Design of a Secure and Accurate Deep Learning-Based Medical System for Stroke Detection

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Abstract: Stroke is one of the most serious medical conditions that requires rapid and accurate diagnosis to avoid its fatal complications. The use of Deep Learning (DL) techniques contributes to enhancing the accuracy of detecting strokes in their early stages, enabling faster medical intervention and reducing long-term damage. In addition to early stroke detection, maintaining the confidentiality of patient information is vital to ensuring trust and protecting sensitive data. DL techniques also help detect unauthorized access or manipulation of patient data, enhancing digital security and ensuring compliance with healthcare privacy standards. In this paper, a precise and safe DL-based medical system for the detection of strokes is proposed. The design includes two stages. First, propose a high-accuracy DL learning algorithm to detect Stroke, which is achieved through a hybrid CNN-LSTM algorithm. The second stage is represented by maintaining the security of the proposed medical system by suggesting an efficient DL algorithm, which is attained using a lightweight Shallow Deep Neural Network (SDNN) algorithm. The performance evaluation of the two former stages, accuracy, security, and memory footprint, has been achieved. The simulation results demonstrate that the proposed hybrid CNN-LSTM algorithm achieves superior performance in stroke detection, reaching an accuracy of up to 99.6 percent when evaluated on the AHA stroke dataset. This performance surpasses that of standalone CNN and LSTM models. In terms of cybersecurity, the SzDNN algorithm also proves effective, maintaining a high detection rate of up to 96.8 percent using the NSL-KDD dataset. These findings highlight the model's strength in both accurate medical diagnostics and reliable network threat detection.

Keywords: Medical System, Stroke, DL, Accuracy, Security, CNN, LSTM, SDNN.

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1. Introduction

Stroke is one of the leading causes of death and disability worldwide, requiring accurate diagnosis and rapid intervention to reduce its devastating effects on patients' health. It accounts for about 11% of all fatalities [1]. Hence, scientific research in the medical field has witnessed remarkable progress in developing prediction models based on artificial intelligence techniques, such as ML or DL techniques, to improve the diagnostic accuracy of stroke [2]. Medical research showes that possible consequences of a stroke better phrased as "can be avoided with early diagnosis [3]. On the other hand, patient information security is critical in stroke prediction systems, as These systems depend on private information like medical history, vital signs, and clinical tests. Securing this information ensures patient privacy and prevents any breach affecting prediction accuracy and medical decision-making. Therefore, incorporating AI technologies, such as deep learning algorithms, to enhance security and accurate stroke prediction is necessary. Encryption, cyber threat detection, and deep learning technologies can protect data, contributing to building reliable and secure systems to support healthcare and effective medical decision-making. However, few studies combine prediction with the security of the information simultaneously within the same system.

For stroke prediction, several studies focused on using clinical data such as blood pressure and other risk factors to predict stroke. Different research studies have used medical image analysis to detect strokes. A subset of machine learning and cutting-edge artificial intelligence (AI), such as Deep Learning (DL), is distinguished in part by its algorithmic features that automatically extract complicated and hierarchical properties from raw input data [4].

To distinguish between a healthy brain, an ischemic stroke, or a hemorrhagic stroke, the authors in [5] presented an Internet of Things (IoT) framework for the classification of stroke from CT scans using Convolutional Neural Networks (CNN). The Transfer Learning idea integrated CNN with various consolidated machine learning techniques, including Bayesian classifiers, multilayer perceptrons, k-nearest neighbors, random forests, and support vector machines. The authors in [6] focused on stroke diagnosis from MRI images using deep learning as the concept underlying this study, where the classification is based on the LeNet model that gained an accuracy of 96-97%, and the segmentation is based on the SegNet model that gained an accuracy of 85-87%. The results support the claim that deep learning models are effective in medical image analysis, especially in stroke diagnosis.

Unlike CNN, a unique memory-based deep neural network, Recurrent Neural Network (RNN) can remember the input from the previous moment and transmit it to the subsequent one [7]. However, for chronological tasks, the RNN application is more comprehensive. The authors proposed the RNN with Long Short-Term Memory (LSTM) hidden units in [8] to assess how well LSTMs can identify trends in the multi-label classification of stroke or cerebrovascular symptoms.

In [9], a deep learning algorithm in a CNN was used to create an automated early ischemic stroke detection system. The system will start image preprocessing as soon as the brain CT picture is entered to eliminate any areas that are not possible for a stroke. The patch photos will then be chosen, and the number of patch images will be increased using the Data Augmentation approach.

The authors in [11] used deep learning and multi-modal human speech and movement data for early stroke detection. They also addressed the effect of noise in audio, where audio-visual asymmetric fusion proceeds through the asymmetrical multi-modal attention (AMMA) audio model.

In [12], using machine learning and deep learning techniques, ultrasound images of the carotid artery were examined for the possible detection of atherosclerotic plaque and the classification of patients. The result shows an accuracy of 96.7%, thus demonstrating the capability of deep learning in detecting cardiovascular diseases.

The authors in [13] used a deep neural network to detect the risk of stroke through health behavior and medical service data of more than 15,099 patients, considering the rising incidence of stroke in South Korea. PCA with quantile scaling successfully extracted features, where the model produced an AUC = 83.48% score superior to five other machine learning methodologies. Doctors and patients can do early screening for stroke.

In [14], since the ischemic stroke constitutes a medical emergency, MRI and CT are the indispensable imaging modalities used for its diagnosis. In contrast, manual analysis may be time-consuming and less accurate. This study proposed a deep-learning object detection approach that includes techniques such as DCNN, YOLO5, and SSD for automatically identifying lesions within medical images. Of note is that the model achieved an accuracy of 96.43%, proving its efficacy in expeditious and accurate diagnosis.

The authors in [15] investigated the CNN-based approach for early stroke diagnosis using medical datasets constructed with 11 attributes. Various feature selection techniques are also employed to increase classification efficiency, and further, the model has been found to attain 95.5% accuracy, surpassing other model architectures. This is an effective early diagnosis and lowers the incidence of stroke by an 80% margin, given that the patient takes up preventive steps promptly.

In [16], the ConvNeXt Base model is used to predict ischemic stroke with high accuracy based on the analysis of MRI images. The model yielded an accuracy of 84% on the validation set, indicating its proficiency in distinguishing stroke risk

patterns. In the future, this approach could lead to early diagnosis and hasten and improve treatment decisions in a clinical setting.
In [17], the authors proposed models developed through machine learning to forecast the likelihood of a stroke, which were founded on five different physiological characteristics. The models mentioned in the study were Logistic Regression, Decision Tree, Random Forest, K-NN, SVM, and Naïve Bayes. Of these, the Naive Bayes model scored the highest accuracy of 82%, qualifying it as the best among all models for predicting the occurrence of stroke.
In [18], the authors used microwave scattering rather than traditional imaging techniques for stroke detection. The author presents a new technique. Using two deep neural networks (DNNs), he classified strokes with more than 94% accuracy (AUC = 0.996) for related classification and other networks to identify the location and size of the hemorrhage, less than 0.004 cm and below 0.02 cm, respectively. The approach combines high speed and low cost for the detection of stroke; it might improve early diagnosis.
Several research studies demonstrate the great potential of AI and deep learning technologies to improve the accuracy and speed of stroke prediction, contributing to better healthcare delivery and reducing associated mortality and disability rates.
With the significant advances in AI and deep learning technologies for early stroke detection, health data has become more vulnerable to security risks, such as unauthorized access or manipulation of information. Health data, including medical images and clinical records, is highly sensitive information, and any security breach can have serious consequences for privacy and patient trust in health systems. The importance of protecting health information is: 1) complying with laws and standards: such as the Health Information Protection Act (HIPAA) and the European Union's General Data Protection Regulations (GDPR); 2) Ensuring integrity by preventing data manipulation to ensure accurate diagnosis and prognosis; 3) Enhancing trust via encouraging patients to adopt AI technologies when their data is protected. Hence, several research studies have been conducted to maintain security in medical systems. The authors in [19] designed a secure consortium blockchain-based system for sharing electronic medical records of stroke patients. The system is designed to store the ciphertext of records in the cloud, whereas the index of the records is assumed to be stored on the blockchain with a combination of privacy mechanisms based on proxy re-encryption and searchable encryption. More precisely, the model provides privacy protection, tamper resistance, and speed in stroke treatment through secure sharing of health information.
In [20], the authors focused on blockchain technology, which is decentralized with safety for keeping data secure within cryptographically-linked blocks, making them

almost impossible to change. It is used in medicine to handle health information securely, for example, in pharmaceutical supply chains and pandemic responses. The authors seek to apply this technology in managing stroke nursing information systems and enhance the level of transparency and protection of patient data.

Care for an acute stroke needs a timely response, and cooperation between health organizations must occur in tandem, emphasizing the necessity of improving data availability via electronic health records (EHRs) and cloud computing. Hence, in [21], the authors proposed a cloud framework, with emphasis on the design of a privacy-preserving application for the management of EHR data sharing during stroke care. The proposed prototype synergizes the framework with a public cloud architecture against unauthorized access and data leakage and presents preliminary results concerning the efficacy and usability of the framework. In [22], the authors proposed protection technologies such as Radio Frequency Identification Devices (RFID) for the automatic identification of users and devices to complement the network database and smart grid-based information management software to enable secure data sharing. Besides, resource recovery strategies and scheduling optimization are established through theoretical algorithms that improve system efficiency and achieve collaboration among doctors and patients. In [23], the authors have come out with a system for sharing Electronic Medical Records (EMR) on blockchain technology to control what patients must share from being fetched from many hospitals for safekeeping. Besides security that could protect data from threats like forgery and privacy intrusions, it also provides scalable, distributed data-sharing methods. This model is implemented using Hyperledger Fabric as an open-source framework.

In [24], the authors developed an intelligent security framework for Smart Healthcare Systems (SHS), primarily based on the latest technology of pervasively interacting computing and IoT communication. The system constitutes the use of various machine learning techniques like ANN, decision trees, random forest, and k-nearest neighbor (KNN) to understand and thereby manage malicious activities and compare biometric data for further discrimination between normal and abnormal behavior. The design was tested against three defense types of introduced attacks, based on eight smart medical devices, showing the values of reliability (91%) and accuracy (F1-score) at 90%.

The combination of information security and deep learning methods is essential to achieving the goals of improving the healthcare system. This ensures the development of systems that not only improve the accuracy of stroke prediction but also provide high levels of security to protect patient data.

2. Research Background

This section discusses the main components of the present research, including the stroke treatment urgency, the applied dataset types, and the theoretical aspect of the proposed DL algorithms.

2.1 Stroke in the Human Body

A stroke is a medical emergency that occurs when blood flow to part of the brain is interrupted, depriving brain cells of essential oxygen and nutrients. If blood flow is not restored quickly, brain cells begin to die, causing permanent damage to the body and mind. Stroke is divided into two main types: ischemic stroke (caused by a blocked blood vessel) and hemorrhagic stroke (caused by a ruptured blood vessel) [25]. The leading causes of stroke are blocked arteries (ischemic stroke), caused by a blood clot or fatty buildup (atherosclerosis). Additionally, a breast vessel rupture (hemorrhagic stroke) is caused by uncontrolled high blood pressure or weakness in the walls of the blood vessel (such as an aneurysm). Other contributing NSL is not an acronyminclude heart disease, diabetes, smoking, obesity, and lack of physical activity.

The importance of stroke and why it needs prompt treatment is that stroke is the leading cause of long-term disability and one of the leading causes of death worldwide. Treating stroke quickly is crucial to minimizing the damage caused by the loss of brain cells. Intervention must be made within the so-called “golden window” of time up to 3 hours from the onset of symptoms. To avoid permanent disabilities [26]. Detriments resulting from delay may lead to loss of brain functions such as movement and speech., Increased risk of death and significant deterioration in patients’ quality of life.

Some of the key modern treatment techniques include Clot-dissolving drugs (such as alteplase), Surgical procedures such as removing blood clots, and contemporary techniques such as artificial intelligence to improve diagnosis and rapid intervention.

2.2 AHA Stroke Dataset

The American Heart Association (AHA) provides comprehensive data and guidance on stroke incidence, mortality, and prevention strategies. According to its 2024 heart disease and Stroke Statistics Update, stroke remains one of the leading causes of death and long-term disability worldwide [27]. Globally, approximately 15 million people suffer a stroke each year, resulting in 5 million deaths and another 5 million cases of permanent disability. In the United States, about 795,000 individuals experience a stroke annually, with around 610,000 being first-time strokes and 185,000 classified as recurrent. Stroke is responsible for nearly 140,000 deaths in the U.S. each year, accounting for approximately one in every six deaths related to cardiovascular disease.

The AHA stresses that up to 80% of strokes are preventable through lifestyle changes and effective risk factor management. Their data, also accessible via the Kaggle platform, underscores several key prevention strategies. A healthy diet rich in fruits, vegetables, whole grains, and lean proteins similar to the Mediterranean diet can play a critical role in stroke prevention. Regular physical activity, such as engaging in moderate aerobic exercise for at least 150 minutes or vigorous activity for 75 minutes per week, helps maintain cardiovascular health. Managing body weight, controlling blood pressure and cholesterol levels, and effectively regulating blood sugar in individuals with diabetes are also crucial. Additionally, avoiding smoking significantly lowers the risk of stroke. These lifestyle and medical interventions highlight the AHA's focus on reducing the global stroke burden through proactive health measures.

2.3 NSL-KDD Dataset

The NSL-KDD dataset, available on Kaggle, is a benchmark resource for evaluating Intrusion Detection Systems (IDS) [28, 29]. While "NSL" does not stand for specific terms, it denotes an improved version of the original KDD Cup 1999 dataset where KDD refers to Knowledge Discovery in Databases [30]. NSL-KDD addresses key limitations of its predecessor by removing redundant records, balancing normal and attack instances, and reducing dataset size to enhance efficiency and model fairness [30].

Designed for training and testing IDS models, the dataset contains labeled records of network activity, categorized as either normal or malicious. It is split into a training set for model development and a distinct test set to support unbiased performance evaluation.

Attacks are grouped into four types: Denial of Service (DoS), which floods systems to block access (e.g., Smurf, Neptune); Probe, which scans for network vulnerabilities (e.g., Nmap, Satan); Remote to Local (R2L), where outsiders gain unauthorized system access (e.g., Guess_Password); and User to Root (U2R), which escalates user privileges (e.g., Buffer_overflow).

Each record includes 41 features capturing various aspects of network behavior, such as connection duration, protocol type, login attempts, and traffic patterns. These features support the development of accurate, reliable IDS models by offering a detailed view of network activity.

3. The Proposed CNN-LSTM Model for Stroke Detection

The proposed structure of the CNN-LSTM hybrid approach combines the features of convolutional neural networks (CNNs) and long short-term memory networks

(LSTMs) to achieve comprehensive and efficient data analysis. The explanation for each of these algorithms is as follows:

3.1 Convolutional Neural Networks (CNNs)

CNNs are used to extract spatial features from data, especially images or time series. The algorithm recognizes local patterns or structures by applying filters or kernels.

The structure of the CNN involves the following layers:

1. Convolutional Layer:

$$Y_{i,j}^{K} = \sum_n \sum_m X_{i+mj+n} \cdot W_{m,n}^{k} + b^{k} \tag{1}$$

where, X is the input data, W is the kernel (filter), b Is the bias and Y Is the output.

2. Pooling Layer: Used to reduce the dimensions of the data while preserving important features (e.g., Max Pooling):

$$P = \max(\ X_{sub}\ ) \tag{2}$$

where, X_{sub} It is a subset of input data.

It is worth stating that the CNN advantage in CNN-LSTM is to process spatial patterns or local features, such as visual patterns or neighboring temporal values.

3.2 Long Short-Term Memory Networks (LSTM)

LSTMs are a special type of recurrent neural network (RNN) used to process sequential data with the ability to remember information for long periods.

The structure of the LSTM comprises the following gates:

Input gate:

$$i_t = \sigma\ (W_i[h_{t-1}, X_t] + b_i) \tag{3}$$

Forget gate:

$$f_t = \sigma\ (W_f[h_{t-1}, X_t] + b_f) \tag{4}$$

Output gate:

$$o_t = \sigma\ (W_o[h_{t-1}, X_t] + b_o) \tag{5}$$

Cell state update:

$$C_t = f_t \odot C_{t-1} + i_t \odot C_t^{\sim} \tag{6}$$

where, $C_t^{\sim}$ Represents the candidate cell state.

Here, the advantage of LSTM over CNN-LSTM is that the LSTM processes long-term temporal patterns in the data generated by CNN.

Now, for the proposed Hybrid CNN-LSTM algorithm, the modification will be as follows:
CNN output:

$$F_{CNN} = CNN(X) \quad (7)$$

LSTM input:

$$Y_{LSTM} = LSTM(F_{CNN}) \quad (8)$$

Then the final output:

$$Y_{output} = softmax(Y_{LSTM}) \quad (9)$$

$where,$ the function

$$softmax(Y_{LSTM}) = \frac{e^{Y_{LSTM}}}{\sum_{j=1}^{N} e^{Y_{LSTM}}} \quad (10)$$

Where, N Is the total number of classes?
$\sum_{j=1}^{N} e^{Y_{LSTM}}$ It is the normalization term that ensures all probabilities sum to 1.
The CNN-LSTM architecture effectively combines convolutional and recurrent neural networks to handle structured, sequential data such as time-series or medical signals. As illustrated in Figure 1, the model begins by reshaping the input data from a flat vector of shape (None, 8) to a 3D format of (None, 8, 1), preparing it for convolutional processing. This reshaped input is passed through two sequential Conv1D layers, each followed by a MaxPooling1D layer, which serve to extract local spatial features and reduce dimensionality.
Following the convolutional stages, the output is flattened and reshaped to align with the input requirements of LSTM layers. The reshaped data is then processed by two stacked LSTM layers, which are designed to learn temporal dependencies across the sequence of features. A Dropout layer is introduced between the LSTM and dense layers to prevent overfitting during training.
The architecture concludes with a fully connected Dense layer with 64 units, followed by an output Dense layer that performs the final classification task, producing a single output. This structure allows the model to capture both spatial and temporal patterns in the input data, enhancing its predictive capability.
Figure 1 provides a detailed layer-by-layer visualization of this architecture, including the input and output shapes at each stage, reinforcing the stepwise data transformation process described above.

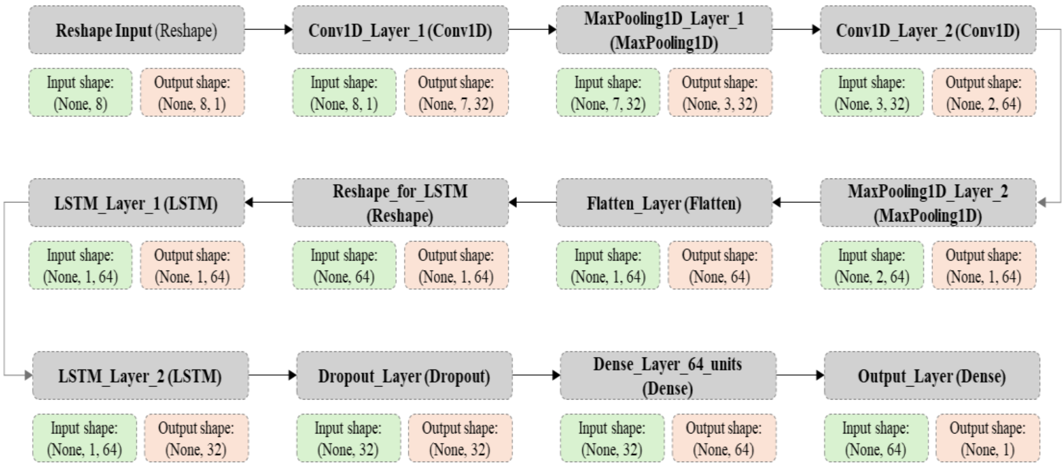

Figure 1: CNN-LSTM model structure.

4. The Proposed Shallow Deep Neural Network Model for Security

The Shallow Deep Neural Network (SDNN) is a neural network with a minimal number of hidden layers, typically 1-2, and fewer neurons per layer. It's designed for tasks requiring efficiency and interpretability while maintaining reasonable accuracy. Hence, the SDNN represents a lightweight security model. Figure 2 illustrates the structure of the SDNN algorithm.

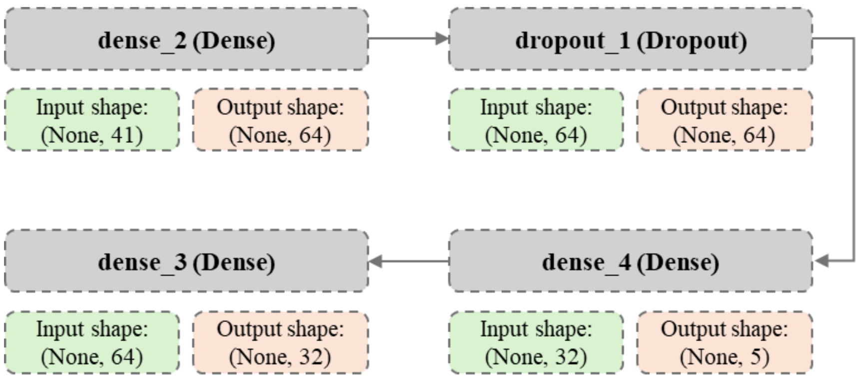

Figure 2: The proposed structure for the security SDNN model.

The CNN-LSTM architecture effectively integrates convolutional and recurrent neural networks to process structured sequential data, such as time-series or clinical measurements. As illustrated in Figure 1, the model begins by reshaping the input

vector from a two-dimensional shape of (None, 8) to a three-dimensional form (None, 8, 1) to enable compatibility with convolutional layers. The data is then passed through two consecutive Conv1D layers, each followed by MaxPooling1D layers, which serve to extract spatial features and reduce dimensionality.
Following feature extraction, the output is flattened and reshaped to the format required by the LSTM layers. Two stacked LSTM layers then capture temporal dependencies across the sequence of features. A Dropout layer is applied to mitigate overfitting by randomly deactivating neurons during training. Finally, the architecture includes a dense layer with 64 units, followed by a final dense output layer that performs binary or multiclass classification, depending on the task.
Figure 1 provides a clear, layer-by-layer visualization of the architecture, showing how the data transitions through each layer in terms of both shape and function, from preprocessing to final output.

5. Simulation Results and Discussion

This paper initially proposes a secure and accurate stroke medical system. Hence, the results are classified into two parts. First, the results of the prediction model to detect the stroke are obtained, and then in the second part, the results of the medical system security will be illustrated.
Three different models (CNN, LSTM, CNN-LSTM) are evaluated using the AHA Stroke Dataset. The employed hyperparameters of the simulated models are demonstrated in Table 1.

Table 1: The model's hyperparameters.

Hyperparameter	**CNN**	**LSTM**	**CNN-LSTM**
Number of Layers	3	2	2 CNN layers + 2 LSTM layers
Filter Size	3x3	N/A	3x3
Number of Filters	32	N/A	32
Activation Function	ReLU	Tanh	ReLU (in CNN layers), Tanh (in LSTM layers)
Dropout Rate	0.2	0.2	0.2
Batch Size	32	32	32
Epochs	200	200	200

Optimizer	Adam	Adam	Adam
Learning Rate	0.001	0.001	0.001
Loss Function	Binary Cross entropy	Binary Cross entropy	Binary Cross entropy

The performance evaluation of the proposed deep learning models, namely CNN, LSTM, and the hybrid CNN LSTM, was conducted using the AHA Stroke Dataset. The training results for each model are presented in Figure 3 through Figure 5, and the corresponding accuracy and loss values are summarized in Table 2.

The CNN model, as shown in Figure 3, achieved an accuracy of 94.7 percent with a loss value of 0.15. This indicates that the model was able to effectively learn spatial patterns relevant to stroke detection. However, its performance is somewhat limited by the lack of temporal awareness, which is important in sequential medical data. Figure 4 illustrates the performance of the LSTM model, which achieved a higher accuracy of 97.8 percent and a lower loss of 0.09.

This reflects the model's ability to capture and process time-dependent features, making it more suitable for medical datasets with temporal dynamics. Despite its strengths, the LSTM model does not capture spatial characteristics, which may be important for certain types of input data.

Figure 5 highlights the performance of the hybrid CNN LSTM model, which achieved the highest accuracy of 99.6 percent and the lowest loss of 0.03. This improvement is attributed to the combination of CNN's spatial feature extraction and LSTM's temporal modeling capabilities. The integration of these two architectures allows the hybrid model to process complex medical data more effectively by learning both local and sequential patterns. These results clearly demonstrate that the hybrid CNN LSTM model offers a significant advantage in predictive accuracy, confirming its suitability for high-performance stroke detection systems.

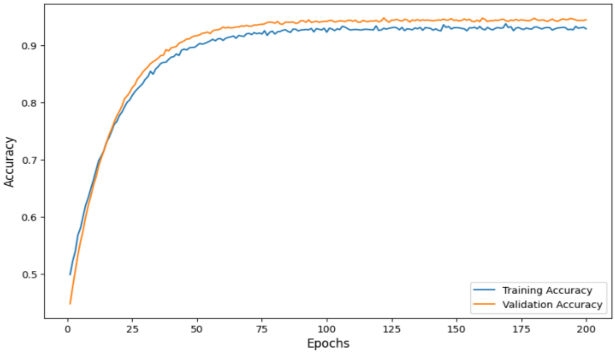

Figure 3: CNN model accuracy

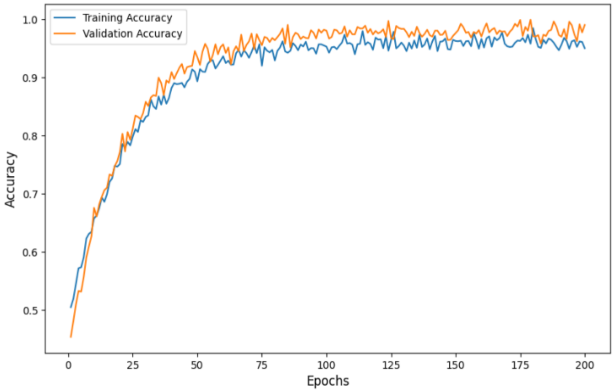

Figure 4: LSTM model Accuracy

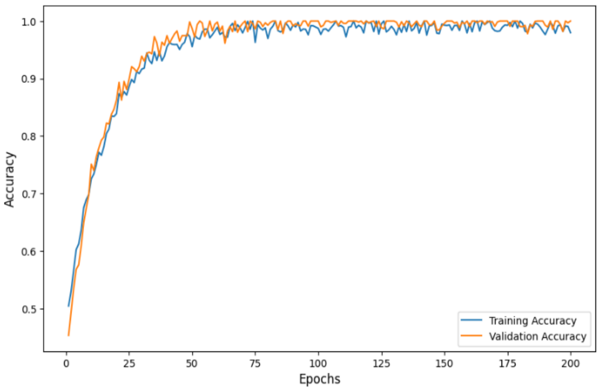

Figure 5: CNN-LSTM model Accuracy

Table 2: Comparison of three model results

Model	Accuracy	Loss
CNN	94.7%	0.15
LSTM	97.8%	0.09
CNN-LSTM	99.6%	0.03

It is worth stating that the algorithm CNNs processes spatial patterns or local properties, such as visual patterns or neighboring temporal values. The LSTMs process long-term temporal patterns in the data generated by the CNN. Hence, the hybrid version of CNN-LSTM achieved high detection accuracy due to utilizing the merits of both algorithms. The second part of the simulation focuses on the application of DL to maintain and achieve the security of high-speed attack detection for the proposed system. Two simulation scenarios are conducted. The first one is represented by using the hybrid CNN-LSTM to testify to the security due to its high accuracy, as shown in the first part. The application of the lightweight ASDNN algorithm is evaluated. First, the hybrid CNN-LSTM in security should be employed using the same structure as in Figure 1. The evaluation results are conducted using the NSL-KDD dataset, as shown in Figure 6.

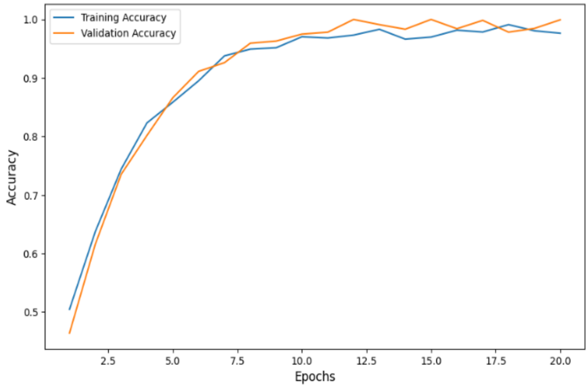

Figure 6 : Results of the security model using CNN-LSTM (99.8% accuracy)

The complexity analysis of the CNN-LSTM is illustrated as

5.1 Reshape Layer for the NSL dataset

The input shape changes from (41,) to (41, 1). No parameters are added here.

5.2 CNN layers

- **Conv1D Layer 1**:
  Filters = 32, Kernel Size = 2
  Parameters = (Input Channels * Kernel Size + Bias) * Filters
  Parameters = (1 * 2 + 1) * 32 = 96
- **MaxPooling1D Layer 1**:
  Pooling reduces the sequence length by half (from 41 to 20). No parameters are added.
- **Conv1D Layer 2**:
  Filters = 64, Kernel Size = 2
  Input Channels = 32 (from the first Conv1D layer)
  Parameters = (Input Channels * Kernel Size + Bias) * Filters
  Parameters = (32 * 2 + 1) * 64 = 4160
- **MaxPooling1D Layer 2**:
  Pooling reduces the sequence length by half (from 20 to 10). No parameters are added.

5.3 Flatten Layer

The model reshapes the output from the second MaxPooling layer into a 1D vector.
Output Size = Sequence Length * Filters = 10 * 64 = 640

5.4 Reshape for LSTM

The vector is reshaped to (1, 640). No parameters are added here.

5.5 LSTM Layers

- **LSTM Layer 1**:
  Units = 64
  Parameters = 4 * (Input Features * Units + Units^2 + Units)
  Parameters = 4 * (640 * 64 + 64^2 + 64)
  Parameters = 4 * (40960 + 4096 + 64) = 180960
- **LSTM Layer 2**:
  Units = 32
  Parameters = 4 * (Input Features * Units + Units^2 + Units)
  Input Features = 64 (from LSTM Layer 1)

Parameters = 4 * (64 * 32 + 32^2 + 32)
Parameters = 4 * (2048 + 1024 + 32) = 12288

5.6 Dense Layers

- **Dropout Layer**: No parameters are added.
- **Dense Layer (Output Layer)**:
  Input Features = 64 (from the previous Dense Layer)
  Output Units = 5 (for five classes)
  Parameters = (Input Features + Bias) * Units
  Parameters = (64 + 1) * 5 = 325

Total number of Parameters

- Conv1D Layer 1: 96
- Conv1D Layer 2: 4160
- LSTM Layer 1: 180960
- LSTM Layer 2: 12288
- Dense Layer (64 Units): 2112
- Updated Output Layer: 325

Total number of Parameters = 197,941

The second simulation scenario for the security model is represented by using the SDNN algorithm. The applied hyperparameters for the evaluation are shown in Table 3.

Table 3: The model hyperparameters

Hyperparameter	Value
Number of Hidden Layers	2
Neurons in Hidden Layers	64 in the first hidden layer, and 32 in the optional second hidden layer
Activation Function	ReLU for hidden layers; Softmax for output layer
Dropout Rate	0.2 (applied after the first hidden layer)
Optimizer	Adam with a learning rate of 0.001
Loss Function	Categorical Crossentropy
Epochs	20
Batch Size	32
Validation Split	30% of the training data is used for validation during training

The evaluation results for the SDNN algorithm. Using the NSL dataset is demonstrated in Figure 7

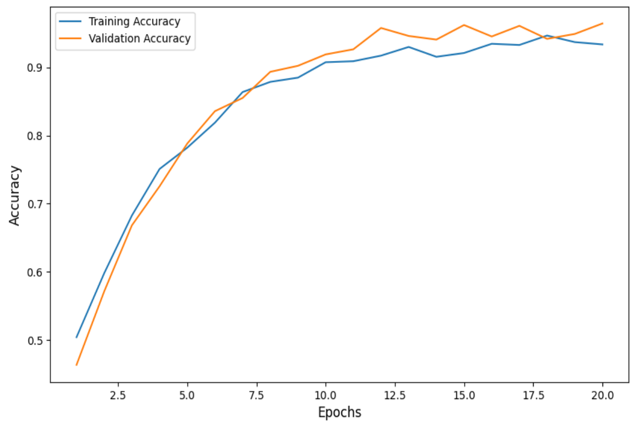

Figure 7: SDNN security model accuracy results

The computational complexity of a neural network is influenced by factors such as the number of parameters, the operations required during training and inference, and the size of the input data.

- **Number of Parameters:**

The model consists of two hidden layers:
First Hidden Layer: 64 neurons, each connected to 41 input features, resulting in 64 × 41 weights. Including 64 biases, this layer has 64 × 41 + 64 = 2,688 parameters.
Second Hidden Layer: 32 neurons connected to 64 neurons from the previous layer, resulting in 32 × 64 weights. Including 32 biases, this layer has 32 × 64 + 32 = 2,080 parameters.
Output Layer: 5 neurons (corresponding to the five classes), each connected to 32 neurons from the previous layer, resulting in 5 × 32 weights. Including five biases, this layer has 5 × 32 + 5 = 165 parameters.
Total Parameters: 2,688 (first hidden layer) + 2,080 (second hidden layer) + 165 (output layer) = 4,933 parameters.
It evident that the overall accuracy of the proposed CNN-LSTM is up to 99.8% compared to the lightweight SDNN security model of 96.8% accuracy. However, in terms of computational complexity, the total number of SDNN network parameters is 4,933 compared to the CNN-LSTM, which has parameters of 197,941. Hence, this can noticeably affect the attack detection speed.

6. Limitation

While the proposed CNN-LSTM-based system demonstrates high accuracy and robust security for stroke detection, several limitations should be acknowledged. First, the model's performance was evaluated using publicly available datasets—namely the AHA stroke dataset for prediction and the NSL-KDD dataset for security testing. Although these datasets are well-established, they may not fully capture the complexity and diversity of real-world clinical environments, particularly in terms of heterogeneous patient populations, comorbidities, and noisy data.
Second, the system was primarily tested on structured data with a limited number of input features. In practical medical scenarios, additional sources such as unstructured electronic health records, real-time monitoring signals, or multimodal imaging data may be involved. The current architecture may require adaptation or enhancement to effectively handle such diverse inputs.
Third, the integration of the SDNN for security is focused on intrusion detection and access control. While it provides a strong foundation for securing medical systems, it does not address all aspects of health data privacy, such as data anonymization, consent management, or compliance with regulatory standards like HIPAA or GDPR.
Furthermore, although the hybrid model achieves high accuracy, it may face deployment challenges in resource-constrained environments. The system's computational requirements for real-time processing, particularly when incorporating both CNN and LSTM layers, may necessitate optimization techniques or hardware acceleration to ensure feasibility in clinical settings.

Lastly, the study was conducted in a controlled simulation environment, and real-world implementation may present unforeseen integration challenges, including interoperability with existing hospital information systems, user interface requirements, and clinician acceptance. Future research should focus on validating the system in clinical trials and expanding its capabilities to address these practical concerns.

7. Conclusion

In this study, a secure and accurate deep learning-based medical system for stroke detection was proposed, combining predictive precision with robust information security. The core of the system is a hybrid CNN-LSTM model designed to leverage both spatial and temporal features from the AHA stroke dataset. The experimental results demonstrated that the hybrid model significantly outperforms traditional standalone approaches, achieving an accuracy of 99.6%, which reflects its ability to process complex clinical data effectively. This high performance confirms that

the integration of CNN and LSTM architectures enables more comprehensive feature extraction, which is critical for timely and reliable stroke diagnosis.
In parallel, the system addresses the pressing need for patient data protection by incorporating a secure classification mechanism using the SDNN model. Evaluated on the NSL-KDD dataset, the SDNN achieved a detection accuracy of 96.8%, ensuring a high level of security with minimal computational overhead. This integration of stroke prediction with cybersecurity components within the same system is a significant contribution, as such dual-focus solutions are rarely addressed in existing research.
Overall, the proposed framework demonstrates that deep learning can serve as a powerful foundation for intelligent healthcare systems that not only offer precise diagnostic support but also safeguard sensitive patient data. The model's success in combining predictive accuracy with real-time security monitoring establishes a promising direction for future developments in medical AI systems, particularly those intended for deployment in connected and data-sensitive healthcare environments.

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تصميم نظام طبي دقيق وآمن قائم على التعلم العميق للكشف عن السكتة الدماغية

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المستخلص: تُعد السكتة الدماغية من أخطر الحالات الطبية التي تتطلب تشخيصًا سريعًا ودقيقًا لتجنب مضاعفاتها المميتة. يُسهم استخدام تقنيات التعلم العميق (DL) في تعزيز دقة الكشف عن السكتات الدماغية في مراحلها المبكرة، مما يُمكّن من التدخل الطبي بشكل أسرع ويُقلل من الأضرار طويلة المدى. بالإضافة إلى الكشف المبكر عن السكتة الدماغية، يُعد الحفاظ على سرية معلومات المريض أمرًا بالغ الأهمية لضمان الثقة وحماية البيانات الحساسة. كما تُساعد تقنيات التعلم العميق في الكشف عن الوصول غير المصرح به أو التلاعب ببيانات المريض، مما يُعزز الأمن الرقمي ويضمن الامتثال لمعايير خصوصية الرعاية الصحية. في هذه الورقة البحثية، يُقترح نظام طبي دقيق وآمن قائم على التعلم العميق للكشف عن السكتات الدماغية. يتضمن التصميم مرحلتين. أولاً، اقتراح خوارزمية تعلم عالية الدقة للتعلم العميق للكشف عن السكتة الدماغية، والتي تُحقق من خلال خوارزمية هجينة من CNN-LSTM. تتمثل المرحلة الثانية في الحفاظ على أمان النظام الطبي المقترح من خلال اقتراح خوارزمية تعلم عميق فعّالة، والتي تُحقق باستخدام خوارزمية خفيفة الوزن من الشبكات العصبية العميقة الضحلة (SDNN). وقد تم تقييم أداء المرحلتين السابقتين من حيث الدقة والأمان ومساحة الذاكرة. تكشف نتائج المحاكاة أن خوارزمية CNN-LSTM الهجينة المقترحة تتمتع بدقة عالية في اكتشاف السكتة الدماغية مقارنة بالإصدارات المستقلة من CNN وLSTM بدقة تصل إلى ٩٩,٦٪ باستخدام مجموعة بيانات السكتة الدماغية AHA: من ناحية أخرى، يحافظ تطبيق خوارزمية SDNN على مستوى عالٍ من الأمان يصل إلى ٩٦,٨٪ باستخدام مجموعة بيانات NSL-KDD.

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الكلمات المفتاحية: النظام الطبي ، السكتة الدماغية، التعلم العميق، الدقة ، الامان ، CNN، LSTM، SDNN