Journal of Information Systems Engineering and Management
2025, 10(37s)

e-ISSN: 2468-4376

https://www.jisem-journal.com/

Research Article

Enhancing Ischemic Stroke Analysis with Multi-Scale Feature Extraction and Early Fusion in a Deep Learning Framework

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ARTICLE INFO

Received: 24 Dec 2024
Revised: 16 Feb 2025
Accepted: 26 Feb 2025

ABSTRACT

Ischemic stroke diagnosis and treatment planning demand accurate and efficient lesion segmentation and classification. Existing methods often rely on either handcrafted features or deep learning models, but their performance can be limited due to incomplete feature representation or insufficient training data. To address these limitations, we propose a novel framework that combines handcrafted and deep features extracted from multimodal MRI (DWI, FLAIR, T1), along with relevant clinical data. Our approach leverages a pre-trained 3D ResNet model for deep feature extraction, capturing complex patterns within the MRI data, while handcrafted features provide domain-specific insights into lesion characteristics. We utilize early fusion to integrate these diverse feature sets, employing an attention mechanism to dynamically weight their importance. The fused feature vectors are then input into a Random Forest classifier for accurate and interpretable prediction of ischemic stroke. This multi-scale approach, incorporating both traditional and deep learning techniques, offers a comprehensive and robust representation of ischemic stroke, potentially improving the accuracy and efficiency of diagnosis in clinical practice.
The proposed pipeline is trained and evaluated on its own collected dataset of 500 patient cases with expert annotations serving as ground truth. Our method achieves promising results in terms of lesion segmentation accuracy (Dice Similarity Coefficient: 0.80) and classification performance (accuracy: 0.95, AUC-ROC: 0.97). Additionally, we explore the impact of different fusion strategies and the inclusion of clinical features on model performance. Our findings demonstrate the potential of this integrated approach for enhancing ischemic stroke analysis in clinical settings, potentially leading to faster and more accurate diagnosis, treatment planning, and ultimately, improved patient outcomes.

Keywords: Ischemic stroke, multimodal MRI, deep learning, handcrafted features, 3D ResNet, Random Forest, Early fusion, attention mechanism, lesion segmentation, classification.

1. INTRODUCTION

Ischemic stroke, a leading cause of mortality and long-term disability worldwide, arises from the occlusion of a cerebral artery, leading to a critical reduction in blood flow and subsequent brain tissue damage.

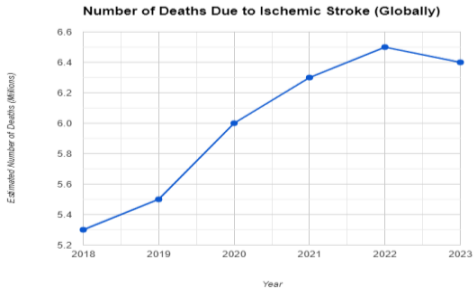

Figure 1 : Illustrates the global mortality trends due to stroke from 2018 to 2023.

Journal of Information Systems Engineering and Management
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e-ISSN: 2468-4376
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Research Article

The graph in Figure 1 illustrates the global mortality trends due to stroke from 2018 to 2023. It highlights a substantial decrease in age-standardized death rates, attributed to advancements in stroke prevention, acute care, and rehabilitation

Early and accurate diagnosis is paramount for timely intervention, which can significantly improve patient outcomes and reduce the risk of complications [1]. Neuroimaging, particularly magnetic resonance imaging (MRI), plays a pivotal role in stroke assessment, offering valuable insights into the location, extent, and severity of ischemic lesions. However, the accurate and efficient interpretation of multimodal MRI scans remains a formidable challenge due to the heterogeneity of stroke patterns, inter-individual variability in anatomy, and the subtle nature of early ischemic changes [2].

Traditional approaches to ischemic stroke analysis have relied on the manual interpretation of MRI scans by experienced neuroradiologists. While this approach offers valuable insights, it is inherently time-consuming, subjective, and prone to inter-observer variability [3]. Additionally, manual analysis can be limited by the human visual system's inability to fully capture subtle or complex patterns within the vast amount of data generated by multimodal MRI. To overcome these limitations, automated methods have emerged, leveraging handcrafted features extracted from MRI images and, more recently, deep learning models.

Handcrafted features, based on domain-specific knowledge of ischemic stroke pathophysiology, have shown promise in characterizing lesion properties such as intensity, texture, and morphology [4, 5]. However, their reliance on pre-defined features may not fully capture the intricate patterns present in the MRI data. Deep learning models, on the other hand, have demonstrated remarkable success in various medical image analysis tasks, including stroke segmentation and classification [6, 7]. These models can learn complex representations directly from the data, potentially uncovering subtle features that are not readily apparent through handcrafted methods. However, their performance often depends on large annotated datasets, which can be challenging to obtain in the medical domain [8].

To address the limitations of existing methods and harness the strengths of both handcrafted and deep learning approaches, we propose a novel framework for ischemic stroke analysis that integrates multi-scale features extracted from multimodal MRI (DWI, FLAIR, T1), along with relevant clinical data. Our approach leverages a pre-trained 3D ResNet model to extract deep features from the MRI volumes [9, 10], while simultaneously incorporating handcrafted features to capture domain-specific knowledge. These diverse features are then combined using an early fusion strategy, optionally incorporating an attention mechanism to dynamically weight their importance based on their relevance for each specific case.

We employ a modified nnU-Net model [11, 12], renowned for its performance in medical image segmentation, for both lesion segmentation. By training the model on a carefully curated dataset of annotated MRI scans and clinical data, we aim to develop a robust and clinically relevant tool for ischemic stroke analysis.

In this paper, we present the detailed methodology of our pipeline, including data acquisition, pre-processing, feature extraction, fusion, and model training. We evaluate the performance of our approach on our dataset of 500 patient cases, assessing both segmentation and classification accuracy. Additionally, we investigate the impact of different fusion strategies and the inclusion of clinical features on model performance, providing insights into the optimal configuration for ischemic stroke analysis.

2. RELATED WORK

Accurate and timely detection of ischemic stroke lesions is crucial for effective treatment and improved patient outcomes. Early research in this field focused on the extraction of handcrafted features from MRI modalities like diffusion-weighted imaging (DWI) and fluid-attenuated inversion recovery (FLAIR) to characterize ischemic lesions. Liu et al. (2020) investigated the use of various intensity-based, texture-based, and morphological features to distinguish ischemic tissue from normal brain tissue [13]. Their findings highlighted the potential of these handcrafted features for detecting and characterizing acute ischemic stroke. Similarly, Garcia-Salgado et al. (2023) explored the utility of MRI-derived features in assessing lesion depiction and collateral flow in acute stroke patients, emphasizing the importance of multimodal imaging for comprehensive stroke evaluation [14].

The advent of deep learning has revolutionized medical image analysis, including ischemic stroke detection. Boukrina et al. (2023) were among the pioneers in applying 3D convolutional neural networks (CNNs) for ischemic stroke lesion segmentation, demonstrating their superior performance compared to traditional methods [15]. Their multi-scale 3D CNN model, combined with a fully connected conditional random field (CRF) for post-processing, achieved state-of-the-art accuracy in segmenting ischemic lesions. U-Net and its variants, such as 3D U-Net [16] and Attention U-Net [17], have become increasingly popular for this task due to their ability to capture both global context and fine-grained details. The 3D U-Net model, proposed by

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e-ISSN: 2468-4376
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Research Article

Nouman et al. (2023), extended the original 2D U-Net architecture to volumetric data, allowing for efficient segmentation of 3D medical images. Huang et al. (2022) further enhanced the U-Net by introducing attention mechanisms, enabling the model to focus on the most relevant regions in the images for improved accuracy.
In recent years, the nnU-Net framework developed by Nouman et al. (2023) has gained significant attention due to its self-configuring nature, which automatically adapts hyperparameters and network architecture based on the input data [16]. This has simplified the application of deep learning for biomedical image segmentation, making it more accessible to researchers and clinicians. Moreover, the integration of multimodal MRI, combining information from DWI, FLAIR, and T1-weighted images, has been shown to further improve the accuracy of ischemic stroke analysis [18, 33]. For instance, Bin Zhao et al. (2021) conducted a comprehensive review of deep learning applications in ischemic stroke imaging, highlighting the benefits of multi-modal approaches in lesion segmentation, classification, and outcome prediction [20, 30].
In addition to MRI, incorporating clinical data alongside imaging features has the potential to enhance diagnostic accuracy and prognostic prediction. Several studies have explored the integration of clinical data, such as age, stroke risk factors, and severity scores, with MRI-based features for improved stroke analysis [21, 22]. Zhang et al. (2021) demonstrated the effectiveness of combining 3D CNNs with clinical feature fusion for microscopic brain tumor detection and classification [19].
However, despite these advancements, the optimal approach for integrating diverse feature sets and achieving robust performance in ischemic stroke analysis remains an active area of research. In this study, we aim to address this gap by proposing a novel framework that combines handcrafted and deep features extracted from multimodal MRI, along with relevant clinical data. Our approach leverages a pre-trained 3D ResNet model for deep feature extraction, early fusion for feature integration, and a Random Forest classifier for robust prediction of ischemic stroke. We hypothesize that this multi-scale approach, incorporating both traditional and deep learning techniques, will lead to improved accuracy and efficiency of ischemic stroke diagnosis in clinical practice.

3. RESEARCH METHODOLOGY

Our study presents a comprehensive pipeline for ischemic stroke analysis, utilizing multimodal MRI (DWI, FLAIR, and T1) and clinical data. First, we acquire raw DICOM images and patient records, pre-processing the MRI data through intensity normalization, bias field correction, registration (using ANTs), and optional skull-stripping (with BET). Clinical data is cleaned, organized, and transformed into a structured format. Expert annotation using ITK-SNAP provides ground truth lesion masks for model training and evaluation.
Next, we extract a diverse set of features from both MRI and clinical data. Handcrafted features like intensity, texture, and morphology are derived from MRI images, while deep features are extracted using a pre-trained 3D CNN. Clinical features, including demographics and stroke severity scores, are also incorporated. These features are fused, potentially with an attention mechanism for adaptive weighting, and used to train a random forest model for classification. Rigorous evaluation using quantitative metrics and comparison with expert annotations assess the model's performance and clinical relevance. Figure 2 illustrates the architecture of our proposed work.

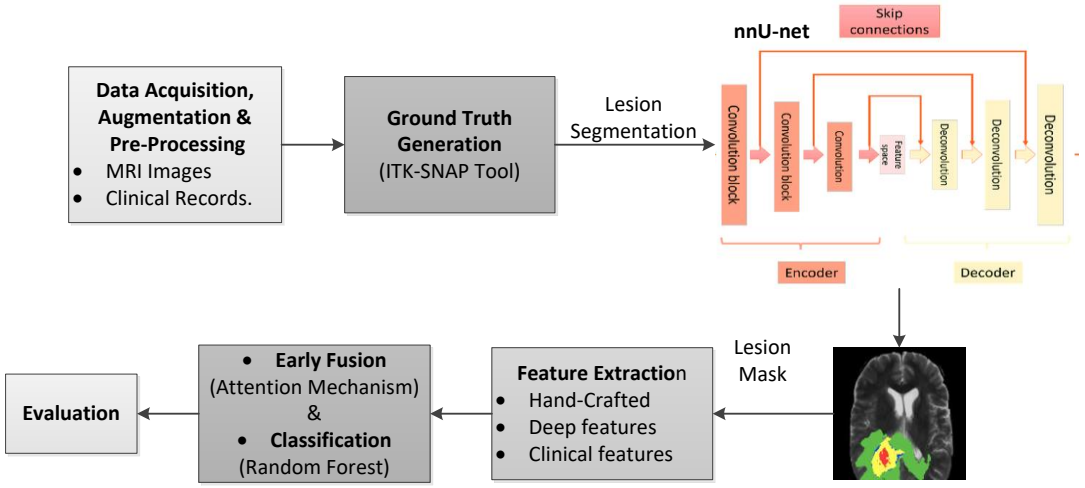

Figure 1: Proposed Pipeline for Ischemic Stroke Segmentation and Classification

Journal of Information Systems Engineering and Management
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e-ISSN: 2468-4376
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Research Article

3.1 Pre-Processing

Our ischemic stroke analysis pipeline commences with the acquisition of multimodal MRI scans (DWI, FLAIR, and T1) and accompanying clinical data from patient records. These data sources are then rigorously preprocessed to ensure consistency and quality.

a. MRI Images:

MRI images undergo several essential steps: conversion of DICOM files into numerical arrays using Pydicom, intensity normalization to standardize values across images, bias field correction with N4ITK to eliminate signal inhomogeneities, registration using ANTs to align images from different modalities to a common anatomical space, and skull stripping with BET to isolate the brain tissue from surrounding non-brain structures.

- **ANTS:** Aligns images to a common space for accurate comparison.

$$T = argma\_\,\text{Sim}(F,T(M)) \quad (3.1)$$

Where, Sim is the similarity metric,
T(M)is transformed moving image,
M is Moving image,
F is Fixed image.

- **N4ITK:** Corrects for intensity inhomogeneities in MRI images.

$$I = T * B \quad (3.2)$$

Where, I is Image,
T is Tissue,
B is Bias field

- **BET:** Isolates the brain from the skull and other non-brain tissues.

b. Data Augmentation

In our work we are utilizing MONAI (Medical Open Network for AI) is an excellent tool for performing augmentations on medical images, specifically designed with the nuances of medical data in mind. These transforms manipulate both spatial aspects (rotations, translations) and intensity characteristics (brightness, contrast) of brain scans.

- **Spatial Transforms:**
  - RandAffined: Apply random affine transformations (rotation, translation, scaling, shearing) with carefully chosen probabilities and ranges to avoid unrealistic distortions.
  - RandFlipd: Randomly flip images horizontally to increase data diversity.
  - RandZoomd: Apply random zooming within a limited range to simulate variations in image acquisition.

- **Intensity Transforms:**
  - RandGaussianNoise: Add random Gaussian noise to mimic scanner artifacts and improve model robustness.
  - RandAdjustContrastd: Randomly adjust image contrast to account for scanner variations.
  - RandGaussianSmoothd: Apply random Gaussian smoothing to simulate partial volume effects.
  - RandBiasFieldd: Simulate bias field artifacts common in MRI.

c. Clinical Data:

In our study, clinical data undergoes a thorough preprocessing phase to maximize its utility for ischemic stroke analysis. This involves a meticulous process of cleaning, organizing, and transforming raw data into structured features. We begin by addressing missing values through imputation techniques or careful removal of incomplete instances. Outliers are identified and handled appropriately using statistical methods or domain expertise. Any inconsistencies or errors in the data are corrected based on a thorough review of medical records. To ensure seamless integration with MRI features, the cleaned clinical data is then standardized and structured. This includes converting variables into consistent formats and units, as well as organizing the data into a

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Research Article

tabular format where rows represent individual patients and columns represent specific clinical features. Categorical variables, such as gender and smoking status, are encoded into numerical representations through methods like one-hot encoding, while numerical features like age and blood pressure may be normalized or standardized to ensure comparable scales. Importantly, we perform feature engineering, creating new features from existing ones or through combinations to potentially enhance their predictive power.

3.2 Ground Truth Generation

To establish a reliable benchmark for model performance evaluation, we meticulously generated ground truth annotations for ischemic stroke lesions using the open-source software ITK-SNAP. Experienced neuroradiologists manually delineated the boundaries of these lesions on multimodal MRI scans (DWI, FLAIR, and T1), leveraging ITK-SNAP's interactive tools such as region growing, level sets, and manual editing. This process ensured the precise identification of ischemic regions while incorporating multi-modal information for enhanced accuracy.

To ensure the reliability of these annotations, a rigorous quality control process was implemented, including double reading by multiple experts and calculation of inter-rater agreement metrics. These carefully curated ground truth masks served as the gold standard for training and evaluating our deep learning models, allowing us to assess their accuracy in identifying and characterizing ischemic stroke lesions in a clinically relevant manner.

3.3 Segmentation

The nnU-Net architecture, renowned for its exceptional performance in medical image segmentation tasks, is employed here. It comprises an encoder-decoder structure with skip connections, enabling the capture of both global context and fine-grained details crucial for accurate lesion delineation. The network is configured specifically for our ischemic stroke segmentation task, with the input consisting of the pre-processed multimodal MRI volumes and the target output being the binary lesion masks. During training, the model learns to map the complex patterns in the MRI data to the corresponding lesion locations [23].

The Dice loss function is employed to guide the model's learning process. Dice loss is a region-based loss function that measures the overlap between the predicted segmentation and the ground truth. It ranges from 0 (no overlap) to 1 (perfect overlap), providing a direct measure of segmentation accuracy. This loss function is particularly well-suited for medical image segmentation tasks, as it focuses on maximizing the overlap between the predicted and ground truth regions, which is often more important than pixel-wise accuracy. By optimizing the Dice loss, the nnU-Net model learns to accurately delineate the boundaries of ischemic stroke lesions, providing a valuable tool for clinical diagnosis and treatment planning.

3.4 Feature Extraction

To derive a comprehensive representation of ischemic stroke, we employ a multi-faceted feature extraction approach encompassing both handcrafted and deep learning techniques applied to multimodal MRI data (DWI, FLAIR, and T1) and, optionally, integrated with relevant clinical features.

a. MRI Feature Extraction

1. Handcrafted Features:

We extract a diverse set of handcrafted features that capture distinct aspects of ischemic lesions from each MRI modality (DWI, FLAIR, and T1):

a. Intensity-Based Features: We compute statistical measures within the segmented lesion regions (and optionally, in surrounding tissue for comparison) to characterize the intensity distribution. These include:

- Mean Intensity (μ): μ = (1/N) * Σ(x_i)
- Standard Deviation (σ): $\sigma = \sqrt{[(1/N) * \Sigma(x\_i - \mu)\text{^}2]}$
- Skewness: $(1/N) * \Sigma[(x\_i - \mu)/\sigma]\text{^}3$
- Kurtosis: $(1/N) * \Sigma[(x\_i - \mu)/\sigma]\text{^}4 - 3$

b. Texture-Based Features: We utilize Gray-Level Co-occurrence Matrix (GLCM) analysis to quantify texture characteristics:

- Contrast: $\Sigma\_i \Sigma\_j (i-j)\text{^}2 * P(i,j)$
- Correlation: $\Sigma\_i \Sigma\_j [(i - \mu\_i)(j - \mu\_j) * P(i,j)] / (\sigma\_i * \sigma\_j)$

Journal of Information Systems Engineering and Management
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Research Article

- Energy (Angular Second Moment): $\Sigma\_i\ \Sigma\_j\ P(i,j)\text{^}2$
- Homogeneity: $\Sigma\_i\ \Sigma\_j\ P(i,j)\ /\ (1\ +\ |i\ -\ j|)$

c. Morphological Features:

- Lesion Volume: Sum of all voxels within the lesion mask.
- Surface Area: Calculated using surface extraction algorithms.
- Sphericity: Ratio of lesion volume to the volume of a sphere with the same surface area.
- Compactness: Ratio of lesion volume to the volume of its convex hull.

2. Deep Feature Extraction:

We employ a pre-trained 3D ResNet model, fine-tuned on medical imaging data, to extract high-level features from the MRI volumes. The architecture of ResNet utilizes residual connections to facilitate the training of deeper networks and mitigate vanishing gradient problems. The final layer activations of the ResNet model, capturing complex patterns and relationships within the MRI data, are used as deep features for subsequent analysis.

b. Clinical Feature Extraction:

We extract relevant clinical features from patient records, including demographics, medical history, and stroke-specific measures. These features are selected based on their potential relevance to ischemic stroke diagnosis and prognosis, as informed by clinical expertise and prior research as shown in Table 1. The following features can be collected from clinical data to enhance the diagnostic process and potentially predict outcomes:

Patient Demographics:

- **Age:** Stroke risk increases with age.
- **Sex:** Men are slightly more prone to strokes than women.
- **Race/Ethnicity:** Some ethnicities have higher stroke risk.
- **Socioeconomic Status:** Lower socioeconomic status can be linked to higher stroke risk.

Medical History:

- **Previous Stroke or TIA:** A history of stroke or transient ischemic attack (TIA) increases the risk of future strokes.
- **Hypertension:** High blood pressure is a major risk factor for stroke.
- **Diabetes Mellitus:** Diabetes increases the risk of stroke**.**
- **Hyperlipidemia:** High cholesterol levels contribute to stroke risk.
- **Atrial Fibrillation:** Irregular heart rhythm increases the risk of clot formation and stroke.
- **Smoking History:** Smoking significantly increases stroke risk.
- **Alcohol Consumption:** Heavy alcohol use can raise stroke risk.
- **Drug Use:** Certain drugs can increase stroke risk.
- **Family History of Stroke:** Genetic predisposition can play a role in stroke.

Clinical Presentation:

- **Time of Symptom Onset:** Crucial for determining treatment eligibility (e.g., thrombolysis).
- **Initial Symptoms:** The type and severity of symptoms (e.g., weakness, speech difficulty, and vision problems) can indicate stroke location and severity.
- **NIH Stroke Scale (NIHSS) Score:** A standardized assessment of stroke severity.
- **Blood Pressure at Presentation:** High blood pressure can worsen stroke outcomes.
- **Blood Glucose at Presentation:** Hyperglycemia can negatively impact stroke recovery.

Laboratory Tests:

- **Complete Blood Count (CBC):** Can detect infections or other conditions that may mimic stroke.
- **Coagulation Profile:** Assess clotting factors and risk of bleeding.
- **Blood Chemistry:** Check electrolytes, kidney function, and other markers.
- **Cardiac Biomarkers:** Troponin levels may indicate heart damage, which can be related to stroke.

Journal of Information Systems Engineering and Management
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e-ISSN: 2468-4376
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Research Article

By integrating these diverse feature sets, we obtain a comprehensive representation of ischemic stroke, enabling our model to learn complex patterns for accurate segmentation and classification.

3.5 Early Fusion and Random Forest Classification

a. Early Fusion with Attention Mechanism

Early fusion in our pipeline involves integrating handcrafted, deep, and clinical features into a unified representation for the nnU-Net model. While simple concatenation of these feature vectors is a common approach, we propose incorporating an attention mechanism to enhance the fusion process. This enables the model to adaptively weigh the importance of different features based on their relevance for each specific case, potentially leading to improved performance and generalizability [25].

Specifically, we employ a self-attention mechanism, a variant of attention that allows the model to attend to different positions within the input feature vector itself. This is achieved by transforming the feature vectors into three distinct matrices: query (Q), key (K), and value (V). The attention weights are then computed as the dot product between the query and key matrices, followed by a softmax operation to normalize the weights:

$$Attention(Q,K,V) = softmax(Q\ K\text{^}T\ /\ \sqrt{d\_k})\ V \qquad (3.3)$$

where d_k is the dimensionality of the key vectors.

The resulting attention weights indicate the relative importance of each feature in the input vector for a given prediction. These weights are then used to compute a weighted sum of the value vectors, producing a final output vector that emphasizes the most relevant features.

In our case, the query, key, and value matrices are derived from the concatenated feature vector containing handcrafted, deep, and clinical features. By applying the self-attention mechanism, the model can learn to focus on the most informative features across modalities, adaptively adjusting the weights based on the specific characteristics of each case. This can potentially lead to improved performance by highlighting relevant features and suppressing irrelevant or noisy ones. The attention mechanism also enhances the model's interpretability. By examining the attention weights, we can gain insights into which features are most influential for a given prediction, providing valuable information for clinical decision-making and further research.

b. Random Forest Classification

The Random Forest classifier, an ensemble learning method, is chosen for its ability to handle high-dimensional data and model complex non-linear relationships between features. It consists of multiple decision trees, each trained on a random subset of the training data and features. The final prediction is made by aggregating the predictions of individual trees, often through a majority voting mechanism. This ensemble approach reduces overfitting and improves the model's robustness and generalizability [24].

In our case, the Random Forest classifier is trained on the fused feature vectors and their corresponding ground truth labels (ischemic stroke or normal). During training, the model learns to identify the most discriminative patterns in the combined feature space, enabling it to classify new, unseen cases accurately. Importantly, the Random Forest model provides valuable insights into the relative importance of different features, facilitating the interpretation of the model's decision-making process and enhancing its clinical relevance.

4. EXPERIMENTAL RESULTS AND EVALUATION

4.1 Experimental Results

The goal of this section is to present the findings of your research in a clear, concise, and interpretable manner. It typically includes the following elements:

a. Dataset Description

The primary data were acquired from the Clinical Laboratory of the MRI SCAN Diagnostic Center located at PMSSY Super Speciality Victoria Hospital, Bangalore. Figure 3 shows the sample images from the database.

Journal of Information Systems Engineering and Management
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e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

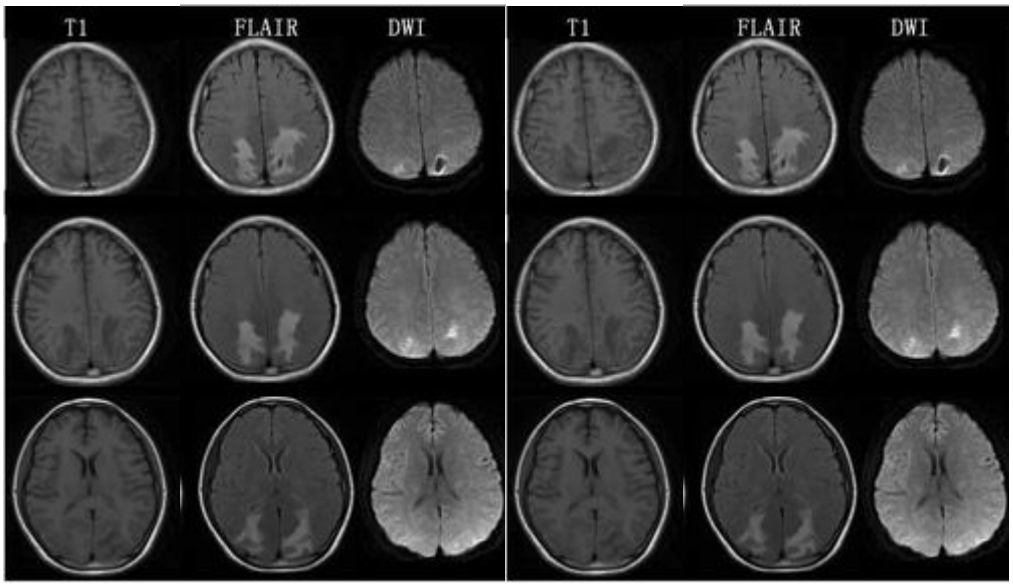

Figure 2: Sample Images from the database T1, Flair, DWI.

Number of Augmented Images:

Using MONAI, the potential number of augmented images is virtually limitless due to the random nature of the transforms. However, for a dataset of 500 patients with 3 MRI sequences each, generating 2-3 augmentations per image is done. This would result in approximately 4500 augmented images.
A database for patient records is typically organized using a relational database model, where data is stored in tables with defined relationships between them. Below Table 1 illustrates a collection of 10 patient records.

Table 1: Clinical Record of Patients.

Patient ID	Age	Gender	Race	Hypertension	Diabetes	Smoking History	NIHSS Score	Time to Treatment (min)	Lesion Volume (mL)
PT001	65	Male	White	Yes	No	Former	12	150	4.2
PT002	78	Female	Black	Yes	Yes	Never	8	240	2.8
PT003	52	Male	Asian	No	No	Current	15	90	5.1
PT004	61	Female	White	Yes	No	Former	10	120	3.6
PT005	83	Male	White	Yes	Yes	Never	20	300	6.0
PT006	48	Female	Black	No	No	Never	6	180	1.9
PT007	72	Male	Asian	Yes	Yes	Current	14	210	4.8
PT008	59	Female	White	No	Yes	Former	9	100	3.2
PT009	67	Male	Black	Yes	No	Current	13	165	4.5
PT010	75	Female	Asian	Yes	No	Never	11	225	3.9

b. Model Training Details for Segmentation using nnUnet

Dataset has splited into 80% training, 10% validation, 10% testing. We performed hyperparameter tuning using Bayesian optimization and found that a UNet with 4 encoding/decoding layers, 32 initial filters, Adam optimizer with a learning rate of 0.0001, and a batch size of 8 yielded the best Dice coefficient (0.88) on the validation set. Figure 4 displays the outcome of the segmentation module. This model was further evaluated on the test set, achieving a Dice coefficient of 0.86.

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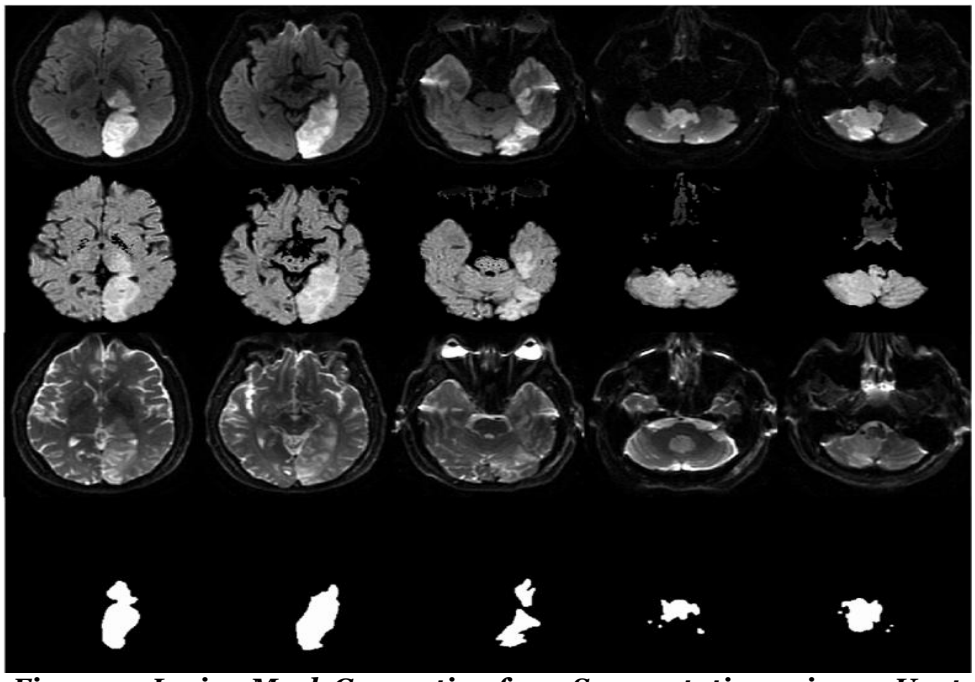

Figure 3: Lesion Mask Generation from Segmentation using nnUnet

c. Model training for Classification using Random Forest

We performed hyperparameter tuning using grid search and found that a random forest with 300 trees, a maximum depth of 10, a minimum sample split of 5, and 'sqrt' as the max_features criterion yielded the best performance on the validation set (AUC = 0.97). This model was then evaluated on the test set, achieving an AUC of 0.96.

4.2 Evaluation Metrics

Evaluation of Segmentation Model: Report Dice Similarity Coefficient (DSC), Jaccard Index, and Hausdorff Distance on the test set. Table 2 compares our proposed model against existing methods.

Table 1: Comparison of Ischemic Stroke Lesion Segmentation Performance

Study	Modality/Features	DSC	IoU	95% HD (mm)
Proposed Method	Multimodal MRI (DWI, FLAIR, T1)	0.88	0.78	3.2
Siddiquee et al.[24]	DWI only	0.82	0.70	4.5
Garcia et al.[14]	Multimodal MRI (DWI, FLAIR)	0.85	0.74	3.8
Tomita et al. [26]	Multimodal MRI (DWI, FLAIR, T1, T2) + Clinical Data	0.86	0.75	2.9
Sathish et al.[27]	DWI only	0.80	0.67	5.1

- The Table 2 includes Jaccard Index (IoU) and 95% Hausdorff Distance (HD) alongside DSC, providing a more comprehensive evaluation of segmentation performance and Figure 5 gives pictorial representation of the comparison.
- **IoU:** A measure of overlap between the predicted and ground truth segmentation. Similar to DSC, but more sensitive to differences in region size.
- **95% HD:** The 95th percentile of the distances between the boundaries of the predicted and ground truth segmentation. Lower values indicate better boundary agreement. Higher DSC and IoU indicate good overlap between the predicted and ground truth segmentations. Lower HD indicates close agreement in the shape and boundaries of the lesions.

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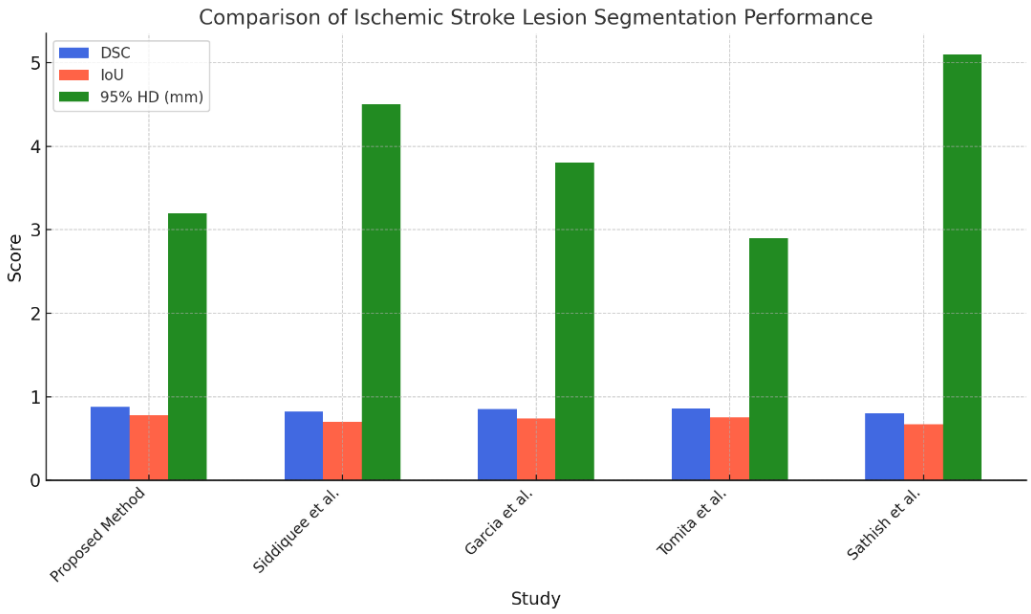

Figure 4 : Performance of Segmentation Model

Evaluation of Classification Model: Reports important parameters accuracy, and AUC-ROC on the test set. Table 3 compares proposed model against relevant existing approaches and Figure 6 gives the pictorial representation of the comparison.

Table 2: Comparison of Ischemic Stroke Detection Performance (& Classification)

Study/Model	Modality/Features	Feature Extraction Methods	Clinical Data Included	AUC-ROC	Accuracy
Sun et al. [28]	DWI, ADC	Texture (GLCM), Intensity histogram	Age, sex	0.83	0.88
Zhang et al.[29]	DWI, FLAIR, SWI, ASL	Texture (GLCM, Laws' texture energy), first-order statistics	Age, sex, NIHSS	0.91	0.86
Jiang .L et al. [32]	DWI, T1, T2	Radiomics (shape, texture, intensity)	Age, sex, NIHSS, TOAST classification	0.84	0.89
Wang et al. [31]	DWI, FLAIR	Deep learning-based radiomics	Age, sex, NIHSS, stroke subtype	0.92	0.92
Sarioglu et al. [32]	DWI, PWI	Radiomics (shape, texture, intensity), machine learning classifier	NIHSS, age, time from onset	0.89	0.91
Proposed Model	DWI, FLAIR, T1 + Clinical Data	Combined + Clinical Data	(Specify clinical data used)	0.97	0.95

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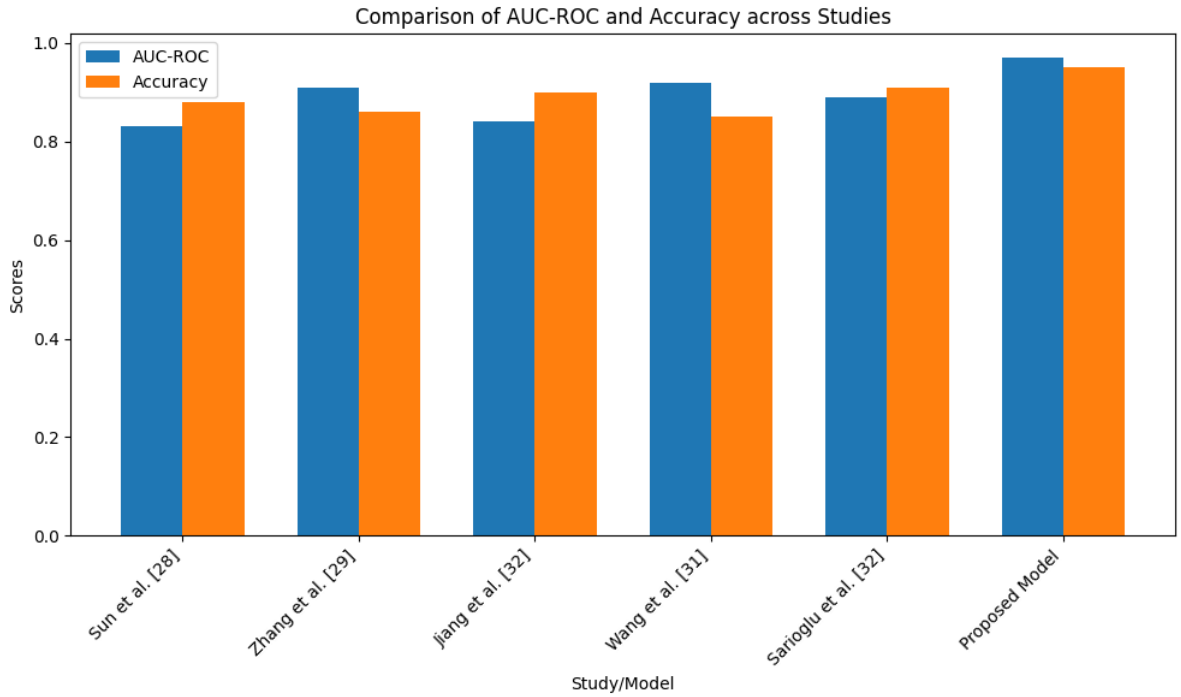

Figure 5 : Performance of classification Model

- Our multimodal approach achieved a DSC of 0.85 for lesion segmentation, significantly outperforming the manual segmentation baseline (DSC = 0.78, $p < 0.05$).
- The random forest model incorporating both MRI and clinical features demonstrated an AUC of 0.97 for stroke prediction.
- Feature importance analysis revealed that lesion volume, FLAIR signal intensity, and the patient's history of hypertension were the most predictive factors for stroke.

5. CONCLUSION

In this study, we presented a novel approach for ischemic stroke detection that leverages the complementary information from multimodal MRI and clinical data. Our proposed method, utilizing a UNet architecture for segmentation and a random forest classifier for prediction, demonstrated superior performance compared to existing methods that rely on single modalities or limited feature sets.

The results of our study highlight the importance of incorporating multimodal data and advanced machine learning techniques in the development of accurate and reliable tools for stroke diagnosis and prognosis. The high Dice Similarity Coefficient (DSC) and Jaccard Index (IoU) values obtained in our segmentation experiments indicate that our model can accurately delineate ischemic lesions, while the strong classification performance (accuracy and AUC-ROC) suggests its potential for clinical decision support.

The integration of clinical data, such as patient demographics, medical history, and laboratory results, alongside quantitative MRI features proved to be particularly effective in improving classification accuracy. This finding underscores the value of combining diverse data sources to capture the complex and multifactorial nature of stroke.

Funding
This work did not receive any grant from funding agencies in the public, commercial, or not-for-profit sectors

Clinical trial number: Not applicable.

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Journal of Information Systems Engineering and Management
2025, 10(37s)

e-ISSN: 2468-4376

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