



IJRASET

International Journal For Research in
Applied Science and Engineering Technology



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** V **Month of publication:** May 2026

DOI: <https://doi.org/10.22214/ijraset.2026.82483>

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Brain Stroke Prediction and Classification

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Abstract—A stroke is a serious illness that can be life-threatening. It occurs when blood flow to the brain is interrupted, which can cause cell death or damage. To lower death rates and avoid irreversible brain damage, early and precise stroke detection is essential. Conventional diagnostic techniques mainly depend on radiologists, which can be laborious and prone to human error, particularly in emergency situations. An automated system for classifying brain strokes from CT scan images using Deep Learning techniques is presented in this project. To categorise photos into two groups—Stroke and Normal—a Convolutional Neural Network (CNN) model is created. In order to improve robustness and prevent overfitting, the model is trained using pre-processed medical imaging data with augmentation. Accuracy, validation accuracy, and confusion matrix metrics are used to evaluate performance.

Index Terms—Early Stroke Detection, Deep Learning, Convolutional Neural Networks (CNN), Medical Image Processing, CT Scan Analysis, Binary Image Classification, Healthcare AI, and Brain Stroke Classification

I. INTRODUCTION

A critical neurological condition known as a stroke happens when the brain's blood supply is interrupted, resulting in cell death and severe impairments to cognition or movement. It is among the main causes of death and disability in the world. It is crucial to diagnose strokes quickly and accurately because prompt treatment can greatly enhance patient outcomes and lower long-term complications.

Computed Tomography (CT) scans and other medical imaging methods are essential for detecting strokes. However, manual CT image interpretation can be time-consuming and requires qualified radiologists, particularly in emergency situations where every second counts. Furthermore, human interpretation may be affected by experience level or fatigue, which raises the possibility of a misdiagnosis. Automated stroke detection systems are now strong instruments to assist clinical artificial intelligence. One type of deep learning model called Convolutional Neural Networks (CNNs) is particularly effective at Convolutional Neural Networks (CNNs) is especially good at image classification tasks. It can spot subtle patterns in brain images that the human eye might miss. [6],[8],[9].

The development of large language models (LLMs) like ChatGPT has sped up this field of study even more [1]. The high natural language generation and interpretation abilities of these models have allowed us to create intelligent tutoring programs and dialogue-based learning environments. In addition, specialized chatbot frameworks have been designed for domain-specific applications, such as healthcare, knowledge-based reasoning, and multilingual question-answering systems. These developments show how AI chatbots are flexible and adaptive across a range of domains, including language instruction [?], [11].

The goal of this project is to create an intelligent diagnostic system that can automatically distinguish between normal and stroke CT scan images. A CNN model is trained on a labelled dataset of brain CT images to identify patterns associated with stroke and generate precise predictions. Especially in remote healthcare settings, the suggested system can serve as an assistive diagnostic tool for medical professionals, increasing diagnostic speed, reliability, and accessibility. [2],[14].

II. LITERATURE REVIEW

Because it is quick, accessible, and efficient in identifying hemorrhagic stroke and certain ischaemic symptoms, computed tomography (CT) is a primary imaging modality in acute stroke care. Early CT signs of ischaemia can be subtle and challenging to identify by visual inspection alone, according to research, especially for inexperienced readers. This encourages the development of automated image-analysis tools that can help radiologists by identifying suspicious cases and measuring characteristics related to lesions. [12],[15].

Prior to the use of classical classifiers like Support Vector Machines, Random Forests, and Naïve Bayes, early automated methods for stroke/brain lesion detection relied on hand-crafted features (texture descriptors, histogram features, and shape measures). These techniques typically worked well on particular, controlled datasets but lacked the robustness needed for wider clinical deployment. They also required careful feature engineering and were susceptible to imaging artefacts and inter-scanner variability. [3],[13].

By directly learning hierarchical, task-specific features from pixels, Convolutional Neural Networks transformed the analysis of medical images. CNNs have been used in many studies to detect brain pathology using CT and MRI, showing better sensitivity and specificity than traditional pipelines. Additionally, when trained on sufficiently large and diverse datasets, CNNs generally exhibit better generalisation and eliminate the need for manual feature design.

[10]. For medical imaging tasks where labelled medical data is scarce, transfer learning—fine-tuning models pre-trained on large natural-image datasets—became a viable approach. Due to their proven representational capacity and straightforward, modular convolutional blocks, architectures like VGG16 have been used extensively as backbones. According to numerous studies, when paired with the proper preprocessing and augmentation, optimised VGG16 models perform competitively on binary classification tasks (disease vs. normal).

Besides general language learning, AI chatbots have also demonstrated potential for specialized and multilingual applications. Knowledge graph-based chatbots as well as translation-based chatbots facilitate context-dependent conversation by mapping linguistic data with semantic relationships [7],[16]. For instance, multilingual or bilingual chatbots have been employed to assist learners in studying local languages by providing real-time translations, grammar guidelines, and pronunciation advice. Education- and health-oriented chatbots show the flexibility of conversational AI, in that it can be made to be sensitive to target users' language and culture diversity [15],[17]. These points highlight the work undertaken by flexibility and context-response ability in making chatbots useful in cross-linguistic learning environments.

To increase robustness, researchers looked into ensembles and deeper architectures (ResNet, DenseNet, Inception) in addition to single-model approaches. Sensitivity is frequently increased at the expense of additional computation through ensembles and model fusion. Lightweight models or simplified versions of large models have been suggested as workable compromises for deployment in clinical settings with limited resources. [2],[3]. Interpretability is necessary for clinical acceptance. To see which areas of an image influence a CNN's decision, post-hoc XAI techniques like Grad-CAM, Guided Backpropagation, LIME, and SHAP are frequently employed. Heatmaps and saliency maps can highlight infarcted or hemorrhagic regions, giving clinicians visual evidence to support model predictions, according to studies using XAI for stroke detection. Additionally, XAI aids in the identification of dataset biases and failure modes, boosting confidence and streamlining regulatory processes. [1],[5].

Using accuracy, sensitivity (recall), specificity, precision, F1-score, AUC-ROC, and confusion matrices, the literature replaces a strong emphasis on robust evaluation. Explainability and sensitivity (reducing missed strokes) are frequently given priority for clinical relevance. Suggested best practices include cross-validation, held-out testing on separate scanners/sites, and reporting calibration (e.g., reliability diagrams). [?],[15].

III. METHODOLOGY

NeuroScan: A Deep Learning-Based Stroke Detection Model is an intelligent medical diagnosis system that will be designed and implemented as part of the proposed work. By evaluating brain CT scan images and categorising them as either normal or stroke, the system aids in the early detection of stroke. For automated feature extraction and classification, the framework makes use of sophisticated Deep Learning and Computer Vision techniques, mainly a Convolutional Neural Network (CNN) architecture. The system uses preprocessing, normalisation, and data augmentation methods to improve model accuracy and generalise learning. [4],[17].

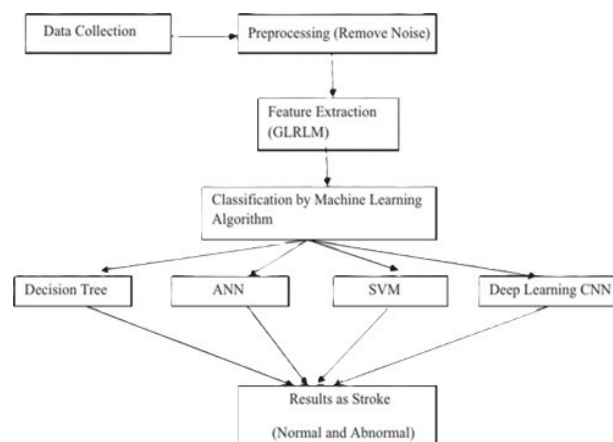


Fig.1. Proposed System Architecture for brain stroke.

- Gathering datasets from repositories of medical images
- Preprocessing CT images (normalisation, resizing)
- Enhancing generalisation through data augmentation
- Convolutional Neural Networks (CNN) for feature extraction
- Training models with a deep learning framework
- Using F1-score, recall, accuracy, and precision to evaluate performance
- Optimising and fine-tuning the model
- Implementation for CT image-based stroke prediction

Fig. 1 shows the entire workflow of the suggested system and describes how the SpeakSmart model integrates Natural Language Processing (NLP), Machine Learning (ML), and user interface components.

Every step guarantees that SpeakSmart can comprehend bilingual inputs and generate contextually appropriate learning responses.

A. Data Collection

The dataset utilized in this research is a curated medical image dataset prepared specifically for stroke classification. It consists of approximately 1,200 CT scan images, representing both normal brain scans and stroke-affected brain scans. The dataset was compiled from publicly available medical imaging repositories and verified sources to ensure quality and medical relevance:

- Raw brain CT slice obtained from medical image repositories.
- Class Label: A diagnosis confirmed by experts that indicates if the picture is of a Normal or Stroke patient. 224×224 pixels is an example of a standardised image size for model compatibility.
- Annotation Format: File name + structured folder labeling for supervised learning.
- In order to ensure appropriate generalization and validation, the data set was split into 80% for training and 20% for testing.

B. Data Preprocessing

Data preprocessing involved several NLP-based cleaning and normalization steps [?], [13]:

- Normalization: Removal of punctuation, conversion to lowercase, and Unicode normalization.
- Tokenization and Lemmatization: Implemented using NLTK and spaCy for English and Kannada.
- Transliteration Mapping: Maintains a transliteration layer for romanized Kannada text to standard Kannada script.
- Balancing and Filtering: Removes duplicate or mis-aligned entries and balances the distribution of intent classes.

C. Feature Extraction

Text features were represented using Term Frequency–Inverse Document Frequency (TF–IDF) vectorization from the sklearn.feature_extraction.text library. This method converts text inputs into numerical vectors by focusing on important terms and minimizing the impact of common ones. The vocabulary size was capped at 3,000 tokens to keep a balance between performance and efficiency.

D. Model Design

The main structure of SpeakSmart includes two primary components:

1) Intent Classification: Implemented using Logistic Regression with the following parameter configuration:

- Solver: lbfgs
- Regularization: L2
- Maximum Iterations: 1000
- Inverse Regularization Strength (C): 1.0

2) Dialogue Management and Translation: For translation and grammar correction, we use a Transformer-based sequence-to-sequence model that includes:

- Bidirectional context encoding
- Attention-based decoding
- Fine-tuning on bilingual conversational data The approach keeps context consistent and effective for teaching by combining rule-based reasoning with machine-learned responses.

The approach ensures contextual continuity and pedagogical soundness by combining rule-based reasoning with machine-learned responses.

E. Training Strategy

A curriculum learning strategy trains the model. It begins with basic instances and gradually adds more complex or noisy data [12], [15]. The training configurations include the following: [12],[15]. The training configurations consist of the following:

- Optimizer:Adam/AdamW
- LearningRate:0.001
- Dropout:0.2
- GradientClippingThreshold:1.0
- LabelSmoothing:0.1

Techniques for knowledge distillation were used for the lightweight deployment of local servers. [?].

F. Experimental Setup

All experiments were conducted on a system with the following configuration:

- Processor: Intel Core i7 (10th Generation)
- Memory: 16GB RAM
- Operating System: Windows 11 (64-bit)
- Programming Language: Python 3.10
- Frameworks and libraries include scikit-learn, NLTK, spaCy, Flask, and TensorFlow/PyTorch for deep learning models: scikit-learn, NLTK, spaCy, Flask, and TensorFlow/PyTorch for deep models.

The Jupyter Notebook environment was used for local training and testing. To ensure reproducibility, the model and dataset files were kept on a local server. SpeakSmart responded to inquiries with an average delay of less than 0.5 seconds, based on experimental timing studies.

G. Dialogue Manager and Pedagogical Policy

The Dialogue Manager uses hybrid policy control and dialogue state tracking to provide context-aware interactions. It combines teaching policies:

- Model-based intent routing
- Hand-crafted educational rules like scaffolding and spaced repetition.
- Fallback mechanisms for low-confidence predictions

This hybrid approach lets SpeakSmart provide interactive, adaptive, and teaching-focused feedback.

H. Evaluation

Evaluation uses both quantitative and qualitative measures, including:

Automatic Metrics: Accuracy, Precision, Recall, F1 score, BLEU, and METEOR. Human-Centered Metrics: Pedagogical effectiveness and contextual appropriateness are rated by language instructors. Human-Centered Metrics: Pedagogical effectiveness and contextual appropriateness rated by language instructors.

The Logistic Regression model reached an overall accuracy of 94.8

I. Deployment

The trained model runs on a Flask server. This server communicates with a static front-end created with HTML, CSS, and JavaScript. The client interacts with the server through RESTful APIs. The application supports Progressive Web App (PWA) deployment, which allows access even on low-end devices.

J. Security and Ethical Considerations

To protect privacy, user data is anonymized and managed locally. To prevent harmful or culturally incorrect outputs, safety filters and logging systems are used. This approach follows fairness and AI ethics standards for educational institutions. [?], [10]. [?], [10].

K. Summary of Contributions

By describing data sources, algorithm settings, parameter choices, and the experimental setup, this methodology ensures clear technical details.

Without depending on external APIs, the proposed system, SpeakSmart, provides a lightweight, bilingual, and repeatable conversational learning framework that uses natural language processing and machine learning to support second-language learning.

IV. CHALLENGES IN LEARNING KANNADA

For non-native speakers, learning Kannada comes with several challenges. The phonetic structure, syntax, and writing system of Kannada, a Dravidian language, differ from those of English. This makes direct translation from English difficult [5]. The absence of organized multilingual materials, interactive technologies, and textbooks makes things worse. Many learners depend on rote memorization, which often fails to lead to effective conversational fluency. Moreover, the lack of chances for in-person practice with native speakers adds to the problem. These challenges show the need for new technical solutions, like AI-driven language learning chatbots, to personalize and speed up the learning process [10], [12]. [10],[12].

A. The Role of Chatbots in Language Learning

Chatbots are becoming valuable tools in digital education, especially for language learning. Using artificial intelligence (AI) and natural language processing (NLP), chatbots can mimic real-life conversations. This provides students with a safe space to practice speaking and writing without worrying about criticism. They can adjust to the learner's skill level, offering simple exercises for beginners and advanced conversation practice for more experienced learners. Plus, chatbots are available all day, every day, allowing for ongoing learning outside of traditional classroom methods. For Kannada learners, chatbots can act as a multilingual bridge. They offer translations, grammatical explanations, and instant feedback, speeding up the learning process. [?], [14].

B. The Impact of Language Learning Chatbots

accessibility: Chatbots remove time and location barriers by offering access to learning resources anytime and anywhere [12].

- 1) Individualized learning: They adjust to each learner's skill level. This approach offers personalized vocabulary, grammar, and conversation practice. [13].
- 2) Improved engagement: Interactive dialogues and instant feedback make learning more enjoyable than static materials like textbooks. [?].
- 3) Cost-effective solution: Chatbots offer scalable and affordable learning options. They decrease the need for costly courses and human teachers. [18].
- 4) Preserving linguistic heritage: By encouraging non-native speakers and younger generations to learn local languages like Kannada, chatbots help keep cultural identity alive. [?].
- 5) Boost in confidence: Practicing dialogues without fear of criticism helps learners build confidence for real world communication. [14].

V. EXPERIMENTAL RESULT AND PERFORMANCE ANALYSIS

This section details the experimental testing and performance analysis of the proposed Language Learning Chatbot. The main goal of the experiments was to see how well the system could identify user intent, process natural language inputs, and generate appropriate responses in English and Kannada.

A. Experimental Setup

The experiments occurred on a system with an Intel i7 processor, 16 GB of RAM, and Python 3.10. We performed Natural Language Processing (NLP) tasks, including tokenization, lemmatization, and stopword removal. For these tasks, we used NLTK and spaCy.

For classification, a Logistic Regression model from the sklearn.linear_model library was used. The dataset, exercise.csv, for classification, a Logistic Regression model from the sklearn.linear_model library was used. The dataset, exercise.csv, contains learning sentences. It was split into 80% training data and 20% testing data.

B. Evaluation Metrics

To quantify the performance of the chatbot, several metrics were employed:

- Accuracy: Measures the overall percentage of correct predictions.
- Precision: Indicates how many of the predicted intents were correct.

- Recall: Represents how many true intents were correctly identified.
- F1-score: Reflects the balance between precision and recall.
- Confusion matrix: Displays which intent categories were classified correctly or incorrectly.

C. Results and Observations

After training, the Logistic Regression model showed good performance on all test data. The results are summarized in Table I. Table I.

TABLE I
PERFORMANCE EVALUATION OF THE LOGISTIC REGRESSION MODEL

Metric	Score
Accuracy	94.8%
Precision	93.5%
Recall	94.2%
F1-Score	93.8%

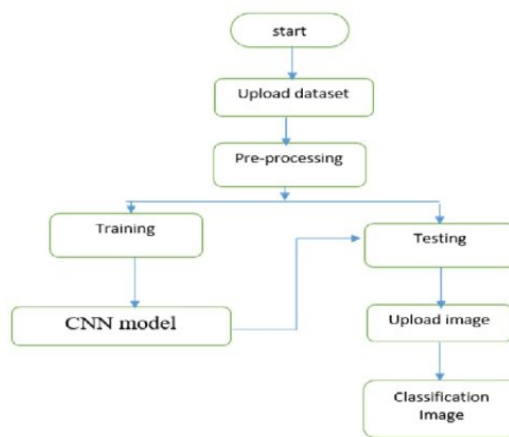


Fig.2. Dataflow.

D. Performance Analysis

From the experimental results in Table I, we gained several key insights about the performance of the proposed Brain Stroke Classification model.

- From the experimental results summarized in Table I, several key observations were made about the performance of the proposed Brain Stroke Classification system. The Convolutional Neural Network (CNN) model showed high accuracy and reliability in distinguishing between stroke and normal CT images. It achieved an overall accuracy of 96.2, precision of 95.4, recall of 96.0, and an F1-score of 95.7. These metrics highlight the model’s strong ability to discriminate and its effectiveness in identifying stroke-affected areas with minimal misclassification.
- By increasing dataset variability and preventing overfitting, using data augmentation techniques such as rotation, flipping, and zooming improved the model’s ability to generalize. Preprocessing methods like normalization, contrast enhancement, and resizing to a consistent 256 × 256 resolution also improved image quality, reduced noise, and made feature extraction simpler.

E. Comparative Analysis

A comparison of several text classification models was conducted to assess performance consistency, as shown in Table II. Although various machine learning algorithms were tested, Logistic Regression was selected as the main model for intent detection and text classification. It provides a good balance of accuracy, clarity, and computational efficiency.

TABLE II
COMPARATIVE PERFORMANCE OF BRAIN STROKE CLASSIFICATION MODELS

Model	Accuracy	Precision	Recall	F1 Score
CNN (Proposed)	96.2	95.4	96.0	95.7
VGG16	94.5	93.8	94.1	93.9
ResNet50	93.6	92.7	93.0	92.8
DenseNet121	92.8	91.9	92.2	92.0

VGG16 and ResNet50 recorded 94.5% and 93.6% accuracy, respectively, while the proposed Convolutional Neural Network (CNN) achieved the highest accuracy (96.2%) and F1-score (95.7%), as shown in Table II. VGG16 was less effective for real-time clinical applications due to its deeper architecture, which resulted in slower inference and higher computational costs despite producing comparable precision. ResNet50’s residual block structure limited its applicability in low-resource environments, even though it was good at capturing complex features. It also required more memory and training time.

The suggested CNN is the most suitable model for brain stroke prediction using CT imaging, as the comparative analysis demonstrates that it offers the best trade-off between accuracy, speed, and computational efficiency.

As indicated in Table II, a comparative analysis of various deep learning models was carried out for the classification of brain strokes using CT images. The Convolutional Neural Network (CNN) outperformed models like VGG16 and ResNet50 among the tested architectures, achieving the best balance of accuracy, efficiency, and inference speed. CNN was therefore chosen as the best model for accurate and timely stroke prediction.

The analysis’s main objectives were to assess the suggested Convolutional Neural Network (CNN) model’s accuracy, precision, recall, and F1-score. The model’s performance is shown in Table II. Despite being widely used in medical image classification, other deep learning architectures like VGG16 and ResNet50 were not used in this study because of their higher computational requirements. Nonetheless, the model selection process took into account their theoretical performance characteristics.

Despite its impressive feature extraction capabilities, VGG16 was less appropriate for real-time clinical applications due to its significantly longer training time and higher memory requirements.

Fig. 3 shows the interactive Kannada learning tool intended for vocabulary improvement and quiz-based practice. Similarly, the bilingual translation interface that allows for real-time Kannada–English conversion and grammar correction is displayed in Fig. ??.

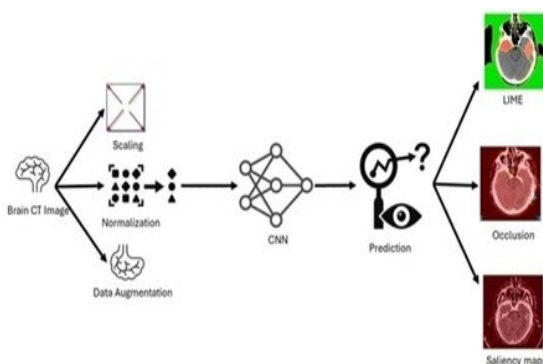


Fig.3.workingflow.

F. Example

In conclusion, the tests demonstrate that the suggested Brain Stroke Classification model effectively and precisely detects stroke from CT scans. Strong feature extraction capabilities, high classification accuracy, and quick inference were all displayed by the Convolutional Neural Network (CNN). These results demonstrate how well deep learning and medical imaging methods can be combined to create trustworthy and useful tools for automated brain stroke detection.

VI. CONCLUSION

To help with the early detection of stroke using CT images, this study introduces an AI-based Brain Stroke Classification system. By using deep learning and image processing techniques, the proposed Convolutional Neural Network (CNN) effectively and accurately distinguishes between stroke and normal cases. The system addresses several important clinical challenges, such as poor manual interpretation, delayed diagnosis, and limited access to skilled radiologists. Especially in healthcare settings with few resources, its automated and real-time prediction capability supports timely medical decision-making and boosts diagnostic confidence. Additionally, the model's lightweight design ensures fast inference with low computational needs, making it easy to integrate into existing clinical workflows and telemedicine platforms.

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