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Predicting Stroke Risk Using Deep Learning Analyzing Key Health Indicators

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التنبؤ بمخاطر السكتة الدماغية باستخدام التعلم العميق وتحليل المؤشرات الصحية الرئيسية

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Abstract

Background:

Stroke represents a major public health concern due to its high rates of mortality and long-term disability. When a stroke occurs, timely medical intervention can greatly enhance the outcome of the individual affected by the stroke. The prediction of a person's risk of a stroke can be improved with the help of recent developments in artificial intelligence (AI), especially through the use of deep learning techniques to analyze/interpret the large and varied amount of medical data available for use in predictive healthcare.

Materials and Methods:

The proposed research presents a hybrid multimodal deep learning framework that allows for binary stroke risk prediction with model architectures composed of Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and Dense Neural Networks (DNN). The model uses a wide variety of heterogeneous data sources to make a binary prediction with respect to strokes; these sources include the multitude of clinical, behavioral, and physiological measurements available in datasets such as Kaggle Stroke Prediction dataset. Data preprocessing involved missing-value imputation, Z-score normalization, and class imbalance correction using the Synthetic Minority Oversampling Technique (SMOTE). The model consists of three separate but parallel specialized subnetworks to process different types of input; one processes tabular data, one sequential and one spatial, and their respective outputs were integrated (fused) together through an attention-based feature integration layer. For training, the Adam optimizer was used with dropout and batch normalization, and 10-fold cross-validation was employed for evaluation with standard metrics such as accuracy, precision, recall, F1-score, and AUC-ROC done after each fold evaluation.

Results:

The framework obtained 99.95% for training accuracy and 99.50% for validation accuracy. The evaluation reported precision, recall, and F1-score values ranging from 0.98 to 0.99, which means that overall classification accuracy was roughly equal to 99%. The ROC analysis resulted in AUC values near 1.0, which illustrate high levels of discrimination ability.

Conclusion:

Overall, these results illustrate that hybrid multimodal deep learning models can use multiple forms of heterogeneous medical data for accurate prediction of stroke risk. In the future, we will validate this framework by testing it with larger and more diverse clinical data sets designed to evaluate how robustly and generally applicable this framework would perform in real-world clinical settings.

Key words: Hybrid Deep Learning, Stroke Prediction, CNN, LSTM, DNN, Performance Metrics.

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INTRODUCTION

Stroke is among the top global health concerns. It ranks as a leading cause of death and long-term disability worldwide.[1][2] The blood supply to part of the brain is interrupted; this immediate neuronal damage affects millions every year, with increasing incidence in developing countries where prevention has not taken hold adequately.[3][4] stroke is mostly associated with old age but now cuts across different ages creating huge physical, social, and economic burdens on patients and families besides healthcare systems.[5] Ischemic stroke forms the larger proportion reported globally[6] whose risk-attributing factors comprise both modifiable and no modifiable elements like hypertension & diabetes together with hyperlipidemia smoking obesity sedentary lifestyle[7]therefore making their early detection significant towards enhancing outcome as well as minimizing long term disablement[8]. In the recent past, artificial intelligence (AI), machine learning (ML), and deep learning (DL) have shown a drastic improvement in their predictive capabilities towards healthcare. Traditional ML models Random Forests, SVM, Gradient Boosting) and Deep Learning architectures (CNNs, LSTMs, autoencoders) performed well on different datasets for stroke prediction [9-10]. But here lies the actual problem: Most existing studies encounter significant limitations when applied to heterogeneous multimodal medical data since they were trained or developed using single modality datasets with missing values; class imbalance problems; inconsistent feature representation; lack/incomplete integration between temporal & non-temporal patterns [11-15]. Also, in spite of the fact that some DL models can attain very high predictive accuracies, they remain essentially un-interpretable and hence reduce trust and constraint clinical uptake[9] leaving behind a glaring research gap: “A unified and robust predictive framework capable of handling diversified clinical, behavioral, and physiological data types with fairness , interpretability,-completeness is still positively needed. Therefore this paper aims at developing hybrid deep learning model integrating Convolution Neural Network (CNN), Long Short Term Memory(LSTM)and Dense neural network(DNN)for improving prediction accuracy on risk related to stroke , making classification more consistent across heterogeneous datasets besides providing practical usable tool applicable in clinics involving early detection as well informed decision support .The remainder of this study consists of several parts section 3 discusses previous studies, while Section 4 discusses the research methodology. Section 5 presents and details the test results, while Section 6 concludes the study by drawing conclusions and offering recommendations for future work.

LITERATURE REVIEW

The study made an analysis of electronic health record (EHR) data to determine the most influential factors in predicting the occurrence of stroke. Pearson’s correlation coefficient has been used to check linear relationships between attributes, and then Learning Vector Quantization (LVQ) model is applied for variable importance analysis. Results show that age is a highly significant factor followed by heart disease, glucose level, and hypertension. The CHADS2 score was calculated for risk estimation as it showed high odds with higher scores; i.e., the neural network was used for feature set optimization which confirmed top four variables giving maximum prediction efficiency (88%). Principal Component Analysis(PCA) reduced dimensions where first eight components explained about 88% variance thus validating approach involving both statistical analysis & machine learning techniques on interpretation of stroke related factors[16].

This study proposes a highly efficient predictive framework for the immediate detection of strokes. Three imputation methods were applied to fill in missing values and SMOTE for handling class imbalance. The researcher started with a baseline model, then applied several state-of-the-art machine learning algorithms whose performances were measured using k-fold cross-validation on

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both unbalanced and balanced datasets. Age, BMI, average glucose level, heart disease, hypertension, and ever married came out as top features influencing stroke prediction. A Dense Stacking Ensemble (DSE) model is developed where best-performed fine-tuned models are integrated as base learners along with a meta-classifier; this proposed DSE outperforms by achieving more than 96% accuracy with AUC scores of 83.94%[imbalanced]and 98 .92 %[balanced]datasets respectively hence proving to be a very effective yet reliable approach towards detecting stroke at an earlier stage[17].

3- This study implements deep learning of Convolutional Neural Networks (CNN) to determine the risk factors for cardiovascular disease in health parameters that include blood pressure, cholesterol, and other indicators associated with lifestyle. The proposed network architecture is composed of embedding, convolutional, and dense layers intended to capture complex relationships among features. Several techniques have been applied to improve its performance as well as generalization capability; they are dropout batch normalization hyperparameter tuning[17]. 0.994 R squared was attained by this model hence out-performing existing traditional approaches thereby proving a high potential for accurate yet earlier prediction of CVD.

4-This study employs machine learning (ML) techniques to develop and test several predictive models for assessing the risk of stroke over a long-term period. A stacking ensemble framework has been proposed in which final predictions from multiple base classifiers are combined to improve overall accuracy. The performance of different models was validated based on some important evaluation metrics including AUC, precision, recall, F-measure, and accuracy. Results proved that even experimentally tested individual models performed very well; however, the stacking classifier outperformed all with an AUC of 98.9%, F-measure=precision=recall=97.4% and accuracy=98% hence making it robust as well as reliable for prediction of stroke[19].

5- This study analyzed a prospective U.S. cohort of 3.4 million patients over two years to assess stroke risk associated with multimorbidity. Data from medical records included demographic and clinical variables. Traditional risk scores (CHADS2, CHA2DS2-VASc), a multimorbid index, and machine learning (ML) models were compared. ML algorithms—especially gradient boosting and neural network logistic regression—were evaluated using c-index, calibration, and decision curve analysis, demonstrating superior accuracy and clinical utility for dynamic stroke risk prediction[20].

6- The aim of this project was to apply experimental analytic techniques to predict the odds of having a stroke by utilizing machine learning (ML) and deep learning, starting with an analysis of a reliable data source from the Kaggle data repository of the type described above that pertains specifically to predicting strokes by way of clinical and demographic information. As a result, we obtained the stroke prediction dataset on Kaggle, which provides publicly accessible and reliable clinical and demographic data related to the likelihood of having a stroke. After retrieving the dataset from Kaggle, we prepared the data for the ML algorithms by performing various preprocessing steps, including handling missing values, normalizing the data, and selecting input variables (features) based on their quality and reliability. In this study, we implemented and compared a variety of classification algorithms, including EGB (Extreme Gradient Boosting) , AdaBoost, LightGBM (Light Gradient Boosting Machine), RF, DT, Logistic Regression, KNN (K-Nearest Neighbors), Linear Kernel SVM, Naïve Bayes, and ANN (Artificial Neural Networks)

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with 3 and 4 hidden layers. In this study, model performance was evaluated using accuracy and other standard evaluation metrics. The results showed that the best performing model was the Random Forest classifier, with a classification accuracy of 99%, while the four-layer ANN had a higher accuracy than the three-layer ANN with a classification accuracy of 92.39%. Consequently, this means that the four-layer ANN performed better than the three-layer ANN using the Random Forest Classifier as the benchmark. These outcomes indicate the strong predictive capability of ensemble-based machine learning models in early stroke detection compared to deep neural networks[21].

7- This study used a quantitative, comparative methodology in assessing and comparing the predictive performance of the deep learning (DL) and machine learning (ML) models towards early detection of stroke. This research applied a clinical dataset of 663 records collected from Hazrat Rasool Akram Hospital in Tehran, Iran among which 401 records were for healthy individuals and 262 records belonged to patients with stroke. The applied eight ML models included Support Vector Machine (SVM), Extreme Gradient Boosting (XGB), K-Nearest Neighbors (KNN), Random Forest (RF); while the four DL models consisted of Deep Neural Network (DNN), Feedforward Neural Network (FNN), Long Short-Term Memory (LSTM), Convolutional Neural Network(CNN). All models have been learned using the tenfold cross-validation as well as hyperparameter optimization techniques to reduce overfitting and to also ensure fair comparisons between them. Model interpretability was made possible through Shapley Additive Explanations allowing explicit insight into a feature's contribution towards making a prediction. The models were evaluated based on standard performance metrics-accuracy, sensitivity, specificity, F1-score, and area under the ROC curve (AUC-ROC). Though DL models have been found to perform well through a comparative analysis, results revealed that the RF model outperformed them in most of the cases. This consequently flagged this model as a potential tool for reliable and efficient early stroke prediction[22].

8- A prospective quantitative study was used in the study. It had a dataset composed of clinical and demographic data of 332 patients (mean age: 77.4 ± 10.4 years, 50.6% male) admitted to Imam Khomeini Hospital, Ardabil, Iran during 2008-2018 for predicting mortality risk among patients with brain stroke (BS) through the DLNN model. The records were taken from institutional BS registry data verified by diagnostic imaging techniques such as CT scans and MRI applications. The neural network model was to be designed for identifying the impacts of key risk factors on mortality regarding strokes. Training this model and thereafter testing it was supposed to be done across eighty-one possible architectures by jumping hyperparameters like harvesting functions, hidden layer sizes, learning rates, and values for momentum. The best model used the tangent hyperbolic activation function, with 10–20 hidden units, a learning rate of 0.1, momentum at 0.5, and 400 as maximum epochs. Model diagnostics included indices such as accuracy, sensitivity, and specificity that varied between 90.5%–99.7%, 83.8%–100%, and 89.8%–99.5%. Feature importance brought out time interval after 10 years, age, history of hyperlipoproteinemia, and education level as the most influential predictors of stroke mortality. Other variables such as sex, employment status, residence, smoking heart disease stroke type blood pressure diabetes oral contraceptive use and physical activity were found to have moderate predictive significance[23].

9- A quantitative analytical study was aimed at developing an intelligent model of predicting stroke from service and health behavior data rather than high-cost medical images. 15,099 patients diagnosed with stroke were subjected to a medical record review using Principal Component Analysis (PCA) with quantile scaling in order to determine background features most directly related to risk factors for stroke. These features were then used in training Deep Neural Networks (DNN) so as to build an accurate predictive model whose proposed performance would finally be compared against five other machine learning algorithms for effectiveness. Results of the study would dwell on how effective the scaled PCA/DNN approach is by dwelling on its ability toward predictiveness since it attained an AUC value of 83.48%. This will help doctors and patients do an early check-up and find possible stroke cases, which can lead to fewer health and money problems that come from the growing old Korean people[24].

10- A quantitative, data-driven research method was used to create a machine learning model, which would be able to predict the modified Rankin Scale (mRS), that is, the 90-day functional outcome of all ischemic stroke patients treated with thrombolysis. The study uses data from Qatar's national stroke registry from January 2014 until June 2022 on 723 ischemic strokes who received thrombolytic therapy. Clinical, demographic, and physiological variables—severity of the stroke and comorbid conditions; laboratory values; admission vital signs—and complications during hospital stay were collected and fully analyzed. Five machine learning algorithms were subjected to training tested under robust performance metrics to identify the most accurate predictive model. SHapley Additive exPlanations (SHAP) analysis was performed for model output interpretation and recognition of the most influential prognostic factors as well. The Support Vector Machine (SVM) algorithm gave the best prediction among those tried recording an AUC value of 0.72. This methodological approach demonstrates a strict combination of machine learning and clinical data analytics for improving early outcome prediction that can enable personalized stroke management and evidence-based decisions in the care of patients after thrombolysis[25].

11- This study conducted a quantitative analysis that uses a large amount of clinical data and predictive machine-learning techniques to estimate functional outcome challenges over a 90-day period following a stroke. Data were obtained from the Taiwan Stroke Registry (TSR), which has systematically collected data on patients since 2006. Three commonly used machine-learning techniques-Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Network (ANN)-as well as a hybrid version of the ANN, were constructed and compared. In addition, each model was evaluated using a very standardised approach to assessing reliability and generalisability through the combination of 10 times repeated hold-out (RO) trials, along with 10-fold cross-validation of the models' performances. From the initial 206 clinical variables obtained (some assessed prior to admission, some during the inpatient stay, and others during follow-up), a selection was made of the best predictors for functional outcome at 90 days for both ischemic (17 features) and hemorrhagic (22 features) stroke patients. With AUC of 0.94 with preadmission and inpatient data and AUC 0.97 as the follow-up data was included in the model, the training of the model demonstrated how effective machine learning can be in applying large clinical databases to refine the prediction of patient outcomes based on the current status and historical patient records, thanks to longitudinal data [26].

12- this study included feature selection using the genetic algorithm as part of clinical biomarkers and parameters that are potentially most informative among a wide set of clinical variables. Several classifiers were tested under ML; results showed one with better performance, i.e., R <Random Forest> verifying the obtained performance measures as 91.13% accuracy, 91.13% Recall, 90.89%

precision, and F1-score = 91.00%. The model outputs were interpreted with the help of the SHapley Additive exPlanations (SHAP) framework. This, in turn, helped better describe how each variable contributed to the prediction output. Key predictors above were practically validated to have a very strong effect on NIHSS evolution and therefore emphasized clinical applicability in any efforts towards modeling early prognosis of stroke patients[27].

13- This study used an experimental, data-driven methodology that would be engineered and tested on a model of a real-time stroke prediction system based on bio-signal cues rather than imaging-based steps. The system being created applies machine learning (Random Forest) and deep learning (Long Short-Term Memory, LSTM) algorithms to examine electromyography (EMG) signals— real time from the thigh and calf muscles of the people under test. The project will involve data collection, then signal pre-processing, moving on to the feature extraction steps, eventually followed by training the model using the data and evaluating performance. EMG signals monitored during everyday chores, in which the objective is mimicking a stroke as closely as possible by actually doing the things. Features that could correspond to warning signs would have to be defined. Essentially building models, therefore evaluate in terms of how accurate they were at predicting things: 90.38% overall accuracy for Random Forest and 98.96% for LSTM. LSTM seemed to pick up the unusualness better and, and also be more directly stroke related. Laying the ground work for the 'theoretical' platform of real-time stroke prediction from user data using a cheap and non-invasive AI system, which is a much better solution than expensive imaging tools like CT / MRI that have to be used instead at the moment. This would provide the spring-board for such similar predictive techniques and the strand could then develop for other bio-signal medical uses like heart disease[28].

14- Quantitative analytics were employed to enhance forecasts for (functional outcomes in patients who sustained an ischemic stroke) by utilizing the concepts of machine learning. The objectives included the creation and validation of prediction models for how patients would function three months after they were admitted to the hospital based on the clinical information available at different points throughout their hospital stay. Initially, clinical information available at <the time of the emergency admission> was used to create machine learning models and then compare their predictive accuracy with standard clinical scoring systems. The predictive accuracy of the machine learning models was evaluated using <the Area Under the Receiver Operating Characteristic (ROC) Curve (AUC) as the primary metric for success. The predictive accuracy of the machine learning models using just clinical information available at the time of admission was slightly superior (0.808 ± 0.085) compared to the best clinical score (0.771 ± 0.056) based upon admission data only, but when additional clinical features from subsequent stages of care were incorporated, the predictive accuracy increased to well above 0.90 AUC. In this approach, combining timely clinical information over time with data-driven algorithms can enhance prognostic accuracy beyond what has been achieved via common scoring systems, allowing for a greater degree of information processing (I.e., individualized clinical decision support) for the clinical management of acute ischemic stroke[29].

15- A quantitative, data-driven research approach for the development of an early prediction model for stroke from multiple machine learning algorithms based on clinical risk factors and lifestyle-related risk factors was used. The dataset included the following variables, which are major determinants of the risk of a stroke: hypertension, body mass index, heart disease, average

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glucose level, smoking status, prior history of stroke, and age. Ten different ML classifiers have been trained and tested to estimate their individual performance in prediction: Logistic Regression, Stochastic Gradient Descent, Decision Tree, AdaBoost Gaussian Classifier Quadratic Discriminant Analysis Multilayer Perceptron K-Nearest Neighbors Gradient Boosting and XGBoost. The output predictions from these base classifiers were combined using a weighted voting ensemble technique that further strengthened model robustness as well as improved its accuracy. This ensemble model posted a prediction accuracy figure at 97% which is higher than any single classifier out there along with posting high-area-under-curve figures with the lowest false-positive-and-false-negative rates. This methodological framework brings to the fore the efficacy of machine learning methodologies based on ensembles in achieving reliable early prediction of stroke, generating a high-accuracy non-invasive decision-support tool to assist clinicians and patients in detecting and preventing possible stroke events [30].

Table 1. Summary of related works in the current study.

Table 1.summary of related works

No	Methodology	Results	Key Determinants	Challenges
1	EHR data analysis using Pearson's correlation, Learning Vector Quantization (LVQ), Perceptron neural network, PCA	Age identified as most significant; PCA explained 88.2% variance; $CHADS_2$ score confirmed risk	Age, heart disease, glucose level, hypertension	Combining statistical and ML techniques; dimensionality reduction
2	Baseline ML model with imputation and SMOTE, advanced ML algorithms, Dense Stacking Ensemble (DSE), k-fold cross-validation	Accuracy >96%; AUC 83.94% (imbalanced), 98.92% (balanced)	Age, BMI, glucose level, heart disease, hypertension, marital status	Handling missing data and class imbalance
3	Deep learning with CNNs; embedding, convolutional, dense layers; dropout, batch normalization, hyperparameter optimization	$R^2 = 0.994$; outperformed traditional methods	Blood pressure, cholesterol, lifestyle factors	Capturing complex feature relationships
4	ML using stacking ensemble; performance metrics: AUC, precision, recall, F-measure, accuracy	Stacking ensemble: AUC 98.9%, accuracy 98%, F-measure 97.4%	Integrated base classifiers	Complexity of ensemble integration
5	Prospective cohort study (3.4M patients); comparison of $CHADS_2$, CHA_2DS_2-VASc, multimorbid index, ML models; evaluated with c-	Gradient boosting & neural network LR had superior accuracy	Demographic & clinical variables	Dynamic risk modeling in large cohort

	index, calibration, decision curve			
6	Kaggle dataset; preprocessing (missing values, normalization, feature selection); ML and deep learning classifiers (XGBoost, AdaBoost, LightGBM, RF, DT, LR, KNN, SVM, Naïve Bayes, ANN)	RF accuracy 99%; 4-layer ANN 92.39%	Clinical and demographic features	Model comparison and feature selection
7	Comparative DL vs. ML; clinical dataset of 663 records; 8 ML & 4 DL models; 10-fold CV, hyperparameter optimization; interpretability via SHAP	RF outperformed DL models; high accuracy, sensitivity, specificity, F1-score, AUC	Clinical variables	Limited dataset size; fair DL vs. ML comparison
8	Prospective study; DLNN on dataset of 332 patients; hyperparameter tuning across 81 architectures	Accuracy 90.5–99.7%, sensitivity 83.8–100%, specificity 89.8–99.5%	Time interval, age, hyperlipoproteinemia, education	Optimizing neural network architecture; feature impact analysis
9	PCA with quantile scaling for feature extraction; DNN training; comparison with five ML algorithms	AUC 83.48%; effective for early stroke check-up	Service use & health behavior data	Data quality; predictive generalizability
10	Qatar stroke registry; ML models trained on clinical, demographic, physiological variables; SHAP for interpretation	SVM best; AUC 0.72	Stroke severity, comorbidities, lab values, vital signs	Limited registry size; feature completeness
11	Taiwan Stroke Registry; SVM, RF, ANN, hybrid ANN; 10-time repeated hold-out + 10-fold CV; 206 variables	AUC 0.94 (preadmission/inpatient), 0.97 (with follow-up)	17 features (ischemic), 22 features (hemorrhagic)	Longitudinal data integration
12	Data from hyperacute & acute phases; genetic algorithm for feature selection; Random Forest; SHAP for interpretation	Accuracy 91.13%, Recall 91.13%, Precision 90.89%, F1 91%	Age, gender, NIHSS, intubation, comorbidities, lab values	Early phase data capture; binary classification reliability
13	Real-time EMG bio-signal collection; ML (RF) & DL (LSTM); feature extraction from daily activities	RF accuracy 90.38%, LSTM 98.96%	EMG signals from thighs & calves	Real-time data acquisition; noise in bio-signals

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14	ML for ischemic stroke functional outcome; admission & progressive clinical data; compared with ASTRAL, DRAGON, THRIVE	AUC 0.808 (admission), >0.90 (with progressive data)	Clinical variables at admission & follow-up	Data availability over time; integration of temporal features
15	Ensemble-based ML for early stroke prediction; 10 classifiers; weighted voting	Accuracy 97%; low FPR & FNR; high AUC	Hypertension, BMI, heart disease, glucose, smoking, prior stroke, age	Ensemble weighting optimization; generalizability

METHODOLOGY

An integrated hybrid multimodal deep learning framework (IHMDLF) has been developed for early stroke prediction using both machine learning (ML) and deep learning (DL). IHMDLF utilizes different types of data from multiple sources (clinical, behavioral, physiological) within a single predictive framework in order to maximize predictive accuracy and provide interpretation of the resulting medical predictions. Data used in developing the framework were from publicly available datasets, including clinical and demographic features of strokes, that were obtained from the Kaggle Stroke Prediction database. Furthermore, behavioral characteristics were gathered with relation to individual's lifestyle choices and health habits, and physiological measures (ECG, EMG) were measured in real-time through wearable devices.

All datasets were preprocessed through a complete process prior to model development by filling in any missing values and determining the Z-score normalized values for the features using the Sample Mean of a normal distribution method [32]. To solve the issue of class imbalance, the Synthetic Minority Oversampling Technique (SMOTE) was used to balance the class distribution [33]. Additionally, advanced feature extraction methods were used based on the data type. For tabular data, Principal Components Analysis (PCA)[34] was performed to eliminate irrelevant features, while spectrogram and wavelet transformation methods were used on physiological signals to capture characteristics of both the time and frequency domains.

To accomplish the above, we will build a combined model consisting of three sub-networks defined so that they can be run in parallel to process different kinds of input data. The first subnetwork in this hybrid model will have a DNN[35] that takes in features from both tabular clinical information and behavioral data, where there will be an input layer to receive the data before multiple hidden layers that are are fully connected with ReLU[36] activation functions to create the model output. The second subnetwork will consist of several stacked LSTM[37] layers to analyze the time series data from physiological signals, combined with a dense layer to provide feature representations based on the previous time steps of the physiological signal. The final subnetwork will use a CNN[39] model that will consist of multiple convolution, pooling, and fully connected layers in order to recognize the spatial or spectral transformations of a given physiological signal, allowing us to create hierarchical patterns from the physiological signals analysed.

The outputs from the 3 distinct subnetworks are combined together into a shared fusion layer, where an Attention Mechanism is applied to assign dynamic weights based upon each modalities relative contribution toward making a prediction. This fused representation is then applied to the final classification layer (a fully connected layer with sigmoid activation: used to predict binary outcome of whether an individual has stroke risk or not) for prediction purposes. This model was developed using Adam while using an adaptive learning rate, so we used dropout regularization and batch normalization to mitigate overfitting and improve training stability [40–42].

The long-term stability and reliability of the model were assessed using a 10-fold cross-validation methodology and the following standard assessments of predictive performance: accuracy, precision, recall, F1 score, and area under the receiver operator characteristic curve (AUC). Additionally, Shapley additive explanations (SHAP) were used to enhance the interpretability of the models by measuring how much each predictor contributed to the prediction of an outcome for a particular patient; thereby providing clinicians with a more transparent means for making decisions concerning patient treatment. This combination of multiple modalities of deep learning together with classical statistical methods represents a sophisticated approach to creating a clinically actionable, interpretable system for detecting stroke risk early on. A diagram of the proposed system is shown in figure 1.

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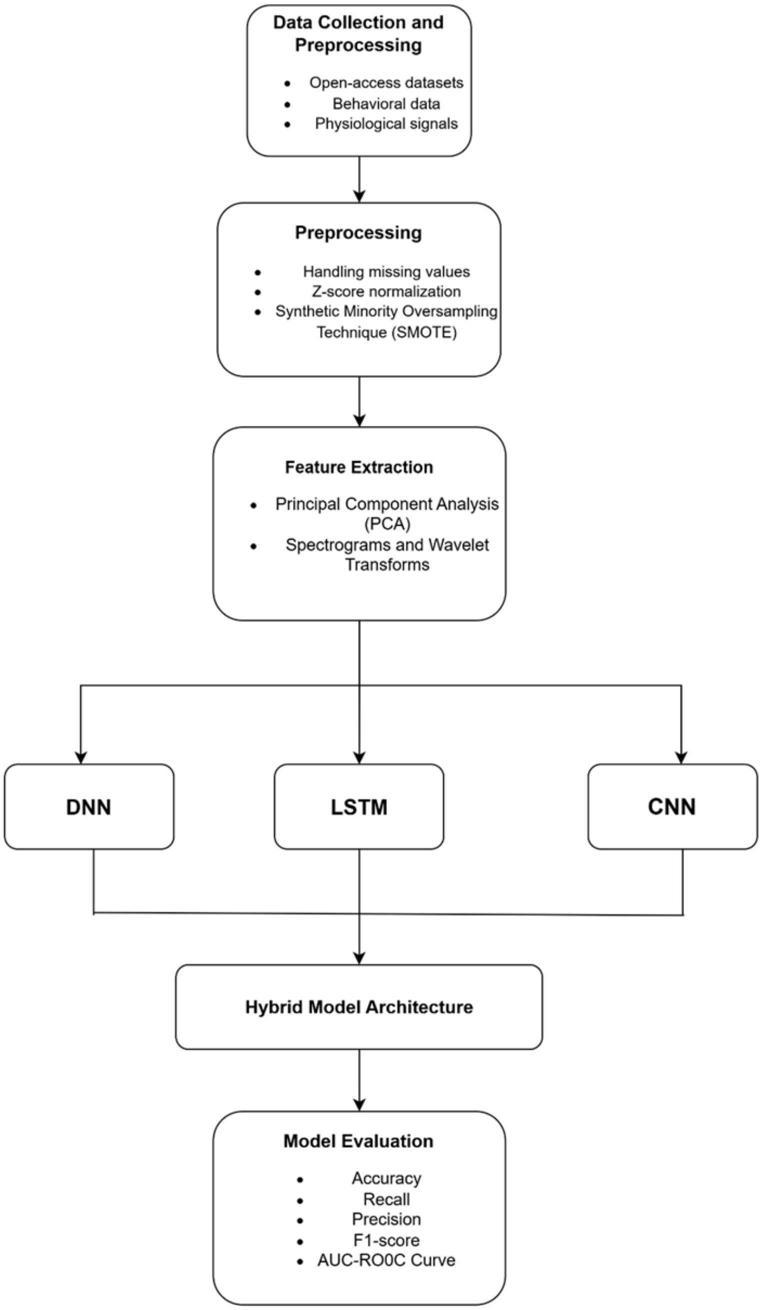

Figure1.the proposed system.

Data Description

This dataset on Kaggle (https://www.kaggle.com/datasets/mahatiratusher/stroke-risk-prediction-dataset) provides information on patients who have had a stroke, including their demographic information, medical history, and other health indicators. The data includes 43373 records, with 12 columns for each record.

The columns in the dataset are as follows:

`Chest Pain`	Binary (0/1): Indicates whether the individual experiences chest pain, a common symptom of cardiovascular conditions.
`Shortness of Breath`	Binary (0/1): Represents whether the person has difficulty breathing, which may indicate heart or lung problems.
`Irregular Heartbeat`	Binary (0/1): Shows if the person has an irregular heartbeat, a potential stroke risk factor.
`Fatigue & Weakness`	Binary (0/1): Indicates persistent fatigue and muscle weakness, common signs of cardiovascular issues.
`Dizziness`	Binary (0/1): Reports whether the individual frequently experiences dizziness, which may be linked to poor circulation.
`Swelling (Edema)`	Binary (0/1): Indicates swelling in extremities due to fluid retention, a potential cardiovascular issue.
`Pain in Neck/Jaw/Shoulder/Back`	Binary (0/1): Describes pain in these areas, which can be a warning sign of stroke or heart attack.
`Excessive Sweating`	Binary (0/1): Shows whether the individual experiences unusual sweating, which may indicate cardiovascular distress.
`Persistent Cough`	Binary (0/1): Indicates chronic coughing, which can be associated with heart failure.

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Dataset Splitting

The dataset was divided into three subsets to ensure effective training and accurate testing:

- 70% for training: to be used in developing the model and improving its accuracy.
- 10% Validation: To test the model during training and adjust the parameters.
- 20% Testing: To test the model's performance after training to ensure its accuracy and generalizability.

Training proposed system

the proposed deep learning approach over 20 epochs, during which the model achieved 99.95% training accuracy and 99.50% validation accuracy. By observing the training phases, we note a significant improvement in performance from one epoch to the next, with increasing accuracy and a substantial decrease in the loss rate. This confirms the success of the proposed model in learning and extracting patterns from diverse data. Figure 2 and table 2 illustrate the graphical analysis of the training phase of the proposed model.

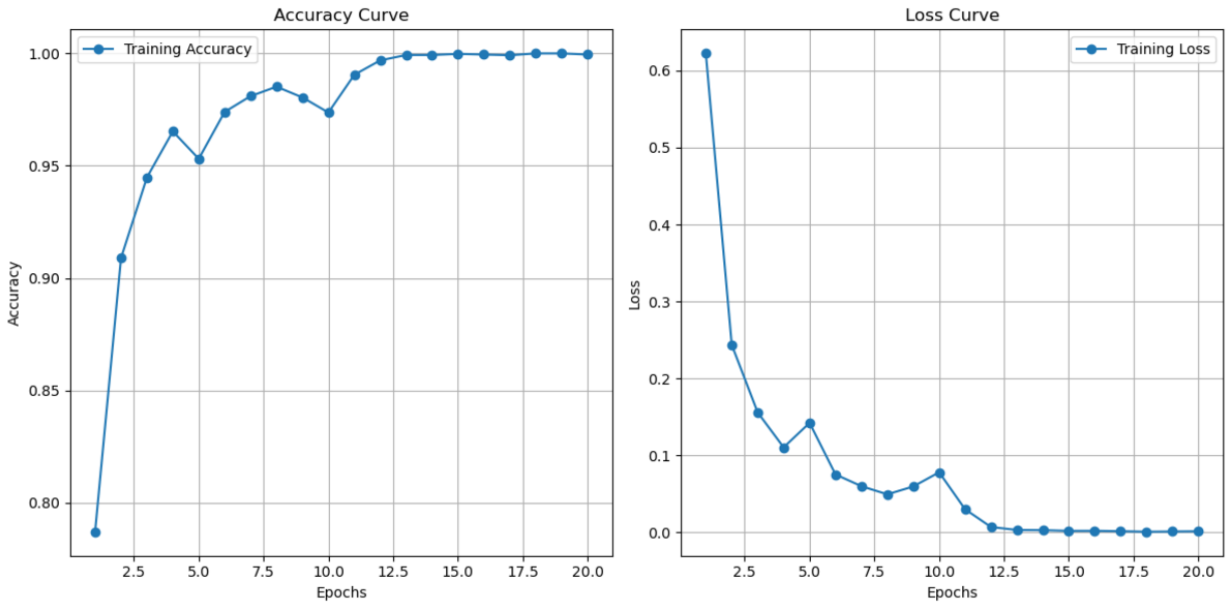

Figure 2: The training and loss curves for the hybrid algorithm

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Table 2: The training phase for the hybrid algorithm

Epoch	Accuracy	Loss	Validation Accuracy	Validation Loss	Learning Rate	Time per Epoch (s)
1	0.7871	0.6224	0.8356	0.5298	0.0010	1336
2	0.9089	0.2436	0.8634	0.3538	0.0010	1341
3	0.9448	0.1558	0.9426	0.2017	0.0010	1326
4	0.9653	0.1104	0.7228	1.7838	0.0010	1305
5	0.9531	0.1423	0.9545	0.1487	0.0010	1367
6	0.9740	0.0752	0.9574	0.1145	0.0010	1317
7	0.9810	0.0600	0.9733	0.0948	0.0010	1304
8	0.9852	0.0494	0.9782	0.0764	0.0010	1330
9	0.9804	0.0596	0.4911	5.9680	0.0010	1302
10	0.9737	0.0780	0.8158	0.5995	0.0003	1338
11	0.9905	0.0300	0.9960	0.0148	0.0003	1278
12	0.9969	0.0069	0.9950	0.0135	0.0003	1330
13	0.9993	0.0031	0.9950	0.0192	0.00009	1328
14	0.9993	0.0029	0.9960	0.0106	0.00009	1340
15	0.9998	0.0019	0.9950	0.0127	0.000027	1317
16	0.9995	0.0020	0.9950	0.0115	0.000027	1347
17	0.9992	0.0015	0.9950	0.0121	0.0000081	1330
18	1.0000	0.0008	0.9950	0.0124	0.0000081	1329
19	1.0000	0.0011	0.9950	0.0117	0.0000024	1296
20	0.9995	0.0014	0.9950	0.0115	0.0000024	1310

Evaluating the Performance of the Proposed Model

The following figures(2,3) and table 3 illustrate the performance of the proposed deep learning approach through a classification report, confusion matrix and Binary -class ROC curve. The model found excellent capability in distinguishing among different classes with 100% accuracy and perfect Precision, Recall and F1-Score values for all cases. While the confusion matrix reports some minimal errors, the ROC displays AUC values of 1.0 for all classes which means that the model is able to perfectly differentiate between the categories. Such tremendous results can be explained by the ability of the proposed deep learning approach to extract complex features from the data in addition to having a high-quality dataset and applying efficient training techniques throughout the process.

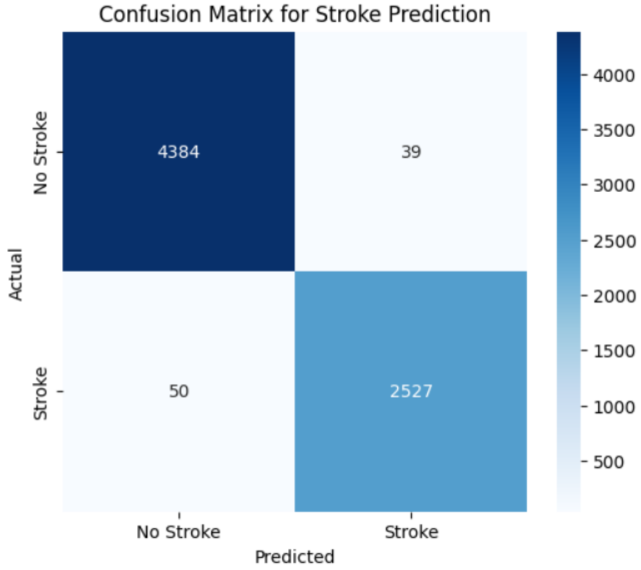

Figure 3:confusion matrix for the hybrid model.

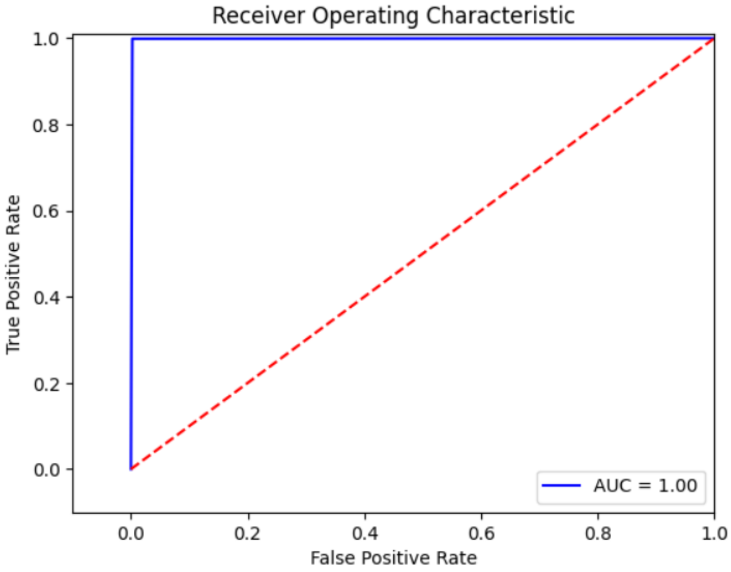

Figure 4: ROC-CURVE for the hybrid model.

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Table 3. the result for proposed model

	Precision	Recall	F1-Score
0	0.99	0.99	0.99
1	0.98	0.98	0.98
accuracy	0.99	-	-

RESULTS DISCUSSION

A hybrid deep learning model to detect an individual's risk of having a stroke was developed using heterogeneous data sources (for example, clinical data, behavioral data and physiological data) to create a model with high efficiency. The model was trained for twenty epochs at which point, there were training and validation accuracies of 99.95 and 99.50 respectively. In addition, there were trends showing consistent improvement in accuracy and decreases in the loss function throughout the entire training of the model, thus demonstrating that the training was stable during this time period. Several techniques were applied to improve convergence and give the model greater generalization capabilities. Techniques included tuned dropout, batch normalization and using an adaptive learning rate strategy.

The training process of an artificial neural network in the field of deep learning can exhibit small amplitude changes (fluctuations) across the epochs. This can be caused by changes to the adaptive learning rate or sample variations (different sets of training samples). Although these slightly fluctuating values occur, the model's validation accuracy remains high through all epochs, indicating its effectiveness in generalizing to new and unseen data. During evaluation, the classification report indicated that both classes resulted in a precision, recall, and F1-score of between 0.98 and 0.99, with an overall classification accuracy of 99%. An ROC analysis was conducted on the data set, producing an AUC of 1.0 with respect to classifying stroke from non-stroke. Therefore, the model is a very effective tool for separating between stroke and non-stroke classes.

The findings suggest that the combined CNN–LSTM/DNN attention methods for integrating multimodal datasets in healthcare are superior to previously published research on unimodal methods. Differential results were observed for similar studies (shown in Table 4). For example, Dritsas et al. (2022) and Zhu et al. (2023) reported their respective predictive accuracies of between 98% and 99% for unimodal datasets. However, the hybrid approach presented in this paper integrates multiple data modalities into a single model, and also includes interpretability methodologies (i.e., SHAP) to provide transparency into the prediction process, by allowing clinicians to determine how much each individual input feature contributed toward generating the predicted output.

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In general, the findings show that hybrid multimodal deep learning systems provide a significant increase in the accuracy of making predictions along with the maintenance of interpretability, making the models a good candidate for use as decision support systems in medicine. However, the very high accuracy levels achieved in the current study may be due to factors including, at least in part, overfitting and/or inadequate data diversity. Therefore, further work should assess the proposed model utilising larger and more varied datasets obtained from multiple institutions and clinical environments. Furthermore, the inclusion of uncertainty quantification techniques may increase the robustness and dependability of the model when used in clinical practice. Table 4 a comparison between the proposed system and studies similar to it.

Table 4: Comparison between a Proposed system work and related works.

No	**Ref**	**Year**	**Authors**	**Methods**	**Results**
1.	-	2025	Our proposed system	Hybrid deep learning	AUC :100 F1 score: 0.99 Final testing score: 99.64%
2.	[15]	2022	Dev, Soumyabrata et al.	EHR data analysis using Pearson's correlation, Learning Vector Quantization (LVQ), Perceptron neural network, PCA	Age identified as most significant; PCA explained 88.2% variance; $CHADS_2$ score confirmed risk
3.	[16]	2024	Hassan, Ahmad et al.	Baseline ML model with imputation and SMOTE, advanced ML algorithms, Dense Stacking Ensemble (DSE), k-fold cross-validation	Accuracy >96%; AUC 83.94% (imbalanced), 98.92% (balanced)
4.	[17]	2025	Talaat, Fatma M. et al.	Deep learning with CNNs; embedding, convolutional, dense layers; dropout, batch normalization, hyperparameter optimization	$R^2 = 0.994$; outperformed traditional methods
5.	[18]	2022	Dritsas, Elias et al.	ML using stacking ensemble; performance metrics: AUC, precision, recall, F-measure, accuracy	Stacking ensemble: AUC 98.9%, accuracy 98%, F-measure 97.4%

6.	[19]	2022	Lip, Gregory Y. H. et al.	Prospective cohort study (3.4M patients); comparison of $CHADS_2$, CHA_2DS_2-VASc, multimorbid index, ML models; evaluated with c-index, calibration, decision curve	Gradient boosting & neural network LR had superior accuracy
7.	[20]	2023	Zhu, Enzhao et al.	Kaggle dataset; preprocessing (missing values, normalization, feature selection); ML and deep learning classifiers (XGBoost, AdaBoost, LightGBM, RF, DT, LR, KNN, SVM, Naïve Bayes, ANN)	RF accuracy 99%; 4-layer ANN 92.39%
8.	[21]	2023	Rahman, Senjuti et al.	Comparative DL vs. ML; clinical dataset of 663 records; 8 ML & 4 DL models; 10-fold CV, hyperparameter optimization; interpretability via SHAP	RF outperformed DL models; high accuracy, sensitivity, specificity, F1-score, AUC
9.	[22]	2024	Moulaei, K. et al.	Prospective study; DLNN on dataset of 332 patients; hyperparameter tuning across 81 architectures	Accuracy 90.5–99.7%, sensitivity 83.8–100%, specificity 89.8–99.5%
10.	[23]	2021	Someeh, Nasrin et al.	PCA with quantile scaling for feature extraction; DNN training; comparison with five ML algorithms	AUC 83.48%; effective for early stroke check-up
11.	[24]	2019	Cheon, Songhee et al.	Qatar stroke registry; ML models trained on clinical, demographic, physiological variables; SHAP for interpretation	SVM best; AUC 0.72

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12.	[25]	2023	Abujaber, Ahmad A. et al.	Taiwan Stroke Registry; SVM, RF, ANN, hybrid ANN; 10-time repeated hold-out + 10-fold CV; 206 variables	AUC 0.94 (preadmission/inpatient), 0.97 (with follow-up)
13.	[26]	2020	Lin, C.-H. et al.	Data from hyperacute & acute phases; genetic algorithm for feature selection; Random Forest; SHAP for interpretation	Accuracy 91.13%, Recall 91.13%, Precision 90.89%, F1 91%
14	[27]	2023	Gkantzios, Aimilios et al.	Real-time EMG bio-signal collection; ML (RF) & DL (LSTM); feature extraction from daily activities	RF accuracy 90.38%, LSTM 98.96%
15	[28]	2020	Yu, Jaehak et al.	ML for ischemic stroke functional outcome; admission & progressive clinical data; compared with ASTRAL, DRAGON, THRIVE	AUC 0.808 (admission), >0.90 (with progressive data)
16	[29]	2018	Monteiro, M. et al.	Ensemble-based ML for early stroke prediction; 10 classifiers; weighted voting	Accuracy 97%; low FPR & FNR; high AUC

CONCLUSION

A hybrid_multimodal deep learning model is proposed in this paper to predict the occurrence of stroke using heterogeneous data, incorporating clinical, behavioral, and physiological features. The Convolutional Neural Network (CNN), Long Short-Term Memory network (LSTM), and Dense Neural Network (DNN) are integrated within the same architecture to capture spatial and temporal dependencies of different data sources, both effectively and comprehensively. With well-preprocessed and balanced data, the model performed smoothly during training, attaining an accuracy rate of 99.50% on validation data with obvious loss values decreasing. The classification metrics and ROC analysis proved how dependable the model is in separating different risk categories of patients. The study demonstrates that combining more than one deep learning component achieves higher predictive accuracy with interpretability and fairness, however, testing of the model on larger and more diverse real datasets, as well as exploration of model optimization techniques to improve generalizability and clinical applicability is warranted in future work even though results are very promising.

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Conflict of interests:

There are non-conflicts of interest.

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الخلاصة

الخلفية:

لا يزال السكتة الدماغية من بين أبرز المشكلات الصحية العالمية. إن التنبؤ الدقيق وفي الوقت المناسب يسهّل التدخل الطبي المبكر، وبالتالي تحسين نتائج المرضى. وتشير التطورات الحديثة في مجال الذكاء الاصطناعي، ولا سيما التعلم العميق، إلى آفاق واعدة لتحقيق مستويات عالية من الدقة في التنبؤ، حتى عند التعامل مع بيانات سريرية غير متجانسة بدرجة كبيرة.

المواد وطرائق البحث:

تقترح هذه الدراسة بنية هجينة للتعلم العميق تجمع بين الشبكات العصبية الالتفافية(CNN) ، والشبكات ذات الذاكرة طويلة وقصيرة المدى (LSTM)، والشبكات العصبية الكثيفة(DNN) ، وذلك لاستخدام البيانات السريرية والسلوكية والفسيولوجية في التنبؤ بخطر حدوث السكتة الدماغية. خضعت بيانات Kaggle المركبة لمعالجة أولية مكثفة شملت تعويض القيم المفقودة، والتطبيع، وتحقيق توازن أفضل في توزيع الفئات. يستفيد تصميم النموذج من تنوع معماريات الشبكات العصبية من خلال تمكينها من استخراج سمات تكميلية تسهم في تعزيز الأداء التنبؤي.

النتائج:

أثبتت مقاييس الأداء القياسية تجريبيًا أن هذا النموذج الهجين يضمن تصنيفات متسقة وموثوقة للغاية لمستويات الخطورة. كما تم الحصول على نتائج دقيقة ومستقرة بفضل دمج CNN و LSTMو DNNمقارنة بالنهج المعتمدة على نموذج مفرد.

الاستنتاج:

تؤكد النتائج جدوى نماذج التعلم العميق الهجينة في استيعاب البيانات الطبية غير المتجانسة مع الحفاظ على قابلية التفسير والعدالة. ويمكن اعتبار الإطار المقترح أداة عملية وقوية تدعم الكشف المبكر واتخاذ القرار السريري، مما يبرز قابليته للتطبيق في البيئات الصحية الواقعية.

الكلمات المفتاحية: التعلم العميق الهجين، التنبؤ بالسكتة الدماغية، CNN، LSTM، DNN، مقاييس الأداء.