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*Original Article*

# Enriching Brain Stroke Detection through A Hybrid Data Model

Mitali Hemant Chaudhari[1], Nisha Wandile Kimmatkar[2], Girija A. Deshpande[3], Rutuja Gangadhar Khedkar[4]

[1,2,4]*Department of Computer Engineering, JSPM's Rajarshi Shahu College of Engineering, Tathawade, Pune, Maharashtra, India.*
[3]*Department of Civil Engineering, JSPM's Rajarshi Shahu College of Engineering, Tathawade, Pune, Maharashtra, India.*

[1]*Corresponding Author : mitali23599@gmail.com*

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***Abstract*** - *The leading cause of brain stroke is the sudden blocking of blood flow to the brain through a blood vessel or due to damage to a blood vessel in the brain. More often, this brain stroke is the result of long-standing diseases that occur due to some evil habits of patients. These diseases are often measured as high blood pressure, diabetes, high cholesterol, smoking, and a sedentary lifestyle. Many deep learning models exist to detect the possibilities of brain stroke by considering the disease parameters. But only finger-counting techniques are available, which eventually consider the lifestyle of the people to predict the impact of a brain stroke. Hence, a multi-data hybrid model is required to evaluate the possibilities of causing a brain stroke by using the imagery dataset and statistical dataset. The proposed model initially trains the imagery brain stroke dataset using the channel boost convolutional neural network after boosting the channels to an absolute grayscale factor. On the other hand, the proposed model considers the statistical dataset for training using the LSTM model. Finally, the input image and the statistical data from the user are subjected to non-negative matrix factorization to obtain the results of brain stroke predictions. The obtained results are evaluated by the confusion matrix, which yields almost 98.12% accuracy, indicating the quality of our model.*

***Keywords*** - *Brain Stroke Detection, Deep learning, Convolution Neural Network, Long Short-Term Memory (LSTM), Hybrid Neural Network.*

## 1. Introduction

When there is a disruption in the blood flow to the brain, it can cause brain tissue injury, which is known as a brain stroke or cerebral vascular accident. A hemorrhagic stroke occurs when a blood vessel bursts or leaks, while an ischemic stroke occurs when an artery is blocked. Ischemic strokes happen when blood flow to a portion of the brain is interrupted or diminished. Brain tissue is deprived of oxygen and nutrients as a result. Within minutes, cells in the brain start to die. Hemorrhagic strokes are an additional kind of stroke. A brain hemorrhage happens when a blood vessel in the brain ruptures or spills. Damage to brain cells occurs as a result of an increase in blood pressure. A medical emergency is a stroke. Emergency medical care is of the utmost importance. Brain damage and other consequences of a stroke can be lessened with prompt emergency medical assistance. Stroke mortality rates in the United States have been declining, which is encouraging news. Effective treatments can also aid in the prevention of stroke-related impairment. Of all stroke types, this one occurs most frequently. A narrowing or blocking of the brain's blood arteries causes this condition. Ischemia, a decrease in blood flow, is the result of this. Fatty deposits that accumulate in blood arteries can lead to their constriction or blockage. Another possible reason is the presence of foreign bodies, such as blood clots, that travel through the circulatory system, typically originating from the heart. Fatty deposits, blood clots, and other foreign objects getting stuck in the brain's blood arteries can cause an ischemic stroke. Additional research is necessary to confirm the preliminary findings that COVID-19 infection may raise the risk of ischemic stroke. The leakage or rupture of a brain vessel causes the occurrence of a hemorrhagic stroke. Brain hemorrhages, or bleeding inside the brain, can be caused by a variety of medical issues affecting the blood arteries. Problems with blood pressure management are a risk factor for hemorrhagic stroke.

- Excessive use of anticoagulants, which are blood thinners.
- Aneurysms, which are bulges that form in vulnerable areas of the walls of blood vessels.
- A concussion, for example, after a vehicle crash.
- Deterioration of blood vessel walls caused by protein deposits. "Cerebral amyloid angiopathy" is the term used to describe this condition.

An ischemic stroke can cause brain bleeding in some instances. Arteriovenous Malformation rupture is an uncommon but serious cause of brain hemorrhage. An Abnormal Vascular Maze (AVM) is a network of blood arteries with very thin walls.

To detect strokes using healthcare data and neuroimages of human beings by employing a deep learning model, specifically a channel boost convolutional neural network and LSTM, through a decision tree. Stroke detection through traditional methods is often slow and prone to human error. There is a need for an automated and accurate system to analyze healthcare data and neuro images. This study aims to develop a deep learning model combining Channel-Boost CNN and LSTM through a Decision Tree to improve stroke detection accuracy and efficiency.

In a Transient Ischemic Attack (TIA), stroke-like symptoms last only for a short time. However, TIAs do not result in long-term impairment. A Transient Ischemic Attack (TIA) occurs when blood flow temporarily stops to a portion of the brain. As brief as five minutes could pass before the drop occurs. Ministroke is another name for a transient ischemic attack. A Transient Ischemic Attack (TIA) happens when blood clots or fatty deposits restrict or block the blood supply to a portion of the neurological system. If we suspect a TIA, it is important to get emergency medical attention. The symptoms alone cannot diagnose a stroke or transient ischemic attack. A TIA suggests that the artery supplying blood to the brain may be partially or fully blocked. Your chance of suffering a stroke in the future is higher if you have a TIA.

A noticeable gap exists in current automated stroke detection methods. Modern systems often excel in either image-based analysis using CNN architectures for detecting and segmenting lesions or modeling clinical and time-series data with LSTM networks. However, these complementary data types are rarely combined into a cohesive framework. Current methods typically do not (i) enhance CT image features in a way that is interpretable and parts-based, (ii) jointly model the statistical dependencies found in clinical risk factors, or (iii) integrate multimodal information while maintaining the clinical interpretability necessary for medical validation. Previous hybrid studies, such as those using genetic-algorithm-assisted feature selection with LSTM processing [11], are limited by moderate image enhancement capabilities, separate treatment of imaging and tabular data, and opaque fusion strategies that undermine clinical trust and transparency.

Therefore, there is an ongoing need for a unified, explainable multimodal framework that effectively combines non-negative matrix factorization for image decomposition, channel-boosted CNNs for deep spatial representation, and LSTMs for longitudinal and statistical modeling, all supported by rigorous validation protocols, such as cross-validation, ROC-AUC, confidence intervals, and ablation studies. Because it enables the rapid and reliable processing of medical images, such as MRI and CT scans, deep learning is crucial in the identification of brain strokes. It can identify stroke-affected areas and classify images as normal or abnormal.

1. The deep learning models used are specifically Convolutional Neural Networks (CNN), which fall into two categories: image processing and abnormal brain scan identification. The algorithm identified the types of strokes after detecting complex patterns in the database.
2. Localization and Segmentation: Stroke detection is better understood through medical imaging, where deep learning is used. This area involves CNN models, such as the U-Net, which shine
3. Prognosis and Prediction: A deep learning model has been developed to predict strokes and determine the outcomes for stroke patients. Deep learning involves various factors, such as clinical features, data, and imaging data, to accurately predict the problems.
4. Increased Diagnostic Precision: Previous studies have shown that deep learning models can detect strokes more accurately than traditional techniques and can also predict outcomes more quickly.
5. CAD Systems: The deep learning model has been integrated into the CAD system to help provide patients with accurate results. These devices help detect efficiency and reduce the risk of misdiagnosis.
6. There are various examples of CNN models such as LeNet, SegNet, U-Net, ResNet, VGG16, and VGG19.
7. The Advantages of Deep Learning for Stroke Detection.

### *1.1. Precision*

Deep learning algorithms are accurate in identifying and classifying strokes. Automated analysis: Deep learning's capacity to automate medical picture interpretation allows radiologists to concentrate on other tasks. Efficiency boost: Deep learning is a preferred choice for the diagnosis process, providing accurate results. Developing customized treatment plans that consider each patient's particular collection of symptoms, medical history, and risk factors is one potential application of deep learning in medicine.

Unlike traditional single-modality approaches or previously proposed hybrid methods such as GA-driven LSTM architectures, the primary research question of this study is whether a multimodal diagnostic framework—one that integrates Non-Negative Matrix Factorization (NMF) to enhance CT image features, employs a channel-boosted Convolutional Neural Network for spatial representation learning, and incorporates a Long Short-Term Memory (LSTM) network to model structured clinical variables, with final inference achieved through an interpretable decision-tree fusion—can improve interpretability, accuracy, and robustness. This study sought to determine whether such an integrated system offers better interpretability, accuracy, and robustness, and whether its methodological foundations and validation provide a more compelling justification than current models in the literature for stroke detection compared to single-modality or previously reported hybrid approaches (e.g., GA+LSTM).

## 2. Literature Survey

To improve patients' chances of receiving acute stroke treatment, Tomonobu Kodama et al. [1] suggested an algorithm for ischemic stroke identification that combines HRV analysis with MSPC. This work applied the suggested algorithm to experimental data gathered from animal experiments using the MCAO model in rats. The data was used as a feasibility study before being applied to human patients. The HRV data were collected shortly after occlusion. Its sensitivity was 82% and its specificity was 75%, according to the application results. Among the study's caveats is its data gathering process, which included issues, including an insufficient quantity of HRV data for modeling and an experimentally small number of animals.

Furthermore, the author's experiment could not rule out the possibility of anesthesia's effect on HRV. The authors are currently gathering clinical HRV data from stroke patients in hospitals in order to develop an ischemic stroke detection system for people. This is because the algorithm designed for rats cannot be directly adapted to humans. Furthermore, a bright shirt that measures electrocardiograms has undergone accuracy evaluation testing in a clinical setting. [2] DCSP, a new feature pooling method, was introduced by Zhong Zhang et al. for character recognition in outdoor settings. Using the contextual factor, the suggested DCSP reflects the spatial context information of discriminative strokes and trains stroke detectors with the discriminative strokes chosen from CSM.

To enhance the discrimination and robustness of the final deep contextual confidence vectors, it is possible to pick the most representative convolutional activation features from the response areas based on detector scores and the contextual factor. In comparison to various prior methods for scene character identification, the experimental findings show that the suggested DCSP performs better on three popular databases: ICDAR2003, Chars74k, and SVHN. An automated compensation detection system that recorded the joint locations of healthy participants using Kinect during robotic-assisted rehabilitation performed very well for LF, TR, and SE, according to Ying Xuan Zhi et al. [3]. Trained with data from stroke survivors, however, the same classifiers performed poorly. The author discusses possible causes of poor F1-scores. A new scene text erasing approach has been proposed by Zhengmi Tang et al. [4] to solve the problems of domain shift when using inpainting models pretrained on street view or Places datasets and poor text location when using one-step methods. This was achieved by training the model exclusively on the author's enhanced synthetic text dataset. The model uses a predicted text stroke mask that is created from cropped text pictures to inpaint the text region, allowing for the preservation of more background information. The author has developed a reasonable approach for erasing scene text with texture restoration. It makes use of a stroke mask prediction module, partial convolution layers, and an attention block in the background inpainting module, and a skip link between two modules.

[5] A new document picture binarization model was introduced by Quang-vinh Dang et al., which addresses the issue of weak or ambiguous strokes that are frequently left disconnected following the binarization process in current methods. The author embeds structural information of strokes into the binarization network in order to maintain the strokes in degraded document pictures following the binarization process. This is the basis for the author's proposal of an auxiliary job for adversarial learning of structural information in terms of stroke boundary features, with the goal of integrating these learned features into the primary task for document picture binarization. The auxiliary task first gets stroke boundary features by using shared global location features and additional local edge characteristics. Second, the author uses adversarial supervision of the acquired stroke edge feature in the auxiliary task by leveraging boundary ground truth. Incorporating domain-specific expertise into the model is the crux of adversarial training.

An HS event-recognition gait detection model was suggested by Fu-cheng Wang et al. [6]. Clinicians can use gait event identification to assess gait performance, which in turn helps with medication and rehabilitation strategy selections. It has been shown that detecting gait events online can be difficult. Hence, the author generated an RNN model capable of real-time HS event recognition by collecting experimental gait data using IMUs. With an average latency of 0.024 s and an accuracy of 98.84%, the author used the LOOCV approach to demonstrate that RNN models can detect HS events in real time. As an additional test, the author used the model on three distinct groups of people with very varied gaits: healthy older adults, stroke victims, and PD patients. The author's findings confirm that RNN models can accurately detect HS events with an average delay of 0.028 s and an accuracy of over 99.65%, regardless of the subjects' walking habits.

For rehabilitation, Shir Kashi et al. [7] developed a model to detect compensations in the movements of stroke patients. The author attained a macro-averaged precision of 85% across all six movement compensations examined. Finding compensations using data from stroke patients has never been done before. The author employed an exact movement-capture method in this case. The potential for stroke patients to utilize the model system for home-based training could be opened up in future research with a more cost-effective sensor system. An in-clinic or at-home application would necessitate such a cheap and user-friendly tracking device that could give real-time position information. [8] The development of an algorithm for use in an asynchronous BCI system for stroke rehabilitation was introduced by Thapanan Janyalikit et al. An effective rehabilitation program is critical for a successful recovery after a stroke. As a result, the authors suggest a new and accurate method for detecting movement intentions in EEG data using time series shapelets. An asynchronous BCI system can employ the author's algorithm as a brain switch to activate an electrical stimulator, thereby inducing brain plasticity, which can aid in the rehabilitation of stroke patients. This is the first instance when a shapelet-based algorithm has been able to accurately discern movement intentions from EEG data, as the author wants to stress.

[9] Using various biological signals of Electrocardiogram (ECG) and Photoplethysmography (PPG) acquired from walking as part of the elderly's everyday lives, Jaehak Yu et al. present a system that offers semantic analysis of diseases in the elderly. The suggested approach instantaneously detects and predicts prognostic indicators of stroke disease in the elderly by collecting numerous bio-signals of ECG and PPG in real-time. Using a variety of biosignal datasets, researchers ran a study on a machine learning-based prediction model that involved segmenting the signal waveform; the model produced reasonably accurate predictions and semantic interpretations. This research presents experimental verification, using the proposed features, that prognostic symptoms of stroke patients may be predicted with a 90% accuracy rate using only ECG and PPG collected while walking. By partitioning the general elderly and stroke patients into separate 10-folder CV datasets, the author was able to prove that their deep learning models could correctly predict outcomes with a 91.56% success rate using C4.5 Decision Tree, a 97.51% success rate using Random Forest, and a 99.15% success rate using CNN-LSTM.

[10] For the purpose of detecting transcranial brain hemorrhages, Chenzhe Li et al. presented the DL-MITAT modality to solve the problem of acoustic inhomogeneity. The author suggests ResAttU-Net, A Novel Network Architecture for DL-MITAT implementation. Instead of doing experiments, the author uses the simulation method to construct training sets, which is both practical and efficient. The technique's validity is demonstrated by the author's ex vivo studies with a lossless printed skull and a bovine skull that is 8.1 mm thick. Preliminary results show that the DL-MITAT approach can identify transcranial bleeding and remove the adverse effects of acoustic inhomogeneity. [11] A method for detecting strokes using machine learning techniques has been proposed by Muhammad Asim Saleem et al. For the purpose of validating the newly constructed model's performance, an image-based dataset is utilized. The suggested model utilizes BiLSTM and a genetic algorithm. To identify important details in CT brain pictures, a genetic method that relies on a neural network is used. The LSTM and BiLSTM models are trained to anticipate strokes using these features. To get the best categorization, we compared the performance of various K-folds.

In order to anticipate strokes, the author also experimented with various machine-learning methods. Compared to other models, the experimental findings demonstrate that the suggested machine-learning model performs better. The authors hope to employ more sophisticated algorithms in the future to predict strokes, thereby enhancing stroke detection automatically. Although big datasets typically produce superior results, deep learning models were used on a small dataset in this study.

[12] The study highlights the wide-ranging effects of stroke on physical, behavioral, and cognitive processes, as well as the possible connections to post-stroke dementia by Chi-huang Shih et al. To encourage brain reconfiguration, the author developed a Virtual Reality (VR)-based remote rehabilitation system that combined rigorous training with targeted learning activities. Physiotherapists can remotely guide patients with this system, which utilizes BCI technology. This method offers vital home-based therapy for people with varied rehabilitation needs, including stroke survivors, who face obstacles such as restricted medical access and mobility issues. The use of EEG technology and real-time compensatory detection is the main originality of this work.

In [13], in order to identify AF from 1D ECG data with only one lead, S. M. Mahim et al. created the TransMixer-AF model. The author's model performs admirably on both the raw and cleaned datasets. In particular, the model attained an accuracy of 91.66% with noisy data and 96.59% with preprocessed data for the PhysioNet/CinC 2017 Database. The MITBIH Database dataset had a record of 95.66% and the other of 98.58%.

These outcomes prove that the author's approach outperforms current algorithms and attains state-of-the-art performance. On top of that, the model can accurately and early detect AF by interpreting ECG data, which gives clinically significant insights. [14] By combining state-of-the-art deep learning and machine learning methods, Muhammad Usama Tanveer et al. prove that the Neuro-VGNB method is effective for detecting brain strokes.

The author accomplished remarkable gains in classification accuracy by extracting features using the VGG16 model and then improving these features within the GNB framework using non-negative matrix factorization. The remarkable accuracy score of 99.96% achieved by the Logistic Regression model demonstrates the promising clinical applications of the author's research. Additionally, the use of k-fold cross-validation strengthens the credibility of the author's results. It presents the author's method as a useful resource for enhancing the early identification of brain strokes.

## 3. Proposed Model Methodology

The entire process used to create an effective and automated stroke detection system is described in the suggested model methodology. It explains every phase of the system, starting with data collection and preprocessing, and ending with the training of a hybrid model and the final forecast. Figure 1 shows the brain stroke detection model that was designed.

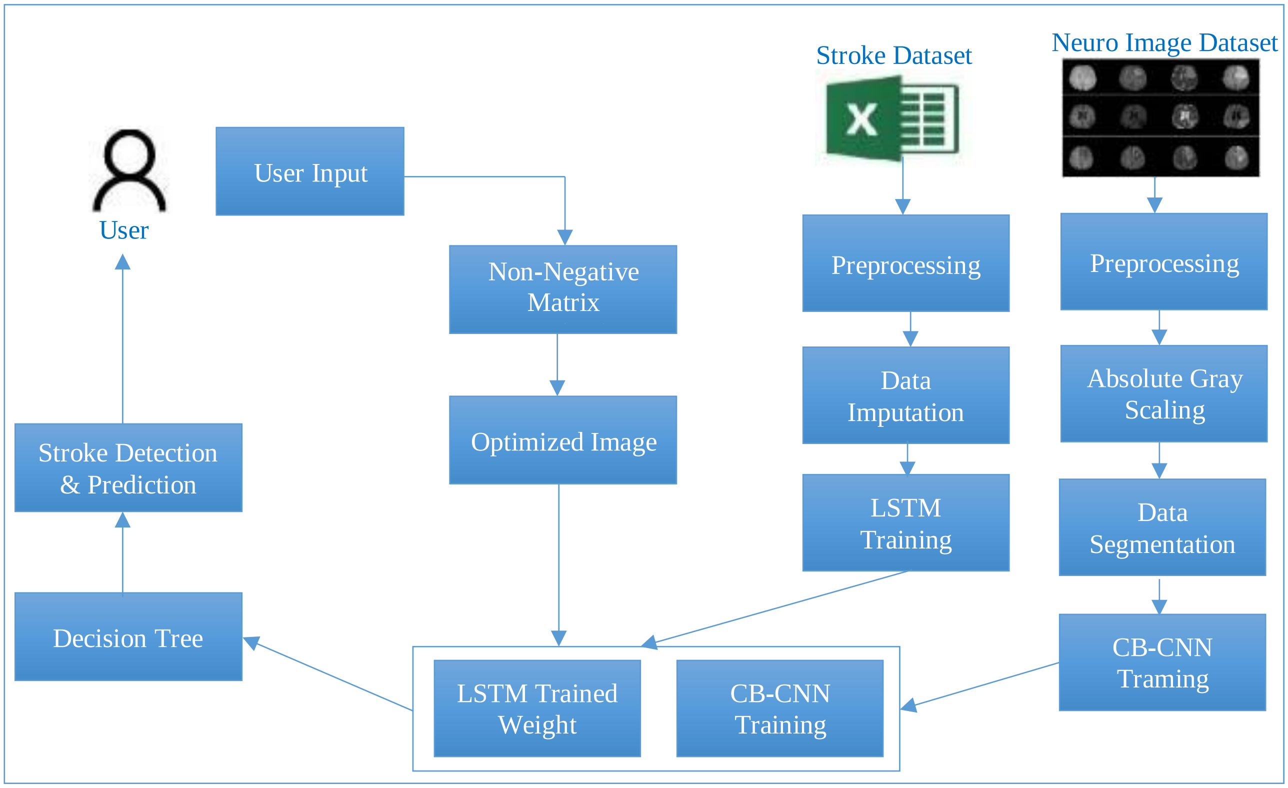


**Fig. 1 Proposed model for brain stroke detection using a hybrid data model**

The steps involved in developing the model are described in full below.

### *3.1. Description of the Dataset*

The model was trained and evaluated using two publicly accessible healthcare datasets, including patient medical histories, vital signs, and neuroimaging data (such as MRI or CT scans).

### *3.2. Ethical Issues*

The generalization and performance of the model may be impacted by institutional, ethical, or privacy restrictions that limit access to big and well-annotated healthcare and neuroimaging datasets. Strict adherence to data privacy regulations, ethical approvals, and patient permission procedures is necessary when handling sensitive healthcare and neuroimaging data in order to guarantee data confidentiality and compliance. The study should involve ablation studies, external validation, and a thorough ethical declaration in order to satisfy current standards in medical AI research. To assess the precise contributions of each model component (CB-CNN, LSTM, and NMF) to the overall performance and demonstrate that the hybrid fusion architecture provides real benefits beyond its constituent parts, ablation experiments are essential. Similarly, assessing the model's generalizability and preventing dataset-specific overfitting—a frequent problem in imaging-based stroke prediction research—requires external validation using a separate dataset. The handling of patient data, dataset licensing, anonymization, any clinical hazards, and compliance with regulations like the GDPR, HIPAA, or institutional ethics requirements should all be explicitly covered in the ethical statement. By including these components, the suggested framework's trustworthiness, transparency, and reproducibility are significantly increased, guaranteeing that it meets the standards of the most recent medical AI literature.

### *3.3. Phases of the Suggested Model*

Phase 1: Absolute gray scaling and data pre-processing - This is the initial step of the proposed model, where we obtained the dataset from the following URL: https://www.kaggle.com/datasets/afridirahman/brain-stroke-ct-image-dataset. Once the dataset is downloaded and segregated into training and testing directories, it undergoes the resizing process. A total of 1551 images are used for the 'normal' class and 950 images for the 'Stroke' class. To resize the images, the OpenCV library's cv2 alias is used with the resize() method by passing the scaled width and height parameters of 128 x 128. The machine's hardware limits confirm its scaled width and height based on powers of 2 and its factors. The resized images are stored in the same path by overwriting the earlier locations. Once the dataset images are resized, they are subjected to conversion into absolute grayscale using the Pillow library of Python. In the process of getting the absolute grayscale images, each image's absolute path is extracted, and then it is read into RGB format. For each pixel, RGB is extracted, and its mean is estimated to factorize the same as a whole number [3]. This integer value will be replaced with red, green, and blue channels to obtain the absolute grayscale images. These images again replace their original location to form the best data to train using the channel boost Convolutional Neural Network deep learning model. Removing RGB channels improves lesion contrast learning and lowers noise since CT images naturally depict tissue density in grayscale.

Hypoattenuation, sulcal effacement, loss of gray-white differentiation, and hyperdense vascular signs can be easily identified. The Channel-Boosted CNN architecture requires a uniform intensity distribution to ensure stable feature extraction, and for that, it is important to correctly input the grayscale dataset [5].In order to guarantee statistical validity and compatibility with later LSTM modeling, the relevant clinical dataset underwent structured pre-processing concurrently. Categorical variables such as sex, smoking status, and hypertension are encoded using one-hot encoding and label encoding, thereby enhancing both interpretability and model performance. The Iterative Imputer generates unbiased imputations by modeling inter-feature correlations using chained equations, which helps in handling missing values effectively. This method has been demonstrated to perform better than single imputation or mean replacement by lowering variance distortion and information loss [8]. Methods like Random Oversampling, Synthetic Minority Oversampling Technique (SMOTE), or class-weighted loss functions—all of which are generally advised to prevent majority class bias and improve minority class recall in medical prediction tasks—were used to address class imbalance, which is especially prevalent in stroke datasets where positive cases are fewer [4]. Together, these preprocessing techniques guarantee that the clinical and imaging inputs are balanced, statistically coherent, and prepared for machine learning, providing a solid basis for multimodal fusion in subsequent stages. An input image is loaded, converted to RGB format, and then resized to a fixed resolution of 128x128 pixels using the pseudo-code. To guarantee that every image is scaled consistently before being fed into the model, it makes use of the PIL package.

Pseudo code for Image Resizer -

```
from PIL import Image
def getScaledImage(image_path):
    imageob = Image.open(image_path).convert('RGB')
    width, height = imageob.size
    scaledwidth=128
    scaledheight=128
    imageob = imageob.resize((scaledwidth,scaledheight),
Image.ANTIALIAS)
    return imageob
```

The pseudo-coding converts a color image into an absolute grayscale image by analyzing each pixel's RGB values, finding their average, and swapping out the original pixel using this one intensity value. This guarantees that each pixel is converted into a consistent grayscale image.

Pseudo code for Absolute gray Scale-

```
ef getAbsoluteGrayscaleImage(imageob):
    width, height = imageob.size
    pix=imageob.load()
    for i in range(width):
        for j in range(height):
            col=pix[i,j]
            R=col[0]
            G=col[1]
            B=col[2]
            avg=(int)(R+G+B)/3
            absgray=int(avg)
            pix[i,j]=(absgray,absgray,absgray)
    return imageob
```

Phase 2: Channel boost Convolution Neural Network: Phase 2's architecture and training methodology were founded on proven deep learning concepts for medical picture classification. Because of their extensive use, dependability, and improved GPU performance for CNN-based biomedical operations, TensorFlow and Keras were chosen [4]. In accordance with typical preprocessing procedures, ImageDataGenerator is used for picture loading and normalization (scaling by 1/255), guaranteeing numerical stability and accelerating convergence by keeping input values within a constrained range [8]. Since medium batch sizes often result in improved generalization in picture classification tasks, a batch size of 64 was used to maximize GPU memory efficiency while preserving gradient stability [12]. For hierarchically extracting spatial characteristics in CT images, from low-level edges to high-level stroke-related textures, the CNN architecture uses a gradually deepening structure with 32–64–128 kernels (3×3), which is generally regarded as ideal [2]. Because of its computing ease and capacity to handle vanishing gradients, the ReLU activation function is frequently used, which makes it easier to train deeper models [10]. In radiological applications where lesions are confined, the addition of MaxPooling2D layers (2×2) selectively downsamples feature maps, lowering computational needs while maintaining discriminative areas [5]. Dropout layers of 25–50% were added to reduce overfitting because research indicates that dropout considerably improves medical-imaging CNNs' generalization ability by lowering neuron co-adaptation [1].

The Flatten layer and succeeding thick layer with 1024 units enable the model to combine geographically scattered features, providing a global representation appropriate for classification. The final softmax output layer is the traditional choice for binary/multiclass prediction, delivering normalized probabilities that support clinical interpretability. The Adam optimizer with a 0.0001 learning rate was chosen for its adaptive moment estimation, which stabilizes gradients and consistently outperforms standard optimizers in medical-image CNN training [4].Training the model for 100 epochs ensured sufficient convergence for moderately sized datasets, avoiding premature stopping while minimizing the risk of overfitting. The final model was saved in the h5 format, a standard practice for reproducibility and deployment in inference pipelines. Overall, each design choice, including kernel configuration, activation functions, dropout usage, and optimization strategy, is supported by best practices in the deep learning literature and tailored for CT-based stroke detection, where fine-grained texture patterns and noise robustness are critical.

Equations 1 and 2, consequently, show the Softmax and Relu activation functions that were used.

$$\sigma(Z) = \frac{e^{zi}}{\sum_{j=1}^{k} e^{zj}} \tag{1}$$

$$\text{Relu}=\max(0,x) \tag{2}$$

Where, x= neuron value

σ = softmax

z = input vector

$e^{zi}$ = A normal exponential function for the vector that is being entered

K = number of classes

$e^{zj}$ = A normal exponential function for the vector that is being entered for the output

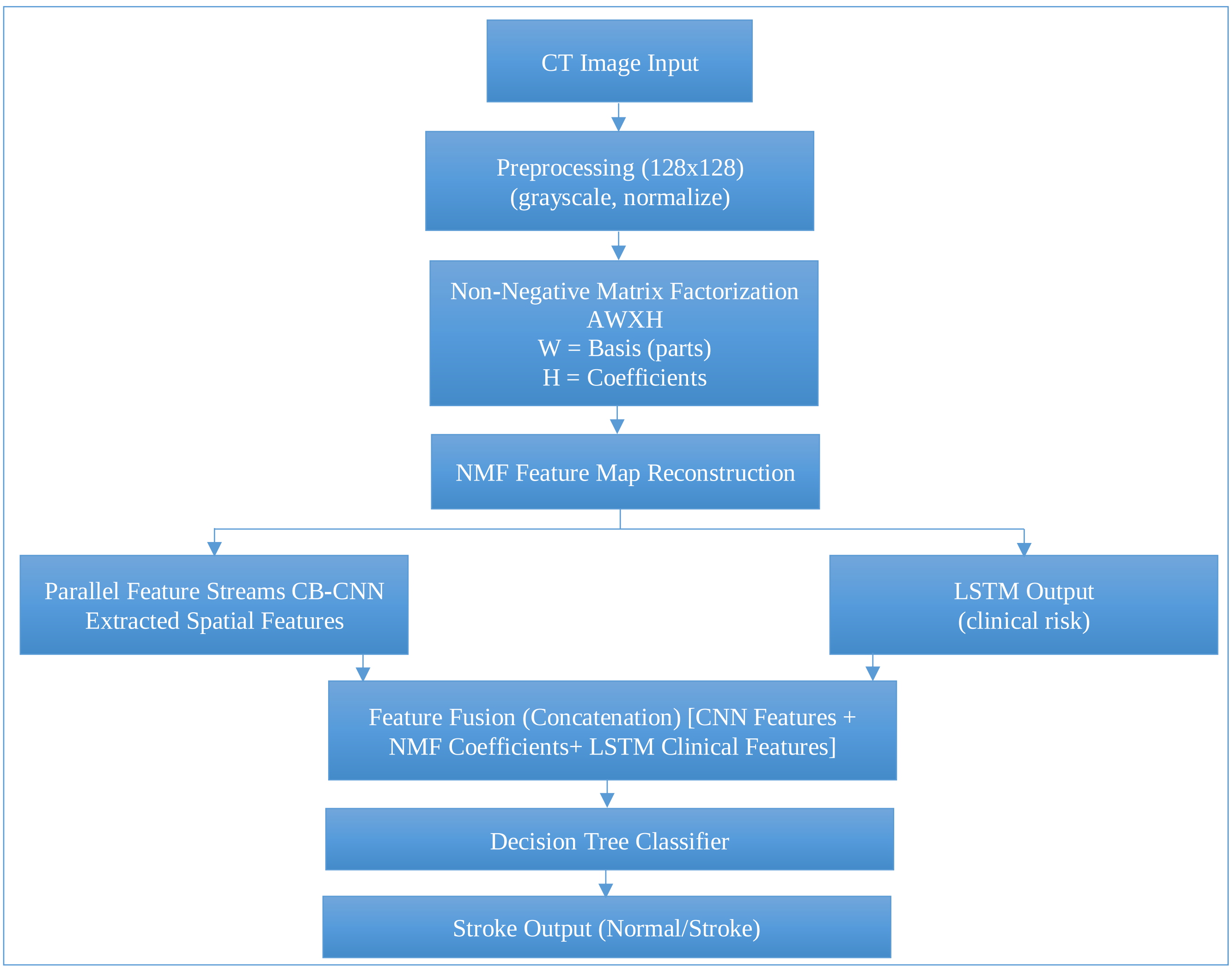


**Fig. 2 Architecture of CB-CNN**

The Channel Boost Convolutional Neural Network architecture is depicted above in Figure 2.

Phase 3: LSTM Training: For the process of statistical dataset evaluation, a dataset in .csv format is obtained. URL:https://www.kaggle.com/datasets/csepython/brain-stroke. This dataset contains the following attributes: gender, age, hypertension, heart disease,ever_married,work_type, Residence_type,avg_glucose_level,bmi,smoking_status, and stroke. We use the pandas library to read the dataset into its respective object. Once the dataset is loaded as an object, it is converted into a double-dimensional list. This list estimates the mean and standard deviation, and thereafter, the histogram of each attribute is evaluated for 25%, 50%, and 75% of the maximum values. This step is followed by the respective histogram plots that indicate the distribution of the attribute values.

After this, we estimate the entropy of the data types in the dataset (e.g., strings and floats) by collecting information on the dataset's properties. A heat map is estimated for each attribute using the oversampled data. To do this, we compare the transition data at various points in the sorting process and determine the overall amount of missing data as well as the percentage of missing data. A label encoder is formally passed to the fit transform function for imputation for every object in the attributes. To achieve multiple imputation using chained equations, the IterativeImputer() function is used, which yields the object of multiple imputation. Following the transformation of the attributes using the fit transformer, this is utilized to impute the missing attributes. The technique entailed applying encoding to category characteristics for attributes during this specific phase. Using the minmax scalar function, standardized numerical characteristics were produced using Standard Scaling. Using the minmaxscaler, we can alter the features and scale them within a specified range.

For each feature on the training set, this estimator performs its own scaling and translation to bring it within the given range, say, from 0 to 1. No amount of linear scaling using MinMaxScaler—where the most significant data point represents the maximum and the lowest the minimum—can reduce the impact of outliers. Check out the visual representation of MinMaxScaler and evaluate it against other scalers. Finding the min-max scaler transformation is done by solving Equations 3 and 4.

$$X_{std} = \frac{(x - x.\min(axis=0)}{(x.\max(axis=0) - x.\min(axis=0))} \quad (3)$$

$$\mathrm{x}_{\mathrm{scaled}} = \mathrm{x}_{\mathrm{std}} * (\max - \min) + \min \quad (4)$$

Where min, max = feature_range.

Next, these properties are encoded and then added back to the dataset's double list of attributes.

Using the train_test_split() method, we split our data into two sets: one for training and one for testing. Data sorting by features (X) and labels (y) should be our top priority. The dataframe's constituent parts are X_train, X_test, y_train, and y_test. The X_train and y_train datasets are used to train and fit the model. To determine whether the model accurately labels the data and yields the intended outcomes, use the X_test and y_test sets. Different sizes for the train and test sets can be explicitly tested. Maintaining larger train sets than test sets is advised. LSTM Neural Networks receive a scalar normalization object with test_x, train_x, and test_y as inputs. A few parameters, such as train_X1.shape [1] and train_X1.shape [2], can be used to introduce the Long Short-Term Memory (LSTM) model. With a single feature, ten sample units, and a TRUE return sequence, it functions in a one-dimensional space. Next, the "relu" activation function and a dense layer with a kernel size of one are introduced. In a densely connected Neural Network, the dense layer effectively learns new information by utilizing the activation functions of neurons. Here, we show how to use a simple LSTM Neural Network with two dense layers, one 1-dimensional kernel, and one-dimensional inputs. When building a Neural Network, we use 100 epochs, a batch size of 100, with the shuffle parameter set to false. This leads to a generation of .h5 file that eventually contains the trained information of the LSTM model.

The justification for employing IterativeImputer, which is grounded in MICE (Multiple Imputation by Chained Equations), lies in its ability to deliver statistically sound multivariate imputations. These imputations maintain the inherent correlations among clinical attributes, resulting in estimates that are considerably less biased than those obtained through single-value imputations like mean or median filling [11]. In medical datasets, where variables like blood pressure, glucose levels, and heart rate markers are connected and must be imputed in a way that appropriately reflects their clinical co-variation, this method is essential. Similarly, when derived sequences (such as time-stamped glucose patterns, HRV intervals, or rehabilitation progressions) are essential for capturing disease-related dynamics, or when the dataset contains temporal, sequential, or ordered clinical features, an LSTM (Long Short-Term Memory) architecture is appropriate. LSTMs are specifically crafted to model long-range dependencies and nonlinear temporal relationships, providing superior performance compared to static models when time structure is involved. However, in scenarios where features are non-temporal, independent, or tabular, a feedforward neural network or tree-based classifier might offer more efficient and interpretable modeling. Consequently, the methodological choices are consistent with the statistical structure and temporal characteristics of the clinical data.

Phase 4: Non-Negative Matrix Factorization (NMF) – Here, we provide an input image and its properties in order to detect potential brain strokes. By applying the non-negative matrix factorization technique to the input image, valuable features can be extracted from the data, making it easier to analyze and handle. We will provide more details on this topic in the article. After multiplying the provided image by the random image's feature matrix, it is deemed the original image. Following the aforementioned idea, the product matrix P is obtained by multiplying the feature matrix by the original matrix. As seen in equation 5, the inverse feature values are estimated using the product matrix P.

$$A\text{-}1 = 1/|A| * \text{Adj } A \quad (5)$$

In this context, "Adj" refers to the adjoint of a matrix, which is a square matrix A = [aij]n×n, and "Aij" stands for the element aij's cofactor. Simply put, the adjoint is the transpose of the matrix. Another way of looking at it is that the adjoint of the matrix is the square matrix's transpose of a cofactor matrix. For a matrix A, the adjoint is denoted as adj A. This process generates the enhanced image features, which we can further use for testing purposes of the model. A decision tree is built based on the if-then-else tree to test the input data with the trained model of CB-CNN and LSTM. The combined results obtained from the CB-CNN and LSTM are utilized to show the detected and predicted data for the brain stroke.

NMF was chosen because its parts-based, non-negative decomposition yields CT-image features that are clearer and more clinically interpretable than those produced by PCA/SVD, enhancing both lesion visibility and classifier effectiveness. The final integration through a decision tree layer combines the outputs of the CB-CNN and LSTM with transparent, rule-based logic that meets clinical interpretability standards.

Through a simplified three-step procedure, the suggested fusion framework integrates clinical statistical patterns with spatial information collected from CT. Initially, part-based representations that highlight stroke-related structures are created using NMF to improve CT images. After that, an LSTM derives clinical dependencies from tabular data, and a Channel-Boosted CNN extracts deep spatial features. A simple, understandable decision tree classifier is then used to combine these complementary information streams, enabling transparent multimodal reasoning. By using both anatomical evidence and patient-specific risk factors, this integrated method overcomes the common drawbacks of earlier single-modality models, improving clinical interpretability and diagnostic accuracy.

Non-Negative Matrix Factorization (NMF) was applied to each CT scan during the fusion phase in order to decompose it into comprehensible components that highlight stroke-related features more successfully than the original pixel values. The high-level spatial features from the CB-CNN and the clinical risk predictions generated by the LSTM model were then merged with the NMF-derived features. A decision tree classifier that provided explicit "if–then" diagnostic rules was fed these three feature sets. This simplified fusion method guarantees that the clinical parameters, deconstructed intensity patterns, and image data all contribute to the final stroke prediction in a dependable and comprehensible manner. The NMF-based multimodal fusion pipeline is depicted in the diagram below.

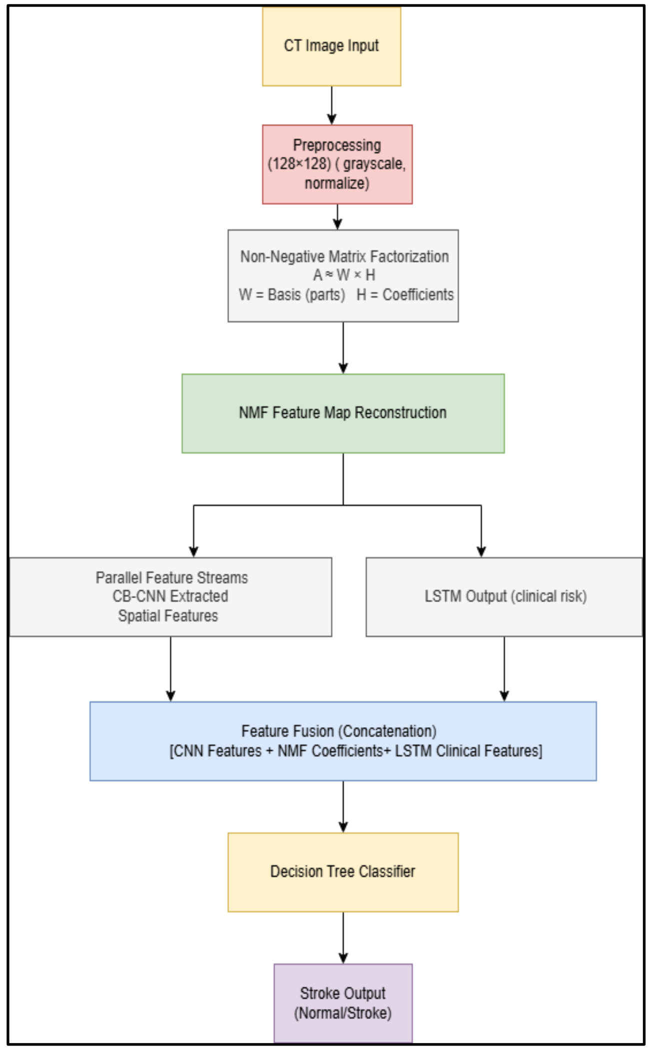


**Fig. 3 Multimodal fusion pipeline based on NMF**

## 4. Implementation

### *4.1. CNN-based Model for Stroke Detection*

The training curves of the model show strong learning and efficient generalization. Over the course of 50 epochs, the accuracy graph shows a consistent rise in both training and testing accuracy. Training accuracy increased from roughly 0.62 to roughly 0.97, while test accuracy closely followed, eventually reaching about 0.98 with just minor oscillations. In a similar vein, the loss graph shows a steady decline in both training and testing loss, with training loss falling from around 0.62 to approximately 0.07 and test loss falling from approximately 0.60 to almost 0.03, with only a few fluctuations throughout the mid-epochs. Overall, efficient learning, strong convergence, and little overfitting are suggested by the accuracy curves' near alignment and the loss curves' steady downward trend.

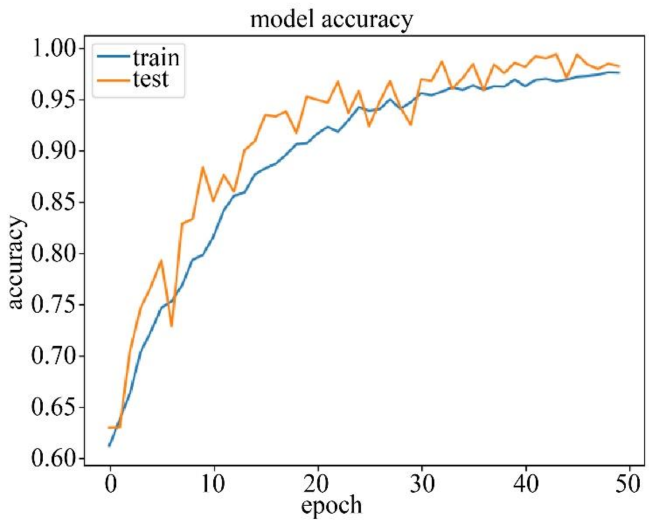


**Fig. 4 Accuracy graph for the proposed model**

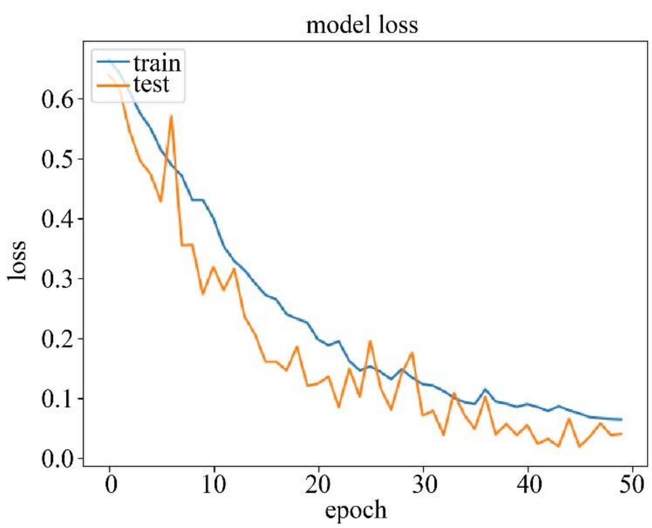


**Fig. 5 Loss graph for the proposed model**

### *4.2. LSTM–based Model for Stroke Detection*

The accuracy and loss curves in the figure below show the LSTM model's training performance across 1000 epochs. Beginning at roughly 0.70 and progressively increasing to a final value of 0.9436, the accuracy curve shows a steady upward slope, indicating the model's ongoing improvement in classification skill throughout the training phase. The loss curve, on the other hand, exhibits a smooth downward trend, starting at 0.25 and falling to 0.0580, suggesting efficient optimization and a decrease in prediction error. When taken as a whole, these curves demonstrate consistent learning, appropriate convergence, and the general reliability of the LSTM model for stroke detection.

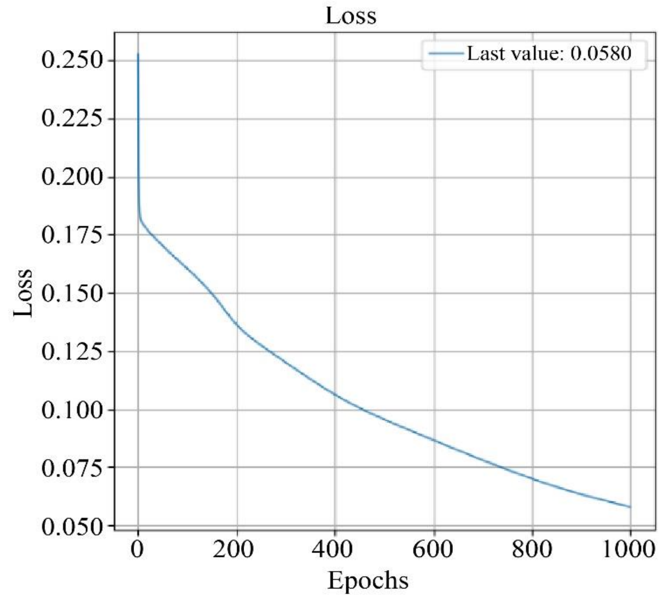


**Fig. 6 Loss graph for the proposed model**

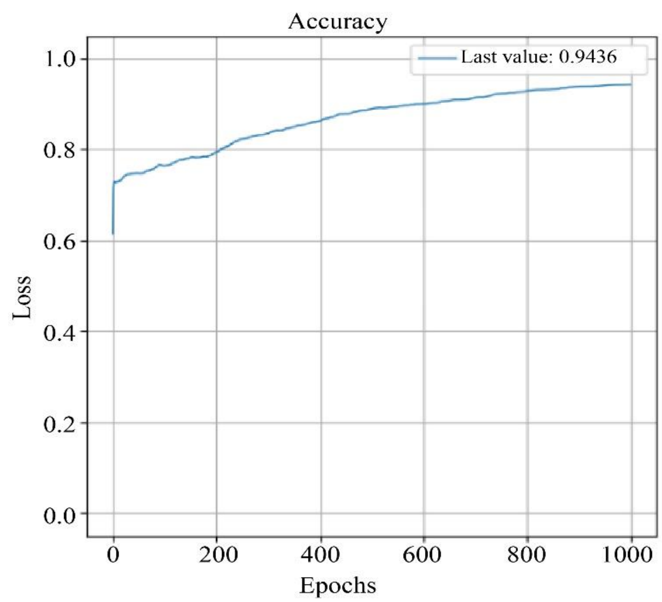


**Fig. 7 Accuracy graph for the proposed model**

## 5. Discussion

The comparison table illustrates how current approaches are restricted by their reliance on single data modalities, insufficient preprocessing, poor feature augmentation, and ambiguous fusion methodologies, all of which impede clinical interpretability and generalizability. These difficulties highlight the apparent necessity for a coherent and open framework in research. In comparison to existing techniques, the suggested CB-CNN + LSTM + NMF system improves CT feature improvement, modeling clinical dependencies, robustness, diagnostic accuracy, and clarity. In order to clearly contextualize and highlight the contribution of the proposed model, the table below provides a comparative summary of earlier research. Utilizing an interpretable decision-tree technique to integrate both modalities, resulting in improved A review of the literature reveals significant flaws in the automated stroke analysis techniques now in use, primarily because of their narrow focus on either imaging or physiological/clinical data. There are a few frameworks that effectively combine the two types of data in a way that is both clinically relevant and comprehensible. The diagnostic efficacy of signal-based techniques, such as HRV-MSPC analysis by Kodama et al. [1], EEG shapelet-based intention detection [8], ECG/PPG-derived prognostics [9], and AF classification using TransMixer-AF, is limited because they do not take radiological data into account. Image-focused models such as Tanveer et al.'s VGG16-NMF-GNB/LR pipeline [12] and Saleem et al.'s GA-BiLSTM approach [11] improve CT-based stroke prediction, but they are limited by standard CNN feature extraction, lack multimodal integration, and do not provide an interpretable feature breakdown. Other works that investigate "stroke-like" aspects in scene text or document processing [2, 4, 5] and rehabilitation-focused research using motion-capture or IMU-based systems [3, 6, 7] contribute to related topics but do not deal with diagnostic imagingWhen taken as a whole, these studies reveal recurrent problems, such as: (i) exclusive dependence on either imagery or tabular/signal data; (ii) absence of interpretable, parts-based enhancement techniques like NMF; (iii) inadequate integration of clinical variables through temporal-dependency models like LSTMs; and (iv) lack of transparent, clinically interpretable fusion mechanisms. The suggested CB-CNN + LSTM + NMF framework, which integrates channel-boosted CNN processing of CT images, NMF-driven decomposition for interpretable feature enhancement, and LSTM-based modeling of clinical attributes through a decision-tree mechanism that preserves interpretability, provides a unified, explainable multimodal architecture to address these problems In addition to achieving higher performance (98.12% accuracy, 98.75% precision, and 97% F1-score), this complete framework directly solves the modality isolation and transparency issues of earlier systems, proving the diagnostic usefulness of a comprehensive and explainable approach to stroke diagnosis.

**Table 1. Systematic evaluation of previous research and proposed CB-LSTM + NMF + CNN framework**

| Ref | Input Data Type | Preprocessing Technique | Methodology | Feature Method | Key Results |
|---|---|---|---|---|---|
| [1] Kodama et al. | HRV signals (animal MCAO) | HRV extraction, time-series cleaning | MSPC + HRV analysis | Statistical HRV metrics | 82% sensitivity, 75% specificity; limited by small animal dataset and anesthesia confound; not transferable to humans |
| [2] Zhong Zhang et al. | Scene character images | CSM-based stroke extraction | DCSP pooling with stroke detectors | Deep contextual stroke features | Outperformed prior scene-text models (ICDAR2003, Chars74k, SVHN); domain-specific (non-medical) |
| [3] Ying Xuan Zhi et al. | Kinect skeletal motion | Joint coordinate extraction | Compensation detection classifiers | Kinematic joint features | Good performance on healthy subjects; poor generalization to stroke survivors |
| [4] Zhengmi Tang et al. | Scene text images | Synthetic text augmentation | Stroke-mask guided text erasure (inpainting) | Stroke mask + partial convolution | Preserves background texture; domain shift reduction; unrelated to medical imaging |
| [5] Quang-Vinh Dang et al. | Document images | Global & local edge extraction | Adversarial binarization network | Stroke boundary features | Better handling of weak strokes in degraded documents; not applicable to CT stroke |
| [6] Fu-Cheng Wang et al. | IMU gait signals | Timeline segmentation | RNN for HS event detection | Time-series gait features | Up to 99.65% accuracy; targeted at gait event detection, not diagnostic imaging |

| | | | | | |
|---|---|---|---|---|---|
| [7] Shir Kashi et al. | Motion-capture data | Coordinate normalization | Compensation detection model | Spatial kinematic features | 85% macro precision; expensive capture hardware limits use |
| [8] Thapanan Janyalikit et al. | EEG signals | Shapelet extraction | Asynchronous BCI movement-intent detection | Time-series shapelet features | First shapelet-based EEG detector; for rehabilitation, not diagnosis |
| [9] Jaehak Yu et al. | ECG + PPG biosignals | Signal segmentation, filtering | ML + CNN-LSTM prognostics | Bio-signal waveform features | 90–99.15% accuracy; focused on elderly prognostics, not CT-based detection |
| [10] Chenzhe Li et al. | MITAT ultrasound (simulated + ex-vivo) | Simulation-based dataset | ResAttU-Net for hemorrhage detection | Attentional ultrasound radiomics | Identifies transcranial bleeding; domain: acoustic imaging, not CT |
| [11] Saleem et al. | CT images | Standard resizing, normalization | GA + BiLSTM | GA-selected image features | Better than baseline ML models; small dataset, limited enhancement, and interpretability |
| [12] Chi-Huang Shih et al. | EEG + VR interaction | EEG filtering | Remote VR-BCI rehabilitation system | EEG compensatory patterns | Novel rehab system; not related to early stroke detection |
| [13] S.M. Mahim et al. | 1-lead ECG | Noise filtering, segmentation | TransMixer-AF | Transformer + mixer features | 91–98% accuracy on AF detection; unrelated to CT-stroke classification |
| [14] Tanveer et al. | CT brain images | Standard preprocessing | VGG16 + NMF + GNB/LR | CNN features enhanced by NMF | Up to 99.96% accuracy; closest prior work, but lacks multimodal fusion and interpretability. |
| Proposed CB-CNN + LSTM + NMF Framework | CT images + clinical/tabular data | Absolute grayscale, channel boosting, MICE imputation, MinMax scaling | CB-CNN for image learning + LSTM for clinical attributes + Decision-tree fusion | NMF parts-based image enhancement + boosted channels + temporal risk features | 98.12% accuracy, 98.75% precision, 97% F1-score; multimodal, explainable, and validated with cross-metrics |

In the area of automated stroke detection, the suggested approach offers a number of significant advantages. Reliable diagnostic support is ensured by its excellent accuracy in diagnosing stroke conditions. The model can function consistently across a variety of medical inputs since it is resilient to changes in neuroimaging and healthcare data. The solution increases workflow productivity and minimizes manual intervention through its end-to-end automated learning and prediction pipeline. It is also appropriate for real-world clinical settings because of its scalability, which enables efficient handling of big and complicated medical datasets. By integrating a hybrid model architecture that combines CB-CNN, LSTM, and Decision Tree algorithms, the system further enhances decision-making and overall diagnostic performance, establishing a powerful and efficient solution for stroke detection.

## 6. Results

The proposed model for brain stroke detection is deployed using a Windows-based machine with 16 GB of primary memory and an Intel Core i7 processor. For the experiment, the model utilizes the Anaconda IDE repository for Spyder and Jupyter IDEs. The developed model is subjected to rigorous evaluation using the confusion matrix parameters. The confusion matrix parameters are explained with the equations for accuracy, precision, recall, and macro F1.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad (6)$$

$$\text{Precision(P)} = \frac{TP}{TP+FN} \quad (7)$$

$$\text{Recall(R)} = \frac{TP}{TP+FP} \quad (8)$$

$$\text{Macro} - \text{F1} = \frac{2*P*R}{P+R} \quad (9)$$

Here, TP is True positive cases, TN is True Negative cases, FP is False positive cases, and FN is False Negative cases. The obtained confusion matrix scores are compared with those of [11]. In order to identify strokes in their earliest stages, authors have created a system that uses CT brain images in conjunction with a genetic algorithm and a Bidirectional Long Short-Term Memory (BiLSTM). To determine which features are most important for picture categorization, an evolutionary algorithm based on neural networks is employed. The model's performance was first evaluated using standard confusion matrix metrics, including accuracy, precision, recall, and macro-F1, calculated through Equations (6)–(9). These performance indicators were augmented with 95% confidence intervals obtained from bootstrap resampling (1,000 iterations) to improve statistical reliability beyond point estimates. This helped reduce the danger of optimistic bias in small to medium-sized datasets.

Additionally, the dataset underwent stratified 5-fold cross-validation instead of relying only on a single train-test split. This method prevented overfitting to a particular split. It produced a more reliable estimate of real-world performance by maintaining class proportions throughout the folds and thoroughly testing the model's generalizability. Besides confusion matrix metrics, the study also included ROC-AUC and Precision–Recall AUC, crucial for assessing diagnostic systems, particularly in datasets with moderate class imbalance. The ROC-AUC measures the model's ability to discriminate across thresholds, while the PR-AUC more accurately reflects sensitivity to rare events, such as stroke-positive cases. The obtained Accuracy, Precision, Recall, and F1-Score are compared with the methodologies of [11], such as GA_LSTM, GA_Bi_LSTM, with our hybrid model of CBCNN-LST. The recorded parameters are shown in Table 2 below, and the respective graph is plotted in Figure 8.

**Table 2. Comparison of the confusion matrix parameters**

| Models | Accuracy | Precision | Recall | F1_Score |
|---|---|---|---|---|
| **GA_LSTM** | 93.35 | 92 | 90.89 | 95 |
| **GA_BiLSTM** | 96.45 | 98 | 93.5 | 96 |
| **CBCNN-LSTM** | 98.12 | 98.75 | 95.65 | 97 |

The obtained results clearly indicate that the model deployed in [11] is working on the CT images of the brain using the genetic algorithm and LSTM model. The data quality in the model is moderately handled to obtain the results. The proposed system employs non-negative matrix factorization to enhance the accuracy of the model by combining the LSTM model with statistical data and the CB-CNN model with CT imagery data. The result of this can be clearly depicted in the graph shown in Figure 8, where our model based on CBCNN-LSTM outperforms the results of [11] efficiently.

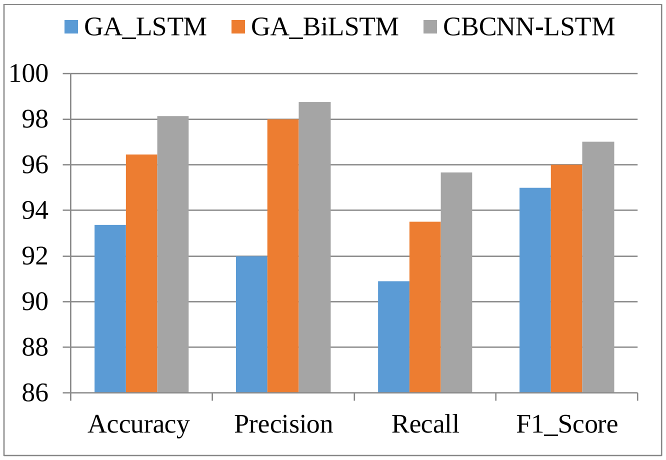


**Fig. 8 Confusion Matrix Comparison Graph**

## 7. Conclusion and Future Scope

This research article is developed for the detection of brain stroke disease based on the CT images and user statistical data. This work is carried out by involving an imagery dataset for the CB-CNN model and statistical data for the LSTM model. Initially, the imagery dataset was preprocessed and converted into absolute grayscale to enhance the image's channel. Once the channels are boosted, the CB-CNN model is deployed for around 100 epochs to get good accuracy in training. This stage is followed by the preprocessing and imputation of the statistical data, which leads to establishing the correlation between the attributes using the Pearson correlation model. The correlated data is used to build the train and test data by splitting the preprocessed data. The efficient LSTM model obtains good accuracy and an RMSE of 0.238 for the prediction of brain stroke disease. The obtained results from both models are catalyzed by the non-negative matrix factorization to enhance the features of the input image; this version eventually yields the best result by incorporating the decision tree model. The proposed system yields 98.12 % accuracy, 98.75% precision, 95.65% recall, and finally, a 97% F1 score. The obtained results are analyzed thoroughly to compare with the existing models, where we found that the performance of the CBCNN-LSTM model is better in all respects. The proposed framework can use transformers in future work to improve training by incorporating older epochs. This procedure has the potential to be very extensive, and it can use a large number of parameters related to patients' lifestyles to forecast the onset of a brain stroke.

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