as FedDeepRiskNet and contributes to the broader vision of healthcare 4.0 by placing a strong emphasis on user experience and human-centered design principles to build a system that is simple to use, productive, and helpful to healthcare professionals.

Here are the details of the rest work organization. Some recent existing approaches related to hospital management to facilitate Healthcare 4.0 is stated in Section 2. Section 3 discusses the details of the proposed technique. Section 4 includes details on the research findings, along with some limitations of the current study. Section 5 wraps up the work, and the next section contains the references.

2. LITERATURE REVIEW

Shanmugam et al. [9] discussed about the current environment challenges faced by healthcare executives with numerous financial obstacles, leading to financial distress as well as prominent bankruptcies in recent times. The particular factors that could cause an organization's financial collapse are little known. There are a number of models that can be used to predict financial distress, but regression analysis may not be enough, especially when the financial variables don't have a normal distribution. And multicollinearity is a major problem for the regression method. Therefore, the stochastic technique cannot adequately predict the likelihood of hospital bankruptcy. This study provides an approach to evaluating hospitals' financial health that incorporates many critical elements. Beginning with bivariate lognormal data, it determines and explain the connection between the hospital's income and expenditures. Then estimate the likelihood of bankruptcy due to a disparity between income and expenditures.

Hsiao et al. [10] discussed about the usual way of reading Intravascular Ultrasound (IVUS) images during Percutaneous Coronary Intervention (PCI) is hard to do as well as doesn't always work. This is because it depends on the knowledge and personal opinion of the doctors. Regulatory constraints and privacy issues also make it difficult to acquire and integrate IVUS data across multiple hospital systems, which makes collaborative research and model building more difficult. A 2D U-Net model with a multi-stage segmentation architecture has been created to improve plaque identification during PCI procedures and to build a consistent and fast technique for IVUS picture segmentation. The methodology maintains data privacy while facilitating collaborative data analysis across multiple healthcare institutions via the use of a federated learning (FL) algorithm.

Arul et al. [11] explained how to avoid healthcare services from becoming inactive by using blockchain-adaptable service compliance (BASC) for blockchain-reliant reasons. As far as obtaining and presenting end users with health information is concerned, the suggested method is reliable in overcoming dormancy issues. The kind of user assistance needed in the forehand is exploited by this suggested compliance. In order for a decentralized dataset to operate securely, a distributed ledger is necessary, as it eliminates the need for a single authority to oversee modification. This work chooses the easily available distributed ledger based on the need and then communicate the information with the end user. By checking the authenticity of the data sent, this technique ensures compliance until the user's need is satisfied. One way to find out which ledger is accessible is to utilize the backpropagation learning approach to fix the weight vector input variables in the backward pass.

Islam et al. [12] focused on the use of the IoT in the deployment of robotic sprayers for disinfection and monitoring purposes related to pandemics. The authors create a architectural framework that can be used to connect smart monitoring robots in healthcare facilities that use narrowband IoT (NB-IoT) technology. The primary goal is to connect these devices to the closest base station with a reliable data transmission pipeline. The edge computing architecture sends the linked data directly to the cloud storage. By doing away with reliance on central data centers, the suggested design improves system performance while bolstering data security. The system's essential parts enable the edge node to send data to the cloud, where the main processing and analysis take place.

Wassan et al. [13] implemented DL, an artificial intelligence (AI) technology, that teach computers to analyse data in a way that mimics the human brain. When given complicated patterns in many forms of data, such as images, text, or audio, DL algorithms may accurately draw inferences and make predictions. Another term for DL is neural networks a DL model's input, output as well as hidden layers are these. The input layer receives raw data and processes it, while the output layer displays the results. Compared to more conventional ML methods, such as k-nearest neighbour, support vector algorithms, along with regression techniques, DL offers several benefits. DL models can read more complicated data sets than more conventional ML techniques. This also cover in depth the process of building comparative or rapid neural networks using different frameworks.

Shoukat et al. [14] highlighted the research as well as application development from the perspective of Digital Twin (DT) home-devices' DT (HDDT) modelling and elaborates on the recommendation and implementation of the model. From the perspective of physical entities to that of virtual entities and connection (data transmission), this modelling technique consists of three stages. This model suggests using DT along with virtual simulation technologies to create a human cyber-physical system (HCPS). This method solves the problems with remote control and lets HD be intelligently controlled through an interactive system. A deep integration as well as interface was developed between the physical along with virtual realms of smart-device information with the HCPS. By using the principles of game theory, it may build HD-based IoT devices such as washing machines, lights, breakers, heaters, kitchen appliances, TVs, air conditioners, etc., that consist of both physical and digital components.

Zaydi et al. [15] defined the storage and processing of health data has become more complex due to the rapid proliferation of IoT devices, necessitating creative solutions to guarantee safe and efficient administration. Cloud computing has long been the predominant paradigm for storing and analysing data collected from a multitude of linked medical gadgets. This paradigm is starting to have issues with latency, throughput, bandwidth, internet dependence, and cost, which rises as resources are depleted, even though the client can process. The sensitivity and criticality of health data, in conjunction with the emergence of big data, underscore this point. Several paradigms, like edge computing and fog computing, have arisen to overcome these restrictions. Table 1 shows the existing reviews.

Table 1: Existing Review

Papers and Authors	**Method**	**Advantages**	**Limitations**
Shanmugam et al. [9]	Stochastic approach	Improved evaluation of hospitals' financial health.	Not every possible factor influences filing for bankruptcy.
Hsiao et al. [10]	FL algorithm	The focus is on model development and collaborative analysis.	The system utilizes only the most fundamental FL algorithms.
Zaydi et al. [15]	advent of the IoT	Ensure the efficient and secure management of health data.	Do not consider IoMT-era healthcare.

3. PROPOSED METHODOLOGY

A hybrid CNN-LSTM architecture termed as FedDeepRiskNet is proposed in this research for classifying patient risk by using FL. This method is meant to solve the problems that come up to manage several hospitals at the same time. To guarantee consistency across diverse sources, data is gathered from numerous hospitals and then pre-processed, which includes normalization and addressing missing variables. By enabling hospitals to train models locally and communicate just model updates, federated learning offers secure, privacy-preserving cooperation. This proposed model design integrates the two components such as LSTM and CNN. LSTM layers capture temporal relationships in the patient data, while CNN extract spatial features. After LSTM layers describe sequential relationships, the CNN uses time-series data to extract local patterns. When training the model, Federated Averaging (FedAvg) is used to generate a global model by aggregating local updates [16]. After training, the model uses patient health data to stratify risks and make predictions. Model validation is carried out using evaluation criteria including precision, F1-score, recall, as well as accuracy and the system is then implemented for real-time patient monitoring. With this approach, data privacy may be preserved while scalable, secure, and efficient patient risk prediction achieved across several hospitals. Figure 1 shows the depiction of the proposed FedDeepRiskNet process flow.

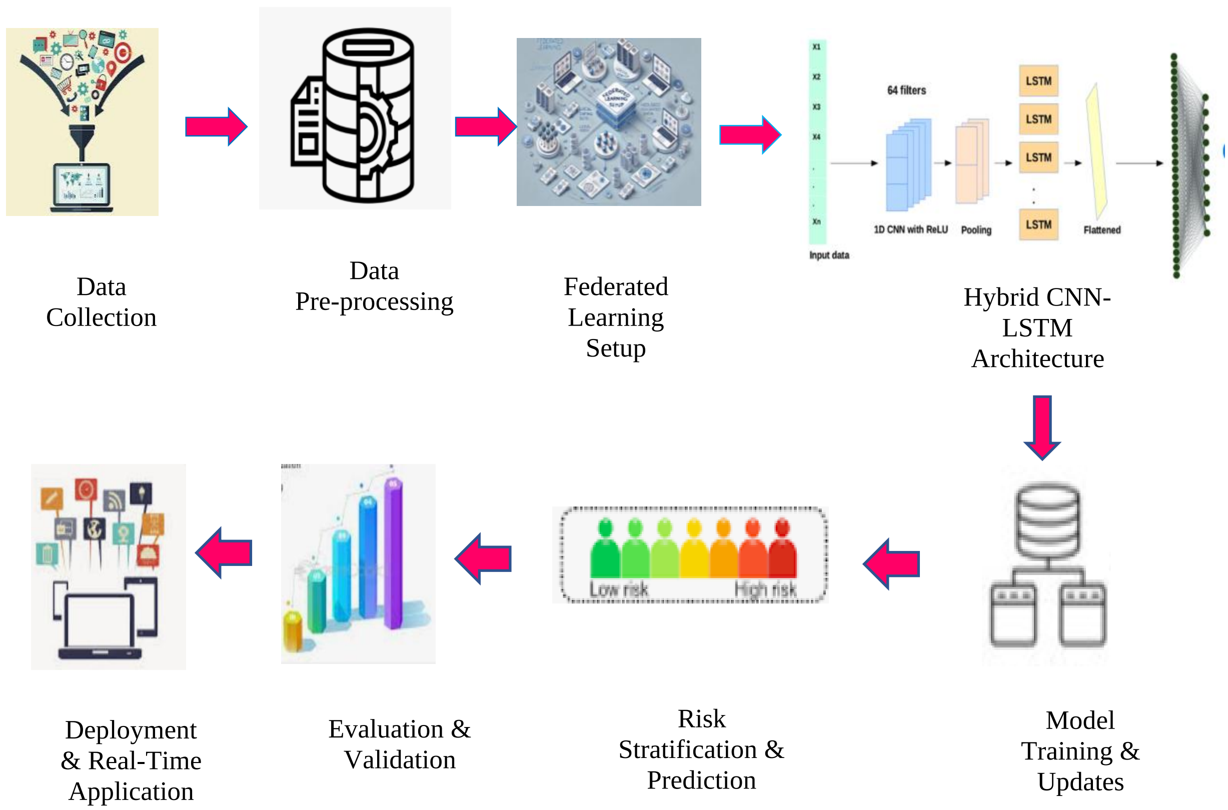

Figure 1. Proposed FedDeepRiskNet Flow

3.1. Data Collection and Preprocessing

3.1.1 Data Collection

Patient demographics, medical histories, and real-time data from IoT sensors (vital indicators like heart rate, blood pressure, oxygen levels, etc.) are gathered from a number of different hospitals. Structured data, such as patients' ages and genders, and unstructured data, like vital signs' time series, make up the dataset. Instead of sharing raw data, hospitals provide model changes to keep patient information private.

3.1.2 Data Preprocessing

This study preprocesses the raw data collected from various hospitals to standardize formats and ensure source-to-source compatibility. For data pre-processing normalization is done where all numerical data (such as vital signs) is normalized to a range of [0,1] using Min-Max normalization in equation (1):

$$X_{norm} = \frac{X - min(X)}{max(X) - min(X)} \tag{1}$$

This study fills missing values using forward fill, mean imputation, or other appropriate approaches, depending on the temporal nature of the data. Time-series data, like patient vital signs, undergoes interpolation or resampling to ensure uniform intervals. The temporal dependencies are captured by extracting characteristics that are dependent on time. Then the features including the sliding window statistics, mean, and variance are estimated.

3.2. Federated Learning Setup

While keeping the data decentralized and private, federated learning enables each hospital to train a model locally. In this study the model is updated only with weights and gradients and are shared, other than the raw data. Following these processes, each hospital trains its local version of FedDeepRiskNet. With this local training data, each hospital trains the CNN-LSTM model. For training to classify risks, the loss function is used is binary cross-entropy loss or mean squared error (MSE) [17] and is equated in equation (2):

$$L(y, \hat{y}) = -\frac{1}{N}\sum_{i=1}^{N}[y_i log(\hat{y}_i) + (1 - y_i) log(1 - \hat{y_i})] \tag{2}$$

Where y is the true label and $\hat{y}$ is the predicted output. After training, each hospital computes the gradient of the loss function with respect to the model parameters θ in equation (3):

$$\nabla_\theta L(\theta) = \frac{1}{N}\sum_{i=1}^{N}\frac{\partial L(y_i, \hat{y}_i)}{\partial \theta} \tag{3}$$

The central server receives these revisions and consolidates them without actually sharing the data itself. The central server aggregates the local updates using Federated Averaging (FedAvg). Given N hospitals, the global model is updated by averaging the model weights from each hospital as in equation (4):

$$\theta_{global} = \frac{1}{N}\sum_{i=1}^{N}\theta_i \tag{4}$$

The global model is then distributed back to the hospitals for the next round of training.

3.3. Hybrid CNN-LSTM Architecture for Risk Stratification

3.3.1 Convolutional Neural Network (CNN)

The input data, which might be vital signs or data from sensors, is processed by the CNN model in order to extract features. The job of the CNN layers is to extract spatial features, including vital signs and time-series signals, from the input data. The CNN detects spatial relationships in the data and works on local patterns. The input layer often uses a multi-dimensional tensor. This would shape into a three-dimensional tensor with the parameters [batch size, time steps, features] for time-series data. Here, [32, 50, 10] may represent the vital signs data tensor, where batch size is 32, number of time steps is 50 (50 measurements of vital signs), and number of features is 10 (heart rate, blood pressure, etc.). By implementing filters on the input tensor, the Conv2D layer is able to extract features from the input data as in equation (5).

$$Output = Conv2D(Input) \tag{5}$$

The filters slide over the input tensor, creating feature maps that represent local spatial features. This work makes use of a Conv2D layer that has 32 filters of size 3x3. The MaxPooling layer downsamples the feature maps to reduce the spatial dimensions while maintaining crucial characteristics. When the pool size is 2x2, the max pooling operation is equal to equation (6).

$$Output = MaxPooling(Conv2D\ Output) \quad (6)$$

This results in a decrease in the feature map's size, for example, from 50x50 to 25x25 [18]. The Conv2D and MaxPooling layers first flatten the data into a 1D vector to prepare it for the LSTM network. This study flattens a 25x25 feature map to create a 625-dimensional vector. In order to get a more abstract representation, the flatten layer's output is routed via a dense layer before the LSTM layer is applied. A 128x128x128 final output, reflecting the CNN's retrieved high-level features, is produced by the dense layer.

3.3.2. Long Short-Term Memory

The LSTM layer is meant to handle the input data (time-series) sequential data by modelling temporal dependencies. The LSTM layer capture the temporal dependencies in the data. The spatial features extracted by the CNN is taken by LSTM to predict the patient risk. The LSTM layer handles the sequential data effectively. In this work the LSTM layer receives the flattened output from CNN to process it in a time-sequential manner. The LSTM updates the hidden state h_t at each time step t using the following equations (7) – (12).

$$f_t = \sigma\left(W_f.[h_{t-1}, x_t] + b_f\right) \text{ (Forget gate)} \quad (7)$$

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \text{(Input gate)} \quad (8)$$

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \text{ (Output gate)} \quad (9)$$

$$C_t = tanh(W_C.[h_{t-1}, x_t] + b_C) \text{ (Cell candidate)} \quad (10)$$

$$C_t = f_t.C_{t-1} + i_t.\tilde{C}_t \text{ (Cell state update)} \quad (11)$$

$$h_t = o_t.tanh(C_t) \text{ (Hidden state update)} \quad (12)$$

A single 100-unit LSTM layer processes the sequence. The model's ultimate output is generated by a dense layer after it has passed through the LSTM layers. A risk score or classification result is often the outcome. A dense layer classifies into binary risk categories using a sigmoid activation function. Consequently, LSTMs are able to forecast patient outcomes over time by capturing temporal relationships.

3.3.3 Hybrid CNN-LSTM Architecture

A hybrid design uses a sequential connection between CNN and LSTM layers. Information such as a patient's vital signs or other multi-dimensional time-series data serves as the input data. Using Conv2D, MaxPooling, and Flatten, the CNN layer handles feature extraction. The LSTM layer sequentially models the retrieved features. The output for classification or regression is finally produced by the dense layer. The following figure 2 clearly show the connection between the CNN and LSTM layers in this design.

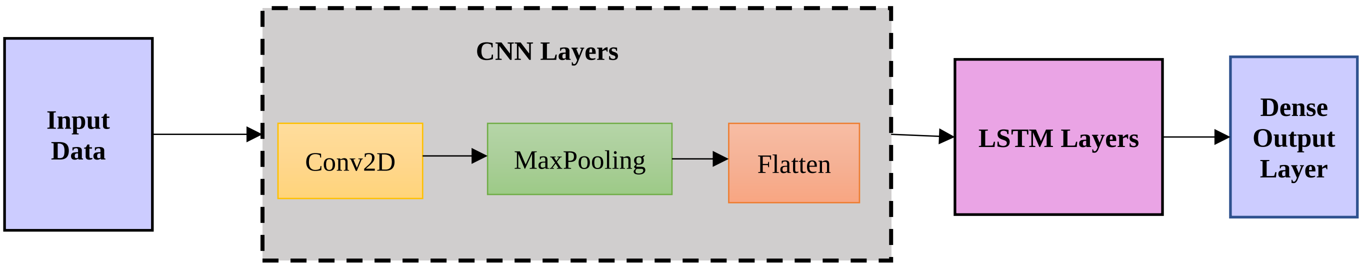

Figure 2. Hybrid CNN-LSTM Architecture Design

This hybrid structure is well suited for healthcare risk stratification applications because of its effective extraction of both spatial and temporal data.

3.3.4 Federated Learning Training Process

Load the local model for each hospital. Run each hospital's dataset to train the local model. Notify the main server of any model changes (weights) when training is complete. Combine all of the local model updates by using FedAvg. Return the revised global model to hospitals.

3.4. Risk Stratification and Prediction

After training the global model, FedDeepRiskNet uses the patients' health data to classify them into risk groups. Finally, the CNN-LSTM model output is passed through a final dense layer that has an activation function). The equation for risk prediction is in equation (13).

$$y_{risk} = \sigma\left(W_{final} . h_{last} + b_{final}\right) \tag{13}$$

Where h_{last} is the output of the LSTM layer, and y_{risk} is the predicted risk score.

Pseudocode for FedDeepRiskNet Methodology

```
Step 1: Data Collection & Preprocessing
data = collect_data_from_hospitals(hospitals)
preprocessed_data = preprocess_data(data)
Step 2: Federated Learning Setup
initialize_federated_learning()
Step 3: Local Model Training
for round in range(num_rounds):
  local_models = []
  for hospital in hospitals:
 #Each hospital trains a local model on its data
    local_model = train_local_model(hospital, preprocessed_data)
    local_models.append(local_model)
 Step 4: Federated Averaging (FedAvg)
  global_model = aggregate_local_models(local_models)
 Step 5: Distribute the Global Model
  distribute_global_model(global_model)
Step 6: Risk Stratification and Prediction
for patient in test_data:
  risk_score = predict_risk(global_model, patient)
  print ("Risk Prediction for patient:", risk_score)
Step 7: Model Evaluation & Validation
evaluate_model(global_model, validation_data)
```

4. Results

To test how well FedDeepRiskNet works, researchers built an experimental platform that depicts the FL framework in which different hospitals work together with patient data kept private. The platform consists of a central federated learning server, local machines that represent specific hospitals, and a real-time data processing and collection model. For secure model training and risk prediction, the framework allows for the use of a CNN-LSTM hybrid architecture. For decentralized model training, the platform includes support for federated learning frameworks like TensorFlow Federated (TFF), which is built using Python and ML libraries like PyTorch and TensorFlow.

Health records from patients are the basis of the training and assessment dataset. These records include information on the patients' vital signs (such as heart rate, blood pressure, and oxygen levels), as well as their age, gender, and medical history. These numbers show how the patient's health has changed over time; which are time-series data. This study pre-processes the dataset by filling in missing data, normalizing values, and aligning their temporal sequences to ensure consistent input to the hybrid CNN-LSTM model [19]. To make sure that the federated learning method handles issues like data privacy and interoperability, the dataset is split up into several virtual hospitals that look like real-life data storage. Each hospital's dataset includes patient ID, age, gender, heart rate, blood pressure, and other vital signs or medical history data throughout time. Table 2 shows the representation of the dataset.

Table 2: Representation of the Dataset

Patient ID	Hospital	Age	Gender	Heart Rate (bpm)	Blood Pressure (mmHg)	Oxygen Level (%)	Timestamp
101	Hospital 1	56	M	75	120/80	98	2025-01-01 10:00
102	Hospital 1	45	F	80	130/85	97	2025-01-01 10:05
201	Hospital 2	60	F	70	125/85	96	2025-01-01 10:00
202	Hospital 2	38	M	78	118/76	98	2025-01-01 10:05
301	Hospital 3	50	M	85	140/90	95	2025-01-01 10:10
302	Hospital 3	33	F	76	120/80	97	2025-01-01 10:15

The dataset features are

- Patient ID: A unique identifier for each patient.
- Hospital: The hospital from which the data is collected (e.g., Hospital 1, Hospital 2, etc.).
- Age: The patient's age.
- Gender: The gender of the patient (Male or Female).
- Heart Rate (bpm): The patient's heart rate in beats per minute (bpm).
- Blood Pressure (mmHg): The patient's blood pressure, recorded as systolic/diastolic (mmHg).
- Oxygen Level (%): The patient's oxygen saturation level in percentage.
- Timestamp: The specific time when the data point was recorded.

The timestamp column illustrates that the dataset is time-series. The model can track the sequential and temporal changes in the patient's health state since each patient's vital signs data is captured at various time points. Data is spread out across many hospitals, with each facility maintaining its own dataset. In a federated learning framework, each hospital uses its own data to train a local model, and only the updated models are shared [20]. With each hospital using its own dataset but making use of a common global model, federated learning guarantees that data privacy is preserved between hospitals.

4.1 Evaluation Metrics

FedDeepRiskNet uses various assessment indicators to evaluate its performance. Accuracy measures the proportion of accurate predictions produced by the model. The precision represents the proportion of high-risk patients that the model accurately predicted. The recall metric evaluates the model's capacity to detect all real patients at high risk. When working with datasets that aren't evenly distributed, F1-Score may help strike a compromise between recall and accuracy. The Area Under the Curve (AUC), is a comprehensive performance measure, that evaluates the model's ability to distinguish between patients at high and low risk in equation (14)- (17).

$$Accuracy = \frac{Correct\ Predictions}{Total\ Predictions} \quad (14)$$

$$Precision = \frac{TP}{TP+FP} \quad (15)$$

$$Recall = \frac{TP}{TP+FN} \quad (16)$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (17)$$

The table below shows how the FedDeepRiskNet model stacks up against models that only use CNN or LSTM and models that don't use federated learning at all. The model uses a hybrid CNN-LSTM architecture with federated learning. Table 3 shows the performance metric results.

Table 3: Performance metric Comparison

Performance Metric	**FedDeepRiskNet**	**CNN**	**LSTM**	**Non-Federated Learning (CNN-LSTM)**
Accuracy	92.5%	88.7%	85.3%	89.0%
Precision	91.2%	87.3%	84.1%	88.5%
Recall	93.0%	89.5%	86.0%	90.1%
F1-Score	92.1%	88.4%	85.0%	88.8%
AUC (Area Under Curve)	0.94	0.91	0.88	0.90

FedDeepRiskNet represents the proposed model in the table, which integrates federated learning and employs a hybrid architecture with CNN and LSTM. It does the best on all metrics because it can use both spatial (CNN) and temporal (LSTM) information, and its training is secure and protects privacy through federated learning. Not only does the existing model not incorporate sequential modeling, but it solely relies on CNN for feature extraction. Not capturing temporal dependencies in the data causes the performance to be somewhat worse than that of the hybrid CNN-LSTM model. While an existing LSTM model can manage sequential dependencies on its own, it performs worse in accuracy and prediction quality when it doesn't have the CNN to extract spatial features. It isn't as effective as the hybrid model in capturing the complex connections in the data. Without federated learning, another existing model depicts the conventional CNN-LSTM architecture. The privacy-preserving advantages of federated learning are absent, and it may face difficulties with data privacy and the inefficiencies of centralized data sharing, despite its excellent performance.

4.2 Discussions

The proposed FedDeepRiskNet model is better at figuring out a patient's risk level than non-federated CNN-LSTM models, individual CNN models, and LSTM models. The model's superior F1 score, AUC, recall, accuracy, and precision confirm this. For a number of reasons, FedDeepRiskNet is the superior model. The first advantage of the hybrid CNN-LSTM design is that it takes the best features of both types of networks and applies them to a problem. By finding significant health indicators and local patterns, the CNN component is excellent at extracting spatial features from time-series data, including vital signs. In healthcare data, where trends in measures like heart rate or blood pressure may provide important insights, this spatial feature extraction is essential. On the other hand, the LSTM part takes into account how health changes over time by capturing how patient data changes over time. The model is able to provide more precise risk predictions because of this two-pronged strategy, which examines both short-term and long-term patterns in the data.

The second advantage is that FedDeepRiskNet uses federated learning to make sure that hospitals may share data while still protecting patients' privacy. The use of centralized data sharing in traditional ML models might put patient privacy at risk. Federated learning, on the other hand, lets individual hospitals keep their data in-house and merely shares model changes. The model can learn from a variety of healthcare data sets without sacrificing security owing to this decentralized learning technique, which also keeps data private and lessens the dangers of data storage. Standalone CNNs and LSTM models aren't as good at making predictions because they can't pull out both spatial and temporal elements at the same time. In addition, issues with data privacy and inefficient central processing plague non-federated learning algorithms. FedDeepRiskNet is thus well suited for healthcare applications across various institutions since it offers a more secure, effective, and precise method for patient risk stratification.

5. Conclusion

For patient risk stratification across several hospitals, this research has proposed FedDeepRiskNet, a novel framework that combines federated learning with a hybrid CNN-LSTM architecture. The model does better at predicting the future than CNN and LSTM, which are two non-federated learning models that work on their own in terms of extracting spatial features and capturing temporal dependencies. With federated learning, hospitals may work together to train models without exposing any patient data, which is a huge concern when it comes to data privacy. This method guarantees safe, effective, and extensible healthcare solutions across networks of hospitals, and it also improves the accuracy of predictions. The results of the experiments show that the FedDeepRiskNet model works well because it improves accuracy, precision, recall, F1-score, and AUC. In healthcare environments that operate in real time, the model provides a viable path forward for patient risk stratification, early disease detection, and efficient resource allocation. Investigating potential new data sources for integration, such as genetic or medical imaging data, may further enhance the accuracy of patient risk predictions.

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