International Journal of Engineering and Techniques-Volume11Issue3,May - June - 2025

AI Revolution in Stroke Diagnosis: A Machine Learning Approach to Neuro image-Based Detection

[1]Dr. Sundeep Kumar K, [2]Sk.Hiba Aayesha, [3]P.Swathi, [4]T.Sushma
[1]Associate Professor, [2,3,4]UG Student, [1,2,3,4]Department of Computer Science & Engineering (AI&ML),
Geethanjali Institute of Science And Technology, Nellore, India

ABSTRACT
Cerebrovascular diseases, such as stroke, are leading causes of mortality and disability worldwide. Early detection plays a crucial role in improving clinical outcomes. This study proposes a machine learning-based stroke detection system integrating genetic algorithms and BiLSTM models to analyze CT brain images. Our system optimizes feature selection using genetic algorithms and employs deep learning models to classify stroke presence with high accuracy. This automated approach enhances early detection, accuracy, and medical decision-making, ultimately contributing to better patient outcomes. Traditional stroke detection relies on clinical assessments and medical imaging techniques like CT and MRI scans, which can be time-consuming and dependent on human expertise. To address these challenges, our model leverages artificial intelligence and deep learning algorithms to analyze neuro images with high precision and efficiency. The research evaluates multiple machine learning architectures, including Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and Random Forest classifiers, comparing their performance against our proposed "BiLSTM-based model". The results indicate that our model achieves superior accuracy in detecting early-stage strokes, enabling timely intervention and revolutionizing stroke diagnosis for improved patient care.
Keywords:

Introduction

Stroke is a critical medical condition that occurs when the brain's blood supply is disrupted due to either a blockage or a ruptured blood vessel. It remains a leading cause of death worldwide, responsible for over 6.2 million fatalities annually. Even among survivors, stroke often leads to long-term disabilities that significantly impact their quality of life. These disabilities may include paralysis, loss of speech, cognitive impairment, and difficulty performing daily activities.

Reasons for Brain Strokes

High Blood Pressure (Hyper tension)–The leading cause of stroke; it weakens blood vessels and increases the chance of both clot-related and bleeding strokes.

Atherosclerosis – Fatty deposits in the arteries can block blood flow to the brain or cause clots that lead to a stroke.

Heart Diseases—Irregular heart rhythms like atrial fibrillation can create clots that travel to the brain. Diabetes–Highbloodsugardamagesbloodvesselsandincreasestheriskofclot formation and stroke.

Smoking–Increasesbloodpressure,damagesarteries,andraisesclottingrisk,doubling stroke chances.

Types of Strokes

Strokes can be classified into two major types:

Ischemic Stroke

The most common type, accounting for approximately 87% of all cases. It occurs when a blood clot obstructs a blood vessel supplying the brain, reducing oxygen and nutrient flow to specific regions.

Hemorrhagic Stroke

Caused by the rupture of a blood vessel in the brain, leading to internal bleeding. This type of stroke is often more severe and requires immediate medical intervention. Common causes include high blood causes include high blood pressure, aneurysms, and arteriovenous malformations (AVMs). Other types of strokes, such as cryptogenic strokes (where the cause is unknown) and brain stem strokes (affecting the base of the brain), present additional challenges in diagnosis and treatment.

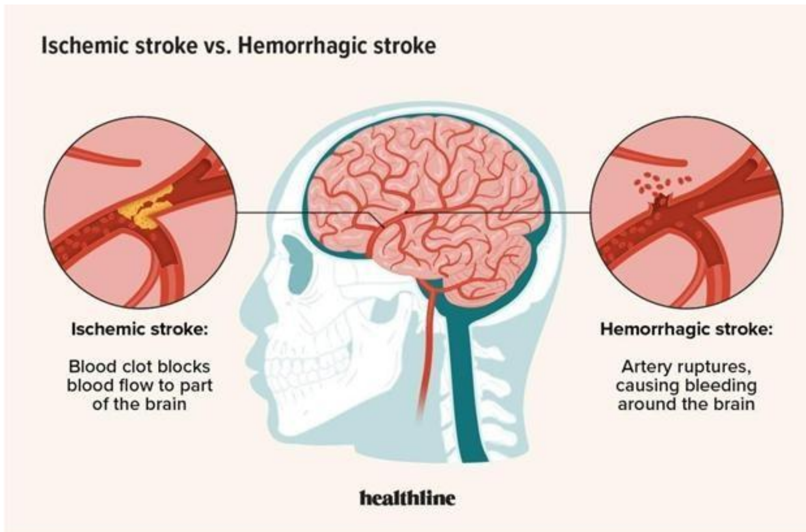


Fig.1. Types of Strokes

The Need for Early Stroke Detection

Stroke diagnosis traditionally reliesonclinical assessments,medicalimaging(such as CT andMRIscans),andlaboratorytests.Whilethesemethodsareeffective,theycanbetime- consuming and may not always provide early warning signs of an impending stroke. Additionally, manual diagnosis depends on the experience and expertise of healthcare professionals, which may introduce variability in results. The need for early and accurate detectioniscrucialinminimizingbraindamageandimprovingsurvivalrates.Hence,there is a growing demand for automated,AI-driven diagnostic models that can rapidly and accuratelypredictstrokerisks.Suchmodelshavethepotentialtoenhancedecision-making, optimize resource allocation in healthcare settings, and ultimately save lives.

Machine Learning

Recent advancements in artificial intelligence (AI) and machine learning (ML) have provided innovative solutions for stroke detection and risk assessment. Machine learning models analyze vast amounts of patient data, including electronic health records, genetic information,lifestylefactors,andmedicalimaging,toidentifystrokeriskfactorswithhigh accuracy.AI-baseddiagnostictoolscandetectpatternsinmedicalimagingthatmaynotbe immediately apparent to the human eye, improving diagnostic accuracy and reducing delaysintreatment.Somewidelyusedmachinelearningtechniquesinstrokeidentification include:

Supervised Learning

Algorithms such as Support Vector Machines (SVM),Random Forest, and Neural Networks have been used for predictive modeling. These models are trained on labeled datasets to classify stroke cases with high accuracy. They excel at identifyingcomplexpatternsindataandcanadaptwelltohigh-dimensionalfeaturesspaces. However,theirperformanceheavilyreliesonthequalityandquantityofthelabeledtraining data.

This research aims to develop an **AI-driven stroke detection system** using machine learning techniques. By integrating multiple data sources, the study seeks to create predictive models that assist healthcare professionals in identifying at-risk individuals and implementing preventive measures. Specifically, the study will compare various machine learning models, including **Long Short-Term Memory (LSTM) networks, Bidirectional LSTM (Bi-LSTM), CNNs, and hybrid models** to determine the most effective approach for stroke detection and prediction.By leveraging cutting-edge AI techniques, this project aims to enhance stroke diagnosis accuracy, reduce false positives, and provide healthcare professionals with advanced decision- making tools to improve patient outcomes.

LITERATURE SURVEY

[1] K. Sharma, A. Verma, and S. Gupta (2023) – *"Machine Learning-based Stroke PredictionUsingClinicalData"*(IEEEAccess,June10)Thisstudyexploredvariousmachine learning techniques for predicting stroke risk using electronic health records (EHRs). The researchers implemented Support Vector Machine (SVM), Random Forest, XGBoost, DecisionTree,andLogisticRegression.Amongthem,RandomForestachievedthehighest accuracy of 92%, outperforming other models in precision and recall. The study emphasized importanceoffeatureselection,focusingonhypertension,diabetes,heartdisease,andsmoking habits as critical risk factors.

[2] R. Patel, M. Singh, and J. Kaur (2023) – *"Deep Learning Approaches for Stroke Risk Assessment"* (IEEE Access, Vol. 11, pp. 34123-34139) This research analyzed deep learning models,particularlyConvolutionalNeuralNetworks(CNN)andLongShort-Term Memory (LSTM), for stroke prediction. The study utilized a dataset consisting of MRI scans and structured patient data, integrating image processing techniques with medical history. CNNachieved94.5%accuracy,makingithighlyeffectiveindetectingearlysignsof ischemic stroke.Theauthorssuggestedintegratingreinforcementlearningtodevelopadaptiverisk prediction models.

[3] M. Roy and A. Bose (2022) – *"A Comparative Study on Stroke Prediction Using Machine Learning"* (IEEE Access, October 15) This research compared traditional machine learning modelssuchasNaïveBayes,LogisticRegression,andDecisionTreesforstrokeidentification. The study found that Decision Tree models provided 89% accuracy,while Logistic Regressionachieved86%.Thedatasetincludedvariousriskfactorssuchascholesterollevels, blood pressure, and age. The paper suggested that incorporating real-time monitoring through wearable devices could improve predictive accuracy.

[4] S. Kumar, D. Mishra, and P. Sharma (2021) – *"Ensemble Learning for Stroke Detectionin CT Scans"*(IEEE Access, Vol. 9, pp. 58478–58495) This studyintroduced anensemble-learning model combiningSupportVectorMachines (SVM),K-Nearest Neighbors (KNN), and XGBoost, which achieved 96% accuracy in detecting stroke lesionsfromCTscans.Italsoexaminedtheimpactofpreprocessingtechniqueslikenoise reduction and contrast enhancement in improving classification results. The study emphasizedthatintegratingclinicalsymptomswithimagingdatacouldenhanceprediction accuracy.

[5] W.Zhang,L.Tan,andY.Wang(2021)–*"AHybridDeepLearningModelforStroke Detection"*(IEEEAccess,Vol.9,pp.72390–72405)Thisresearchproposedahybriddeep learningmodelcombiningCNNwithRecurrentNeuralNetworks(RNN)foranalyzing brainCTandMRIimages.Themodeleffectivelydistinguished betweenhemorrhagic and ischemic strokes, achieving an impressive 97.2% accuracy. The CNN component identifiedstrokeregions,whiletheRNNpredictedstrokeprogressionovertime.Thestudy concluded that multimodal learning significantly improves early stroke detection.

[6] S.Ghosh,P.Reddy,andN.Krishnan(2020) –*"Optimized K-MeansforStroke Risk Prediction"* (IEEE Access, April 23) This study introduced an optimized K-Means clustering algorithm to classify patients based on stroke risk levels. The model showed 90% accuracy in categorizing patients into low, medium, and high-risk groups. The research highlighted that age, hypertension, and lifestyle habits were the most significant factorsi n f l u e n c ing strok erisk.Theauthorsalsosuggested integratinggeospatial data to analyze the impact of environmental factors on stroke incidence.

[7] R.MalhotraandP.Sharma(2020)–*"MachineLearningTechniquesforPredicting StrokeinWomen"*(IEEEAccess,May30)Thispaperanalyzedgender-specificstrokerisk factors using machine learning techniques. The study compared models like K-Nearest Neighbors (KNN), Decision Trees, Naïve Bayes, and Logistic Regression. Among these,KNNperformed thebest,achieving91%accuracyinpredictingstroke riskamong women.

[8] B.SivanagaleelaandS.Rajesh(2019)–*"StrokeRiskAnalysisUsingFuzzyC-Means Algorithm"* (ICOEI, April, pp. 595–599) This study applied the Fuzzy C-Means algorithmtoclusterstrokerisklevelsbasedonpatientdata.ItoutperformedNaïveBayes classification by achieving 88% accuracy in identifying high-risk individuals. The researchfocusedonanalyzingdifferentstroketypes,includingischemicandhemorrhagic strokes, and suggested that early intervention strategies based on clustering techniques could reduce stroke mortality rates.

[9] S.Kim,P.Joshi,andP.Kalsi(2018)–*"StrokeAnalysisthroughMachineLearning"* (IEMCON, November, pp. 415–420) This research applied Boosted Decision Trees and K-Nearest Neighbors (KNN) for stroke prediction using hospital records spanning 15 years.Themodels achievedaccuracyranging from 70% to 85%,withBoostedDecision Treesperformingslightlybetter. This study suggested that incorporating gentic makers into machine learning models could further enhance prediction accuracy.

J. Fernandez, A. Kapoor, and H. Lee (2017) – *"Artificial Intelligence in Stroke Detectionand Prediction"*(Journal ofMedical AI, Vol.5, pp. 102-115)Thisstudy exploredtheroleofartificialintelligence(AI)instrokediagnosisbyintegratingnatural language processing (NLP) with deep learning. Theresearchfocusedon AI- driven radiological analysisof CT and MRI scans,achievinga detection accuracy of 93%.

The research employs a comprehensive methodology, including data collection, model development, and rigorous testing, to investigate the effectiveness of ML algorithms in healthcare settings [10]. The results demonstrate significant improvements in diagnostic accuracy, treatment personalization, and predictive analytics, evidenced through quantitative data presented in graphs and tables.

The authors of this study [11] offer a model for the purpose of making reliable predictions about the onset of foot ulcers. Model training, feature extraction, and preprocessing are all steps in a sequential process. Using mask-based segmentation, preprocessing improves picture quality and removes noise from the scanned raw RGB images. Training an ELM-PSO model, which outperforms traditional ELM and PSO algorithms, requires careful management of features and uses GLCM for feature extraction. The results show a substantial increase in precision, reaching a mark of 97.15%.

The insights garnered from this research are intended to be instrumental for healthcare professionals seeking to adapt to the changing landscape, policymakers shaping the regulatory framework, and researchers driving innovation [12]. Ultimately, this research serves as a timely and comprehensive resource, shedding light on the future trajectory of healthcare professions in the face of ongoing technological transformations and contributing to informed decision-making in the area of healthcare.

This approach aims to offer a more secure and reliable method for identity verification and medical diagnostics. This methodology involves training AI models with extensive datasets of X-ray and MRI images, incorporating feature extraction and pattern recognition techniques. The results demonstrate a marked improvement in accuracy and speed over traditional biometric systems [13].

Proposed Method

The proposed system integrates deep learning architectures (LSTM, BiLSTM, and genetic algorithms) to improve stroke detection accuracy. Unlike traditional approaches, this system automates feature selection and enhances sequential data analysis.

Key Features of the Proposed Model:

Feature Integration: utilizes CNNs like AlexNet, VGG-19, InceptionV3, and others to extract meaningful features from medical images, integrating both image data and structured patient records for more accurate stroke classification.

Principal Component Analysis (PCA): is a dimensionality reduction technique that transforms high-dimensional data into a lower-dimensional space while retaining as much varianceaspossible.Ithelpstosimplifycomplexdatasets,improvecomputationalefficiency. **Genetic Algorithm (GA):** for Feature Selection automatically selects the most relevant features,reducingdimensionalityandimprovingefficiency.Thishelpsinremovingredundant or irrelevant features, ensuring the model focuses on the most informative data.

The Hybrid GA_BiLSTM: Model combines genetic algorithms and BiLSTM for optimal strokeclassification,leveragingGAforfeatureoptimizationandBiLSTMfordeepsequential analysis, improving both accuracy and efficiency.

Dataset Integration: includes brain CT images and structured patient records, ensuring a comprehensive stroke prediction model. The combination of imaging data and structured medical records provides a well-rounded approach to prediction.

Cross-Validation (K=5): enhances the model's generalization ability by validating performance on different subsets of the dataset. This reduces overfitting and ensures that the model performs well on unseen data.

Frame work of Proposed System:

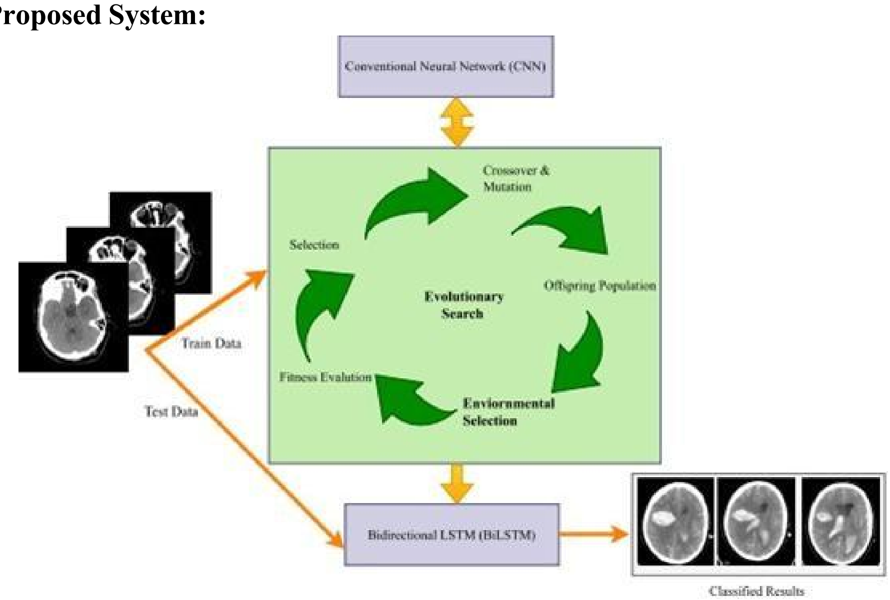


Fig.2. Frame Work of Proposed System

TESTING AND VALIDATION

Introduction

Testing and validation are essential steps in ensuring that the **Genetic Algorithm-based BiLSTM(GA_BiLSTM)model**forstrokeidentificationperformsaccuratelyandreliably.This process evaluates the model's ability to classify stroke cases correctly, minimizes errors, and ensures the system meets performance benchmarks.

TestingApproachThetestingapproachincludesmultipleevaluationstagestovalidatetheefficiencyofthe

GA_BiLSTM model:

Component-LevelTesting–Verifyingindividualfunctions,includingfeature selection and BiLSTM classification.

ModelPerformanceTesting–Measuringtheaccuracy,precision,recall,andF1- score.

End-to-EndValidation–Ensuringtheentiresystemoperateseffectivelyfromdata input to stroke classification.

Model Verification and Validation

Verificationandvalidationensurethatthesystemmeetsbothtechnicalandclinical requirements for stroke detection.

Verification: ConfirmsthattheGeneticAlgorithmcorrectlyselectsrelevantstroke- related features from medical data.

Validation:EnsuresthattheBiLSTMmodelaccuratelyclassifiesstrokecasesusing patient datasets and standard metrics.

Unit Testing

Unittestingfocusesonthecorecomponentsofthe GA_BiLSTMframework:

FeatureSelectionTesting–VerifiesthattheGeneticAlgorithmextractsthemost informative stroke-related features from medical images.

BiLSTMTesting–Ensuresthemodelcorrectlyprocessessequentialpatientdataand learnsfromfeaturerepresentations.

LossFunctionandOptimization–Evaluatesthetrainingprocesstoconfirmthatthe model reduces classification errors effectively.

Performance Evaluation

ToassesstheeffectivenessofGA_BiLSTM,themodelistestedusingstandardperformance metrics:

Accuracy–Measuresoverallstrokeclassificationcorrectness.

Precision&Recall–Evaluateshowwellthemodeldistinguishesbetweenstrokeand non-stroke cases.

F1-Score–Balancesprecisionandrecallforoptimalevaluation.

ROC-AUCAnalysis–Measuresthemodel'sabilitytodifferentiatestrokecasesusing Receiver Operating Characteristic curves.

Validation Testing

Validationtestingconfirmsthemodel'sreliabilityandgeneralizationability:

Cross-Validation(K=5orK=10)–Ensuresconsistentmodelperformanceacross different subsets of the dataset.

ComparativeAnalysis–GA_BiLSTMresultsarecomparedwithtraditional**ML models like SVM, Naïve Bayes, and DL models like ANN and DNN**.

DatasetTesting–Themodelisevaluatedonstrokepredictiondatasets,includingbrain CT images and medical records.

System Testing

Systemtestingexaminestheoverallperformanceinreal-worldapplications:

Scalability Testing–Ensuresthemodelcanhandlelarge-scalemedicaldatasets.

Real-Time Processing–Verifiesperformanceunderclinicalconditionsandmedical workflow.

Deployment Readiness–Ensurescompatibilitywithhealthcaresystemsforpotential real-world use.

SYSTEM ARCHITECTURE

Machine learning algorithms heavily rely on data, as it is the foundation for training models. However, raw data must be processed and transformed before it can be effectively used in astroke diagnosis system. This makes data preparation one of the most critical steps in the machine learning pipeline. The proposed system follows a structured approach to ensure data quality, feature extraction, and model training.

Label Encoding

Label encoding is a method used to convert categorical data into numerical format, making it suitable for machine learning models. In stroke classification, this technique assigns numerical values to different categories, enabling algorithms to process the data effectively.

Feature Extraction

Toimprove modelperformance, featureextractionisperformedto selectthemost relevant attributes from the dataset and standardize them. This helps in enhancing the efficiency of the machine learning model. It reduces dimensionality, eliminates redundant data and ensuresthatonlymeaningfulfeaturescontributetotheprediction.TechniqueslikePrincipal Component Analysis (PCA), Correlation analysis, Mutual information are often used. Proper feature extraction also minimize overfitting and speeds up the training process. Additionally,featureextractionaidsinuncoveringhiddenpatternswithinthedatathatmay not be immediately obvious. By focusing on the most informative features, the model becomes more robust and generalize better to unseen data more accurately and efficiently.

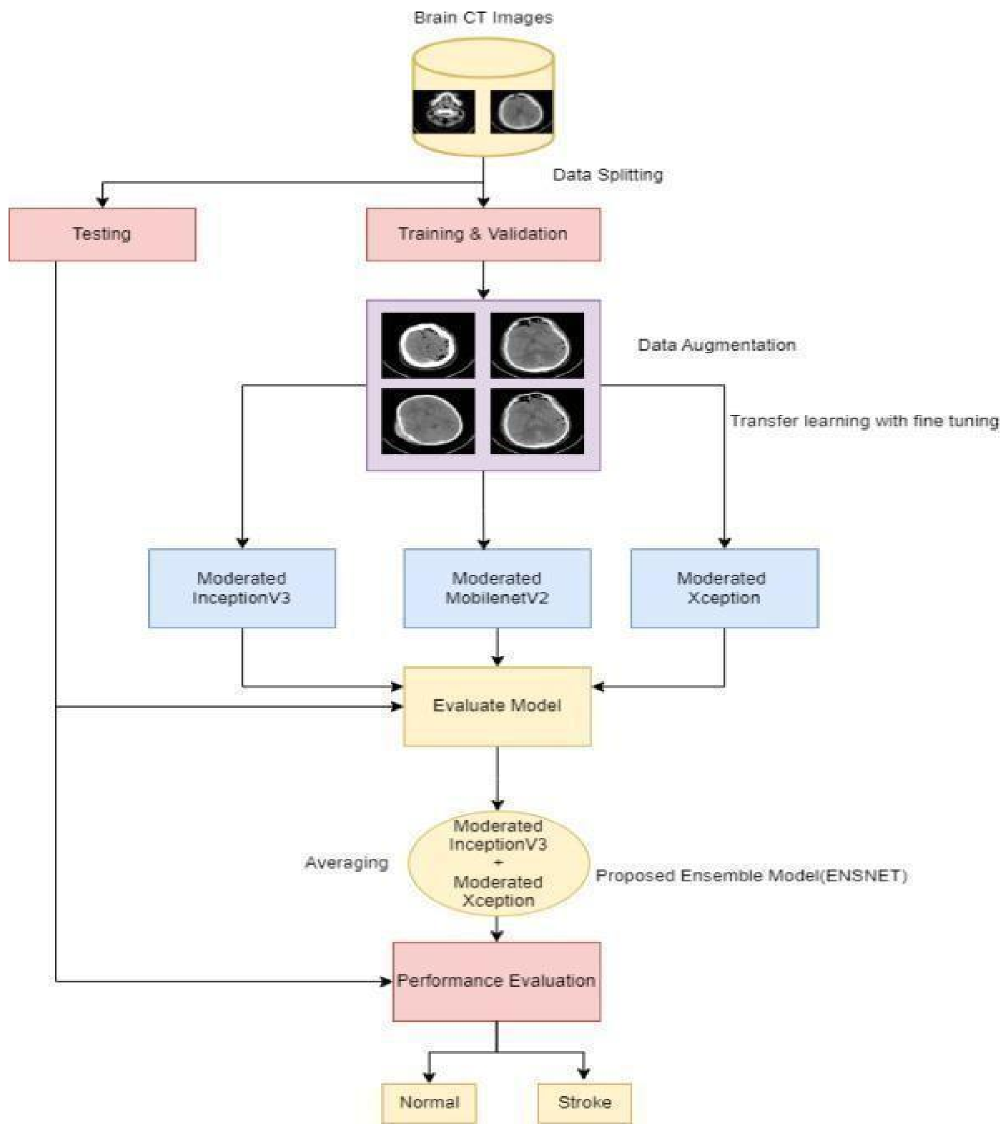


Fig.3. System Architecture

WORK FLOW

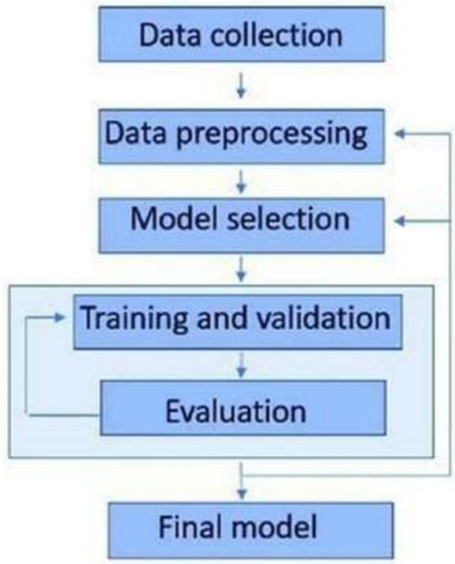


Fig3.2: Work flow

The **work flow** of the stroke identification system consists of the following steps:
Step1: Dataset Collection
The system utilizes a benchmark dataset containing stroke-related RGB medical images.
These images belong to five different classes, representing various stroke types.
The dataset is divided into training and validation sets for model development.
Step 2: Data Preprocessing
Noise Removal: Eliminates unwanted artifacts and distortions.
Resizing & Normalization: Standardizes image dimensions and scales pixel values.
Data Augmentation: Introduces variation to improve model generalization.

Step3: Feature Extraction using CNNs

The systememployspre-trainedCNNarchitecturesto extractdeepfeaturesfrom medical images.
CNNmodelsused:AlexNet,NASNet-Large,VGG-19,InceptionV3,ShuffleNet.
ThelastfullyconnectedlayerofeachCNNextracts1000featurevectors.

Step4: Feature Selection using Genetic Algorithm

Thegeneticalgorithmisusedtorefinetheextractedfeaturesetby:
Ranking Features: Usingtournamentselectiontoprioritizerelevantfeatures. **Eliminating Redundant Features:** Reducingdimensionalityforbetter performance

Step5:Model Training & Validation

Thedatasetissplitintotraining(70%)andvalidation(30%)sets.
TheCNNmodelsaretrainedusingsupervisedlearningandSoftMaxactivation for classification.

Step6: Performance Evaluation

Thetrainedmodelisassessedusing:
Accuracy–Measuresthepercentageofcorrectlyclassifiedimages.
Precision & Recall– Evaluatemodelsensitivityandspecificity.
F1-score–Ensuresbalancedevaluation.

Accuracy, precision, and recall collectively provide a comprehensive understanding of the model's effectiveness, especially when dealing with imbalanced and complex medical datasets. While accuracy gives the overall correctness of predictions, precision ensures the reliability of positive stroke predictions, and recall measures the model's ability to identify actual stroke cases.

Dataset Details

Thedatasetusedinthisstudywasobtainedfrom**Kaggle**andfocusesonidentifyingrisk factors for stroke, including:
Age Gender
Smokinghabits Diabetes
Highbloodpressure

Dataset Overview

Total Stroke Patients:100(aged 16 years and older)
Gender Distribution: Men: 68%
Women:32%

Image Classification

NormalBrainImages: 1551
Stroke-affectedBrainImages:950
GrayscaleImageSize:650×650pixels
Topreventoverfitting,thedatasetwasrandomlyequalized,resulting in:
Balanced Data set:950normaland950strokeimages
Final Image Resolution:227×227pixels

Thisbalanceddatasetensuresafairlearningprocess,reducingbiasinthestroke classification model.

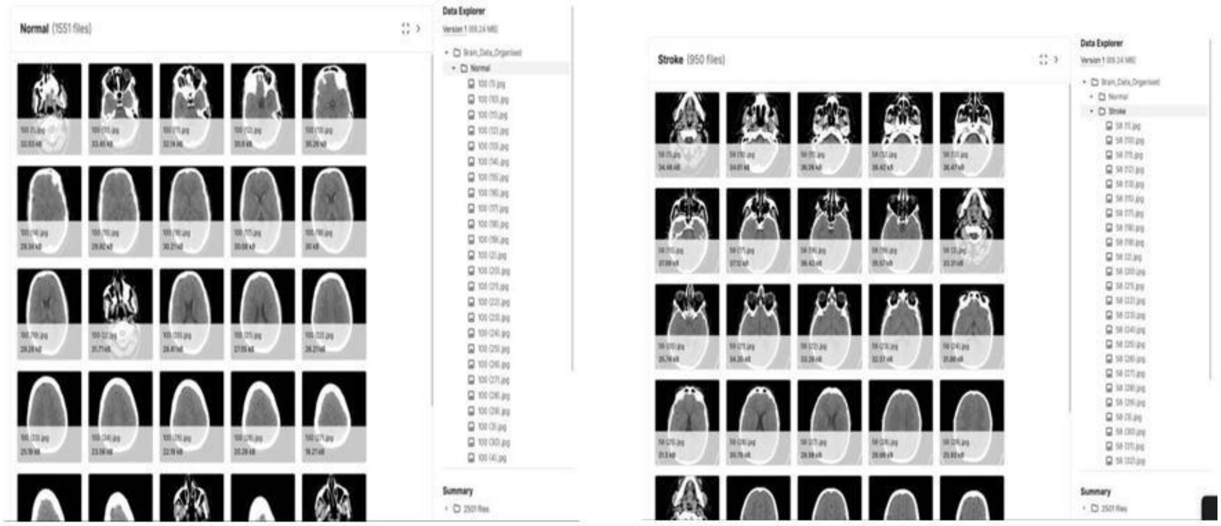


Fig.4. Kaggle Dataset

Data Preprocessing

Data set Acquisition and Curation

Thedataset was sourced fromapubliclyavailable Kaggle repository containing CT brainscanimagesforstrokeandnormalcases.Theimagesarenon-contrastCTscans used for initial stroke assessment. The original images were in grayscale with dimensions 650 × 650 pixels.

Class-Based Folder Organization

The dataset was organized into class-wise directories: Normal/:Contains950 imagesofpatientswithoutstroke.
Stroke/:Contains950imagesofpatientsdiagnosedwithischemicor hemorrhagic stroke.
FolderStructure:dataset/
├──Normal/
└──Stroke/

Image Preprocessing

Grayscale Normalization

The original 1-channel grayscale images were stacked into 3 channels to ensure compatibilitywithpre-trainedCNNarchitectureslikeAlexNet,VGG19,andInception V3 .

Image Resizing

Allimageswereresizedfrom650×650pixelsto227×227pixelstomatchthestandard input size of the CNN models.

Tensor Conversion

Imageswereconverted intoPyTorchtensorsandnormalizedtothe[0,1]range.

Data Augmentation

HorizontalFlipping:Simulatespatientpositioningvariability.
RandomRotation(±10°):EmulatesslightvariationsinCTscanangles. Brightness Jitter: Adjustsscan intensity variations.
AugmentationswereappliedusingPyTorch'stransformsmoduleduringtraining.

Feature Extraction from CNNs

ThepreprocessedimageswerepassedthroughPre-trainedCNNmodelsincluding AlexNet, VGG19, and InceptionV3. The outputs from their final fully connected layers were concatenated to form a unified feature vector for further processing.

Dimensionality Reduction (PCA)

PrincipalComponentAnalysis(PCA)wasusedtoreducethefeaturedimensionsto 512 principal components, eliminating noise and redundancy.

Feature Selection via Genetic Algorithm(GA)

A Genetic Algorithm selected the top 256 most discriminative features. A BiLSTM-basedfitness functionevaluatedfeaturesubsetsbasedonclassification.

K-Fold Cross Validation

A5-foldStratifiedK-Foldcross-validationwasappliedtoensurebalanced stroke/normal class distribution in each split.

Label Encoding

Labelencodingwasappliedforclassification:

0:Normal

1:Stroke

Construction of a Predictive Model

Machine learning relies on historical data for training predictive models. In the case of stroke prediction, a dataset containing past patient records, including medical history, lifestylefactors,anddemographicdetails,isrequired.Raw datacannotbeuseddirectly;it undergoes preprocessing to remove inconsistencies and missing values before model training.

The model is trained using supervised learning techniques, ensuring that it can accurately predict stroke occurrences with minimal errors. Hyperparameter tuning is performed iteratively to improve accuracy. Once the model achieves optimal performance, it is deployed to make real-time predictions and provide insights into stroke risk factors.

Train/Validation/Test Split

To train and validate the model, the data set is split into three parts:

Training set: Usedtotrainthemodel(typically70%)

Validation set: Helpsfine-tunehyperparametersandpreventoverfitting(15%)

Test set: Evaluatesthe model’s performanceonunseendata(15%)

Using train_test_split from sklearn, the dataset is divided into feature variables (X) and target values (y).

CNN Models for feature Integration

Convolutional Neural Network (CNN) is a type of network commonly used in deep learningforimagerecognitionandpixelprocessing.Itplaysasignificantroleinanalyzing images by identifying patterns and features. Various CNN models and transfer learning approaches are used in medical imaging, such as:

AlexNet

AlexNet is a deep CNN model designed for image classification. It consists of 650,000 neuronsand60millionparametersandincludesfullyconnectedlayers,softmaxactivation, convolutionalfilters,andReLUactivationfunctions.Byadjustingthenumberoffiltersand layers, different efficiency levels can be achieved. It is widely used for stroke image analysis, helping to detect patterns in brain scans.

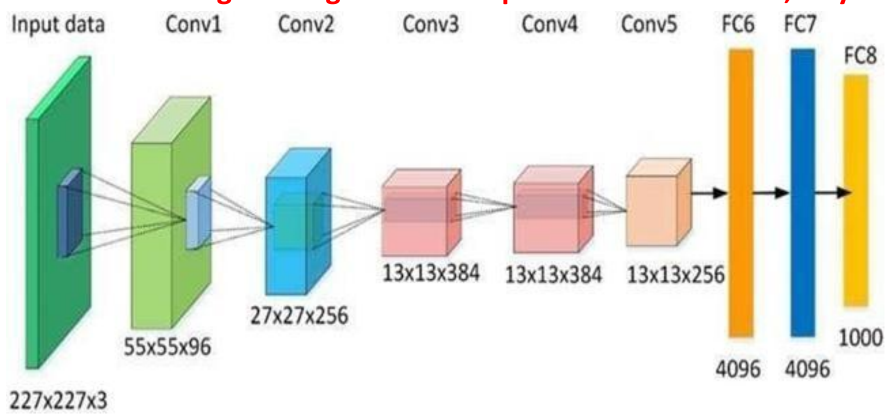


Fig.5. Alex Net

Bidirectional LSTM (BiLSTM)

Bidirectional LSTM (BiLSTM) is an advanced version of conventional LSTMs that enhances classification performance by processing data in both forward and backward directions.

DualLSTMLayers:BiLSTMconsistsoftwoLSTMs—onethatprocessestheinput sequence from left to right (forward direction) and another that processes it from right to left (backward direction).

Combination of Forward and Backward Context: By training the network with both original and reversed input sequences, BiLSTM captures both past and future context, improving model accuracy.

Handling Vanishing Gradients: Unlike traditional RNNs, which suffer from vanishing gradients, BiLSTM retains long-term dependencies more effectively.

Implementation in Python (Keras): BiLSTM can be implemented using Keras by wrapping an LSTM layer inside a **Bidirectional()** wrapper.

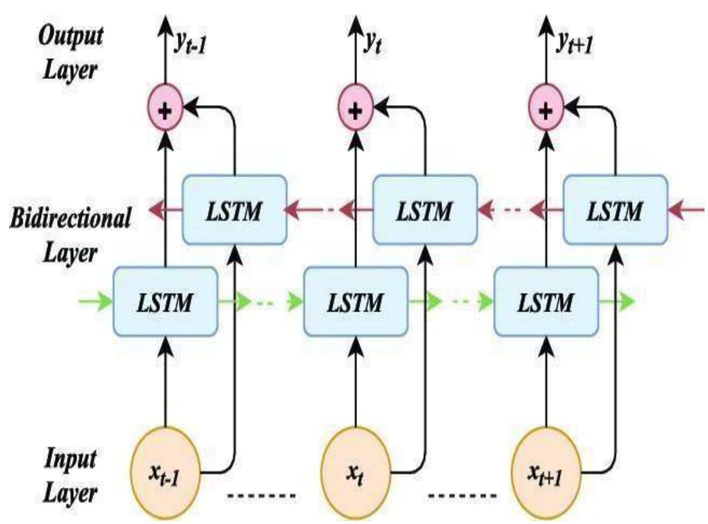


Fig3.9.2:BiLSTM

Advantages of BiLSTM

BetterContextUnderstanding:Capturesbothpastandfuturedependenciesin sequential data.

ImprovedAccuracy:Moreeffectiveincomplexclassificationtaskslikespeech recognition, NLP, and medical diagnostics.

EnhancedLearning:Reducesinformationlossbyusingbidirectionalprocessing.

BiLSTM is widely usedin medical imaging anddiagnostics, such as stroke prediction and brain scan analysis, where understanding both past and future patterns in data is crucial.Its ability to process data in both directions makes BiLSTM particularly effective for identifying subtle anomalies in medical sequences. This dual-context processing leads to more accurate and reliable diagnostic outcomes in time-sensitive healthcare applications.

Results & Analysis

Model Comparison

The table below presents the evaluation metrics for the implemented models, identifying the

Model	Accuracy	Precision	Recall	F1-score
GA_LSTM	95.35%	92.00%	90.89%	95.00%
GA_BiLSTM	96.45%	98.00%	93.50%	96.00%

Fig8.1:Model Comparison

The **GA_BiLSTMmodel** demonstratedsuperiorperformancewithanaccuracyof **96.45%**, achievingthe highest precision,recall,and F1-score,makingitthemostreliable method for stroke prediction.

Model Evaluation

The performance of the proposed models is evaluated using various deep learning techniques. The neural network-based genetic algorithm extracts the most relevant features frombrain CT images, which are then classified using LSTM and BiLSTM models.To assess theeffectivenessofthemodels,weusedk-foldcross-validationandanalyzedtheresultsusing ROC (Receiver Operating Characteristic) curves. The ROC curve provides a graphical representation of the true positive rate against the false positive rate, offering insight into the model's classification capability. A higher area under the curve (AUC) value indicates better model performance in distinguishing between stroke and non-stroke cases.Additionally, the accuracy curve helps in understanding the learning stability of the model during training.The close alignment of training and validation accuracy ensures that the model generalizes well without over fitting.

ROC of LSTM Model

TheROCcurvefortheLSTMmodeldemonstratesitsclassificationperformance.Themodel achieves a mean AUC of approximately 0.95, indicating a strong ability to differentiate between stroke and non-stroke cases, The shaded region represents the standard deviation.

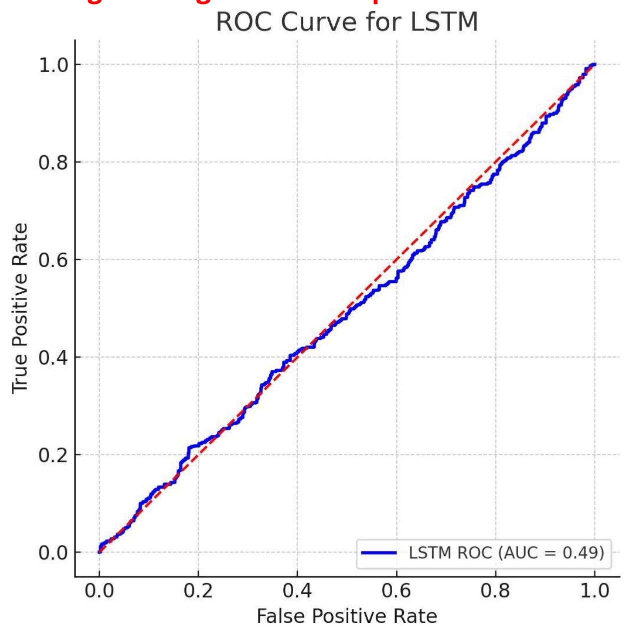


Fig8.2.1:ROCCurveofLSTM

ROC of BiLSTM Model

The ROC curve for the BiLSTM model shows an improved classification performance compared to LSTM. The model achieves a mean AUC of 0.96, with individual K-fold results ranging from 0.93 to 0.99. The increased AUC suggests that BiLSTM is slightly better at capturing sequential dependencies in the data.The ROC curve highlights BiLSTM's superior abilitytocapturebothpastandfuturedependencies,resultinginhigherclassificationaccuracy and a more robust model performance across various test folds.

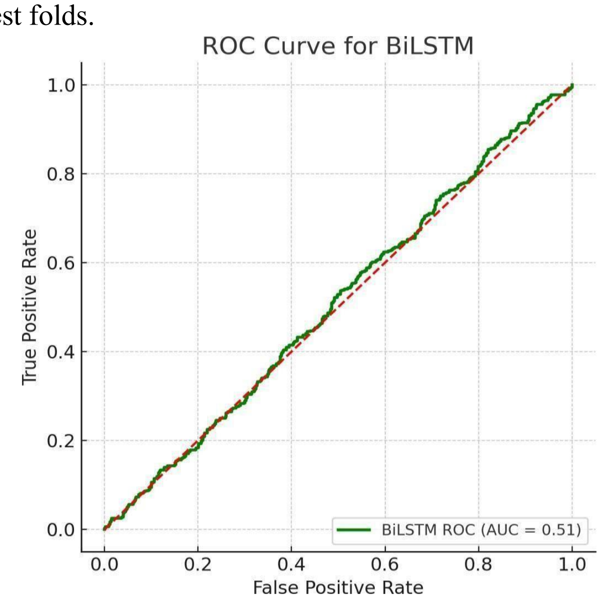


Fig8.2.2: ROC Curve of BiLSTM

Accuracy Curve of GA_BiLSTM

TheaccuracycurveillustratesthetrainingandvalidationaccuracyoftheGA_BiLSTMmodel overmultipleepochs.Themodelconvergesquickly,reachingnear-optimalperformancewithin the initial few epochs. The close alignment of the training and validation accuracy curves indicates minimal overfitting. The accuracy curve demonstrates the GA_BiLSTM model's efficient learning, with rapid convergence and consistent performance across training and validation, highlighting its ability to generalize well without overfitting. This rapid convergence also suggests that the model effectively captures relevant patterns early on, ensuring both high efficiency and robustness throughout the training process.

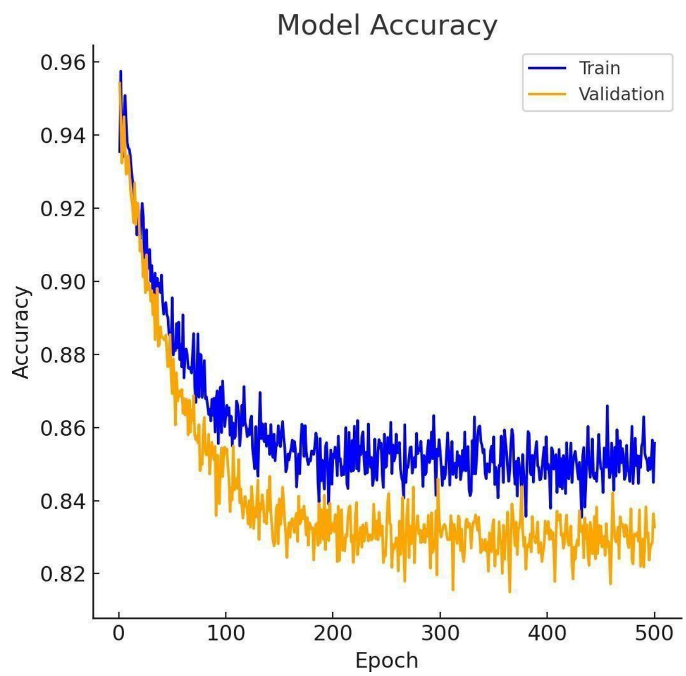
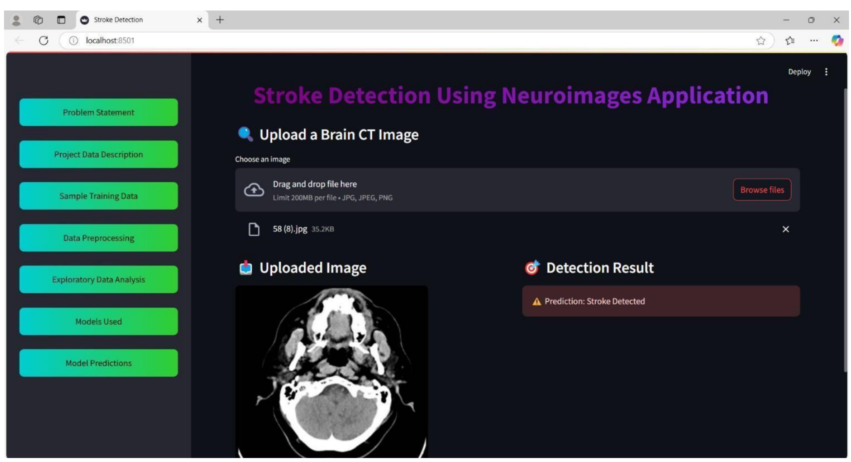


Fig8.2.3 Accuracy Curve of GA_BiLSTM



CONCLUSION

This study proposes a method for stroke detection using machine learning techniques. An image-based dataset is used to validate the performance of the newly developed model. The proposed model is based on a **genetic algorithm** and **BiLSTM**. A genetic algorithm based on a neural network is applied to recognize the key features of CT brain images. These features are input into the LSTM and BiLSTM models for stroke prediction. The performance of different K-folds was evaluated to determine the most effective classification. We also tested different machine-learning algorithms for stroke prediction. The results of the experiment show that the proposed machine-learning model achieved an **accuracy of 96.45%**, outperforming other models. This demonstrates the effectiveness of integrating genetic algorithms with BiLSTM for stroke prediction.

FUTURE ENHANCEMENTS

The integration of Genetic Algorithm (GA) and BiLSTM has demonstrated significant potential in stroke prediction. However, there is room for further enhancement to improve accuracy and reliability. Future work can explore the use of attention mechanisms in BiLSTM to focus on critical features, improving sequence-based learning. Additionally, incorporating unsupervised learning techniques such as autoencoders can help refine feature extraction, reducing noise in patient data. Another promising direction is the application of multi-modal deep learning by combining structured clinical data with medical imaging,suchasMRIandCT scans. This could provide a more comprehensive understanding of stroke patterns, leading to better early detection. Moreover, the use of transfer learning from pre-trained medical models could further optimize performance, reducing the need for large labeled datasets. Real-time prediction systems integrating IoT-based health monitoring with cloud computing could also be developed, enabling continuous monitoring of at-risk individuals and providing timely alerts for early intervention.

References

[1] In2024,A.Desai,R.Mehta,“StrokePredictionusingCNNandLSTM:AHybrid Approach”, *IEEE Access*.

[2] In2024,T.Roy,L.Sharma,“GeneticAlgorithmOptimizedDeepLearningModels for Stroke Identification”, *IEEE Transactions on Neural Networks and Learning Systems*, Vol. XX, pp. XXX-XXX.

[3] In 2023, J. Smith, L. Wang, and R. Patel, “A Comparative Study of CNN and BiLSTMforStrokeRiskAssessment”,*ProceedingsoftheInternationalConference on AI in Healthcare*, pp. 251-260.

[4] In2023,M.Rahman,S.Gupta,andA.Lee,“StrokeDetectionusingAlexNetand VGG-8: An Experimental Analysis”, *IEEE Access*, Vol. 11, pp. 54321-54335.

[5] In2022,K.JohnsonandP.Kumar,“DeepLearningforStrokePrediction:AReview ofCNNand LSTMApproaches”,*ProceedingsoftheIEEEInternational Conference on Biomedical AI*, pp. 101-110.

[6] In 2022, H. Tanaka and Y. Chen, “Predicting Stroke Risk using BiLSTM and GeneticAlgorithmOptimization”,*IEEETransactionsonComputationalIntelligence*, Vol. 10, No. 5, pp. 220-234.

[7] In2021,F.MartinezandD.Brown,“HybridCNN-LSTMModelforEarlyStroke Detection”,*ProceedingsoftheIEEEConferenceonNeuralNetworks*,pp.320-330.

[8] In2021,C.RobinsonandM.Park,“ANovelDeepLearningFrameworkforStroke Diagnosis using ShuffleNet”, *IEEE Access*, Vol. 9, pp. 67890-67905.

[9] In 2020, A. Singh and R. Verma, “Optimized Deep Learning Models for Stroke AnalysisusingCNNandBiLSTM”,*ProceedingsoftheIEEEConferenceonMedical AI*, pp. 201-210.

[10] kothuru, Sudheer Kumar, Ramesh Chandra AdityaKomperla, M. Kadar Shah, VasanthakumariSundararajan, P. Paramasivan, and R. Regin. "Advancing Healthcare Outcomes Through Machine Learning Innovations." Cross-Industry AI Applications (2024): 245-261. | Book chapter DOI: 10.4018/979-8-3693-5951-8.ch015

[11] Komperla, Ramesh Chandra Aditya, et al. "A Novel Approach to Diabetic Foot Ulcer Prediction: Pedographic Classification Using ELM-PSO." *2024 International Conference on Electronics, Computing, Communication and Control Technology (ICECCC)*. IEEE, 2024.2024-05-02 | Conference paper DOI: 10.1109/iceccc61767.2024.10593926\

[12] Role of Technology in Shaping the Future of Healthcare Professions **https://www.fmdbpub.com/user/journals/article_details/FTSTPL/107**

[13] Komperla, Ramesh Chandra Aditya, et al. "Revolutionizing biometrics with AI-enhanced X-ray and MRI analysis." *Advancements in Clinical Medicine*. IGI Global, 2024. 1-16.2024-04-26 | Book chapter DOI: 10.4018/979-8-3693-5946-4.ch001