

A Thorough Examination of a Stroke Detection using Deep Learning Models

Mitali Hemant Chaudhari¹ and Nisha Wandile Kimmatkar²

^{1,2}JSPM's Rajarshi Shahu College of Engineering, Pune, India

Email: mitali23599@gmail.com, nishakimmatkar@gmail.com

Abstract—Brain stroke or paralysis is a devastating condition for human health, leaving the patient completely numb for the remainder of their life and causing complete trauma to the patient's family members while they are still alive. Early brain stroke prediction is a challenging task for the medical field, as it requires continuous evaluation of the disease through numerous tests. Artificial intelligence plays a vital role in disease prediction and detection through its high-end models, like deep learning. Most deep learning models work on a single type of data, such as brain stroke neural images or statistical data related to the disease. This single neural network is insufficient for accurately predicting and detecting brain stroke possibilities. Therefore, the proposed model leverages heterogeneous data, such as images and statistical data, to accurately predict and detect the risk of brain stroke. To achieve this, the proposed model uses neural images to train a tailor-made channel boost convolution neural network, along with a non-negative matrix factorization technique, which catalyses the identification of the stages of brain stroke proneness. Conversely, we employ statistical data to identify potential brain strokes through a long-short-term neural network methodology. The outcomes from both neural networks are combined to enhance results using a decision tree model.

Index Terms— Convolutional neural network, Deep learning, Pattern classification, Feature fusion, Stroke identification.

I. INTRODUCTION

When blood flow to the brain is suddenly cut off, it causes brain tissue damage known as a brain stroke (BS). Impaired coordination and mobility can be caused by hemiplegia or hemiparesis, which can be a result of BS. Problems with walking, carrying out daily tasks, and retaining independence in these areas may result from this. Aphasia, a disorder defined by poor speech and language abilities, can be caused by BS. Issues with speaking, understanding, reading, and writing are all possible outcomes of brain damage, the specifics of which are dependent on the affected regions. Memory loss, trouble focusing, and reduced problem-solving abilities are among cognitive difficulties that BS survivors may have. These approaches can enhance the efficiency and precision of stroke detection while minimizing the need for costly imaging tools and specialized expertise. The current methods for detecting strokes often depend on the subjective evaluations of radiologists, which leads to misdiagnoses, delays in treatment, and missed opportunities for intervention. In addition, the diagnostic accuracy and reliability of classic ML approaches may be limited since they cannot understand the complex patterns and subtleties shown in CT images.

The structure of this literature review study is as follows: In the form of a review of the literature, Section II examines earlier research; Section III, IV, delineates the recommended approach; and Section V makes recommendations for more research.

II. LITERATURE REVIEW

In this section, we discuss the literature review. Research has previously been conducted on predicting strokes. Strokes remain a major cause of death and long-term disability worldwide, imposing a significant burden on both society and healthcare systems. Alhatemi, Rusul Ali Jabbar et al. [1] introduces a method for automatically identifying brain cancers from magnetic resonance imaging (MRI) scans is detailed in this research. This method relies on transfer learning and makes use of popular CNN designs. The experimental findings revealed that even with a limited dataset, a classifier could be effectively trained using pre-trained deep learning models to detect strokes in brain MR images. In particular, the EfficientNetB2 DL model blew away the competition with a 98.8 percent accuracy rate, surpassing the state-of-the-art in recall, precision, and F1-score. Using large brain stroke datasets and various feature selection methods, we plan to create a novel model for detecting different types of brain sickness in author's next work. Work by J. Yu et al. [2] focuses on obtaining ECG and PPG data from senior people's daily lives, which is used in a semantic analysis system for aged disorders. The proposed approach identifies and forecasts stroke prognostic indicators in the elderly by utilizing real-time ECG and PPG bio-signals. By dividing elderly and stroke patients into 10-fold cross-validation datasets, the authors' deep learning models achieved prediction accuracies of 91.56% with the C4.5 Decision Tree, 97.51% with Random Forest, and 99.15% with CNN-LSTM. ECG and PPG may be measured cheaply and quickly during normal life, making this technology useful for predicting prognostic symptoms and stroke start in academia. Biju Nageswara Rao et al. [3] present a ResNet-based transfer learning model for classifying 2D head CT images. This model distinguishes between ICH and normal images, employing ResNet-50 along with a dense fully connected layer. The model was tested using 1,166 NCCT brain images from 62 patients with hemorrhagic stroke. In this paper, Mak J. et al. [4] introduced their AREEN system, which integrates an AR headset with a BCI architecture, and developed and tested an EEG-based SN detection BCI. Future investigations can detect band synchronizations between hemispheres and brain areas. Author demonstrated how different classifiers identified EEG characteristics and how common spatial patterns may retrieve them. Chen et al. [5] propose that CNN-based deep learning can differentiate between hemorrhagic and ischemic strokes from unenhanced brain CT images. CNN-2, VGG-16, and ResNet-50 were pre-trained using transfer learning and compared. J.S. Suri et al. [6] highlighted the prediction of cardiovascular disease and stroke risk for PD patients within the COVID-19 cohort in this comprehensive study. Zhang et al. [7] observed that many disorders can cause cerebral stroke (CS). According to experimental data, the suggested approach has a high recall rate of 85.3% and accuracy rates of 94.1% and 91.7%. The recall rate stands out, making the algorithm accurate, resilient, and generalizable. Dr. O. Karadima and colleagues [8] experimentally validated the DBIM-TwIST algorithm, which integrates the distorted born iterative method with two-step iterative shrinkage thresholding, for detecting and distinguishing brain strokes. Janyalikit et al. [9] designed a stroke recovery method compatible with asynchronous BCI systems. Effective rehabilitation tools and software are crucial for successful stroke recovery. Therefore, the authors propose a time series shapelet-based approach to consistently detect movement intentions in electroencephalogram data. Hwang YT et al. [10] suggest that functional analysis can predict the trajectory of data collected by IMU sensors, with the resulting coefficients serving as features for assessing hand function. S. Afzal et al. [11] wrote that modern computer vision and image processing methods are best for micro bleed detection. ResNet50 and AlexNet with augmentation achieved 97% accuracy. S. Jeon et al. [12] propose a two-wristband system to reduce WUS and speed stroke treatment. This system relies on an EDIS architecture to recognize in-sleep strokes quickly and accurately. Hiroshige, Xie Setting et al. [13] note that many mental illnesses are linked to gut microbiota. However, how post-stroke sleep disturbances affect gut microbiota is unknown. The author investigated sleep disorder prognosis three months after hospitalization using the Pittsburgh Sleep Quality Index (PSQI). G. Oliveira et al. [14] propose a clinically significant yet difficult-to-accurately-predict functional outcome in stroke patients. Of 743 individuals who suffered an ischemic stroke, the author evaluated data from a multi-centre cohort. In order to achieve this goal, author trained deep learning models to make predictions using solely CT data and models that also take into account other patient factors. Sailaja, Y et al. [15] demonstrate that deep learning models can correctly identify brain strokes from MRI data, aiding in the early detection and successful treatment of this grave illness. Anas W. Abulfaraj et al. [16] found that incorporating SqueezeNet v1.1, MobileNet V3-Small, feature fusion, and CatBoost models into a stroke identification model enhances medical image analysis. The author can extract both local stroke pathophysiology

features and global trends using SqueezeNet v1.1 and MobileNet V3-Small. DL structures can accurately depict stroke lesions in MRI scans by detecting key features. Feature fusion combines representations from multiple architectures to improve distinctiveness. The summarized related work is shown in Table I.

TABLE I. LITERATURE SURVEY

Paper No.	Model	Pre-Processing	Comparison Parameter
[1]	DenseNet121, ResNet50, Xception, MobileNet, VGG16, and EfficientNetB2	Transfer learning	Accuracy - 98.8 Precision - 98.8 Recall - 98.8 F1-score - 98.8
[2]	CNN-LSTM ECG PPG multi-modal bio-signal	Multimodal bio-signals of ECGs and PPGs	Accuracy - 99.15 Precision - 99.22 Recall - 99.13 F1-score - 99.11
[3]	ResNet-50 with dense layers	Otsu's Thresholding and Element-wise Multiplication	Accuracy - 99.6 Precision - 99.7 Recall - 99.4 F1-score - 99.5
[5]	(CNN)-based deep learning CNN-2, VGG-16, and ResNet-50	MicroDicom	Accuracy - 98.7 Precision - 98.0 Recall - 98.0 F1-score - 98.0
[6]	Deep learning (DL)	PRISMA	Accuracy - 98.7 Precision - 98.0 Recall - 98.0 F1-score - 98.1
[7]	CNN, AC-YOLOv5	AC-YOLOv5	Accuracy - 94.10 Recall - 85.30
[16]	Squeeze Net v1.1 , Mobile Net V3-Small , Cat Boost	Feature Fusion	Accuracy - 99.1 Precision - 99.0 Recall - 98.8 F1-score - 98.9

After evaluating most of the methodologies in this section, the cumulative results of some of the works are shown here in the above Table I. This research study aims to address a research gap identified in the aforementioned literature survey. Immediate treatment of stroke is crucial to prevent complications. Developing an ML model could aid in early stroke diagnosis and reduce its severe effects. This study evaluates the effectiveness of various ML systems in predicting stroke using physiological factors. The study may enhance framework models with a larger dataset and machine learning models like AdaBoost, SVM, and Bagging. Worldwide stroke is a threat. Recovery should occur before worsening. Machine learning methods can predict strokes early in this critical situation. This article predicts stroke outcomes using machine learning classification. The recommended method incorporates stroke dataset loading, data preprocessing, hyper parameter tweaking, classifier evaluation, and cross validation. Support Vector Machine and Random Forest classifiers are most accurate at 99.99% and 99.85%. For better results presentation, a user-friendly website and mobile app are created. Future studies will use image processing and deep learning to produce accurate results.

III. METHODOLOGICAL APPROACH

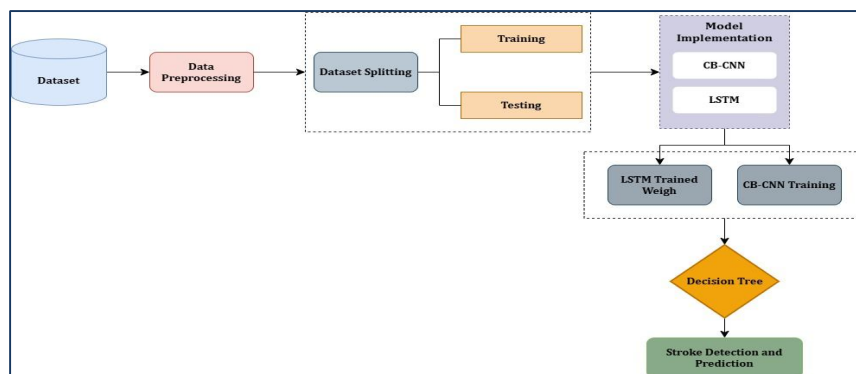


Figure 1. Proposed System Architecture

This section will outline the methodology adopted in this study and the framework employed for this research. The proposed framework is illustrated in Figure 1, depicting the architecture of the proposed computer-aided stroke diagnosis system.

We used two datasets from the Kaggle library, including statistical datasets for stroke diagnosis and neuro-image datasets. The neuro-image dataset, which consists of MRI pictures, is particularly well-suited for training the Convolutional Bidirectional Convolutional Neural Network (CB-CNN). The statistical dataset, which includes personal health details such as blood pressure, work environment, alcohol intake, and lifestyle characteristics, is well-suited for training Long Short-Term Memory (LSTM) networks. The proposed methodology of our system can be explained through following modules which is preprocessing, Feature Extraction, in models which are CB-CNN and LSTM, Decision tree. Preprocessing data is a vital step in stroke detection using deep learning and machine learning models, as it ensures the input data is clean, consistent, and properly formatted for model training. Initially, data is collected from various sources, including CT (Computed Tomography) scans, MRI (Magnetic Resonance Imaging) scans, and patient clinical data, such as age, gender, medical history, and blood pressure. To increase model accuracy and efficiency, feature extraction in stroke detection entails choosing the most pertinent clinical, physiological, imaging, and behavioral data. CB-CNN (Convolutional Block Attention Module with Convolutional Neural Networks) is a method that can be used in stroke detection systems. The input to the LSTM model is a statistical dataset that includes various patient-related information such as demographic details (age, gender, ethnicity), clinical data (blood pressure, cholesterol levels, glucose levels), medical history (hypertension, diabetes, prior stroke incidents), and time-series data (e.g., heart rate and blood pressure readings over time). The decision tree employs an advanced procedure intended for the identification and prediction of strokes.

IV. IMPLEMENTATION

This section outlines the workflow for stroke detection and prediction. Figure 2 illustrates the stroke detection strategy. This strategy includes datasets, data preprocessing, data segmentation, data imputation, CB-CNN training, and LSTM training weight.

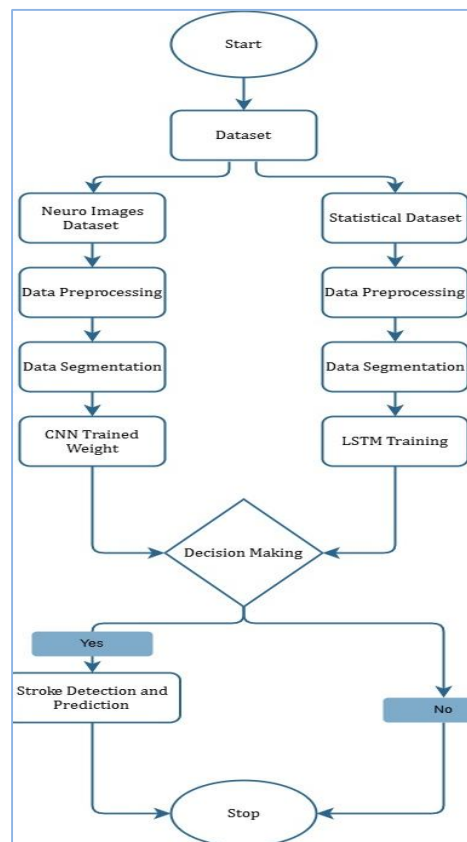


Figure 2. Workflow for Stroke Detection and Prediction

Figure 2 above shows the diagram of the Work Flow. In the Work Flow model, the statistical dataset is initially obtained to acquire the pre-processed attribute after its imputation. Once the dataset is efficiently pre-processed, it is divided into training and testing datasets [17]. The dataset is effectively split, and then the LSTM model is employed to train the model for the required epochs. Meanwhile, brain stroke images are effectively used to enhance the alpha channel of the images. The obtained images are segregated into train and split and then subjected to training using the channel boost convolution neural network model. We efficiently use the trained data from LSTM and CB-CNN to predict the likelihood of brain stroke [18]. This section discusses the performance of a newly proposed method for stroke detection and compares it with various machine learning-based methods that researchers have recently proposed. We assessed the classification accuracy of the suggested method against alternative approaches that predicted strokes using the same Kaggle dataset of brain CT images [19]. The previously proposed diagnostic system achieved an accuracy of 96.5%. We also compared the previous performance of the proposed model with Logistic Regression, Decision Trees, Random Forests, Naive Bayes, and Support Vector Machines. With the previously proposed diagnosis system, physicians can make informed decisions about early stroke prediction [20]. Now we discuss the performance of a newly proposed method for stroke detection. In the newly proposed system, we used a decision tree for better accuracy purposes [21]. Also, we used CB-CNN training weight and LSTM training weight to find the stroke detection stage and how many chances to detect the stroke to the person.

V. CONCLUSION

Paralysis or a brain stroke is a terrible illness that will ruin a person's life; it will leave them numb for the rest of their days and traumatize their loved ones even while they're still with them. Predicting an early brain stroke is difficult for medical professionals because the disease must be monitored constantly with a battery of tests. Disease prediction and detection rely heavily on AI's advanced models, such as deep learning. In the case of brain stroke, for example, most deep learning models will only process images of the affected area's neurons or disease-related statistics. It is not possible to reliably anticipate or detect the likelihood of a brain stroke using just this one neural network. Thus, in order to reliably diagnose and forecast the likelihood of a brain stroke, the suggested model makes use of heterogeneous data, including pictures and statistical data. A custom-made channel boost convolution neural network and a non-negative matrix factorization algorithm are utilized in the suggested model to train in order to accomplish this goal of identifying the stages of brain stroke proneness. Contrarily, we use statistical data in a long-short-term neural network fashion to identify possible brain strokes. With the use of the decision tree model, the output from the two neural networks is combined to yield superior outcomes.

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