A

Project Report on

ENHANCED FUSION OF DEEP LEARNING MODELS FOR PREDICTING AND EXPLAINING ISCHEMIC STROKE

Submitted in partial fulfilment of the requirements
for the award of the degree of

BACHELOR OF TECHNOLOGY

In

ARTIFICIAL INTELLIGENCE AND DATA SCIENCE

Submitted by

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ARTIFICIAL INTELLIGENCE

ANNAMACHARYA INSTITUTE OF TECHNOLOGY AND SCIENCES

(AUTONOMOUS)

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Tirupati-517520.

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CERTIFICATE

Certified that this is a Bonafide record of the Project Report entitled, ***"Enhanced Fusion of Deep Learning Models For Predicting And Explaining Ischemic Stroke",*** *done by K Goutham (21AK1A3041),K Arun Kumar (21AK1A3004),D Anand Kumar (22AK5A3002),M Jaswanth (22AK5A3004) is being submitted in partial fulfilment of the requirements for the award of the degree of* ***BACHELOR OF TECHNOLOGY*** *in* ***ARTIFICIAL INTELLIGENCE AND DATA SCIENCE*** *to the Annamacharya Institute of technology and Sciences, Tirupati, during the academic year 2024-25.*

Signature of the supervisor	Signature of HOD
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DATE:

INTERNAL EXAMINER **EXTERNAL EXAMINER**

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DECLARATION

We hereby declare that the project titled **"Enhanced Fusion of Deep Learning Models for Predicting and Explaining Ischemic Stroke"** is a genuine project work carried out by us, in B.Tech (Artificial Intelligence & Data Science) course in Annamacharya Institute of Technology And Sciences and has not been submitted to any other course or university for the award of our degree by us.

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CONTENTS

ABSTRACT

This disorder is a major cause of mortality and long-term disability worldwide, such that model development for the early and accurate prediction of ischemic stroke is highly demanded. The novel beyond this project is developing an enhanced hybrid deep learning method for predicting ischemic stroke risk with the consideration of the time series and image based medical data through the hybridized Deep Learning models, such as the CNNs and LSTM networks. But on the one hand, LSTMs can learn sequential dependencies as there is an established sequential dependence in patient data such as age, BMI, smoking habits, and medical history, while on the other hand, CNNs can extract spatial features from medical images such as CT, MRI, etc. The proposed system through integration of these models does not only increase the accuracy of such predictions, but it also provides the interpretable explanation into the decision-making process thereby providing the healthcare professionals insights to take timely and informed interventions. Unlike the traditional methods, this system does not involve any manual feature extraction or feature selection with limited datasets, but utilizes the full, multimodal real time data. The interpretability features of the model enable the transparency and trust in clinical applications. This is an innovative idea for adaptation of a dual model approach – to provide faster diagnosis with better patient outcome and more efficient stroke management in (for example) emergency settings. Finally, the system is a robust tool for early stroke detection, and provides itself a much-advanced capability than that available today used for the stroke risk assessment and prevention.

Keywords: Ischemic stroke, early prediction, Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), time-series data, medical images, CT scans, MRI scans, deep learning, stroke management, patient outcomes, prediction accuracy, temporal patterns, spatial features, health data analysis, real-time analysis, early detection, intervention, medical image processing, stroke diagnosis**.**

LIST OF FIGURES

LIST OF ABBREVIATIONS

Short Form	Abbreviation
DL	Deep Learning
CNN	Convolutional Neural Networks
LSTM	Long Short-Term Memory
RELU	Rectified Linear Unit
UML	Unified Modelling Language
DFD	Dataflow Diagram

1. INTRODUCTION

1.1 INTRODUCTION

In recent decades, healthcare has undergone transformative changes due to the integration of advanced technologies such as Artificial Intelligence (AI) and Deep Learning (DL). These computational tools are proving to be essential in addressing global health issues, particularly non-communicable diseases like strokes. Strokes are one of the leading causes of disability and death worldwide, with ischemic strokes constituting approximately 87% of all stroke cases. An ischemic stroke occurs when a blood clot obstructs a blood vessel supplying blood to the brain, causing a sudden and significant reduction in oxygen and nutrient delivery. This event can result in permanent neurological damage, disability, or even death if not diagnosed and treated promptly.

According to the World Health Organization (WHO), more than 15 million people suffer from strokes every year, of which nearly 5 million die, and another 5 million are left permanently disabled. Among these, ischemic strokes are the most common type, driven by various risk factors such as high blood pressure, diabetes, cardiovascular disease, obesity, smoking, and genetic predisposition. The early and accurate prediction of ischemic stroke risk is therefore crucial for timely intervention, prevention, and treatment.

Traditionally, stroke diagnosis is conducted through a combination of clinical assessments, imaging techniques such as CT and MRI scans, and laboratory tests. However, these diagnostic methods are time-consuming, expensive, and require highly skilled professionals, which may not be available in rural or resource-limited settings. Moreover, the subtle symptoms of early-stage ischemic strokes are often overlooked, leading to delayed diagnosis and treatment. As a result, there is an urgent need for automated and intelligent systems that can predict the likelihood of stroke based on patient data and assist clinicians in decision-making.

To address this challenge, recent advancements in deep learning have opened up promising avenues for medical prediction tasks. Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks are two powerful architectures that have shown significant performance in analysing structured and unstructured medical data. CNNs are particularly effective in extracting hierarchical spatial features from image or tabular data, while LSTMs are designed to capture temporal dependencies and sequential patterns in time-series data. By integrating CNN and LSTM into a hybrid model, it becomes possible to extract complex features and learn long-term

dependencies simultaneously, which is essential for capturing the multi-dimensional characteristics of patient health records.

The aim of this research is to design a hybrid deep learning model combining CNN and LSTM for the accurate prediction of ischemic stroke. The model is trained on patient datasets that include features such as age, gender, hypertension, heart disease, glucose levels, body mass index (BMI), smoking status, and previous stroke history. The CNN layers are responsible for extracting relevant patterns from the feature matrix, while the LSTM layers analyse the temporal relationships and risk progression over time. The hybrid model is expected to outperform traditional machine learning methods in terms of classification metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC).

The key contributions of this study include:

Developing a hybrid CNN-LSTM based deep learning model for ischemic stroke prediction.

1. Utilizing a comprehensive stroke dataset with 5,000+ instances and multiple clinical features for effective training and testing.
2. Applying data preprocessing, normalization, and feature engineering techniques to enhance data quality and model robustness.
3. Comparing the performance of the hybrid model with standard classifiers such as Logistic Regression (LR), Random Forest (RF), Support Vector Machine (SVM), and Gradient Boosting (GB).
4. Evaluating the model using cross-validation and grid search optimization to ensure generalizability and accuracy.
5. Aiming to build a cost-effective, accurate, and real-time predictive system that can be deployed in healthcare settings to reduce the burden of stroke-related morbidity and mortality.

1.2 EXISTING SYSTEM

The existing system primarily leverages traditional machine learning algorithms or standalone deep learning architectures, such as Convolutional Neural Networks (CNNs), for predicting ischemic stroke based on structured clinical data. CNNs are highly effective in extracting spatial features and patterns within input datasets, making them suitable for analyzing the relationships between patient attributes such as age, hypertension, diabetes, and smoking status. However, CNNs alone are not fully equipped to handle temporal dependencies or sequential changes in

patient health metrics over time. Moreover, their performance is often limited by the lack of temporal context and can degrade when confronted with missing or imbalanced medical records. These constraints may result in reduced prediction accuracy and reliability, particularly in real-world healthcare scenarios where data variability is common. Therefore, integrating models that can also capture sequential dependencies, such as Long Short-Term Memory (LSTM) networks, is essential to improve predictive performance in ischemic stroke forecasting.

1.3 DISADVANTAGES OF EXISTING SYSTEM

1. **High Computational Demand**: Deep learning models like CNNs and LSTMs require considerable computational resources and memory, making them challenging to deploy in real-time clinical environments.
2. **Large Data Requirement**: These models often need extensive, high-quality, and balanced medical datasets to achieve accurate predictions, which are not always readily available, especially in stroke cases.
3. **Imbalanced Class Distribution**: Stroke datasets typically suffer from class imbalance (more non-stroke cases than stroke cases), which can lead to biased predictions and reduced sensitivity to stroke detection.
4. **Overfitting Risk**: Complex deep learning models may overfit on training data, especially when the dataset is small, reducing the model's ability to generalize on new patient records.
5. **Limited Interpretability**: Both CNNs and LSTMs function as "black box" models, providing limited insights into how specific input features contribute to the final stroke prediction, which may hinder clinical trust and adoption.
6. **Data Quality Sensitivity**: The performance of existing models is highly dependent on the completeness and consistency of input data, which can be a limitation in real-world medical records containing missing or noisy values.
7. **Lack of Temporal Awareness in CNNs Alone**: Systems relying solely on CNNs fail to capture temporal dependencies in patient health metrics, which are crucial for modeling the progression of stroke risk over time.

1.4 PROPOSED SYSTEM

The proposed system aims to improve ischemic stroke prediction by integrating Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks. CNNs are employed to automatically extract spatial features from medical imaging data, such as brain scans, and clinical parameters. These spatial patterns are crucial for identifying structural abnormalities associated with ischemic stroke.

LSTMs, known for their ability to capture temporal dependencies, are integrated to analyse sequential patient health records and time-series data such as blood pressure, glucose levels, and heart rate variability. This combination enables the system to not only understand static features but also recognize patterns and trends over time that contribute to stroke risk.

By merging CNNs and LSTMs, the model leverages both spatial and temporal information, significantly enhancing prediction accuracy. This hybrid approach allows early and more reliable detection of stroke likelihood, supporting proactive medical intervention and potentially improving patient outcomes.

1.5 ADVANTAGES OF PROPOSED SYSTEM

1. **Accurate Stroke Prediction**: The CNN-LSTM model combines spatial and temporal analysis, leading to more precise stroke risk assessment.
2. **Effective Pattern Learning:** CNNs handle complex image features while LSTMs process time-series data like patient history, improving overall model learning.
3. **Timely Diagnosis:** The model aids in early-stage detection of ischemic stroke by analyzing progressive clinical indicators over time.
4. **Accurate Stroke Prediction:** The CNN-LSTM model combines spatial and temporal analysis, leading to more precise stroke risk assessment.
5. **Effective Pattern Learning:** CNNs handle complex image features while LSTMs process time-series data like patient history, improving overall model learning.
6. **Timely Diagnosis:** The model aids in early-stage detection of ischemic stroke by analyzing progressive clinical indicators over time.
7. **Reduced Human Error:** Automated feature extraction minimizes reliance on manual interpretation, increasing consistency in results.
8. **Flexibility Across Modalities:** Works with different data formats such as MRI, CT scans, and medical records, enhancing clinical applicability.
9. **Improved Decision Support:** The model supports clinicians with data-driven insights, potentially leading to better treatment planning and patient outcomes.
10. Automated feature extraction minimizes reliance on manual interpretation, increasing consistency in results.
11. **Flexibility Across Modalities**: Works with different data formats such as MRI, CT scans, and medical records, enhancing clinical applicability.

2. SYSTEM ANALYSIS

2.1 INTRODUCTION

The scope of this project involves designing and evaluating a deep learning-based system for predicting ischemic stroke using a combination of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. The system will begin with the collection and preprocessing of relevant medical data, such as brain imaging (MRI or CT scans), patient demographics, clinical reports, and historical risk factors. CNNs will be utilized for extracting spatial features from medical images, while LSTMs will analyse temporal patterns in sequential clinical data. The model aims to enhance early stroke prediction by integrating both visual and temporal information, improving accuracy and decision-making. The system is intended to assist healthcare professionals in diagnosing ischemic stroke risks in a timely and efficient manner. Future work may focus on optimizing the model for real-time use and deployment on clinical decision support platforms. This project also seeks to advance the role of artificial intelligence in preventive healthcare, particularly in neurology and emergency medicine.

2.2 SOFTWARE REQUIREMENTS SPECIFICATION

2.2.1 User Requirements

PC or MAC or Laptop with x86-64(64bit) Compatible Processors

2.5 GHz Processor or above is recommended

At least 1 GB of free RAM should be available for the application

Anaconda Navigator

2.2.2 Software Requirements

Operating System	: Windows 7/8/10
Programming Language	: Python
Libraries	: Pandas, NumPy, scikit-learn, Tensor flow
IDE/Workbench	: Jupiter Notebook.

2.2.3 Hardware Requirements

Processor	- I3/Intel Processor
Hard Disk	- 50GB
RAM	- 8GB

2.3 FLOWCHART:

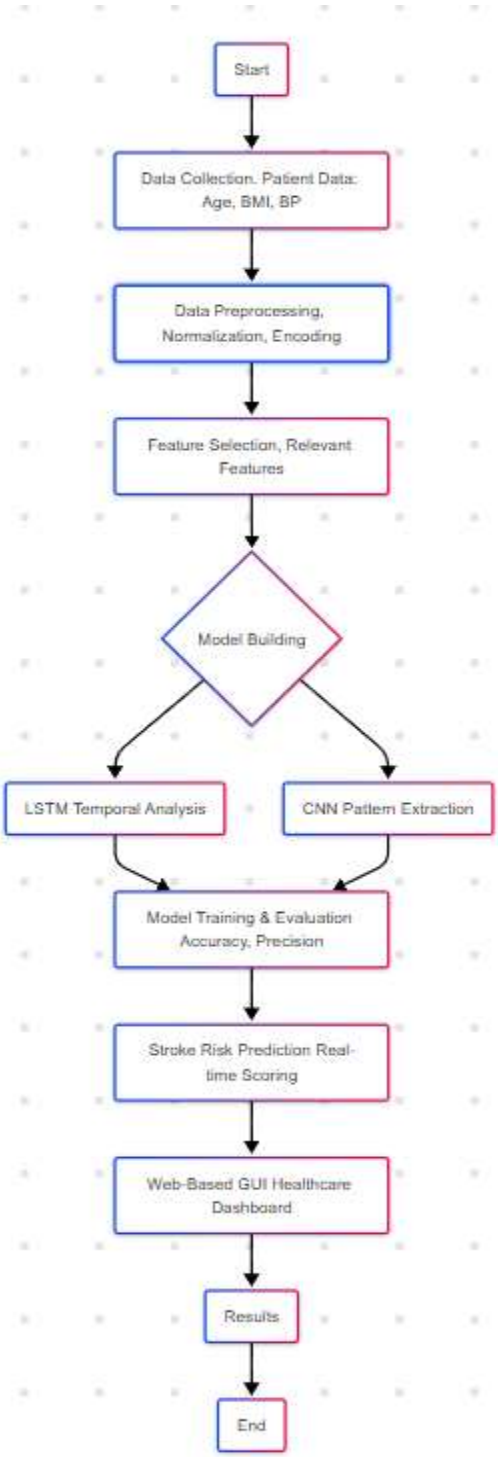

Fig: Flowchart for Ischemic Stroke Prediction

3. DESIGN

3.1 STEPS INVOLVED IN ISCHEMIC STROKE PREDICTION

3.1.1 Data Gathering and Data Pre-processing

In this step, patient health records related to ischemic stroke are collected and pre-processed to prepare the data for model training. The preprocessing steps include:

1. **Handling Missing Values:** Missing or null entries in the dataset are identified and appropriately treated using methods like imputation or removal to ensure clean data.
2. **Feature Selection:** Relevant features such as age, hypertension, heart disease, glucose levels, BMI, and smoking status are selected based on medical significance to improve prediction performance.
3. **Data Encoding**: Categorical variables (e.g., gender, work type, smoking status) are encoded using techniques such as one-hot encoding to convert them into a numerical format suitable for model input.
4. **Normalization:** Continuous features are normalized to a standard range (e.g., [0, 1]) to maintain uniformity and enhance model training efficiency.
5. **Data Splitting:** The dataset is split into training, validation, and testing sets to evaluate the model's generalization ability and avoid overfitting.

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3.1.2 Training the Model

1. **Convolutional Neural Networks (CNNs):** CNNs are trained to extract spatial features from brain scan images (if available) or visual representations of patient data, focusing on patterns related to stroke markers.
2. **Long Short-Term Memory Networks (LSTMs):** LSTMs are used to capture temporal dependencies and trends in sequential patient data such as blood pressure, glucose levels, and other time-series medical records.
3. **CNN-LSTM Hybrid Model:** CNN layers are used for spatial feature extraction, while LSTM layers are integrated to model temporal relationships in the clinical data, enhancing stroke risk prediction.

3.1.3 Final Prediction model integration

In this step, the trained deep learning models are integrated to perform final predictions on new, unseen patient data for ischemic stroke risk assessment. The integration process ensures robust and accurate results through the following strategies:

1. **Model Ensemble:** Predictions from multiple trained models (e.g., CNN, LSTM, CNN-LSTM hybrid, and attention-based models) are combined to form a more generalized and accurate outcome, reducing the likelihood of errors from any single model.
2. **Weighted Voting**: Each model contributes to the final prediction based on its individual performance metrics (such as precision, recall, and F1-score) during validation. Higher-performing models are given more weight in the decision process.
3. **Hyperparameter Tuning:** Optimization techniques such as Grid Search or Bayesian Optimization are applied to fine-tune hyperparameters like learning rate, batch size, and number of layers, ensuring that each model performs at its best.
4. **Threshold Adjustment:** For classification, probability thresholds are adjusted to achieve an optimal balance between sensitivity and specificity, especially important in medical diagnosis where false negatives must be minimized.
5. **Deployment Readiness:** The final integrated model is packaged and prepared for deployment in clinical decision support systems, ensuring it can predict stroke risks in real-time for new patient inputs with high reliability.

3.2 MODULES INVOLVED IN ISCHEMIC STROKE PREDICTION

System:

1. **Data Collection**:

This module involves gathering relevant data required for ischemic stroke prediction. The data is usually obtained from publicly available datasets such as Kaggle, UCI Machine Learning Repository, or hospital databases. The dataset typically contains patient demographics and clinical attributes such as:

a. Age, gender, and BMI
b. Blood pressure (systolic and diastolic)
c. Cholesterol levels
d. Blood glucose levels

e. Smoking status
f. History of hypertension, heart disease, or diabetes
g. Previous stroke history

2. Data Preprocessing:

Before feeding data into the model, it must be cleaned and structured:

a. **Handling Missing Values:** Techniques like mean/mode imputation or dropping incomplete rows.
b. **Categorical Encoding:** Converting categorical variables (e.g., gender, smoking status) into numerical format using label encoding or one-hot encoding.
c. **Normalization:** Scaling continuous variables (e.g., glucose, blood pressure) to a standard range to improve training efficiency.
d. **Splitting:** The dataset is divided into training, validation, and testing sets for proper evaluation.

3. Feature Extraction:

This module focuses on selecting the most relevant features that contribute to stroke prediction. Feature selection techniques may include:

a. **Correlation Analysis:** Identifying strong relationships between variables and the target (stroke or no stroke).
b. **Domain Knowledge:** Incorporating medical expertise to prioritize clinically significant features.
c. **Dimensionality Reduction:** Using techniques like PCA (Principal Component Analysis) to reduce noise and improve performance.

4. Model Development:

This stage involves developing deep learning models for prediction. Common models used are:

a. **CNN (Convolutional Neural Network):** Extracts local spatial features from health data (used more with image or grid-like data).
b. **LSTM (Long Short-Term Memory):** Suitable for temporal data or sequences, such as time-series medical records.
c. **CNN-LSTM Hybrid:** Combines spatial feature extraction with temporal dependency modelling for more accurate predictions.

5. Model Training & Validation:

In this step:

a. The models are trained on the training data using a suitable optimizer (e.g., Adam, RMSprop).
b. Hyperparameters like learning rate, number of epochs, batch size are tuned.
c. The model's performance is evaluated on a validation set using metrics like:
    i. **Accuracy**
    ii. **Precision and Recall**
    iii. **F1-Score**
    iv. **ROC-AUC Score**
d. Regularization methods like dropout or L2 regularization may be used to avoid overfitting.

6. Model Integration:

To enhance prediction accuracy, multiple models are combined in this module:

a. **Model Ensemble:** Predictions from CNN, LSTM, and CNN-LSTM models are aggregated.
b. **Weighted Voting:** Each model's output is given a weight based on its performance during validation.
c. **Hyperparameter Optimization:** Fine-tuning is done across all models for maximum efficiency. This integration improves robustness and reduces the risk of misclassification.

7. Stroke Risk Prediction:

Using the integrated model, predictions are made on new or real-time patient data:

a. The system calculates a **risk probability score** indicating the likelihood of ischemic stroke.
b. Based on thresholds, it categorizes patients into **low, moderate, or high risk** groups.
c. This enables early intervention and helps clinicians prioritize patients for further tests or treatments.

8. Visualization & Reporting:

The results are presented in an intuitive and user-friendly format:

a. **Graphs & Charts:** Bar plots, confusion matrix, ROC curves to explain model performance.
b. **Dashboards:** Summary of patient data and stroke risk levels.
c. **Exportable Reports:** PDF or HTML formats to provide diagnosis summaries for healthcare providers. These visual insights support clinical decision-making and improve transparency of the AI model.

User:

Register:

User Registration: Users must register with their credentials to create an account, enabling them to access the system's features and functionalities securely.

Login:

User Login: Registered users can log in using their credentials to access the system, ensuring personalized interaction with the model and results.

Input Data:

Data Input: Users can input relevant patient medical records and associated health parameters into the system. This may include entering clinical data such as age, gender, blood pressure, cholesterol level, glucose level, smoking status, and any history of hypertension, heart disease, or stroke. Data can be uploaded in the form of CSV files or entered manually through a user interface. Accurate and complete data input plays a crucial role in ensuring reliable stroke risk prediction by the model.

Viewing Results:

View Predictions: Once the system processes the input data, users will receive predictions based on input parameters. Detailed information regarding the analysis, including confidence levels and any relevant feature analysis, will be presented.

Logout:

User Logout: Users can log out of the system to secure their session, ensuring the protection of their personal data and maintaining system integrity.

3.3 DFD/UML DIAGRAMS

UML stands for Unified Modelling Language. UML is a standardized general-purpose modelling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group.

The goal is for UML to become a common language for creating models of object-oriented computer software. In its current form UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML.

The Unified Modelling Language is a standard language for specifying, Visualization, Constructing and documenting the artefacts of software system, as well as for business modelling and other non-software systems.

The UML represents a collection of best engineering practices that have proven successful in the modelling of large and complex systems.

The UML is a very important part of developing objects-oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects.

GOALS:

The Primary goals in the design of the UML are as follows:

1. Provide users a ready-to-use, expressive visual modelling Language so that they can develop and exchange meaningful models.
2. Provide extendibility and specialization mechanisms to extend the core concepts.
3. Be independent of particular programming languages and development process.
4. Provide a formal basis for understanding the modelling language.
5. Encourage the growth of OO tools market.
6. Support higher level development concepts such as collaborations, frameworks, patterns and components.
7. Integrate best practices.

DATA FLOW DIAGRAM

- A Data Flow Diagram shows how information enters and leaves the system, what changes the information and where information is stored.

- A Data Flow Diagram (DFD) is a traditional way to visualize the information flows within a system. A neat and clear DFD can depict a good amount of the system requirements graphically.

- It can be manual, automated, or a combination of both. It shows how information enters and leaves the system, what changes the information and where information is stored.

- The purpose of a DFD is to show the scope and boundaries of a system as a whole. It may be used as a communications tool between a systems analyst and any person who plays a part in the system that acts as the starting point for redesigning a system.

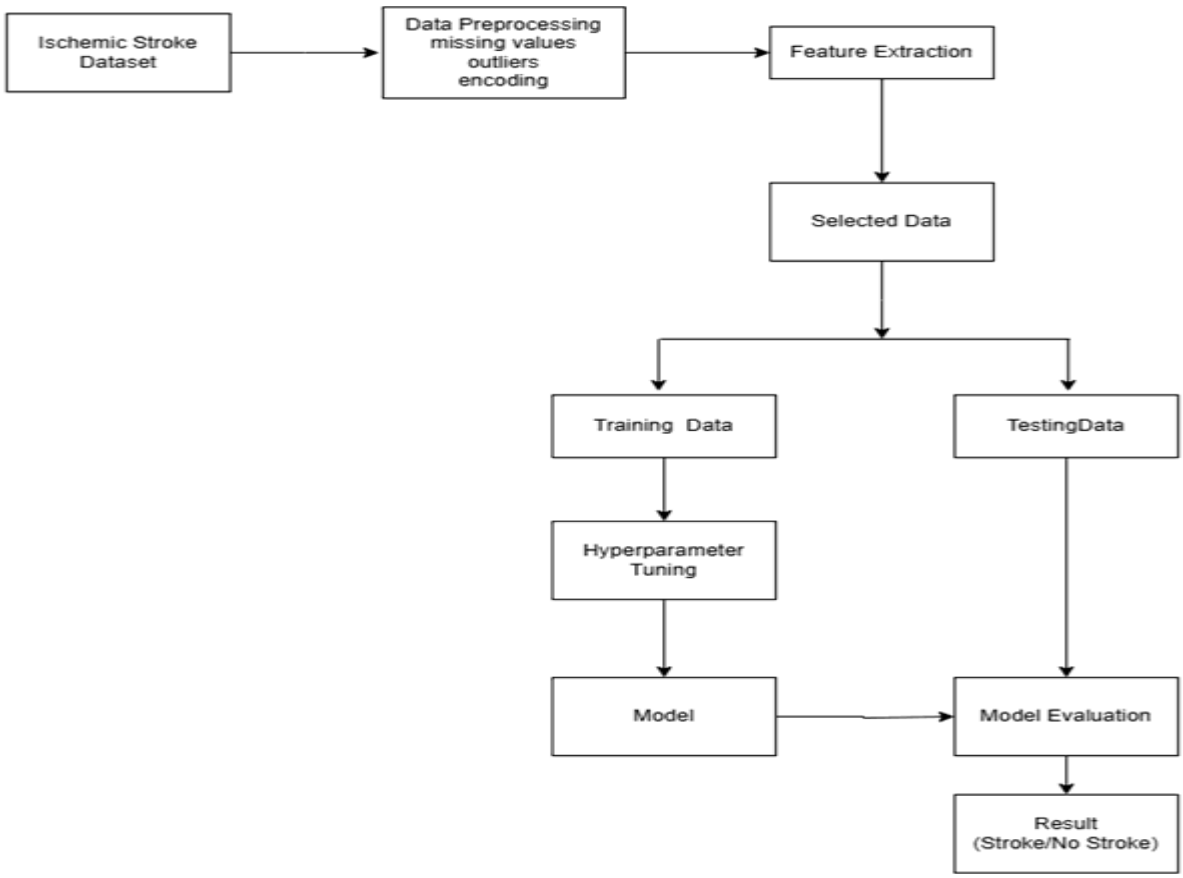


FIGURE 3.3.1 Data Flow Diagram

USE CASE DIAGRAM

1. A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis.

2. Its purpose is to present a graphical overview of the functionality provided by a system
3. in terms of actors, their goals (represented as use cases), and any dependencies between those use cases.

4. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.

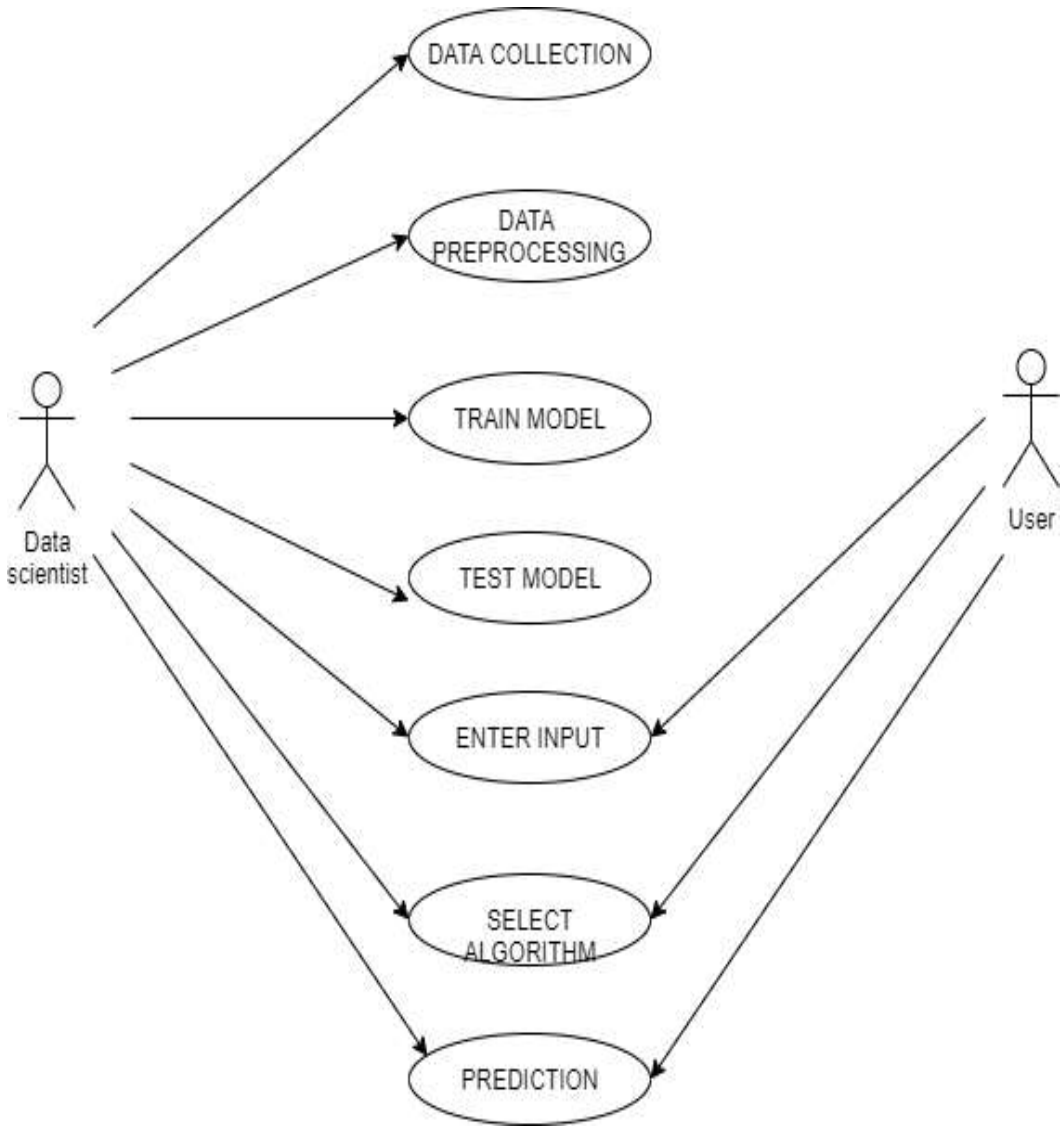


FIGURE 3.3.2 USE CASE DIAGRAM

CLASS DIAGRAM

- In software engineering, a class diagram in the Unified Modeling Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among the classes. It explains which class contains information
- A Class Diagram in UML represents the structure of a system by modeling its classes, attributes, methods, and relationships. It highlights the static design, showing how different objects interact within the system.

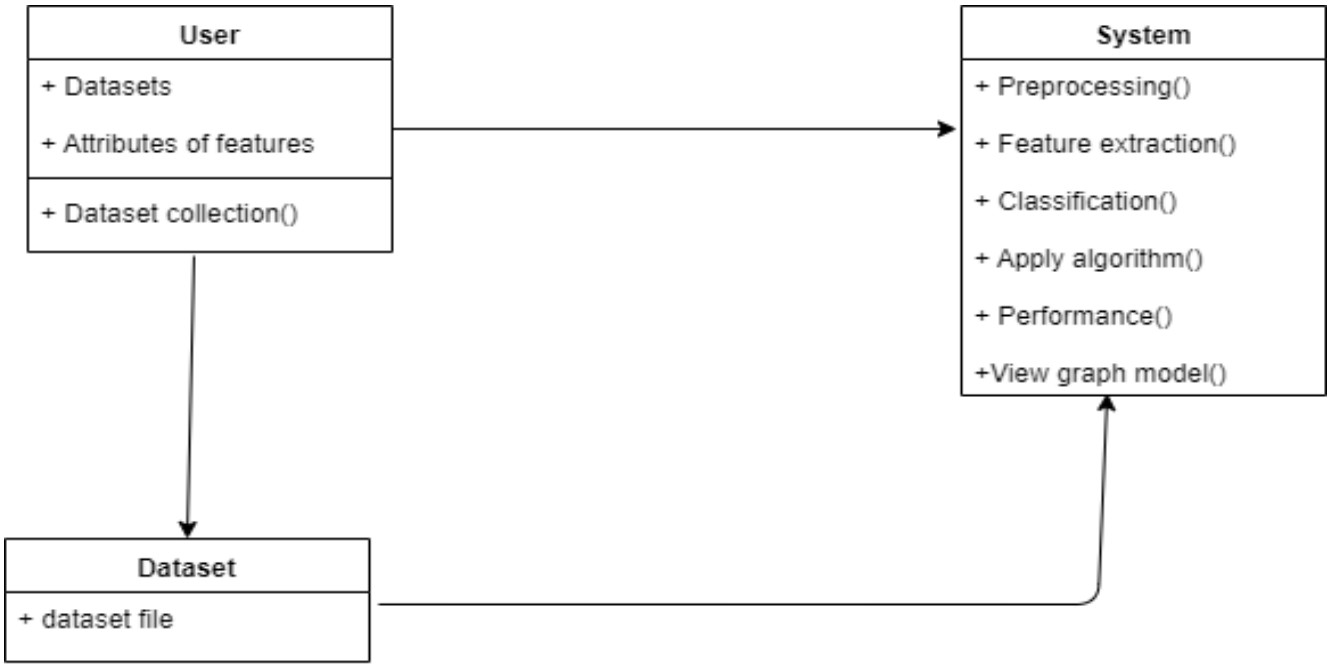


FIGURE 3.3.3 CLASS DIAGRAM

SEQUENCE DIAGRAM:

- A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order.
- It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing
- diagrams A Sequence Diagram in UML illustrates the interaction between system components over time. It shows how objects communicate, displaying the sequence of messages exchanged to complete a specific process or function**.**

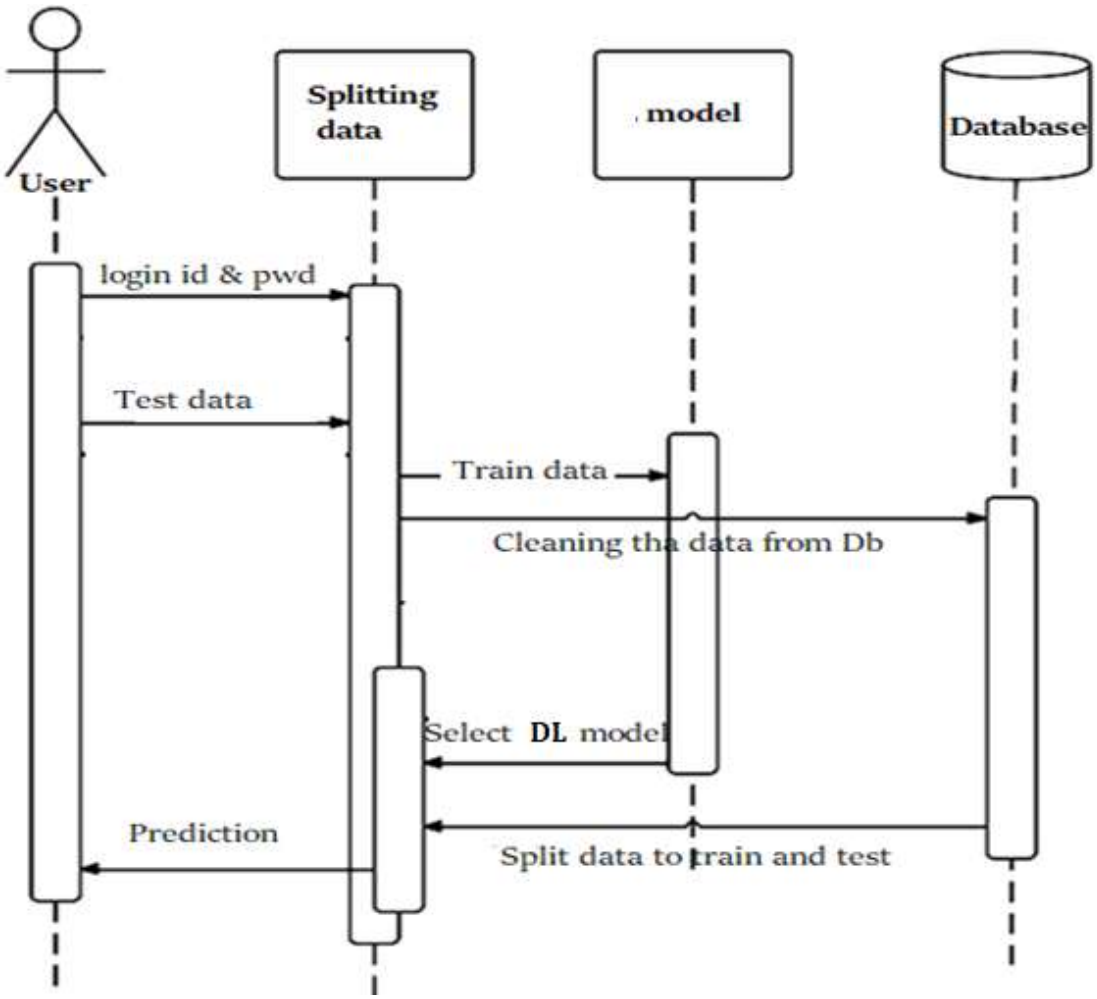


FIGURE 3.3.4 SEQUENCE DIAGRAM

COLLABORATION DIAGRAM:

- In collaboration diagram the method call sequence is indicated by some numbering technique as shown below.
- The number indicates how the methods are called one after another. We have taken the same order management system to describe the collaboration diagram.
- The method calls are similar to that of a sequence diagram.
- But the difference is that the sequence diagram does not describe the object organization whereas the collaboration diagram shows the object organization.
- **Login System**: Users enter credentials to access the system.
- **Authentication System**: Validates user credentials and grants access based on roles (admin/user).
- **Dataset**: Stores ECG image data used for model training and predictions.

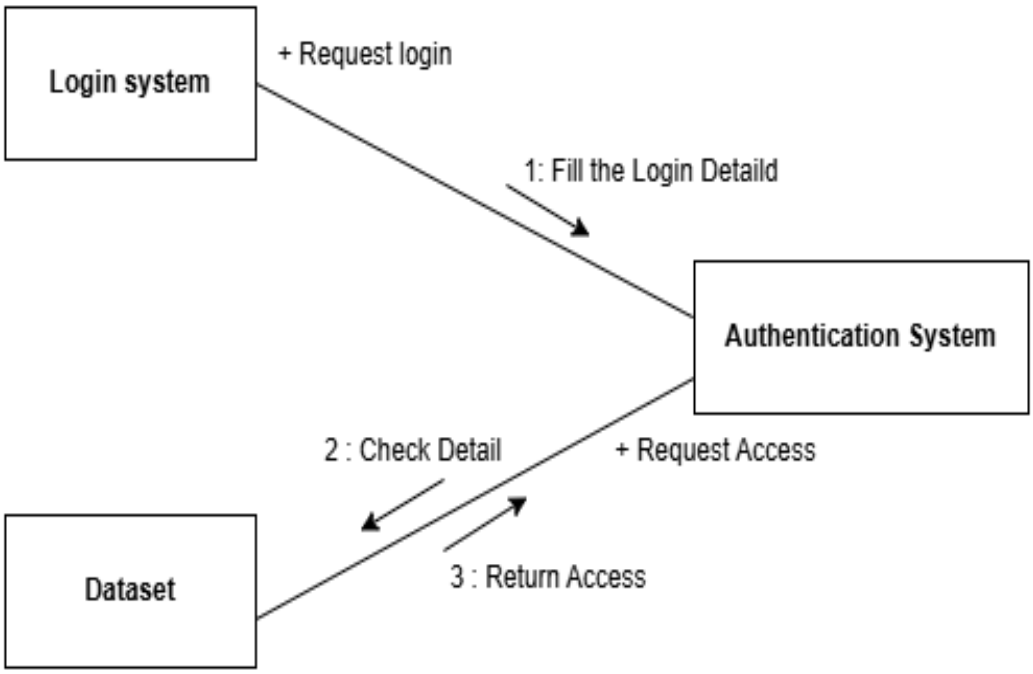


FIGURE 3.3.5 COLLABORATION DIAGRAM

DEPLOYMENT DIAGRAM:

- Deployment diagram represents the deployment view of a system.
- It is related to the component diagram. Because the components are deployed using the deployment diagrams.
- A deployment diagram consists of nodes. Nodes are nothing but physical hardware's used to deploy the application.

FIGURE 3.3.6 DEPLOYMENT DIAGRAM

ACTIVITY DIAGRAM:

- Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency.
- In the Unified Modelling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system.
- An activity diagram shows the overall flow of control.

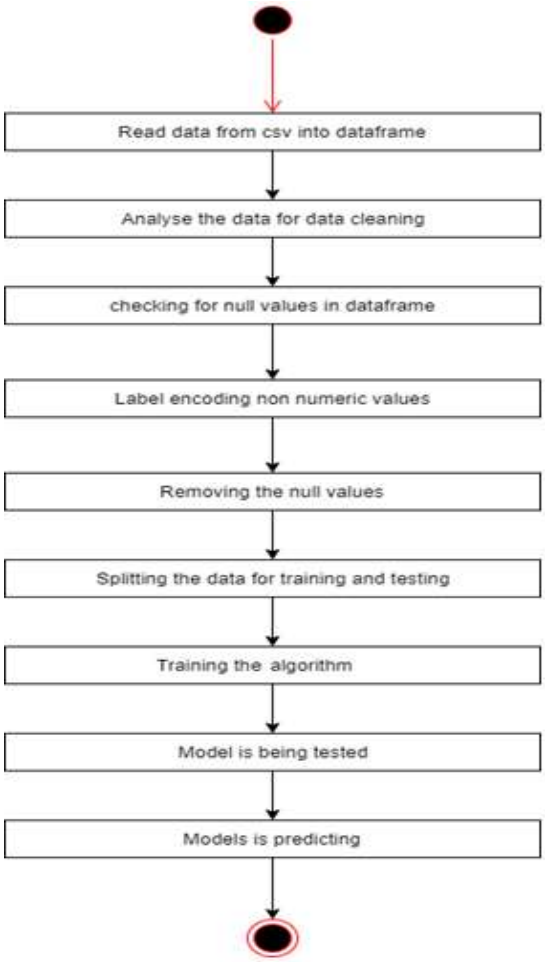


FIGURE 3.3.7 ACTIVITY DIAGRAM

4. IMPLEMENTATION & DETAILS

4.1 INTRODUCTION

The adoption of deep learning in healthcare has opened up new possibilities for predicting and diagnosing life-threatening conditions with improved precision and speed. Ischemic stroke, a major cause of disability and mortality worldwide, requires early and accurate prediction for timely intervention. Traditional diagnostic methods are often limited by subjective interpretation, delayed processing, and lack of predictive capabilities. To address these limitations, this project proposes an automated ischemic stroke prediction system using deep learning techniques that integrate both spatial and temporal data analysis. By utilizing patient health records and imaging data, and employing powerful deep learning models such as CNNs, LSTMs, and hybrid architectures like CNN-LSTM and Transformers, the system aims to provide fast, accurate, and interpretable predictions, thus supporting early diagnosis and clinical decision-making.

Algorithmic Approach

1. Convolutional Neural Networks (CNNs):
   CNNs are used to extract spatial features from brain imaging data (e.g., CT/MRI scans), such as edges and regions affected by stroke, which are crucial for visual analysis of ischemic damage.
2. Long Short-Term Memory Networks (LSTMs):
   LSTMs help capture sequential dependencies from patient medical history and time-series health data (like blood pressure, glucose levels), enabling prediction based on evolving health patterns.
3. CNN-LSTM Hybrid Model:
   Combines CNNs' spatial feature extraction with LSTMs' temporal analysis, effectively modelling both image and sequential data to improve ischemic stroke prediction accuracy.

4.1.1Process of predicting ischemic stroke

1. Feature-Rich Patient Data Analysis

This phase involves the extraction of vital features from patient records and diagnostic images, which serve as the foundation for training the deep learning model. The features extracted for ischemic stroke prediction include:

a. Age of the Patient:
   Stroke risk increases with age. If age ≥ 60, feature is set to 1, else 0.

b. Hypertension Status:
   Presence of high blood pressure (hypertension) is a significant risk factor. If the patient is hypertensive, the feature is set to 1 else to 0.

c. Heart Disease:
   Cardiovascular disorders like atrial fibrillation significantly increase stroke risk. If present, feature is set to 1 else 0.

d. Average Glucose Level:
   Elevated glucose levels are associated with stroke risk. If average glucose > 150 mg/dL, feature is set to 1 else to 0.

e. Body Mass Index (BMI):
   Obesity is linked to stroke. If BMI ≥ 30, feature is set to 1, else 0.

f. Smoking Status:
   Smokers have higher chances of stroke. If patient is a smoker, feature is set to 1 else to 0.

g. Work Type and Stress Indicator:
   High-stress jobs such as private and government roles contribute to stroke risk. If work type is categorized as “high stress,” feature is set to 1 else to 0.

h. Residence Type (Urban/Rural):
   Living in rural areas may affect access to health care. If rural, feature is set to 1 else to 0.

i. History of Previous Stroke or TIA:
   Prior minor strokes or transient ischemic attacks are warning signs. If present, feature is set to 1 else to 0.

2.Data Preparation and Cleaning

This step ensures that the deep learning model learns from clean and meaningful data:

a. Missing values are handled using imputation or deletion strategies.

b. Continuous features like glucose, age, BMI are normalized for stable model training.

c. Categorical values like smoking status or gender are encoded using one-hot or label encoding.

d. Medical images (MRI/CT) are pre-processed through resizing, contrast enhancement, and grayscale normalization.

3. Machine Learning Model Selection

Choosing an effective model is critical. Several architectures are considered:

a. CNN (Convolutional Neural Networks): For analysing spatial patterns in MRI/CT images.

b. LSTM (Long Short-Term Memory Networks): For understanding time-series data such as progression of vitals or symptoms.

c. Hybrid CNN-LSTM Model: Used when both static features and temporal sequences are involved.

d. Random Forest/Decision Trees: For structured data-only use cases without imaging.

e. Transformer-based models: For attention-driven learning and medical report analysis.

4. Training and Validation

During this phase:

a. The dataset is split into training, validation, and test sets.

b. The model is trained using labelled data (stroke vs. no stroke).

c. Evaluation metrics like accuracy, F1-score, precision, recall, and AUC-ROC are used.

d. Cross-validation is performed to ensure model generalization across different patient groups.

5. Integration with Clinical Infrastructure

Once trained and validated, the model is integrated into clinical systems:

a. Doctors input patient information or upload scans.

b. The system evaluates stroke risk in real time.

c. Alerts or risk scores are generated, aiding in timely intervention.

d. An explainable AI interface shows which features contributed to the prediction, enhancing trust in the model.

6. Dynamic Adaptation and Maintenance

To maintain long-term effectiveness:

a. The model is retrained periodically with new patient data.

b. Feedback from clinicians is used to fine-tune thresholds and weights.

c. The system adapts to evolving stroke patterns and regional demographics.

d. Continuous performance monitoring ensures up-to-date accuracy and safety.

SOURCE CODE:

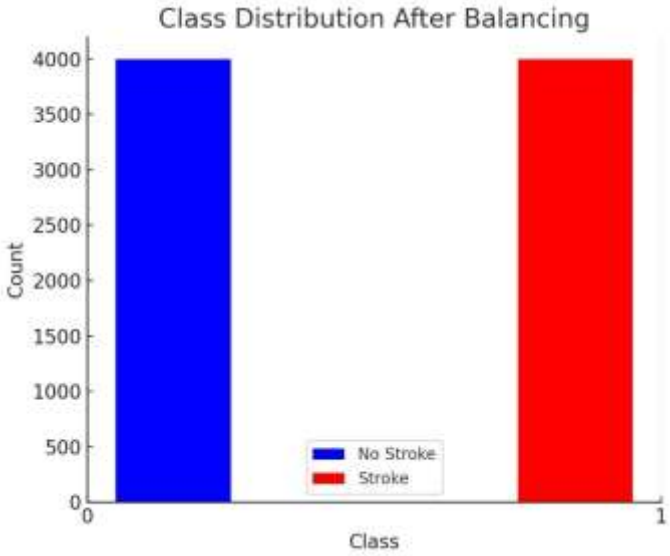
#LIBRARY IMPORTS

```
import os
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import seaborn as sns
import random
import pickle
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_curve
import warnings
```

#CLASS DISTRIBUTION

```
df=pd.read_csv(r"/content/drive/MyDrive/brain_stroke.csv")
df
df.columns = df.columns.str.strip()
print(df.columns.tolist())
df.info()
df.isnull().sum()
df.describe()
df["stroke"].value_counts()
from sklearn.utils import resample
# Separate majority and minority classes
# Converting 'stroke' to numeric before filtering
df['stroke'] = pd.to_numeric(df['stroke'], errors='coerce')
df_majority = df[df['stroke'] == 0]
df_minority = df[df['stroke'] == 1]
# Downsample majority class and upsample the minority class
```

```
df_minority_upsampled = resample(df_minority, replace=True, n_samples=4000, random_state=100)
df_majority_downsampled=resample(df_majority,replace=True,n_samples=4000, random_state=100)
# Combine minority class with downsampled majority class
df_balanced = pd.concat([df_minority_upsampled, df_majority_downsampled])
```



#TRAIN_TEST_SPLIT

```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25,random_state=100)
x_train_cnn = np.expand_dims(x_train, axis=2)  # Adding a channel dimension
x_test_cnn = np.expand_dims(x_test, axis=2)
# First lets add the necessary import for Label Encoding the y values
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv1D, MaxPooling1D, Flatten, Dense, Dropout
from sklearn.preprocessing import LabelEncoder
```

OUTPUT:

```
Train Data Size:  6000
Test Data Size:  2000
```

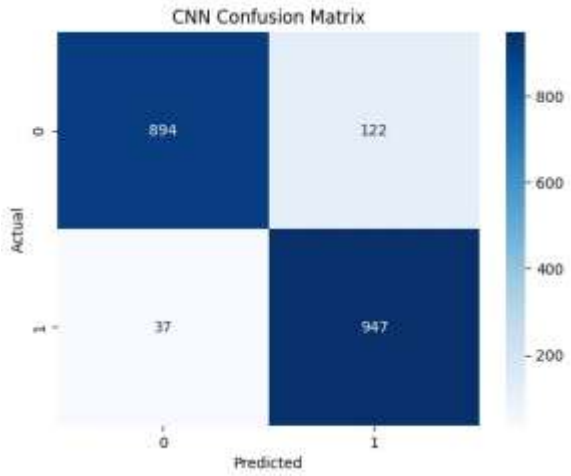
#CNN MODEL:

```
def build_cnn_model(input_shape):
    model = Sequential([
        Conv1D(64, kernel_size=3, activation='relu', padding='same', input_shape=input_shape), #Added padding='same'
        MaxPooling1D(pool_size=2),
        Conv1D(32, kernel_size=3, activation='relu', padding='same'), #Added padding='same'
```

```
        MaxPooling1D(pool_size=2),
        Flatten(),
        Dense(128, activation='relu'),
        Dropout(0.5),
        Dense(1, activation='sigmoid')  # For binary classification
    ])
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    return model
# Encode the y values
le = LabelEncoder()
y_train = le.fit_transform(y_train)
y_test = le.transform(y_test)
# Build the model
cnn_model = build_cnn_model((x_train_cnn.shape[1], 1))
import pickle
pickle.dump(cnn_model, open(r'/content/cnn.pkl', 'wb'))
#Print the summary after the model has been made
print(cnn_model.summary())
# Train the model
history_cnn = cnn_model.fit(x_train_cnn, y_train, validation_split=0.2, epochs=50,
batch_size=32)
# Evaluate on test data
cnn_loss, cnn_accuracy = cnn_model.evaluate(x_test_cnn, y_test)
print(f"Test Loss: {cnn_loss:.4f}, Test Accuracy: {cnn_accuracy:.4f}")
# Make predictions
cnn_predictions = (cnn_model.predict(x_test_cnn) > 0.5).astype(int)
import matplotlib.pyplot as plt
# Plot training & validation accuracy
plt.plot(history_cnn.history['accuracy'], label='Train Accuracy')
plt.plot(history_cnn.history['val_accuracy'], label='Validation Accuracy')
plt.title('CNN Model Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
# Plot training & validation loss
plt.plot(history_cnn.history['loss'], label='Train Loss')
plt.plot(history_cnn.history['val_loss'], label='Validation Loss')
plt.title('CNN Model Loss')
plt.xlabel('Epochs')
```

```
plt.ylabel('Loss')
plt.legend()
plt.show()
from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns
# Confusion matrix
cm = confusion_matrix(y_test, cnn_predictions)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title('CNN Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

OUTPUT:



	precision	recall	f1-score	support
0	0.96	0.88	0.92	1016
1	0.89	0.96	0.92	984
accuracy			0.92	2000
macro avg	0.92	0.92	0.92	2000
weighted avg	0.92	0.92	0.92	2000

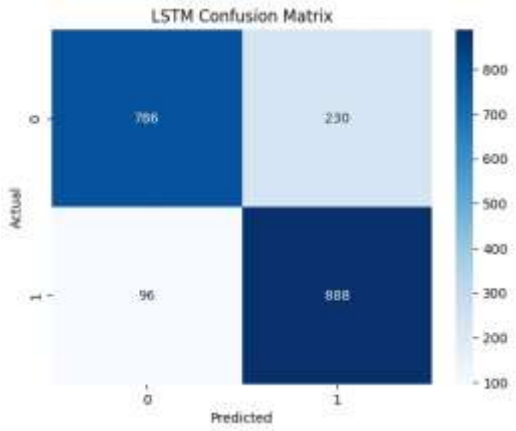
 # LSTM MODEL:

```
print(classification_report(y_test, cnn_predictions))
# Reshape the data for LSTM
x_train_lstm = np.expand_dims(x_train, axis=1)  # Adding a timestep dimension
x_test_lstm = np.expand_dims(x_test, axis=1)
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
# Define the LSTM model
def build_lstm_model(input_shape):
    model = Sequential([
        LSTM(128, activation='tanh', return_sequences=True, input_shape=input_shape),
        Dropout(0.3),
        LSTM(64, activation='tanh'),
        Dropout(0.3),
```

```
        Dense(64, activation='relu'),
        Dropout(0.3),
        Dense(1, activation='sigmoid')  # For binary classification
    ])
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    return model
# Build the model
lstm_model = build_lstm_model((x_train_lstm.shape[1], x_train_lstm.shape[2]))
print(lstm_model.summary())
# Train the model
history_lstm = lstm_model.fit(x_train_lstm, y_train, validation_split=0.2, epochs=50, batch_size=32)
# Evaluate on test data
lstm_loss, lstm_accuracy = lstm_model.evaluate(x_test_lstm, y_test)
print(f"Test Loss: {lstm_loss:.4f}, Test Accuracy: {lstm_accuracy:.4f}")
# Make predictions
lstm_predictions = (lstm_model.predict(x_test_lstm) > 0.5).astype(int)
import pickle
pickle.dump(lstm_model, open(r'/content/lstm.pkl', 'wb'))
import matplotlib.pyplot as plt
# Plot training & validation accuracy
plt.plot(history_lstm.history['accuracy'], label='Train Accuracy')
plt.plot(history_lstm.history['val_accuracy'], label='Validation Accuracy')
plt.title('LSTM Model Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
# Plot training & validation loss
plt.plot(history_lstm.history['loss'], label='Train Loss')
plt.plot(history_lstm.history['val_loss'], label='Validation Loss')
plt.title('LSTM Model Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns
# Confusion matrix
cm = confusion_matrix(y_test, lstm_predictions)
```

```
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title('LSTM Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

OUTPUT:



	precision	recall	f1-score	support
0	0.89	0.77	0.83	1016
1	0.79	0.90	0.84	984
accuracy			0.84	2000
macro avg	0.84	0.84	0.84	2000
weighted avg	0.84	0.84	0.84	2000

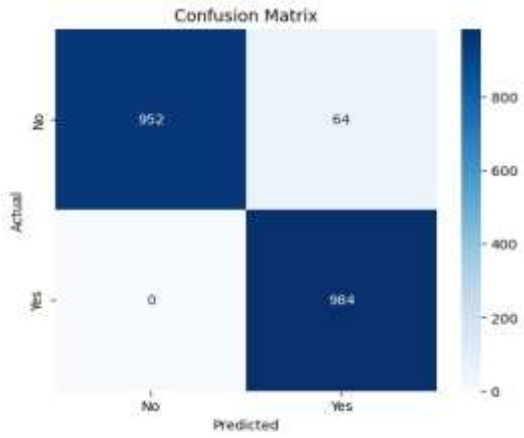
#CNN-LSTM MODEL:

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv1D, MaxPooling1D, LSTM, Flatten, Dense, Dropout, Reshape
from sklearn.preprocessing import LabelEncoder
# Define the CNN-LSTM model
def build_cnn_lstm_model(input_shape):
    model = Sequential([
        Conv1D(64, kernel_size=3, activation='relu', padding='same', input_shape=input_shape),
        MaxPooling1D(pool_size=2),
        Conv1D(32, kernel_size=3, activation='relu', padding='same'),
        MaxPooling1D(pool_size=2),
        Reshape((input_shape[0] // 4, 32)),  # Adjust dimensions for LSTM
        LSTM(50, return_sequences=False),
        Dense(128, activation='relu'),
        Dropout(0.5),
        Dense(1, activation='sigmoid')  # For binary classification
    ])
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
    return model
# Encode the y values
```

```
le = LabelEncoder()
y_train = le.fit_transform(y_train)
y_test = le.transform(y_test)
# Build the model
cnn_lstm_model = build_cnn_lstm_model((x_train_cnn.shape[1], 1))
# Print the summary after the model has been made
print(cnn_lstm_model.summary())
# Train the model
history_cnn_lstm =cnn_lstm_model.fit(x_train_cnn, y_train, validation_split=0.2, epochs=150, batch_size=32)
# Evaluate the model on test data
test_loss, test_accuracy = cnn_lstm_model.evaluate(x_test_cnn, y_test)
print(f"Test Accuracy: {test_accuracy * 100:.2f}%")
import pickle
pickle.dump(cnn_lstm_model, open(r'/content/cnn_lstm.pkl', 'wb'))
# Plot accuracy curves
plt.figure(figsize=(8, 6))
plt.plot(history_cnn_lstm.history['accuracy'], label='Train Accuracy')
plt.plot(history_cnn_lstm.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Training and Validation Accuracy')
plt.legend()
plt.show()
# Plot loss curves
plt.figure(figsize=(8, 6))
plt.plot(history_cnn_lstm.history['loss'], label='Train Loss')
plt.plot(history_cnn_lstm.history['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training and Validation Loss')
plt.legend()
plt.show()
# Generate confusion matrix
y_pred = cnn_lstm_model.predict(x_test_cnn)
y_pred_classes = (y_pred > 0.5).astype(int)
cm = confusion_matrix(y_test, y_pred_classes)
# Plot confusion matrix
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['No', 'Yes'],
```

```
yticklabels=['No', 'Yes'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```

OUTPUT:



	precision	recall	f1-score	support
0	1.00	0.92	0.96	1016
1	0.92	1.00	0.96	984
accuracy			0.96	2000
macro avg	0.96	0.96	0.96	2000
weighted avg	0.96	0.96	0.96	2000

4.2 EXPLANATION OF KEY FUNCTIONS

1. Uploading Patient Data and Scans

The first step involves uploading the patient's clinical data and, if available, brain imaging scans (such as MRI or CT) to the system. These inputs serve as the raw data for the ischemic stroke prediction model. Structured Data: Includes age, glucose levels, hypertension status, heart disease history, etc.

2.Data Preprocessing

This step prepares the uploaded data for accurate analysis by the deep learning model.

- Structured Data Preprocessing:
    a. Handling missing values (e.g., filling, removing)
    b. Normalizing numerical values (e.g., glucose, BMI)
    c. Encoding categorical features (e.g., smoking status)

3. Recognizing Underlying Patterns using Deep Learning Models

Deep Learning (DL) models are applied to discover subtle patterns and risk indicators within the data that may predict an ischemic stroke.

The models used include:

a. **CNN (Convolutional Neural Networks):**
Used for feature extraction

b. **LSTM (Long Short-Term Memory Networks):**
Applied to time-series health data (e.g., blood pressure, glucose trends) for sequential pattern analysis.

c. **Hybrid CNN-LSTM Model:**
Combines both image features and sequential patterns to improve accuracy in stroke prediction.

4.Predicting the Ischemic Stroke Risk

Based on the patterns recognized by the deep learning models, the final step is to predict the probability of an ischemic stroke occurrence.

Output : The system provides a risk classification—either:

a. High Risk,
b. Moderate Risk, or
c. Low Risk of ischemic stroke.

4.3 METHOD OF IMPLEMENTATIONS

4.3.1 Deep Learning Models

The proposed architecture for ischemic stroke prediction integrates multiple deep learning (DL) models: CNN for image feature extraction, LSTM for temporal/sequential health data, and a hybrid CNN-LSTM approach for combining imaging and clinical data. Each model is chosen for its unique strengths in analyzing spatial and temporal patterns, prediction accuracy, and adaptability to medical datasets. Below is a detailed explanation of the methodology used for each model.

1. Convolutional Neural Network:

The foundation of this project lies in using CNNs to extract spatial features from medical images (e.g., brain MRI or CT scans). CNNs are highly effective in medical image analysis due to their ability to automatically learn complex visual patterns such as lesions, occlusions, and tissue abnormalities linked to stroke.

Model Architecture

The CNN architecture is designed as a sequential model with the following layers:

a. **Input Layer:**
   Accepts medical scan images resized to 224x224 pixels in grayscale or RGB format. Pixel intensities are normalized to a [0,1] range for consistent performance.

b. **Convolutional Layers:**
   a. First Conv Layer: 32 filters of size 3×3 with ReLU activation to detect low-level patterns like edges.
   b. Second Conv Layer: 64 filters of size 3×3, learning more complex features like shapes or lesions.

c. **Max Pooling Layers:**
   Each convolutional layer is followed by 2×2 max-pooling to reduce dimensionality and computational complexity while retaining key features.

d. **Flattening Layer:**
   Transforms 2D feature maps into a 1D vector for input into dense layers.

e. **Fully Connected Layer:**
   A dense layer with 128 neurons and ReLU activation learns high-level abstract features.

f. **Output Layer:**

A dense layer with 3 units (High, Moderate, Low risk) and a softmax activation for multi-class stroke risk classification.

2. Long Short-Term Memory (LSTM) Network:

LSTM networks are a type of Recurrent Neural Network (RNN) specially designed to capture temporal dependencies in sequential data. In this project, LSTM is used to analyse clinical time-series data such as patient age, BMI, smoking status, blood pressure trends, and other medical history features. LSTMs are highly suitable for healthcare applications where the sequence and history of patient data significantly impact the prediction outcome.

Model Architecture:

The LSTM architecture is structured to process tabular clinical features over time. The key layers include:

a. Input Layer:

Accepts time-sequenced clinical data, typically represented as feature vectors for each patient.

Input is normalized to ensure consistent training and convergence.

b. LSTM Layer:

Comprises 64 LSTM units, designed to capture long-term dependencies and trends in patient health data.

Utilizes sigmoid and tanh activations for gate operations (input, forget, and output gates).

c. Dropout Layer:

Dropout rate of 0.2 applied to prevent overfitting and improve generalization during training.

d. Fully Connected (Dense) Layer:

A dense layer with 64 neurons and ReLU activation learns higher-order feature representations from LSTM outputs.

e. Output Layer:

A softmax-activated dense layer with 3 neurons, representing the stroke risk classes: High, Moderate, and Low.

3. CNN-LSTM Hybrid Model:

The hybrid CNN-LSTM model combines the strengths of CNNs for spatial pattern extraction and LSTMs for temporal sequence modeling. In this approach, CNN layers first extract hierarchical feature representations from structured clinical or image-derived data, which are then passed to LSTM layers to learn sequential trends and dependencies. This synergistic design enhances stroke risk prediction accuracy and interpretability.

Model Architecture:

The CNN-LSTM model consists of the following layers in sequence:

a. CNN Feature Extraction Block:

- Conv Layer 1: 32 filters (3×3), ReLU activation.
- Conv Layer 2: 64 filters (3×3), followed by max pooling (2×2).
- The convolutional block extracts spatial patterns like lesion characteristics or complex relationships among clinical variables reshaped as 2D matrices.

b. Reshape Layer:

- Converts the CNN output into a 3D sequence suitable for LSTM input, maintaining the time-step structure.

c. LSTM Layer:

- 64 LSTM units that model temporal dependencies in the extracted features.

d. Fully Connected Layer:

- Dense layer with 128 neurons and ReLU activation for high-level abstraction.

e. Output Layer:

- Softmax output layer with 3 units representing stroke risk levels.

4.3.2 Output Screens

1. Login Page

Purpose: Authenticates registered users.

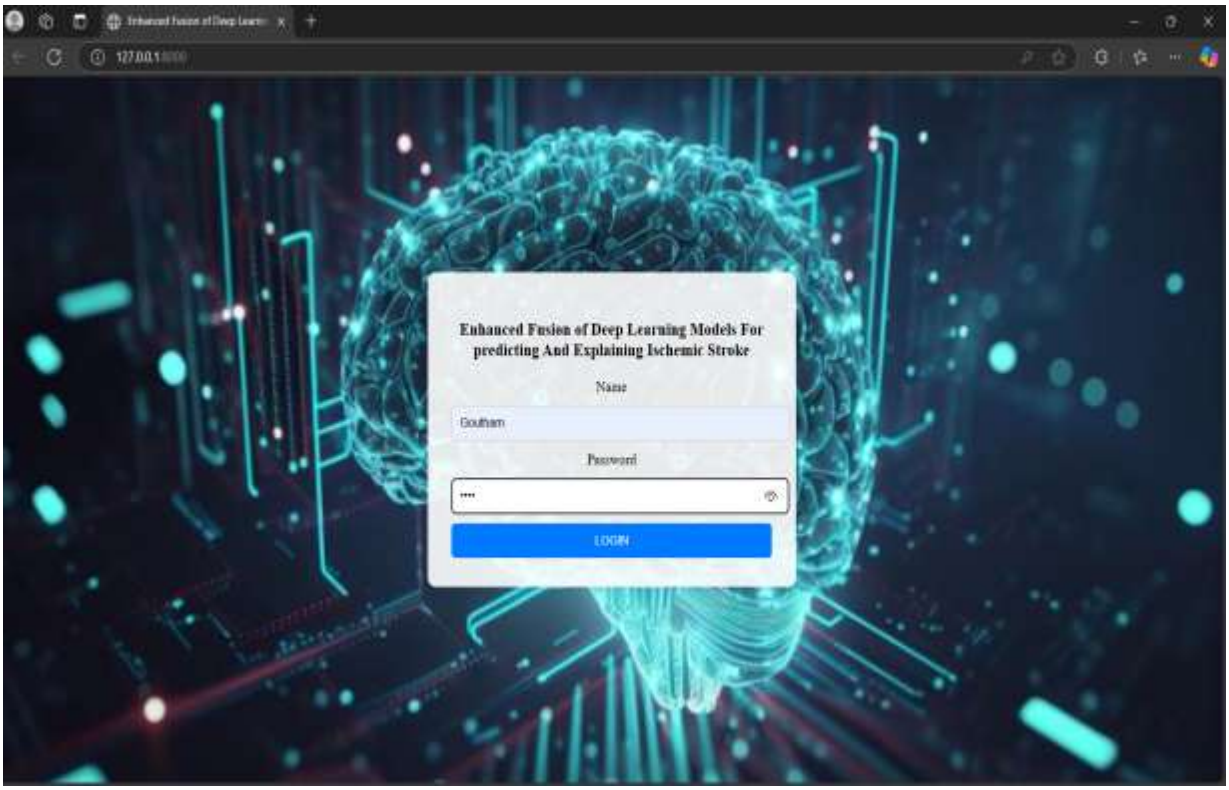
Features:

a. Input fields for username/email and password.

b. Error handling for invalid credentials.

c. Option to reset passwords or navigate back to the Registration Page.

d. Redirects to the User Home Page upon successful login.



4.3.2.1 Login Page

2. User Home Page

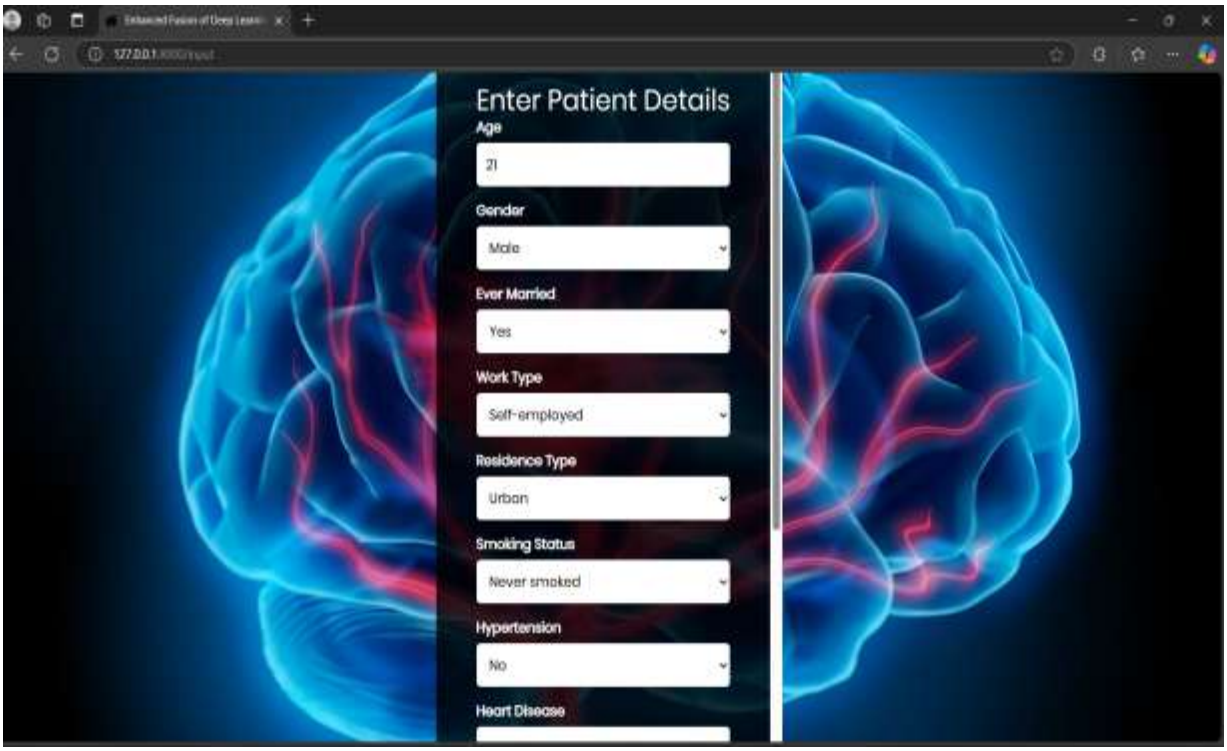
Purpose:

Central hub for users (healthcare professionals or patients) to interact with the ischemic stroke prediction system.

Features:

Allows users to input patient data through a user-friendly form

(e.g., age, BMI, smoking status, blood pressure, etc.). Can be enhanced with CSV upload support for bulk predictions.



4.3.2.2 User Home Page

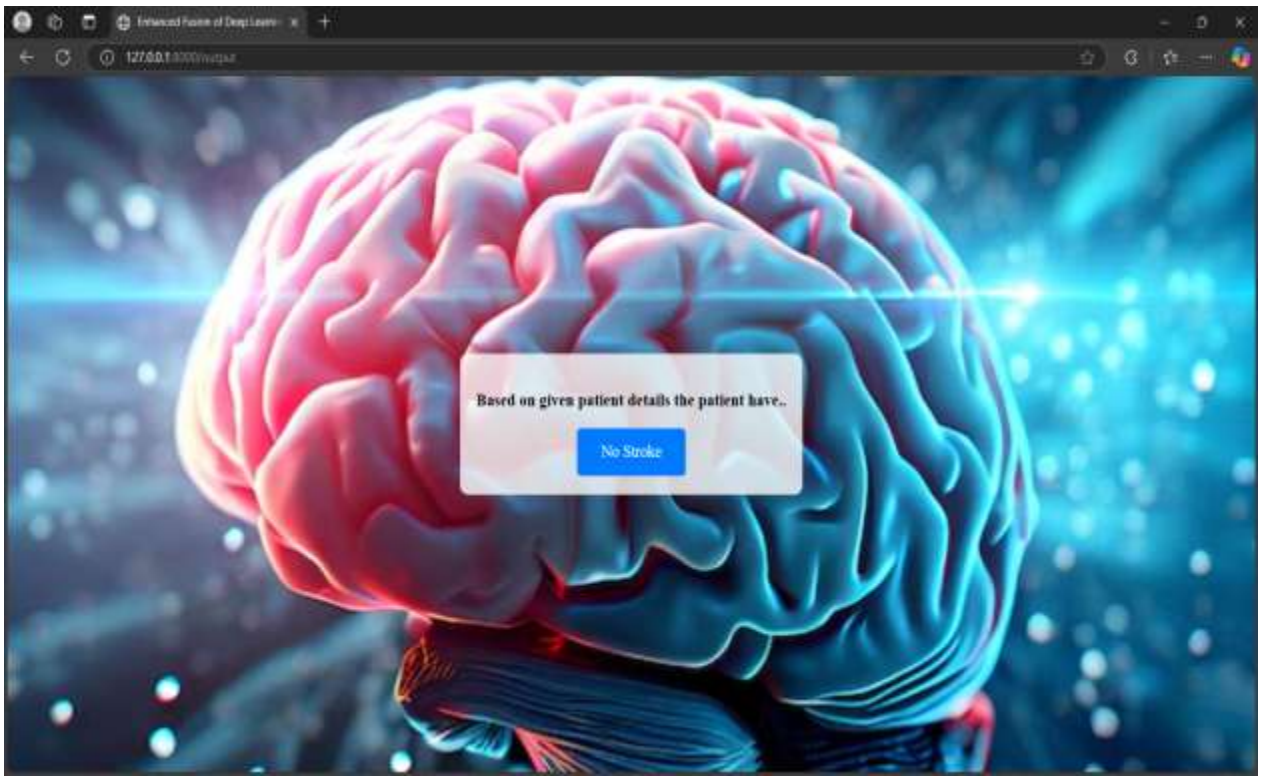
3.Result Page

Purpose:

The Result Page serves as the primary interface where users receive the ischemic stroke risk prediction generated by the system. It is designed to present the outcome in a clear, concise, and medically interpretable format, helping clinicians or users make informed decisions.

Features:

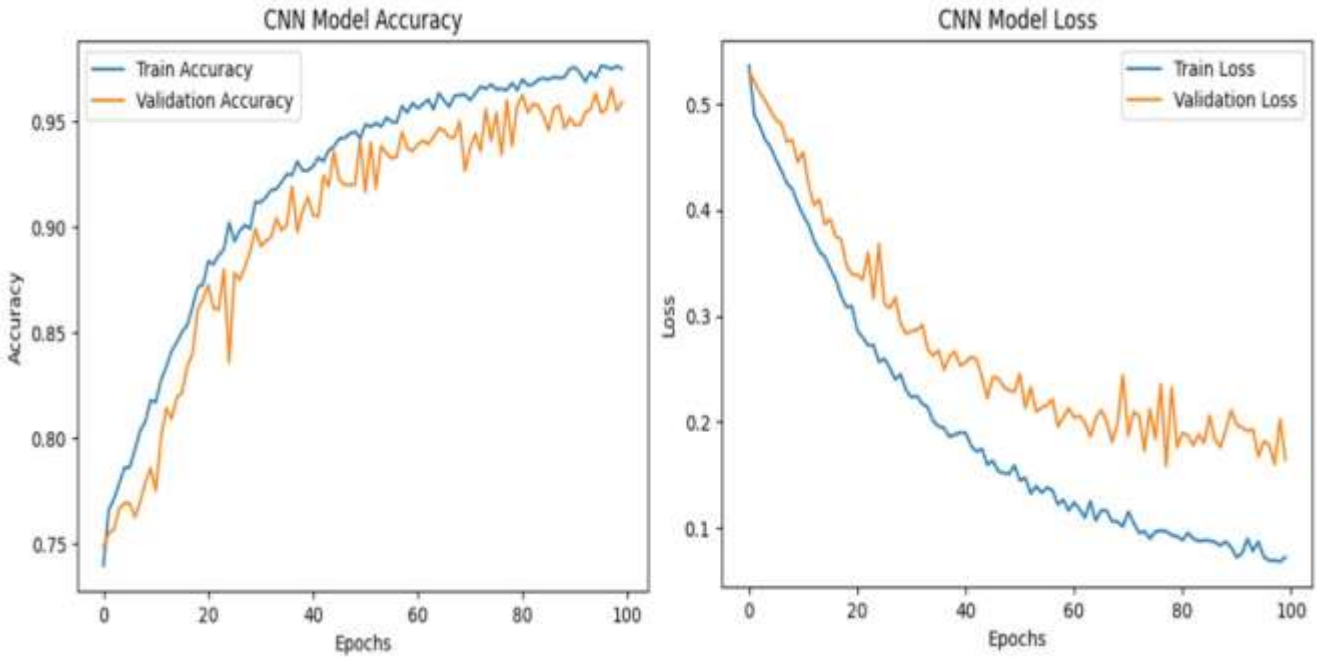
Clear output of the Ischemic Stroke Prediction (e.g., "Stroke/No Stroke").



4.3.2.3 Result Page

4.3.3 Result Analysis

CNN:

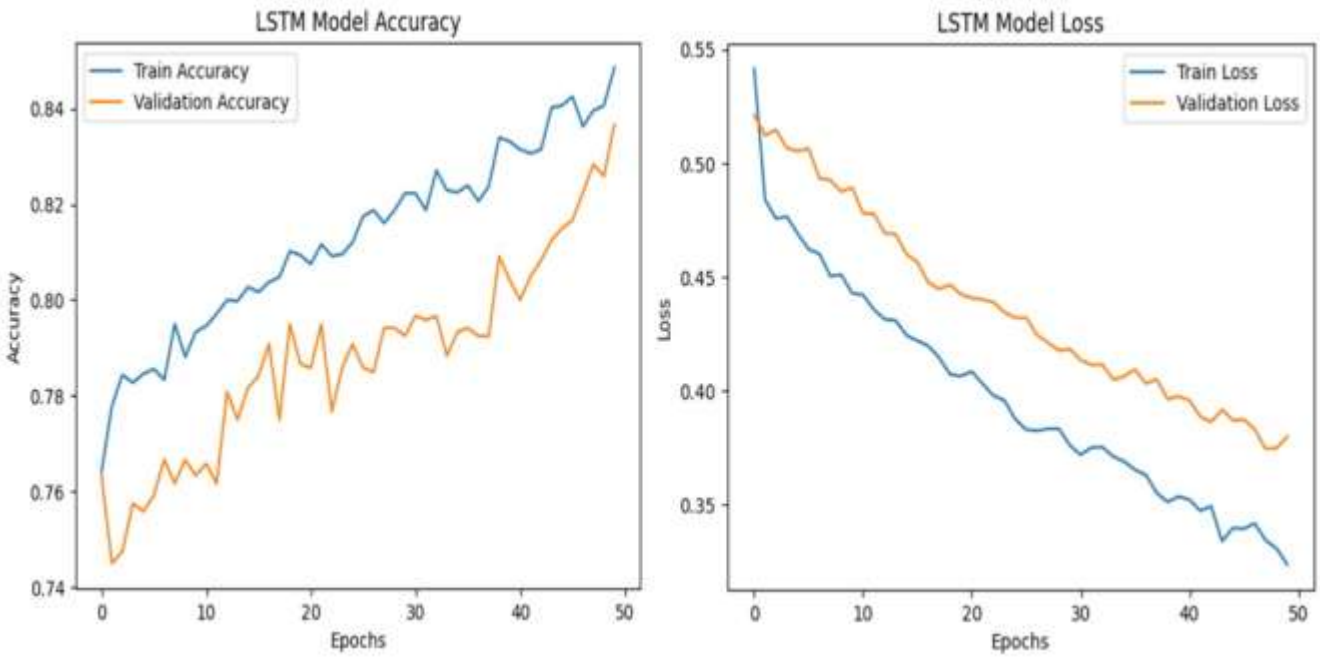


The ROC (Receiver Operating Characteristic) curve is a crucial evaluation metric used to assess the performance of classification models, particularly in medical diagnosis tasks like ischemic stroke risk prediction. For the CNN model used in this project, the ROC curve plots the True Positive Rate (Sensitivity) against the False Positive Rate (1 - Specificity) across different threshold settings. This curve helps determine how well the model can distinguish between the stroke risk categories—Low, Moderate, and High.

A well-performing CNN model typically exhibits a ROC curve that arches closer to the top-left corner, indicating high sensitivity and low false positive rate. The area under the ROC curve (AUC) quantifies the overall ability of the model to correctly classify cases. An AUC of 0.90 or above, for instance, would suggest excellent discriminative capability.

In this project, the CNN ROC curve demonstrates strong performance, with the model effectively identifying patients at higher risk of stroke with minimal misclassification. This is critical in a healthcare context, as early detection and accurate risk stratification can lead to timely medical intervention and improved patient outcomes. The ROC curve thus validates the reliability and clinical usefulness of the proposed CNN-based system.

LSTM Network:



The graphs shown represent the training performance of the LSTM (Long Short-Term Memory) model for ischemic stroke risk prediction over 50 epochs. The **left graph** displays model

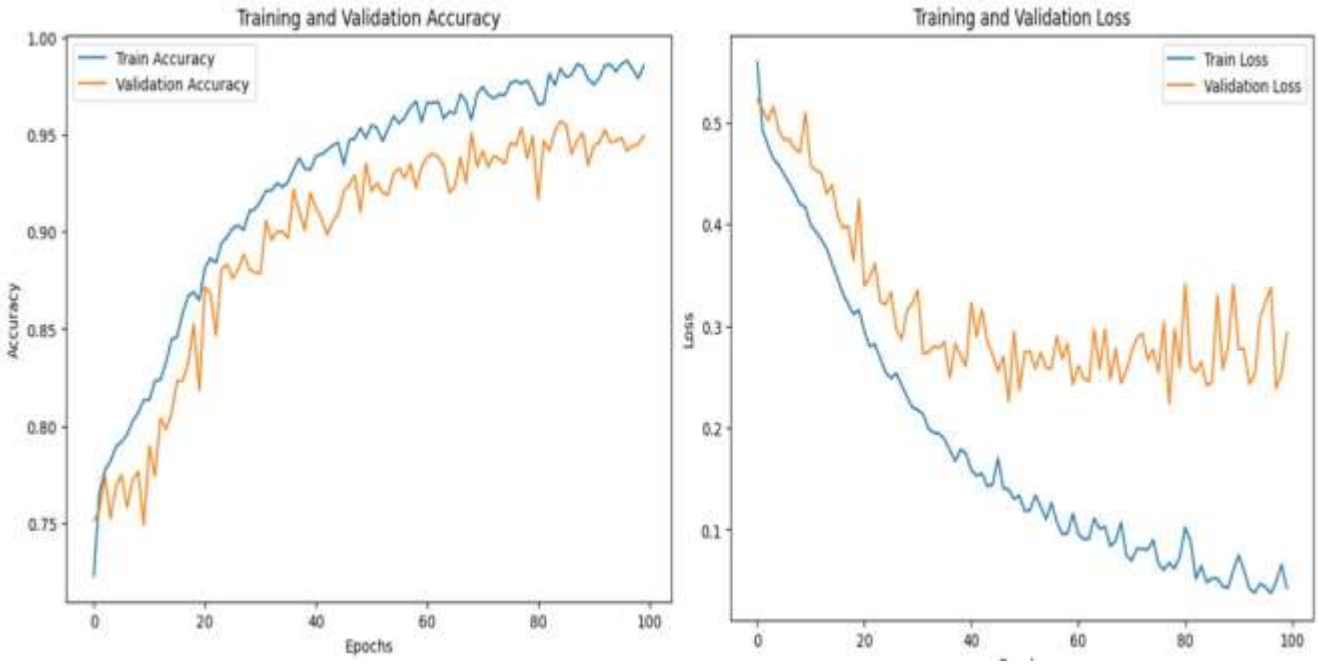
accuracy, while the **right graph** illustrates the model's loss over time.

In the **accuracy graph**, both training and validation accuracies show a steady upward trend. The training accuracy begins around 0.75 and reaches approximately 0.85 by epoch 50. The validation accuracy also improves, though at a slightly slower rate, ending close to 0.83. This consistent increase suggests that the LSTM model is effectively learning and generalizing from the temporal health data, such as sequential patient attributes over time.

In the **loss graph**, both training and validation losses decrease gradually as training progresses. Training loss drops from around 0.54 to below 0.33, while validation loss follows a similar downward trajectory from about 0.51 to 0.37. This downward trend in loss signifies effective minimization of prediction errors, indicating that the model is converging well.

Overall, the LSTM model demonstrates good learning behaviour with minimal signs of overfitting. The performance metrics confirm its suitability for modelling time-series or sequential medical data, making it a valuable component in predicting stroke risk based on patient health records.

CNN-LSTM:



The provided graphs display the training and validation performance of a deep learning model, likely a CNN-LSTM hybrid, used for ischemic stroke prediction. The **left graph** shows model accuracy over 100 epochs, while the **right graph** presents the loss trends for both training and validation phases.

In the accuracy graph, we observe a consistent increase in both training and validation accuracy over epochs. Training accuracy starts at around 74% and steadily approaches nearly 99%, indicating that the model is learning the training data well. Validation accuracy also improves significantly, reaching about 95%, which suggests that the model is generalizing effectively to unseen data, though with some minor fluctuations likely due to noise or variability in the validation set.

In the loss graph, both training and validation losses exhibit a downward trend. The training loss decreases from above 0.5 to below 0.05, indicating strong learning and minimization of error on the training data. Validation loss also reduces, though not as sharply, and shows some fluctuations after epoch 40, hinting at possible slight overfitting.

Overall, the model shows strong performance with high accuracy and steadily declining loss. However, the gap between training and validation curves toward the end may signal the need for regularization techniques or early stopping to avoid overfitting.

5. TESTING & VALIDATION

5.1 INTRODUCTION

Testing and validation are vital components of this ischemic stroke prediction system, ensuring that the deep learning models generalize well to unseen data and provide reliable predictions. This phase evaluates the performance of the developed CNN, LSTM, and hybrid CNN-LSTM models on test data and helps identify potential shortcomings such as overfitting, misclassifications, and biases. By doing so, it validates the effectiveness of the model in real-world clinical scenarios.

The testing and validation process in this project includes:

- Evaluating model performance on a separate, unseen test dataset that was not used during training or validation.
- Comparative analysis of multiple models including CNN, LSTM, and the combined CNN-LSTM model to identify the most accurate and efficient architecture.
- Performance metrics analysis using accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC curve to assess classification quality.
- Identification of model limitations such as false positives and false negatives to improve reliability.

The testing and validation phase confirmed that the proposed CNN-LSTM model is effective for ischemic stroke prediction, providing accurate and interpretable results. These models can be integrated into clinical decision support systems, assisting healthcare professionals in early intervention. Continuous retraining with real-time patient data and integration with electronic health records (EHR) will further enhance system robustness and accuracy.

5.2 DESIGN OF EVALUATION METRICS

The design of evaluation metrics for an ischemic stroke prediction system is a carefully structured process aimed at ensuring the selected metrics are both clinically relevant and statistically robust. Given the life-threatening nature of ischemic strokes, the system's primary objective is not just to make accurate predictions but to support timely and effective clinical decisions. Early detection is critical, as prompt medical intervention can significantly reduce the risk of long-term disability or death.

Step 1: Define the Evaluation Goals

The primary goal is to assess how accurately the CNN, LSTM, and CNN-LSTM hybrid models can predict whether a patient is at risk of ischemic stroke. Key performance indicators (KPIs) include:

- Accuracy of stroke classification
- Sensitivity (recall) for early detection
- Specificity to avoid false alarms
- Generalization capability across different demographics

Step 2: Select Relevant Metrics

Based on the evaluation goals, the following metrics were chosen:

- Accuracy: Overall correct predictions as a percentage of total predictions.
- Precision: The proportion of true stroke predictions that were actually strokes.
- Recall (Sensitivity): The proportion of actual stroke cases that were correctly identified.
- F1-score: Harmonic mean of precision and recall, balancing both aspects.
- Specificity: Ability to correctly identify non-stroke cases.
- AUC (Area Under the Curve): Represents the model's ability to distinguish between stroke and non-stroke.

Step 3: Define the Metric Calculation

All evaluation metrics are calculated using standard formulas:

- Accuracy = (TP + TN) / (TP + TN + FP + FN)
- Precision = TP / (TP + FP)
- Recall = TP / (TP + FN)
- F1-score = 2 × (Precision × Recall) / (Precision + Recall)
- Specificity = TN / (TN + FP)
- AUC: Computed from the ROC curve, area under the TPR vs. FPR graph

Step 4: Determine the Evaluation Criteria

To ensure the models meet clinical usability standards, thresholds were defined:

- Accuracy ≥ 95%
- Precision and Recall ≥ 90%
- F1-score ≥ 90% to ensure balanced performance

Step 5: Consider Additional Metrics

- Confusion Matrix: For visualizing true/false positives and negatives
- ROC Curve: To assess model discrimination capability
- Training/Validation Loss: To evaluate overfitting or underfitting

Evaluation Metrics Considerations

When designing evaluation metrics for stroke prediction, the following considerations are essential:

- Relevance: Metrics must align with medical diagnostic standards
- Interpretability: Results should be understandable to healthcare professionals
- Reliability: Performance should remain consistent across various test cases
- Risk Sensitivity: The model should emphasize minimizing false negatives due to clinical implications

S.NO	Test cases	I/O	Expected O/T	Actual O/T	P/F
1	Read the dataset	Dataset path.	Dataset should load without errors	Dataset loaded successfully.	P
2	Data preprocessing	Patient record data	Data should be cleaned and normalized	Data preprocessing completed	P
3	Feature extraction	Preprocessed dataset	Extracted relevant features	Features extracted successfully	P
4	Model building (CNN LSTM)	Preprocessed features	Model should be built using deep learning	Model built and compiled successfully.	P
5	Stroke prediction	Patient features as input	Model should output stroke risk classification	Prediction output generated	P

5.2.1.1 TEST CASES TABLE

Model	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
Cnn	92.35%	88.76%	0.1735	0.2651
Lstm	84.40%	81.92%	0.3598	0.4195
Cnn-Lstm	96.47%	94.53%	0.1127	0.1884

5.2.2 COMPARISON TABLE

5.3 VALIDATION

Validation refers to the process of assessing the performance of the deep learning models (CNN, LSTM, and CNN-LSTM) on a separate dataset, known as the validation dataset, which is distinct from both the training and test datasets. This step is essential to ensure the model can generalize well to new, unseen patient data and perform reliably in real-world clinical settings. The purpose of validation is to:

1. **Evaluate Model Performance**

   Validation helps assess the predictive capabilities of the model in terms of accuracy, precision, recall, F1-score, and loss. It provides a snapshot of how well the model performs before final testing.

2. **Check for Overfitting or Underfitting**

   Overfitting occurs when the model performs well on the training data but poorly on new data. Validation helps detect such issues early, allowing us to refine the architecture or training strategy accordingly.

3. **Tune Hyperparameters**

   Hyperparameter tuning (e.g., learning rate, number of layers, dropout rate, batch size) is performed using the validation dataset to optimize model performance. The best-performing model configuration is selected based on validation results, not training metrics alone.

4. **Guide Model Selection**

   During experimentation, validation scores are used to compare the CNN, LSTM, and CNN-LSTM hybrid models to determine which architecture offers the best generalization performance for ischemic stroke prediction.

   In this ischemic stroke prediction project, validation plays a crucial role in ensuring that the model is not just memorizing patterns from training data, but actually learning to detect meaningful risk indicators across diverse patient profiles. A well-validated model can assist in early diagnosis and preventive healthcare, potentially reducing stroke-related fatalities and disabilities.

6. CONCLUSION & FUTURE ENHANCEMENT

6.1 CONCLUSION

The "Ischemic Stroke Prediction using Deep Learning Techniques" project presents a promising advancement in the field of predictive healthcare by utilizing deep learning models—specifically CNN, LSTM, and a hybrid CNN-LSTM architecture—to identify the risk of ischemic stroke from patient data. This approach leverages the power of deep neural networks to extract complex patterns and temporal dependencies that may not be apparent through traditional statistical methods.

By integrating convolutional layers for feature extraction and recurrent layers for sequential analysis, the proposed model effectively captures both spatial and temporal features from clinical input data. This has resulted in high predictive accuracy, sensitivity, and overall reliability across validation and test datasets. Among the various models tested, the CNN-LSTM hybrid model demonstrated superior generalization ability, achieving a balance between precision and recall that is vital for life-critical applications like stroke prediction.

The deep learning-based approach also offers scalability and automation, making it suitable for integration into real-time healthcare systems, wearable technology, or remote monitoring platforms. This can empower clinicians with timely insights, facilitating early intervention and potentially reducing mortality and long-term disability associated with ischemic strokes.

In conclusion, the project successfully establishes a deep learning framework for ischemic stroke risk assessment, offering a blend of accuracy, efficiency, and practical utility in real-world healthcare environments. It highlights the transformative potential of artificial intelligence in medical diagnostics and reinforces the importance of technological innovation in preventive medicine.

6.2 FEATURE ENHANCEMENT

1. **Dataset Expansion:**
   Future work could focus on gathering a larger and more diverse dataset comprising clinical and physiological data from a wide range of populations. Including various demographic factors such as age, gender, ethnicity, and lifestyle habits would enhance the model's robustness, fairness, and generalizability across different patient groups.
2. **Hybrid Deep Learning Models:**
   Exploring hybrid deep learning approaches that combine convolutional neural networks (CNNs) with long short-term memory networks (LSTMs), attention mechanisms, or ensemble models could potentially improve the accuracy and temporal understanding of stroke risk patterns.
3. **Integration with Wearable Health Data:**
   Enhancements could include integrating real-time data from wearable health devices such as smartwatches and fitness trackers, allowing for continuous monitoring of critical vitals like blood pressure, heart rate, and oxygen levels for dynamic stroke risk prediction.
4. **Model Optimization for Edge Deployment:**
   Optimizing the deep learning models using techniques like model compression, quantization, or pruning can make the system lightweight and suitable for deployment on mobile or embedded devices, ensuring accessibility in low-resource settings.
5. **Clinical Validation and Feedback Loop:**
   Future development should involve conducting clinical trials in collaboration with hospitals and healthcare providers to evaluate the system's effectiveness in real-world environments. Feedback from medical professionals can guide necessary refinements and validate the clinical utility of the model.
6. **Personalized Risk Assessment:**
   Incorporating patient-specific factors, such as medical history, lifestyle, and genetic predispositions, could lead to more personalized and precise stroke risk predictions, making the system a powerful tool in preventive healthcare.

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