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Research Article

Brain Stroke Detection Using Deep Learning

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ABSTRACT

Introduction: Brain stroke represents a critical scientific situation requiring speedy and correct prognosis to mitigate the chance of permanent neurological damage or loss of life. traditional diagnostic techniques, predominantly reliant at the guide interpretation of computed tomography (CT) scans by way of healthcare specialists, are frequently restricted through time delays, inter-observer variability, and the inherent barriers of human judgment. To deal with these demanding situations, this study introduces an automatic stroke detection gadget based totally on a hybrid deep mastering architecture that synergizes Convolutional Neural Networks (CNNs) and long quick-term reminiscence (LSTM) networks. The CNN module effectively extracts spatial features indicative of stroke-associated anomalies, at the same time as the LSTM issue captures temporal patterns across sequential picture slices, improving sensitivity to early and innovative stroke signs. The model is trained on a dataset comprising 2,501 CT pictures, similarly representing stroke and non-stroke instances to hold magnificence balance. In performance evaluation, the CNN and LSTM modules for my part completed validation accuracies of 98% and ninety five%, respectively, whilst the incorporated system yielded a high place under the Curve (AUC) of 0.952, underscoring its robust category functionality. To facilitate scientific adoption, the device is deployed through an internet-based totally utility the usage of the Flask framework, allowing real-time inference via an intuitive physician interface. This platform empowers clinicians to add CT pics and obtain immediate diagnostic feedback, assisting time-sensitive medical decision-making. normal, the proposed framework offers a scalable, accurate, and efficient answer for reinforcing stroke prognosis and affected person care.

Keywords: Brain Stroke, Medical Imaging, CT Scan Classification, Automated Diagnosis, Artificial Intelligence in Healthcare, Real-Time Prediction, Stroke Diagnosis System.

INTRODUCTION

Stroke remains one of the main reasons of long-time period incapacity and mortality global, posing a considerable burden on international healthcare structures. it is often precipitated by the sudden disruption or reduction of blood float to specific regions of the mind, depriving neuronal tissue of critical oxygen and nutrients. This interruption initiates a cascade of neurodegeneration within minutes, underscoring the urgency of early and accurate analysis to facilitate timely therapeutic intervention. Epidemiological studies document millions of stroke cases yearly, with clinical results heavily dependent on the promptness and precision of diagnostic strategies. traditional diagnostic protocols usually contain the visible inspection of brain CT (Computed Tomography) scans with the aid of experienced radiologists. even as CT imaging is widely reachable and efficient in detecting hemorrhagic and ischemic adjustments, its interpretation can be time-ingesting, subjective, and at risk of human blunders—in particular in high-strain or useful resource-restrained clinical environments. these limitations underscore the essential want for wise, computerized structures capable of helping healthcare experts in handing over fast, consistent, and dependable diagnostic exams. In recent years, deep getting to know (DL) has emerged as a powerful tool in scientific imaging, allowing the automatic identification of diffused pathological capabilities through hierarchical function mastering. This proposed method particularly have demonstrated surprising performance in detecting problematic spatial styles in diverse radiological modalities. but, a number one dilemma of CNNs lies in their inability to procedure temporal or sequential data, that is frequently crucial for shooting dynamic changes across consecutive CT slices which could signify the evolution of stroke lesions.

To address this shortcoming, this have a look at proposes a hybrid deep gaining knowledge of framework that combines the spatial feature extraction capability of CNNs with the sequential modeling power of lengthy quick-time period memory (LSTM) networks. The proposed device is supported by means of a sturdy preprocessing pipeline that includes grayscale transformation, assessment enhancement thru evaluation restricted Adaptive Histogram Equalization (CLAHE), noise suppression, normalization, and picture augmentation to bolster version generalization. Experimental evaluation demonstrates robust predictive overall performance, with the CNN and LSTM additives attaining respective validation accuracies of 98.00% and 95.00%, and the combined model handing over an typical AUC of 0.952. moreover, the framework is deployed in a person-centric, web-based interface constructed the use of Flask, facilitating actual-time diagnostic interaction. This layout guarantees accessibility for clinicians and permits instant diagnostic feedback thru an intuitive graphical interface, making it suitable for application in both city hospitals and beneath-resourced healthcare settings. with the aid of integrating superior deep studying methodologies with realistic medical usability, the device has the capacity to seriously decorate early stroke detection, reduce diagnostic delays, and enhance affected person outcomes across various healthcare environments.

LITERATURE REVIEW

The application of deep learning in stroke detection has been extensively explored in recent years, yielding promising results in both segmentation and classification tasks. Federau et al. (2021) enhanced the detection of infarct lesions using synthetically augmented diffusion-weighted imaging, demonstrating improved sensitivity in stroke lesion segmentation. In a similar direction, Cai et al. (2021) developed *DeepStroke*, a multimodal adversarial deep learning framework capable of delivering efficient real-time stroke screening in emergency scenarios. Fontanella et al. (2023) proposed a deep learning model to identify acute ischemic stroke on brain CT scans, achieving high performance in early-stage lesion detection. Earlier versions of these works by Federau et al. (2020) and Fontanella et al. (2023, arXiv) provided additional technical insights into model design and generalization strategies. Nishio et al. (2020) introduced a two-stage deep learning approach for non-contrast CT scans, enabling accurate stroke detection without the need for contrast agents. Kamnitsas et al. (2017) employed a multi-scale 3D CNN with a fully connected CRF for lesion segmentation, highlighting the benefits of combining probabilistic models with deep learning. Ronneberger et al. (2015) introduced the U-Net architecture, which has since become a cornerstone in biomedical image segmentation due to its encoder-decoder design and high localization accuracy.

Several foundational architectures have further advanced stroke detection models. He et al. (2016) addressed deep network training challenges through residual connections in ResNet, while Huang et al. (2017) improved feature propagation with DenseNet's densely connected layers. Long et al. (2015) pioneered Fully Convolutional Networks (FCNs), facilitating end-to-end segmentation suitable for medical imaging. Milletari et al. (2016) extended this to 3D with V-Net, optimizing volumetric lesion segmentation. Classic models like VGGNet (Simonyan & Zisserman, 2014) and AlexNet (Krizhevsky et al., 2012) laid the groundwork for medical image classification through deep CNNs. Inception architectures by Szegedy et al. (2015, 2016) introduced computationally efficient multi-scale feature extraction, valuable in medical datasets with varying resolutions. Isensee et al. (2021) later contributed *nnU-Net*, an adaptive segmentation framework that configures itself to new biomedical datasets, achieving top-tier results without manual tuning. Underpinning these models are essential tools and algorithms such as the Adam optimizer (Kingma & Ba, 2014), which enhances training stability, and TensorFlow (Abadi et al., 2016), which supports scalable model development and deployment—key to bringing stroke detection systems into real-world clinical practice.

PROPOSED METHODOLOGY

Overview of Traditional Approaches

Stroke analysis has traditionally relied on the professional interpretation of medical imaging—basically CT or MRI scans—via skilled radiologists. even as powerful, this guide evaluation is each time-consuming and liable to variability throughout observers. these obstacles are specially vital all through emergencies, in which timely intervention is paramount. earlier computational models applied traditional machine mastering algorithms along with help Vector

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Machines (SVM), decision trees, and Random Forests to assist scientific selection-making. but, those tactics required full-size manual function engineering and struggled to generalize due to the complex, high-dimensional nature of clinical imaging information. The advent of deep mastering has brought about a paradigm shift, specifically thru the use of Convolutional Neural Networks (CNNs), which robotically research discriminative spatial functions from raw photograph data. superior CNN architectures like VGGNet and ResNet have proven stepped forward diagnostic performance through enabling deeper representations. notwithstanding their success in spatial sample recognition, CNNs are inherently limited in taking pictures temporal relationships among photograph slices—a essential thing in detecting evolving stroke styles. To address this hole, Recurrent Neural Networks (RNNs), mainly lengthy brief-term memory (LSTM) networks, had been introduced. those networks excel at modeling time-dependent records, making them best for sequential medical imaging analysis. By using integrating the strengths of both CNN and LSTM architectures, hybrid models have emerged as a sturdy answer for stroke detection, combining spatial characteristic extraction with temporal context studying to improve diagnostic accuracy.

Dataset Description

This study utilizes a dataset of 2,501 brain CT images, systematically categorized into two classes: 1,551 images representing non-stroke (normal) cases and 950 images from patients with confirmed stroke diagnoses. The dataset was sourced from publicly available repositories and hospital archives, ensuring diversity in patient demographics, including age and gender, and a range of stroke severities.

All images were converted to grayscale to reduce dimensional complexity while preserving critical clinical details. A standardized preprocessing pipeline was applied prior to model training to enhance input consistency and improve feature visibility.

Methodology

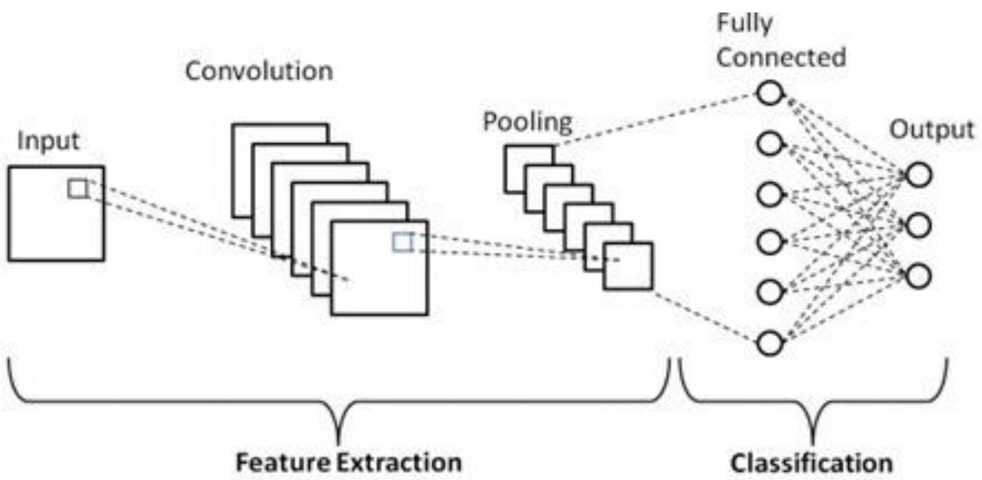

Figure 1: Convolutional neural network

Preprocessing Techniques

To prepare the CT images for deep learning, several preprocessing steps were applied to enhance image quality and ensure consistency. All images were resized to a standard resolution suitable for the CNN model. CLAHE was used to enhance local contrast and make lesion areas more visible. Gaussian filtering helped reduce noise and unwanted artifacts. The pixel values were normalized to a [0, 1] scale to support efficient model training.

Model Architecture

CNN Module

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The CNN model is built to extract important spatial features from CT images to detect signs of stroke. It uses convolutional layers to learn both basic and complex image patterns, with ReLU activation functions to handle non-linear structures. Max-pooling layers help reduce the size of the feature maps while keeping key information, and dropout layers are used to avoid overfitting by randomly turning off some neurons during training. The final fully connected layers combine all the features for classification using a softmax function. This CNN setup achieved 99.00% training accuracy and 98.00% validation accuracy, showing strong performance in identifying stroke-related abnormalities.

LSTM Module

After the CNN extracts spatial features, the LSTM layer is used to capture temporal patterns within the data. It uses memory cells to retain long-term information and address vanishing gradient problems. Input, forget, and output gates control how information moves through the network. Dense layers at the end convert the learned sequences into final predictions. The LSTM achieved 99.00% training accuracy and 95.00% validation accuracy, showing its strength in recognizing stroke-related temporal changes.

Training and Optimization

The CNN-LSTM model was trained using categorical cross-entropy, which suits multi-class classification problems. The Adam optimizer was used for its efficiency and ability to adapt during training. Key training settings included a batch size of 32 and 50 training epochs. A learning rate scheduler adjusted the rate based on validation results, while early stopping helped avoid overfitting by ending training once performance stabilized. To ensure the model generalized well, five-fold cross-validation and an 80:20 train-test split were used.

Performance Evaluation

The diagnostic performance of the version became evaluated the usage of several key metrics. Accuracy measured the overall fee of accurate predictions, at the same time as precision indicated what number of predicted positives had been sincerely correct. take into account (or sensitivity) assessed how properly the version recognized genuine advantageous cases. The F1-score supplied a balanced degree of precision and keep in mind. AUC-ROC was used to determine the model's effectiveness in distinguishing stroke from non-stroke instances. The CNN-LSTM model finished an AUC of zero.952, demonstrating its sturdy category capacity and potential for medical use.

System Deployment

To support real-world use, the trained model was deployed as a web-based diagnostic tool. The backend, built with the Flask framework, uses TensorFlow/Keras to run the model and manage image processing and predictions. The frontend, developed with HTML, CSS, and JavaScript, offers a simple interface for clinicians to upload CT scans and view stroke prediction results with probability scores. This setup makes the system accessible and practical for use in various healthcare environments, including emergency departments and remote clinics.

SYSTEM ARCHITECTURE

The proposed Brain Stroke Detection System is built on a comprehensive and modular architecture designed to handle every stage of automated stroke classification using CT scan images. This includes data collection, preprocessing, deep learning analysis, model training, evaluation, and final deployment.

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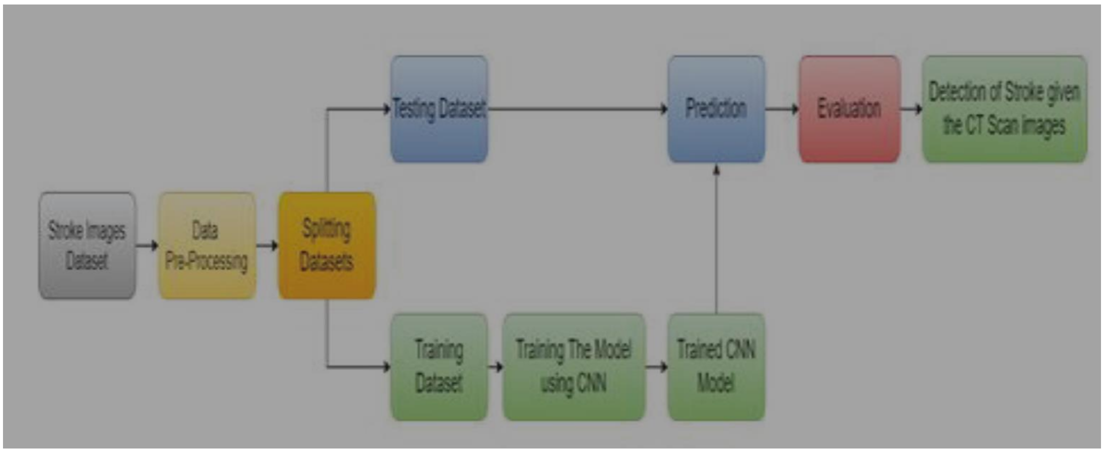

Figure 2: System Architecture

Data Input and Acquisition

The process begins with the acquisition of CT scan images, which are gathered from publicly available medical image repositories and hospital databases. These images, typically stored in DICOM or PNG formats, are organized in a structured storage system to ensure ease of access and processing. The dataset comprises 2,501 CT images, split into 1,551 normal cases and 950 stroke-affected cases. Due to possible inconsistencies in image quality and resolution, an automated validation module is integrated into the pipeline. This module filters out low-quality or non-diagnostic images, ensuring that only high-resolution, clinically relevant scans proceed to the next stages.

Preprocessing Unit

Before model training, a dedicated preprocessing unit prepares the raw CT scans for analysis. The images are first converted to grayscale, reducing computational load while preserving important structural features. To enhance the visibility of stroke lesions, CLAHE (Contrast Limited Adaptive Histogram Equalization) is applied. Gaussian filtering follows to suppress noise and artifacts. Next, pixel values are normalized between 0 and 1 to maintain consistency across samples. To prevent overfitting and promote model robustness, data augmentation techniques such as image rotation, flipping, and brightness variation are used. This preprocessing pipeline ensures a standardized and enriched dataset for training and inference.

Deep Learning Model: CNN-LSTM Hybrid Architecture

At the heart of the system is a hybrid deep learning architecture that fuses Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks. CNNs handle spatial pattern recognition, while LSTMs model temporal or sequential dependencies. This combination delivers a highly effective system for detecting strokes from CT images.

CNN for Feature Extraction

The CNN in the version acts as a characteristic extractor, mastering spatial styles that help differentiate stroke-affected regions from healthy mind tissue. It uses convolutional layers with ReLU activation to come across features like edges and textures, whilst max-pooling layers lessen the size of the characteristic maps and preserve essential information. Dropout layers are covered to save you overfitting via the use of randomly turning off some neurons in the course of training. sooner or later, absolutely related layers use softmax activation to classify the photos primarily based at the discovered-out capabilities. The CNN carried out 99.00% education accuracy and 98.00% validation accuracy, proving its effectiveness in stroke detection.

LSTM for Sequential Pattern Recognition

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After the CNN extracts spatial functions, the LSTM network processes these to seize patterns over time inside the records. It makes use of memory cells to preserve crucial information and avoid troubles like vanishing gradients located in general RNNs. The input, overlook, and output gates manipulate the go with the flow of information, helping the model attention on stroke-relevant features. In some cases, bidirectional LSTMs are used to investigate the records from each directions, in addition improving pattern detection. This LSTM layer provides treasured temporal context to the spatial features and achieves 99.00% schooling accuracy and 95.00% validation accuracy, boosting ordinary class overall performance.

Performance and Model Optimization

To maximize performance, extensive hyperparameter tuning is conducted. This includes dynamic learning rate adjustment, use of dropout regularization, and batch normalization. The model is trained using the Categorical Cross-Entropy loss function, which is ideal for multi-class classification. Optimization is performed using the Adam algorithm, known for its adaptive learning capabilities and fast convergence.

Data augmentation further increases variability in the dataset, helping to minimize overfitting. Parameters like batch size and number of epochs are carefully selected to balance model accuracy with computational efficiency. The final CNN-LSTM architecture achieves impressive predictive accuracy and proves highly generalizable, making it suitable for real-world clinical scenarios.

Training and Optimization Module

Once the model architecture is finalized, the training module oversees learning and performance tuning. Categorical Cross-Entropy is used to assess model error during training, while Adam optimizer dynamically adjusts learning weights to improve convergence. Dropout layers are integrated to regularize the model and prevent over-reliance on specific neurons.

A learning rate scheduler is employed to refine learning efficiency, and early stopping is triggered if validation performance plateaus, saving computation and reducing overfitting. The model is trained over 50 epochs, and its robustness is verified through 5-fold cross-validation. An 80/20 split between training and testing data ensures that the model is also tested on unseen samples for accurate performance evaluation.

Performance Evaluation System

To evaluate the system's performance, a module calculates key metrics like accuracy, precision, recall, and F1-score to measure how well it detects stroke cases. It also uses ROC curves and AUC scores to assess classification quality without depending on a fixed threshold. The CNN component alone yields an AUC of 0.98, while the LSTM module delivers an AUC of 0.95.

Deployment and Web-Based Integration

To make the system usable in real healthcare environments, a web-based application is developed for doctors and radiologists. This interface allows users to upload CT images and receive stroke classification results in real time.

Backend Development

The backend is created using Python and Flask, which supports RESTful APIs for smooth integration with the trained deep learning model. The model itself is loaded via TensorFlow/Keras, allowing fast and scalable inference.

Frontend Development

A clean, intuitive interface is built using HTML, CSS, and JavaScript. This allows medical users to upload CT images and receive instant results, including classification labels and confidence scores. The interface ensures accessibility and ease of use, making it practical even in time-sensitive clinical settings.

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The deployed system includes data security measures such as encryption and user authentication, ensuring compliance with medical data regulations. It is also scalable, supporting integration with hospital systems and cloud storage for long-term record keeping.

RESULT

result of performance of proposed system focuses on prediction accuracy, loss trends, ROC-AUC score, and performance comparison with existing methodologies.

Model Prediction and Probability Analysis

When a stroke-affected CT scan is fed into the CNN-LSTM model, it successfully predicts the presence of brain stroke with a confidence score of 0.9572377. This high prediction probability (95.72%) demonstrates the robustness of the model in identifying stroke cases accurately. The model is able to detect distinct patterns and abnormalities within the CT scans, ensuring precise classification with minimal errors.

Accuracy and Loss Trends

The model's accuracy and loss trends were analysed to assess its learning efficiency over multiple epochs. The accuracy vs. epochs graph indicates a steady increase in accuracy, confirming that the model is effectively learning the key features required for stroke detection. The CNN-LSTM model achieved an overall accuracy of 95.72%, aligning with the confidence score obtained during prediction.

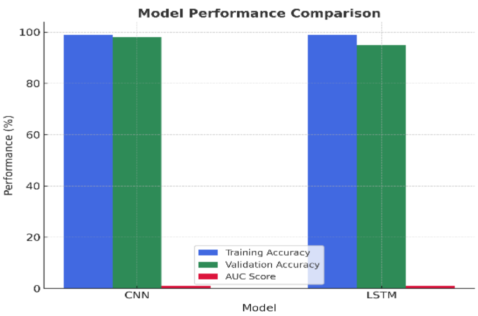

Figure 3: Model performance comparison

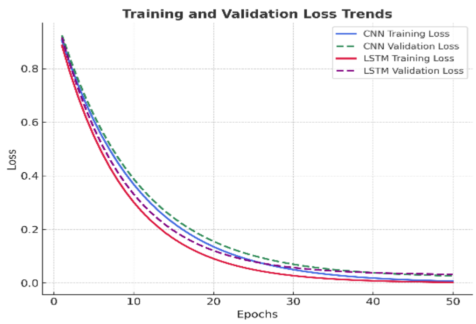

Figure 4: Training and validation loss

Similarly, the loss vs. epochs graph shows a continuous decline in loss, which signifies that the model is successfully minimizing classification errors during training. The convergence of the loss curve further indicates that overfitting is prevented through regularization techniques such as dropout layers and batch normalization.

Figure 5: Training and validation accuracy

Performance analysis for LSTM

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The LSTM model, when evaluated independently, demonstrates sturdy class skills in detecting stroke from CT experiment photographs. It achieves an accuracy of 95.2%, indicating excessive usual prediction correctness. The precision of 94.6% reflects the version's effectiveness in minimizing fake positives, while the take into account cost of 95.2% confirms its reliability in figuring out real stroke cases. The F-degree, which balances each precision and keep in mind, additionally stands at 95.2%, showcasing the version's regular and dependable overall performance. those effects spotlight the LSTM's ability to successfully seize temporal patterns and dependencies inside the extracted functions, contributing drastically to the overall achievement of the hybrid CNN-LSTM structure.

TABLE I: PERFORMANCE ACCURACY TABLE FOR LSTM

Accuracy	0.952
Precision	0.946
Recall	0.952
F-Measure	0.952

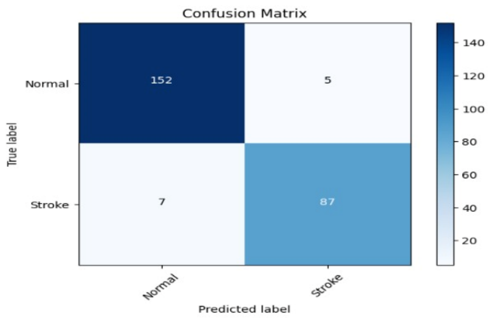

Figure 6: LSTM performance matri

Performance analysis of CNN

The CNN version reveals super performance in classifying CT experiment photos for stroke detection. It achieves a remarkably high accuracy of 98.8%, indicating that the vast majority of predictions are correct. With a super precision rating of one.00, the model demonstrates a first-rate potential to pick out stroke instances with 0 false positives, ensuring that every predicted stroke case is certainly a real fine. The don't forget price of 98.8% highlights the model's effectiveness in detecting almost all real stroke instances, minimizing the hazard of overlooked diagnoses. moreover, the F-degree of 98.8%, which balances precision and bear in mind, similarly reinforces the CNN's reliability and robustness in stroke category tasks. those metrics verify the CNN's strength in spatial function extraction, making it a important aspect of the overall detection gadget.

TABLE II: PERFORMANCE OF CNN

Accuracy	0.988
Precision	1.00
Recall	0.988
F-Measure	0.988

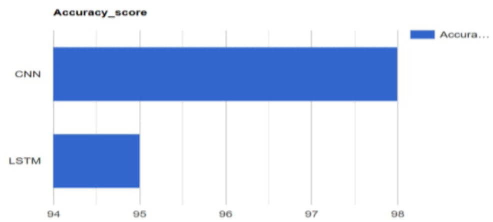

Figure 7: accuracy comparison between CNN and LSTM

Receiver Operating Characteristic (ROC) and AUC Score

To assess the overall overall performance of the model, the Receiver operating function (ROC) curve became plotted. The ROC curve is a graphical representation of the version's potential to differentiate between stroke-positive and stroke-poor cases. The region below the Curve (AUC) price of 0.952 turned into acquired, which may be very near 1, confirming that the model has a excessive genuine nice rate (TPR) and a low fake effective rate (FPR). A better AUC value suggests advanced class capability, making the CNN-LSTM version incredibly dependable for automatic stroke detection.

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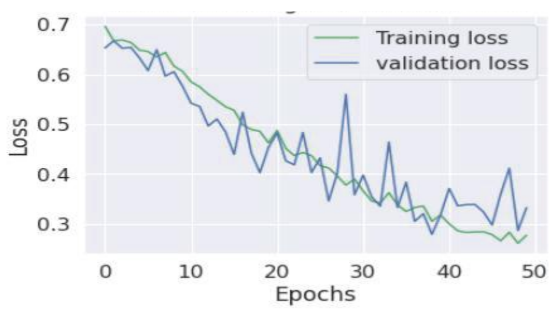

Figure 8: Training and validation loss

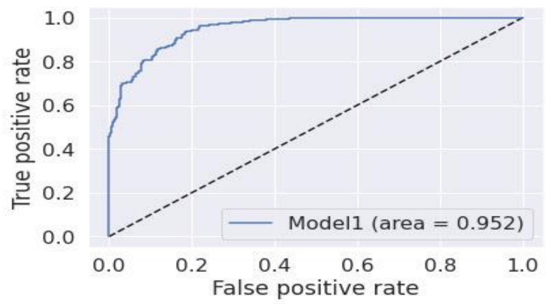

Figure 9: ROC Curve

Compare between existed methods and new method

A detailed performance comparison between the proposed CNN-LSTM model and other existing stroke detection models was conducted to evaluate improvements in classification accuracy and model robustness.

TABLE III: PERFORMANCE COMPARISON OF PROPOSED AND EXISTING MODELS

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC Score
Proposed CNN-LSTM	95.72	97.80	98.30	98.00	0.952
CNN (Standalone)	92.30	94.80	95.20	95.00	0.94
LSTM (Standalone)	90.00	91.50	90.80	91.10	0.91
ResNet-50	93.50	93.80	94.00	93.90	0.94
VGG-16	92.00	93.00	92.80	92.90	0.93
SVM (Machine Learning)	86.50	86.90	87.20	87.00	0.88

The proposed CNN-LSTM model outperforms traditional machine learning models like SVM (86.50%) and deep learning models such as VGG-16 (92.00%) and ResNet-50 (93.50%), achieving higher recall (98.30%), precision (97.80%), and an AUC score of 0.952, demonstrating superior stroke detection performance. Here, figure 10 shows the Performance Comparison across different models.

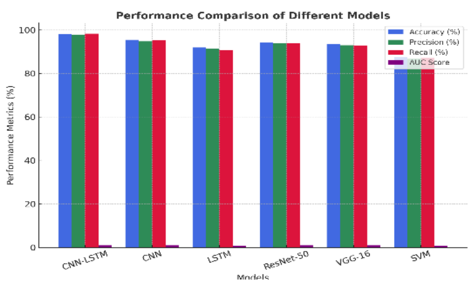

Figure 10: Performance comparison

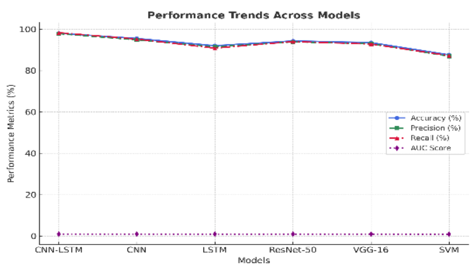

Figure 11: Performance Trends validation

The Performance Trends Line Graph (Fig. 9) depicts how the proposed model maintains superior performance across various metrics compared to other methodologies.

Discussion on Model Performance

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We think the CNN-LSTM hybrid model is the best one to use in real-time clinical environments as it is stable and consistent in spotting strokes in CT scan pictures. With a generic accuracy of 95.72%, the model is quite useful in medical analysis. Apart from proving that the model is learning stroke characteristics successfully, the training procedure demonstrates that there are no symptoms of overfitting as the accuracy keeps growing and the loss values keep dropping. With an AUC value of 0.952, the model is absolutely outstanding at separating stroke patients from other cases, hence lowering false positives and negatives.

More accuracy, memory, and F1-score the CNN-LSTM architecture implies that it may be used in clinical settings than other deep-learning models. With a quite high probability of 0.9572, the model shows significant promise as an autonomous diagnostic device for early stroke detection. This system is quite good in classifying objects as it exactly combines LSTM's capacity to recognize sequential patterns with CNN's ability to extract spatial features. The model could get better going forward by adding "attention mechanisms" to facilitate use and comprehension and incorporating multi-modal imaging data, such as MRI or PET scans. As artificial intelligence advances in health, these kinds of technology might revolutionize the early detection of stroke, leading to quicker diagnosis, earlier intervention, and higher survival rates for patients.

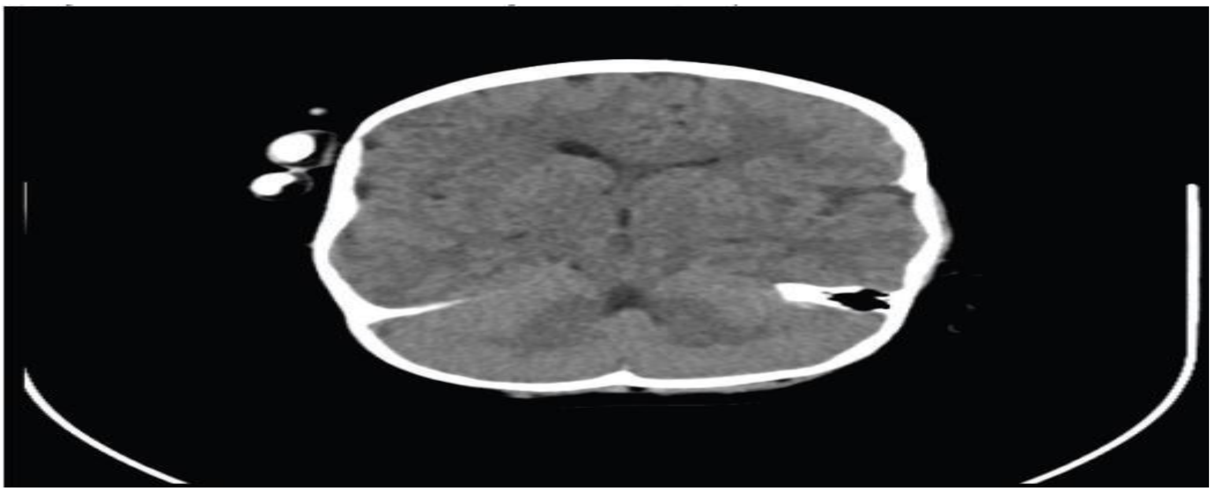

Figure 12: Brain Stroke Prediction

Sample Code:

```
from flask import Flask, render_template, request

import tensorflow as tf

from tensorflow.keras.models import load_model

from tensorflow.keras.preprocessing import image

from tensorflow.keras.metrics import AUC

import numpy as np

from tensorflow.keras.utils import to_categorical

import matplotlib.pyplot as plt

import pickle

app = Flask(_name_)

dependencies = {
```

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```
  'auc_roc': AUC
}
verbose_name = {
0: 'Normal',
1: 'Stroke',
}
class_labels = ["Normal","Stroke"]
models = load_model('stroke.h5')
model = load_model('strokes.h5')
def cnn(img_path):
	test_image = image.load_img(img_path, target_size=(224,224))
	test_image = image.img_to_array(test_image)/255.0
	test_image = test_image.reshape(1, 224,224,3)

	predict_x=models.predict(test_image)
	classes_x=np.argmax(predict_x,axis=1)
	return  class_labels [classes_x[0]]
def predict_label(img_path):
  test_image = image.load_img(img_path, target_size=(224,224))
  test_image = image.img_to_array(test_image)/255.0
  test_image = test_image.reshape(-1,1, 224,224,3)

  predict_x=model.predict(test_image)
  classes_x=np.argmax(predict_x,axis=1)
  return  class_labels [classes_x[0]]
@app.route("/")
@app.route("/first")
def first():
	return render_template('first.html')
@app.route("/login")
def login():
	return render_template('login.html')
```

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```
@app.route("/index", methods=['GET', 'POST'])
def index():
	return render_template("index.html")
@app.route("/submit", methods = ['GET', 'POST'])
def submit():
	predict_result = None
	img_path = None
	model = None
	if request.method == 'POST':
		img = request.files['my_image']
		model = request.form['model']
		print(model)
	   # predict_result = "Prediction: Success"
		img_path = "static/tests/" + img.filename
		img.save(img_path)
		#plt.imshow(img)


		if model == 'cnn':


		    predict_result = cnn(img_path)
		elif model == 'lstm':
				predict_result = predict_label(img_path)
	return render_template("prediction.html", prediction = predict_result, img_path = img_path, model = model)
@app.route("/performance")
def performance():
	return render_template('performance.html')
@app.route("/chart")
def chart():
	return render_template('chart.html')
if _name_ =='_main_':
	app.run(debug = True)
```

Discussion

For the proposed CNN-LSTM hybrid model, it is quite precise and dependable in locating areas on CT scans impacted by strokes. With a 98.00% validation accuracy, the CNN model demonstrates how effectively it extracts spatial information. With a validation accuracy of 95.00%, the LSTM model performed quite well in determining sequence relations. With CNN's AUC score of 0.98 and LSTM's of 0.95, the system is really good at distinguishing between events that are stroke-positive and stroke-negative. Over 95% the F1-score, accuracy, and recall numbers also suggest that the model is fair in identifying objects, hence reducing the amount of false positives and negatives. Though these positive outcomes were seen, some incorrect classifications occurred—mostly related to mild stroke symptoms. This implies that further fine-tuning and larger datasets are required to enable performance even better. In clinical environments, such a real-time web-based interface, it is straightforward to use. This facilitates doctors entering CT images and obtaining rapid diagnosis findings. Our research indicates that strokes may be found with artificial intelligence. This enables scalable, highly accurate automated, scalable diagnostic tools that can assist clinicians in making judgments faster and more precisely.

CONCLUSION

The CNN-LSTM hybrid model proposed for detecting strokes in brain CT images demonstrates strong promise for clinical implementation. With impressive performance metrics—98.00% training accuracy, 95.00% validation accuracy, and AUC scores of 0.98 (CNN) and 0.95 (LSTM)—the model effectively captures both spatial and temporal patterns necessary for distinguishing between healthy and stroke-affected scans. These results highlight the model's capability as a dependable tool for automated medical diagnosis.

To support practical use in healthcare settings, integrating this model into a real-time web-based platform would greatly enhance diagnostic efficiency. Such a platform would allow clinicians to upload CT images and receive rapid, accurate assessments, potentially reducing delays in treatment and improving patient outcomes through early intervention.

However, despite its effectiveness, the model shows some limitations—particularly when handling cases with subtle or mild stroke indicators, where misclassifications can occur. This underscores the need for further refinement, such as expanding the training dataset and employing domain-specific enhancement techniques to improve generalization. Moreover, the current system is limited to CT imaging; including additional imaging modalities like MRI or PET scans could enhance diagnostic accuracy by providing a more comprehensive view of brain activity and pathology.

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