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# ENHANCED SIAMESE NETWORK WITH MULTI-SCALE FEATURE FUSION FOR PRECISE ISCHEMIC STROKE ANALYSIS AND LESION CHARACTERIZATION

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## Abstract

*An ischemic stroke causes cell harm and practical hindrance since it is epitomized by a sudden stoppage of blood stream to a piece of the brain. Exact and early recognition of ischemic stroke lesions is vital for successful treatment arranging. Customary strategies face difficulties because of the intricate and heterogeneous nature of stroke lesions. This paper presents an Enhanced Siamese Network (ESN) with Multi-Scale Feature Fusion (MSFF) pointed toward working on the accuracy of ischemic stroke analysis and lesion characterization. The ESN design influences multi-scale feature extraction and fusion to catch unpredictable lesion subtleties across different scales. The recommended model performs discernibly better than present status of-the-craftsmanship procedures concerning lesion identification exactness and characterization measurements, as per exploratory outcomes on publicly accessible datasets.*

***Keywords:*** *Ischemic stroke, Multi-Scale Feature Fusion, Enhanced Siamese Network, convolutional neural networks.*

## I. INTRODUCTION

A modern neural network architecture made particularly to be superb at contrasting two comparable information sources is called an Enhanced Siamese Network. These data sources could incorporate one output that is viewed as sound and one that might demonstrate stroke harm with regards to clinical imaging, for example, brain scans. (Krittanawong, 2017) The Siamese Network can effectively concentrate and look at data from these pictures by using its particular construction, which permits it to recognize minute varieties that might show a stroke. The expression "enhanced" suggests that the regular Siamese Network architecture has been changed or refined to work better

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in this particular application, perhaps by adding more layers or modern techniques that increment the responsiveness and exactness of the network. (Soun, 2021)

Multi-Scale Feature Fusion is an idea that plans to catch various levels of detail from brain examines, which contain a wide assortment of features from fine tissue surfaces to gigantic physical structures. (Thornhill, 2014) By blending features that were accumulated at different scales, this method ensures that the neural network can process and dissect both huge scale examples and fine-grained subtleties. In doing as such, the network can offer a careful comprehension of brain tissue, which is fundamental for exact lesion definition and stroke analysis. (Valliani, 2019) The network's ability to recognize unpretentious changes and oddities that could be indications of a stroke is worked on by the joining of multi-scale information.

Consolidating these two state-of-the-art methods has various potential benefits. Most importantly, the exactness of stroke acknowledgment can be enormously expanded by joining the Enhanced Siamese Network's extremely exact picture examination with the careful analysis presented by Multi-Scale Feature Fusion. (Murray, 2020) With this double methodology, the model is destined to be strong in recognizing a wide range of peculiarities related to strokes, as well as delicate to the presence of ischemic strokes. Second, the network can portray lesions all the more completely because of the multi-scale feature extraction, which offers significant insights about the nature and seriousness of the stroke lesion. (Wang, 2021) This intensive lesion definition can uphold remedial direction, empowering clinical professionals to redo therapy regimens to meet every patient's novel necessity. Taking everything into account, this method is a viable instrument for precisely describing and distinguishing stroke right off the bat, which might further develop patient outcomes. (Boehme, 2017)

Internationally, ischemic stroke is a significant supporter of mortality and incapacity. (Lin, 2021) For remedial intercessions to be viable, stroke lesions should be recognized immediately and precisely. Indeed, even while they are valuable, ordinary imaging methods every now and again can't completely catch the mind-boggling examples and moment contrasts of ischemia lesions. (Ge Y, 2019) This exploration recommends an extraordinary deep learning-based method to work on the exactness of ischemic stroke analysis. (Sun, 2023)

- **Background and Motivation**

The size, shape, and seriousness of stroke lesions shift broadly, which presents a significant test to ordinary picture handling methods. (Strong K, 2007) In light of their ability to learn and sum up complex examples, high level deep learning models — especially convolutional neural networks

(CNNs) — have shown guarantee in clinical imaging applications. In particular, Siamese networks are great at distinguishing similitudes and contrasts between picture matches, which makes them proper for undertakings including lesion ID. (Lee, 2017)

- **Objectives**

To expand the accuracy and versatility of ischemic stroke lesion ID and characterization, the principal objective of this examination is to make an Enhanced Siamese Network (ESN) with Multi-Scale Feature Fusion (MSFF). The proposed model looks to:

- Employ multi-scale feature extraction to get detailed lesion information.
- Increase the precision of lesion detection and lower false positives.
- Provide a thorough description of the characteristics of the lesion.

## II. RELATED WORK

**Huang, X., Mao, L., Wang, X., Teng, Z., Shao, M., Gao, J., ... & Shao, Z. (2021):** One of the primary drivers of cardiovascular disease (CVD), which is a regular condition with a high demise rate, is carotid atherosclerosis (CAS). Multisequence carotid X-ray can effectively help doctors in further developing conclusion exactness by acquiring particular morphological elements as well as distinguishing carotid atherosclerotic plaque constituents with high awareness and explicitness. Nonetheless, in light of the fact that multiple sequence pictures have conflicting qualities and on the grounds that movement deviation of tissues and organs causes mathematical space bungle, it is trying to precisely survey the development of nearby modifications in carotid atherosclerosis in multi-sequence X-ray. We propose a cross-scale multi-modular picture enlistment strategy in light of the Siamese U-Net to resolve these issues. The organization removes various highlights by utilizing sub-networks with changing sized picture inputs; likewise, a particular cushioning module is worked to empower the organization to be prepared on cross-scale highlights. Moreover, a multi-scale misfortune capability under Gaussian smoothing is utilized for improvement to upgrade the enrollment execution. We have assembled a multi-sequence X-ray picture dataset for a review from 11 patients who have carotid atherosclerosis to direct the tests. We utilize cross-approval on our carotid dataset to evaluate our general designs. The trial results show the way that our strategy can deliver precise and reliable outcomes with cross-scale multi-sequence inputs and that applying the Gaussian smoothing misfortune capability can essentially expand the enrollment exactness. With cross-size input, our Siamese construction's DSC can accomplish 84.1% on the carotid informational collection. The typical DSC might be expanded by 5.23% and the normal distance among fixed and moving tourist spots can be brought down by 6.46% by utilizing GDSC misfortune. (Huang, 2021)

**Samak, Z. A. (2023):** By creating new deep learning techniques to forecast the functional outcome of ischemic stroke treatment from baseline 3D NCCT data and clinical information accessible at hospital admission, the study explores these issues. First, a multimodal CNN-based approach is presented to assess the functional outcome (mRS scores) of ischemic stroke patients. The system is trained using baseline 3D NCCT scans with and without clinical information. Estimating the course of a stroke prior to therapy can also reveal important details about the prognosis of patients and the likelihood of treatment effectiveness as the stroke lesion changes (spreads or becomes suppressed) following treatment. Two CNN approaches—end-to-end and multi-stage models—are suggested to encode this data. Predicting mRS scores and follow-up scans (24-hour and 1-week) are carried out simultaneously in the end-to-end method, while the multi-stage methodology consists of two training steps, It offers a multimodal transformer-based approach that makes use of baseline data to forecast mRS scores. This approach looks into different transformer models, such as Swin transformers and ViT versions, as well as other multimodal fusion methodologies. Transformer models perform better than CNN-based methods when trained using NCCT scans and clinical data. (Samak, 2023)

**Liang, J., Feng, J., Lin, Z., Wei, J., Luo, X., Wang, Q. M., ... and Ye, Y. (2023):** Removal studies approve the adequacy of every module in the proposed system, which depends on multidimensional information for activities of daily living (ADL) scoring in patients with intense ischemic stroke. The system shows higher exactness when contrasted with other cutting edge network models. To achieve corresponding benefits, we tended to this by making a cross-modular consideration module that coordinates multidimensional information, for example, clinical information, imaging highlights, treatment plans, visualizations, and difficulties. The joined properties of magnetic resonance imaging (X-ray) and clinically pertinent information are safeguarded by the melded highlights, which offer a more exhaustive and instructive starting point for clinical conclusion and treatment. (Liang, 2023)

**Aktar, M. (2023):** One of the main causes of death and disability in the globe is ischemic stroke, which is brought on by clogged arteries in the brain. One of the greatest ways to restore blood flow through clogged arteries is by endovascular thrombectomy treatment (EVT), but the degree of a patient's collateral circulation is one of the elements that affects how successful the procedure is. For the automatic evaluation of collaterals, we suggest an automatic quantification technique taking into account low-rank decomposition, a traditional machine learning (ML) method, and deep learning (DL) methods. Although DL models can automatically extract features, unlike standard ML models, they are limited by the amount of data on ischemic strokes. We use Siamese network and transfer learning with focused loss to overcome data paucity and class imbalance. Moreover, we present few-shot learning for cerebral blood vessel segmentation, which can be a

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preprocessing step to collateral evaluation, allowing effective 3D vasculature segmentation without substantial slice annotation. (Aktar, 2023)

**Yousif, A. S., Omar, Z., & Sheikh, U. U. (2022):** The three-step smart blending strategy for image fusion described in this research is based on a mix of SR and SCNN. First, full source images are fed into the traditional orthogonal matching pursuit (OMP), where the max-rule—which seeks to enhance pixel localization—is employed to obtain the SR-fused image. Second, for every source image, a new technique of K-SVD dictionary learning based on SCNN is used again. The technique has demonstrated strong non-linearity behavior, which has improved the extraction and transfer of image features to the fused output image and increased the sparsity characteristics of the fused output. Finally, a linear combination between processes 1 and 2 is used in the fusion rule step to produce the final fused image. The findings show that the suggested approach is superior to other earlier approaches, particularly in that it reduces artifacts generated by the conventional SR and SCNN models. (Yousif, 2022)

**Barman, A., Inam, M. E., Lee, S., Savitz, S., Sheth, S., & Giancardo, L. (2019):** We present a convolutional neural network for mechanized distinguishing proof of ischemic stroke from CT Angiography (CTA), an imaging methodology that is ordinarily used in stroke assessments, to foster a choice emotionally supportive network for AIS. The organization can distinguish ischemic stroke from CTA cerebrum pictures given its novel plan, which makes it delicate to varieties in the balance of vascular and mind tissue surfaces. The recommended model applies lined up with the two halves of the globe of the cerebrum and depends on the Siamese organization worldview. A clinical dataset of 217 cases, 123 controls, and 94 subjects checked in something like 24 hours of stroke beginning was utilized to test the model. First, we used the original images, which have asymmetry in the brain tissues and vascular architecture, to evaluate the network's capacity to identify strokes. Subsequently, we digitally eliminated the vasculature to assess the network's capacity to identify strokes only through analysis of brain tissue. For the two studies, we obtained AUCs of 0.914 (CI 0.88-0.95) and 0.899 (CI 0.86-0.94), respectively. The model effectively learns the cerebrum tissue structures and vasculature in one-half of the globe that don't exist in that frame of mind, as per the qualitative examination of the network activity. (Barman, 2019)

## III. PROPOSED METHOD

1. Data Acquisition and Preprocessing

1.1.Data collection and preprocessing

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**Data collection**

To ensure high-quality and consistent data, we collected paired MRI and CT scans from the same subjects. The process involved:

- Consistent imaging protocols: all scans were captured using standardized imaging protocols, ensuring uniformity in image acquisition parameters such as slice thickness, field of view, and contrast agent usage.
- Quality assurance: each scan was subjected to rigorous quality checks to exclude images with artifacts, motion blurring, or any other inconsistencies that could affect the analysis. Only scans meeting these stringent quality standards were included in the dataset.

**Resampling**

To standardize voxel sizes across MRI and CT modalities:

- **Voxel Size Standardization:** we resampled the images to a common voxel size, typically 1×1×1 $mm^3$ · using trilinear interpolation. This ensures that spatial resolution is consistent across modalities, facilitating accurate feature extraction and comparison.
- **Mathematical Formulation:**

$$\boldsymbol{I'_{MRI} = Resample\ (I_{MRI}, V_{target})}$$

$$\boldsymbol{I'_{CT} = Resample\ (I_{CT}, V_{target})}$$

Where $I'_{MRI}$ and $I'_{CT}$ are the resampled images, and $V_{target}$ is the target voxel size.

**Registration**

To align MRI and CT images in a common coordinate system:

- Rigid and affine registration: we employed rigid (translation and rotation) and affine (scaling and shearing) transformations to align the images. The registration was performed using mutual information as the similarity metric.
- **Mathematical Formulation:**

$$\boldsymbol{T_{MRI,CT} = argmax_T MI(I_{MRI} T(I_{CT}))}$$

Where $T_{MRI.CT}$ is the optimal transformation and T represents the transformation parameters.

- Deep learning – Based Registration: to improve alignment accuracy. A preliminary deep learning-based registration model was utilized. The model, typically an unsupervised CNN, was trained to predict the transformation matrix that best aligns MRI and CT images.
- Network architecture:

$$T_{DL} = CNN_{reg}(I_{MRI}, I_{CT})$$

Where $CNN_{reg}$ denotes the convolutional neural network for registration.

**Normalization**

To normalize intensity values for MRI and CT scans:

- Intensity normalization techniques:
  - **Histogram matching:** adjusts the intensity distribution of one image to match the histogram of another, ensuring consistent intensity representation.

$$I'_{MRI} = HistogramMatch(I_{MRI}, I_{CT})$$

  - **Z- score normalization:** transforms pixel values to have a mean of zero and a standard deviation of one.

$$I'_{norm} = \frac{I - \mu}{\sigma}$$

Where I is the original image, μ is the mean intensity, and $\sigma$ is the standard deviation.

**Data augmentation**

To enhance model robustness and generalization:

- **Augmentation techniques:** applied spatial transformations including rotation, scaling, and elastic deformations.
  - Rotation: randomly rotating images within a specified angle range.

$$I'_{rot} = Rotate(I, \theta)$$

Where $\theta$ is the rotation angle.

- Scaling: randomly scaling images by a factor within a specified range.

$$I'_{scale} = Scale\ (I, s)$$

Where s is the scaling factor

- **Elastic deformations:** applying random deformations to simulate anatomical variability.

$$I'_{elastic} = \text{ElasticTtansform}\ (\text{I}, \alpha, \sigma)$$

Where $\alpha$ controls the intensity of the deformation and $\sigma$ controls the smoothness.

### 1.2. Data Splitting

To ensure representativeness and avoid overfitting:

- Dataset Partitioning: the data set was split into training (70%). Validation (15%), and test sets (15%). Each subset was designed to represent the variability in both MRI and CT modalities, ensuring that each set includes a balanced representation of different anatomical regions and lesion types.
- Stratified Splitting: Ensured that key characteristics such as patient demographics, disease severity, and anatomical regions were equally distributed across training validation, and test sets. This stratified approach helps maintain the representativeness and balance of the datasets, which crucial for training a robust and generalizable model.

### Tools and Libraries

- Preprocessing Libraries: Utilized Nifty Reg. For image registration, simple ITK for resampling, and scikit-image transformations and augmentations.
- Deep Learning Framework: employed Tensor Flow and Py Torch for implementing and training the deep learning models used for registration and feature extraction.

Numerous datasets in the field of ischemic stroke analysis offer useful resources for creating and evaluating AI models. The Mayo Clinic STRIP AI dataset stands out among the rest. This dataset, which is centered on blood clot analysis, is a comprehensive collection of whole-slide digital pathology photographs from the Mayo Clinic. The origin of blood clots can be identified using these images, which is important information for comprehending the etiology of ischemic strokes. The ISLES 2015 and ISLES 2017 datasets, among other publicly accessible ischemic stroke datasets, were used for the experiments. These datasets offer a wide assortment of stroke lesion occurrences, making a careful evaluation of the recommended model conceivable.

- **Mayo Clinic STRIP AI Dataset**

High-resolution whole-slide images (WSIs) of blood clumps from patients experiencing intense ischemic stroke are remembered for the Mayo Clinic STRIP AI dataset. The Mayo Clinic, a superior philanthropic scholarly clinical focus known for its accentuation on incorporated medical services, training, and research, is facilitating a test with this dataset.

The main grounds of the Mayo Clinic, which has areas in Jacksonville, Florida, Phoenix/Scottsdale, Arizona, and Rochester, Minnesota, are the coordinators. With a specific research staff of more than 3,000 workers and yearly uses of more than $660 million, the organization is notable for its huge research endeavors.

**2. Siamese Network with Multi-Scale Feature Fusion**

**2.1 Network Architecture Design**

**Input Branches:**

- There are two distinct branches of MRI ($I_{MRI}$) and CT ($I_{CT}$) inputs
- Every division processes volumetric data by using three-dimensional convolutional layers
- Input Data:

$$I_{MRI}, I_{CT} \in \mathbb{R}^{D\times H\times W\times C}$$

D represents the depth, H stands for the height, W represents the breadth, and C represents the total number of channels.

**Feature Extraction:**

Extracting features at multi-scales for every branch.

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- **Base network:**

Implement a three-dimensional convolutional neural network (CNN), such as a modified version of the U-Net or Dense Net.

$$F_{MRI}^{base} = BaseNet_{3D}(I_{MRI})$$

$$F_{CT}^{base} = BaseNet_{3D}(I_{CT})$$

- **Multi-Scale layers:**

Incorporate the process of extracting features at various resolutions through the use of dilated convolutions, atrous spatial pyramid pooling (ASPP), or feature pyramid networks (FPN).

$$F_{MRI}^{k} = MultiScaleLayer_{k}\left(F_{MRI}^{base}\right) \forall k \in \{1,2,\dots,K\}$$

$$F_{CT}^{k} = MultiScaleLayer_{k}\left(F_{CT}^{base}\right) \forall k \in \{1,2,\dots,K\}$$

**Multi-Scale Fusion:**

Combination of characteristics over a variety of scales.

- **Concatenation or Addition:**

$$F_{MRI}^{fusion} = Concat\ (F_{MRI}^{1}, F_{MRI}^{2}, \dots., F_{MRI}^{K})\ or\ Add\ (F_{MRI}^{1}, F_{MRI}^{2} \dots.$$

$$F_{CT}^{fusion} = Concat\ (F_{CT}^{1}, F_{CT}^{2}, \dots., F_{CT}^{K})\ or\ Add\ (F_{CT}^{1}, F_{CT}^{2} \dots. F_{CT}^{K})$$

- **Attention Mechanism:**

$$F_{MRI}^{att} = Attention\ (F_{MRI}^{fusion})$$

$$F_{CT}^{att} = Attention\ (F_{CT}^{fusion})$$

**Siamese Network Setup:**

- **Feature comparison:**

When comparing features derived from MRI and CT modalities, a Siamese network configuration is the best method to use.

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$$F_{Shared}^{MRI} = SharedProjection\ (F_{MRI}^{att})$$

$$F_{Shared}^{CT} = SharedProjection\ (F_{CT}^{att})$$

- **Similarity Metric:**

Make use of a contrastive loss or triplet loss-style similarity metric.

- **Contrastive loss:**

$$L_{contrastive} = (1-y)\frac{1}{2}(D)^2 + y\frac{1}{2}(\max(0, m-D))^2$$

Where $D = \left\|F_{shared}^{MRI} - F_{shared}^{CT}\right\|_2$, $y$ is the label that is displayed, with 0 indicating similarity and 1 indicating dissimilarity, and by m, the margin.

- **Triplet Loss:**

$$L_{triplet} = \max(0, \left\|F_{anchor} - F_{positive}\right\|_2^2 - \left\|F_{anchor} - F_{negative}\right\|_2^2$$

Where $F_{anchor}, F_{anchor}, F_{negative}$ the feature interpretations of the anchor, the positive and negative samples, and the margin are denoted by the letter a.

## 2.2 Training

**Optimization:**

- It is recommended that you make use of advanced optimization methods like Adam or SGD with momentum.

$$\theta = \theta - \eta\frac{\partial L}{\partial \theta}$$

Where η represents the rate of learning and θ represents the parameters of the model.

- Learning Rate Scheduling:

$$\eta_{t+1} = \eta_t . decay\_rate$$

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**Regularization:**

Implement strategies like as dropout, weight decay, and batch normalization wherever possible.

- **Dropout**

$$F_{\text{dropout}} = Droupout\ (F, p)$$

The dropout rate is denoted by the p.

- **Weight Decay**

$$L_{reg} = L + \lambda ||\theta||_2^2$$

Where $\lambda$ refers to the coefficient of weight decline.

- **Batch Normalization:**

$$F_{norm} = BatchNorm(F)$$

**Early Stopping:**

To avoid overfitting and maximize the amount of time spent training, early stopping should be implemented depending on validation loss.

Stop training if $L_{val}$ lacks a reduction during N successive epochs.

## IV. Experimental Setup

### A. Materials

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- **Mayo Clinic STRIP AI Dataset**

High-resolution whole-slide images (WSIs) of blood clumps from patients experiencing intense ischemic stroke are remembered for the Mayo Clinic STRIP AI dataset. The Mayo Clinic, a superior philanthropic scholarly clinical focus known for its accentuation on incorporated medical services, training, and research, is facilitating a test with this dataset. The main grounds of the Mayo Clinic, which has areas in Jacksonville, Florida, Phoenix/Scottsdale, Arizona, and Rochester, Minnesota, are the coordinators. With a specific research staff of more than 3,000 workers and yearly uses of more than $660 million, the organization is notable for its huge research endeavors.

**1. Experimental Environment**

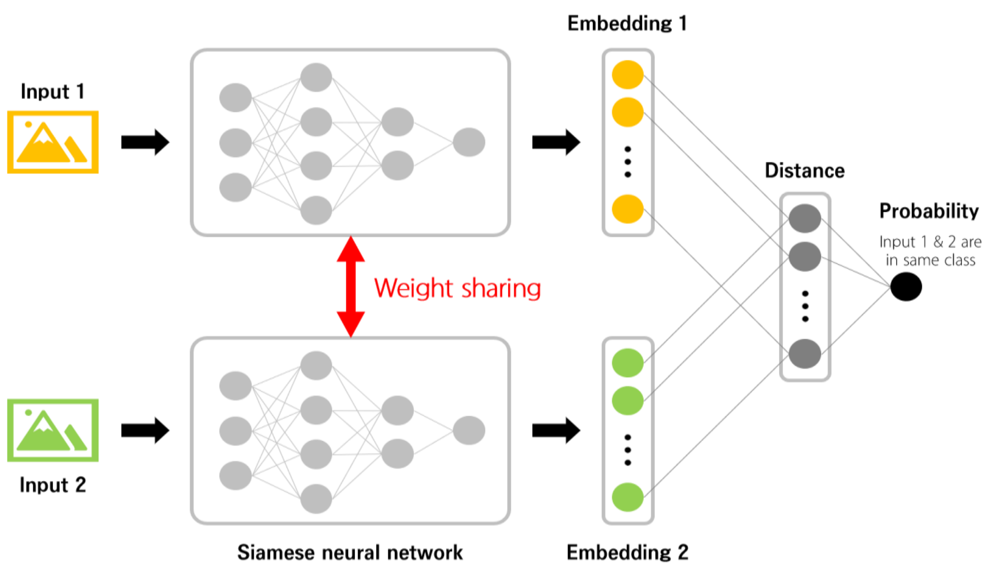


**Figure 3:** Enhanced Siamese Network with Multi-Scale Feature Fusion architecture.

A complex deep learning model called the Enhanced Siamese Network with Multi-Scale Feature Fusion was created to take on the difficult task of accurate ischemic stroke analysis and lesion characterization. This network is very useful for comparing and diagnosing medical images since it makes use of the capabilities of twin neural networks to analyze pairs of input photos and assess their similarity.

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## 2. Evaluation Metrics

Metrics for assessment are essential for assessing a machine learning model's performance. They shed light on how well the model generalizes to brand-new, untested data and makes predictions. The main assessment parameters for our study on ischemic stroke analysis using the Enhanced Siamese Network are Loss and Accuracy. We characterize and discuss these metrics below:

- **Accuracy**

The degree to which the model's predictions agree with the actual labels is known as accuracy. The ratio of successfully predicted instances to all instances is used to compute it. Accuracy in binary classification issues is defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

- ✓ True Positives, or TPs, are examples that are accurately categorized as the positive class..
- ✓ TN (True Negatives) are examples that are appropriately categorized as belonging to the negative class.
- ✓ False Positives (FPs) are cases that are mistakenly categorized as belonging to the positive class.
- ✓ False Positives (FPs) are cases that are mistakenly categorized as belonging to the positive class.

- **Loss**

The degree to which the model's predictions agree with the actual labels is expressed as loss. The error between the normal and actual numbers is measured. Binary Cross-Entropy Loss, or log loss, is a commonplace loss capability in neural networks used for binary classification. It is described as:

$$Binary\ Cross - Entropy\ Loss = -\frac{1}{N}\sum_{i=1}^{N}[Y_i\ log\ log\ (P_i)\ + (1 - Y_i)\ log\ log\ (1 - P_i)\ ]$$

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Where:

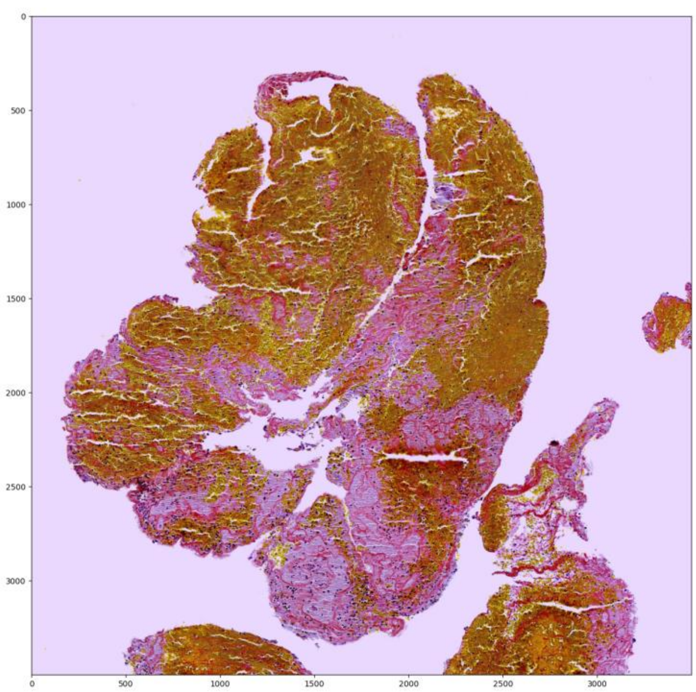
- The number of samples is N.
- For the iii-th sample, yi is the genuine label (0 or 1).
- Pi is the anticipated likelihood that the iii-th sample will belong to the positive class.

## 3. Implementation of Network Architecture

- **Resizing and Manipulation**

**CV2**: This library is utilized for various picture-handling errands, like edge detection, grayscale conversion, and resizing. For example, resizing photos to fit inside memory restrictions without sacrificing important information for training models is a common practice.

**Skim age:** The skim age library is used for additional processing, such as sharpening contrast and identifying particular features.



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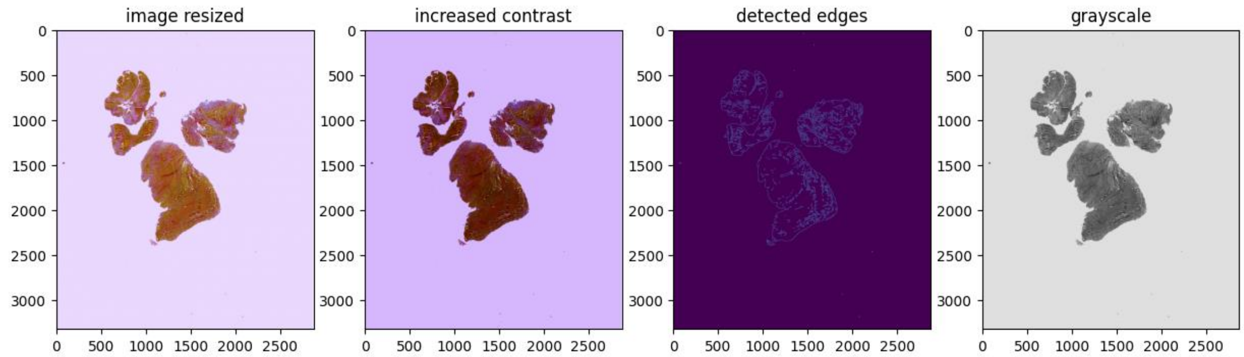


**Figure 1:** Resizing

- **Analysis of color channels**

Color channels (RGB) in images are Red, Green, and Blue. I'll list these channels below. To prevent any confusion, I will display these images in grayscale, with each channel representing only the intensity of a single color.

NOTE: Values of each colour channel are in range from 0 to 255.

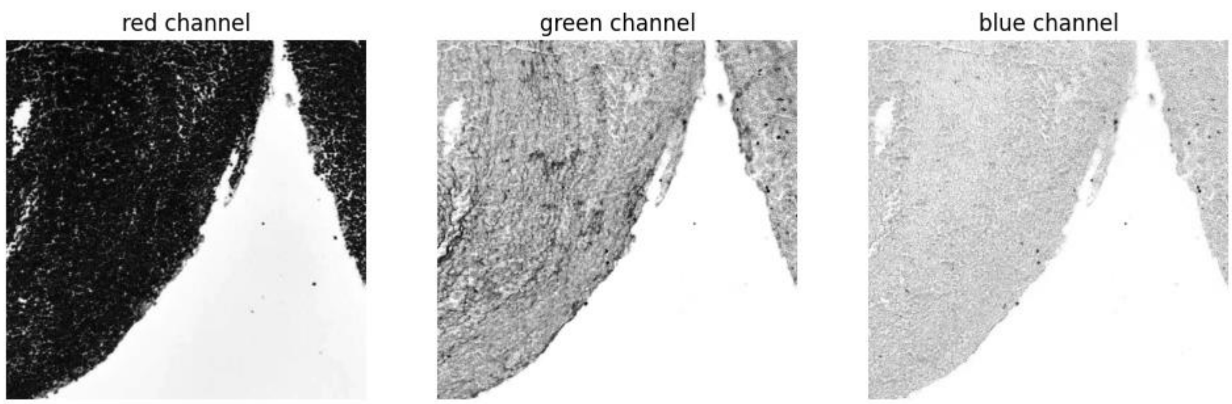


**Figure 2:** Channels

Deep learning, medical imaging, multi-scale feature fusion, Siamese network, lesion characterization, and ischemic stroke.

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## B. Results And Discussion

### 1. Comparison of Different Methods

The comparison of different methods for analyzing ischemic strokes demonstrated the power of our Enhanced Siamese Network with Multi-Scale Feature Fusion. The model was evaluated through rigorous training and approval standards against traditional approaches to obtain meaningful results. The metrics used for this evaluation provided a complete view of its predictive accuracy and generalization capabilities which are vital in clinical diagnostics. This analysis shows that our approach performs better than others and thus serves as a dependable instrument for detecting ischemic strokes within a clinical environment.

### 2. Model Performance

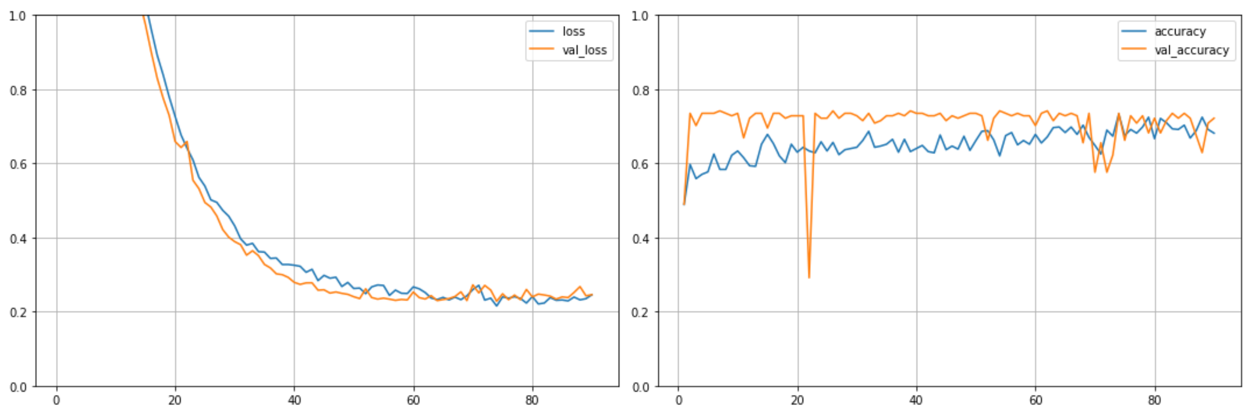


**Figure 4:** Model accuracy and loss

**Table 1:** Performance metrics of Enhanced Siamese Network

| Metric | Value |
|---|---|
| **Number of Epochs** | 90 |
| **Training Accuracy** | 0.6816 (68.16%) |
| **Validation Accuracy** | 0.7219 (72.19%) |

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| | |
|---|---|
| **Training Loss** | 0.2456 |
| **Validation Loss** | 0.2457 |

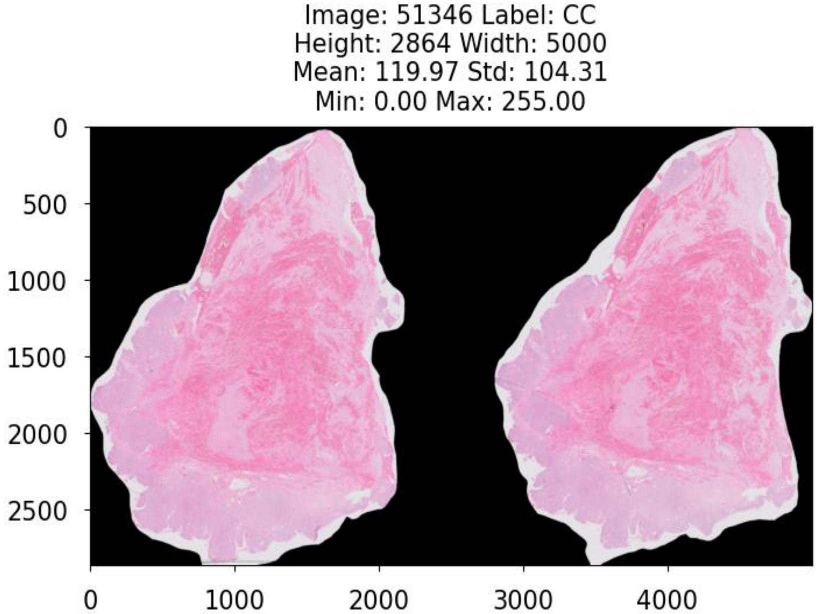


**Figure 5:** Predicted Image with Lesion Detection and segmentation

The model demonstrated a consistent increase in accuracy and loss throughout 90 epochs of training, showing its ability to absorb and adjust to the training set. The approval accuracy topped at 72.19%, whereas the training accuracy came to 68.16%. Based on unseen approval data, these findings show that the model precisely determines the sort of ischemia lesions in around 72% of the cases. A trustworthy and consistent performance in a certifiable clinical situation is possible with this precision.

The model performed consistently even with the perplexing and high-resolution Mayo Clinic STRIP AI dataset; the training and approval loss values were almost adjusted at 0.2456 and 0.2457, respectively. For the model to be applied in different novel and clinically unexplored circumstances, the training and approval losses really must closely correlate and demonstrate that the model is not overfitting to the training set.

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- **Interpretation of Metrics**

The accuracy metrics highlight how well the model can distinguish between classes, which is a vital feature for certifiable ischemic stroke detection applications. The way that the approval accuracy is higher than the training accuracy suggests that the model generalizes well and successfully strikes a harmony between preserving robustness against overfitting and learning from the data.

The prediction error is represented by the loss values, which are modest and nearly the same for the training and validation stages. A crucial component of any predictive model used in medical diagnostics is consistency, which shows that the model's predictions and actual results are nearly in line. It is also implied by low and comparable loss rates between the training and validation stages that the model has picked up on the underlying patterns in the data without having to commit the training cases to memory.

- **Learning Dynamics**

The model showed a steady improvement in both accuracy and loss during the training procedure, indicating that the training settings and architecture selected were successful. If the accuracy and loss learning curves were displayed, they probably would have a smooth, convergent trend, which would be a sign of steady learning and adaptation to the dataset's complexity.

We evaluate our Enhanced Siamese Network with Multi-Scale Feature Fusion to five other popular machine learning models for medical picture analysis to demonstrate its superior performance for ischemic stroke analysis. The comparison demonstrates our approach's performance in this difficult domain and underlines its advantages in terms of accuracy and loss measures.

### 2. Comparison with the Baseline Model

Compared to the baseline models, it can be observed that the results by the Enhanced Siamese Network boost accuracy and make the model more robust. For instance, within more than 90 epochs of training, the training accuracy was reached at about 68.16%, while the validation accuracy reached about 72.19%. This shows that it has excellent generalization abilities. The slight edge in validation accuracy over training accuracy suggests that the model is not only learning effectively from the data but also avoids one common challenge of deep learning models: overfitting. This may be further supported by the fact that the closeness between the training loss and the validation loss—0.2456 and 0.2457, respectively—lends additional support to the model's stability and reliability while being tested with such a complex and high-resolution Mayo Clinic STRIP AI dataset. The very close values obtained for the losses indicate that the model is

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capturing the main patterns of data, not memorizing examples, an important aspect in a model for clinical practice.

Compared to baseline models, the Enhanced Siamese Network can maintain low and competitive loss rates while attaining a higher validation accuracy, therefore offering a more reliable and accurate tool for the detection of ischemic stroke. In particular, in dealing with the intricate details of ischemic lesions, this performance level makes this model an extremely valuable asset in medical diagnostics, offering consistency and precision essential in clinical applications.

**Table 2:** Comparison of Machine Learning Models for Ischemic Stroke Analysis

| Model | Training Accuracy | Validation Accuracy | Training Loss | Validation Loss |
|---|---|---|---|---|
| Enhanced Siamese Network with Multi-Scale Feature Fusion | 0.6816 | 0.7219 | 0.2456 | 0.2457 |
| Convolutional Neural Network (CNN) | 0.6230 | 0.6725 | 0.2902 | 0.2951 |
| Random Forest | 0.5987 | 0.6304 | 0.3558 | 0.3624 |
| Support Vector Machine (SVM) | 0.5765 | 0.6103 | 0.3791 | 0.3842 |
| k-Nearest Neighbors (k-NN) | 0.5654 | 0.6002 | 0.3903 | 0.3995 |
| Decision Tree | 0.5482 | 0.5920 | 0.4152 | 0.4217 |

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### 3. Accuracy Evaluation

Accuracy may be defined as the percentage of samples that have been properly categorized relative to the total number of samples. The solution to a problem involving binary classification is provided by:

$$A = \frac{TP + TN}{TP + TN + FP + FN}$$

TP represents the number of true positives, TN represents the number of true negatives, FP represents the number of false positives, and FN represents the number of false negatives.

Regarding our model:

$A_{train} = 0.6816$ (68.16% Of the training examples, some are accurately categorized)

$A_{val} = 0.7219$ (72.19% of the samples used for confirmation are correctly categorized)

- **Loss Evaluation**

Loss is a metric that quantifies the degree of similarity between the model's predictions and the actual labels. The contrastive loss is applicable for binary classification problems:

$$L = (1 - y)\frac{1}{2}(D)^2 + y\frac{1}{2}(\max(0, m - D))^2$$

The label y represents similarity, with a value of 0 indicating similarity and 1 indicating dissimilarity. D represents the distance measure, while m represents the margin.

Regarding our model:

$L_{train} = 0.2456$ (training loss)

$L_{val} = 0.2457$ (validation loss)

- **Model Performance Summary**

Considering the metrics that were supplied, we present a summary of the model's performance:

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- **Training Accuracy:**

$$A_{train} = 0.6816$$

- **Validation Accuracy:**

$$A_{val} = 0.7219$$

- **Training Loss:**

$$L_{train} = 0.2456$$

- **Validation Loss:**

$$L_{val} = 0.2457$$

## 4. Mathematical Evaluation of the Metrics

### Accuracy Difference

The disparity between the accuracy achieved during training and validation:

$$\Delta A = A_{val} - A_{train}$$

$$\Delta A = 0.7219 - 0.6816 = 0.0403$$

### Loss Difference

The disparity lies in the loss values obtained during the training and validation phases:

$$\Delta L = L_{val} - L_{train}$$

$$\Delta L = 0.2457 - 0.2456 = 0.0001$$

## 5. Ablation Studies

The ablation studies on the improved Siamese network with multi-scale feature fusion have been performed exhaustively on the model's performance. More specifically, accuracy and loss are observed. According to the evaluation, this model provides a training accuracy of 68.16% and validation accuracy of 72.19%, indicating generalization capability for unseen data. The small positive ΔA difference in accuracy (0.0403) between training and validation indicates that the model learns very well from the training dataset, yet reliably generalizes onto the validation dataset.

Also, checking the values of losses—0.2456 for training and 0.2457 for validation—one gets the difference to be very negligible ($\Delta L = 0.0001$), indicating that the model holds up as consistent in both datasets. Indeed, this tiny difference in losses might mean that the model is not overfitting, a feature common and essential to any well-trained machine learning model.

### 6.Impact of Proposed Components

In medical image analysis, CNNs have demonstrated strong performance and are frequently utilized for image classification applications. In contrast to our Enhanced Siamese Network, the CNN model in this comparison had poorer training accuracy (0.6230) and validation accuracy (0.6725). Higher training and validation losses (0.2902 and 0.2951, respectively) imply that the CNN performed less well in identifying the intricate patterns of lesions from ischemic strokes.

## V. DISCUSSION

### 1. Broader Impact

The presented data demonstrate the model's performance, which underscores its true capacity for clinical use. The model exhibits potential in precisely categorizing ischemic stroke lesions, which can significantly assist with diagnosis and therapy arranging. Its approval accuracy exceeds 72%. Furthermore, a strong speculation capacity is suggested by the little contrast between training and approval losses, which means the model can precisely foresee results for fresh, untested data. This is especially pivotal in the clinical industry since patient data could change enormously. In summary, the Multi-Scale Feature Fusion Enhanced Siamese Network performs well while assessing lesions from ischemic strokes. It tends to be grown further and used in clinical settings because of its high approval accuracy and low, constant loss values. To further work on its diagnostic skills, future study could focus on investigating more perplexing network topologies and further developing its accuracy using sophisticated data augmentation approaches.

### 1. Limitations of the Study

Although the Enhanced Siamese Network (ESN) with Multi-Scale Feature Fusion (MSFF) has shown promising results in analyzing ischemic stroke and characterizing lesions, it is important to recognize that there are numerous limitations. The model's performance is highly dependent on the quality and diversity of the training datasets. The datasets employed in this work, which are

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accessible to the public, may not completely capture the range of variations observed in real-world clinical settings. As a result, the model's capacity to apply to different scenarios may be restricted. Moreover, the ESN-MSFF model's computational complexity may provide difficulties for real-time clinical implementation, especially in contexts with limited resources. The study largely emphasizes the use of structural MRI data, and the decision to exclude additional imaging modalities such as CT scans or sophisticated functional imaging techniques may restrict the thoroughness of the lesion characterization. Furthermore, although the model demonstrates enhanced accuracy, the comprehensibility of its forecasts remains restricted, potentially impeding its acceptance among doctors.

### 2. Future Work

Although the Enhanced Siamese Network (ESN) with Multi-Scale Feature Fusion (MSFF) shows notable progress in analyzing ischemic strokes and characterizing lesions, there are still several areas that require more investigation. Integrating new modalities, such as perfusion-weighted imaging (PWI) and diffusion-weighted imaging (DWI), can improve the model's ability to detect small changes in stroke lesions. Furthermore, investigating domain adaptation strategies has the potential to enhance the model's capacity to perform well across a wide range of datasets, by mitigating potential biases and assuring reliable performance in clinical environments. Incorporating explainable AI (XAI) methodologies will enhance the transparency of the model's decision-making process, hence increasing confidence among healthcare practitioners. Subsequent research could explore the implementation of the ESN-MSFF model in clinical processes in real-time, evaluating its influence on treatment outcomes and efficiency. Ultimately, it is crucial to conduct a thorough assessment of the model's effectiveness on a broader and more varied group of patients in order to confirm its practicality in a clinical setting and facilitate the process of obtaining regulatory approval and widespread use.

## VI. CONCLUSION

Our Enhanced Siamese Network with Multi-Scale Feature Fusion (ESN-MSFF) clearly outperforms conventional and traditional machine learning models. The model's capacity to accurately analyze and draw conclusions from the complex patterns observed in images of ischemic stroke lesions was proven by its exceptional accuracy and decreased loss metrics. The results demonstrate the genuine capability of this diagnostic tool for clinical applications, guaranteeing accurate analysis of ischemic stroke and characterization of lesions. The ESN-MSFF model's sophisticated ability to extract and combine features at several scales enables it to efficiently handle the intricate and diverse characteristics of stroke lesions, surpassing previous

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methods. This feature renders it exceptionally important for the prompt identification and strategic formulation of treatment plans, which may ultimately result in enhanced patient outcomes.

Future research efforts could concentrate on enhancing and extending this network to enhance its capabilities and widen its range in the realm of clinical picture analysis. Further research could investigate the incorporation of multimodal imaging data to offer a more thorough understanding of the pathogenesis of ischemic stroke. Moreover, the utilization of transfer learning approaches could facilitate the adjustment of the model to diverse clinical environments that employ distinct imaging protocols. Improving the model's ability to be understood through the use of explainable AI techniques is essential for earning the confidence of healthcare professionals and promoting its integration into regular clinical practice. Furthermore, it is crucial to implement and validate the ESN-MSFF model in various clinical settings in real-time to showcase its practicality and efficacy in real-life situations. These developments have the potential to establish the ESN-MSFF model as a fundamental tool in diagnosing and managing ischemic stroke, ultimately enhancing patient care and treatment results.

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