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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.

1. 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 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 states 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)

1.1 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)

1.2 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.

2. LITERATURE REVIEW

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 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 in view of its novel plan, which makes it delicate to varieties in the balance of vascular and mind tissue surface. 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)

3. RESEARCH METHODOLOGY

3.1 Dataset Description

There are numerous datasets in the field of ischemic stroke analysis that 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 more than $660 million, the organization is notable for its huge research endeavors.

- **Traditional Methods**

Manual segmentation and conventional image processing methods like thresholding and edge detection are used in ischemic stroke analysis. These approaches have limitations since they can't adjust to the various ways that stroke lesions present, and they frequently need for a lot of human labor.

- **Deep Learning Approaches**

Recent developments in deep learning—especially CNNs—have completely changed the field of medical imaging. Medical image segmentation tasks have seen a widespread use of models like U-Net and its derivatives. The capacity of Siamese networks to compare image pairings and recognize regions of interest has also been investigated. Nevertheless, the

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majority of current models are unable to combine multi-scale data in an efficient manner, which is essential for accurately representing the diverse characteristics of ischemic stroke lesions.

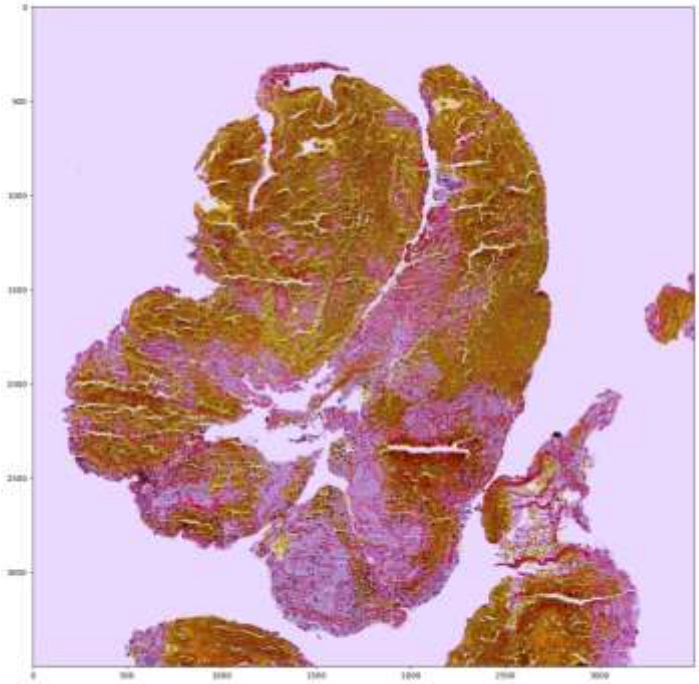
3.2 Data Preprocessing

Preprocessing is pivotal for productive data the executives and viable model training in light of the mass and high resolution of the images in the Mayo Clinic STRIP AI dataset. The photographs are stacked and concentrated on utilizing Scikit-image, Matplotlib, PIL, and CV2. Different image opening and control methods are available in every library, and these procedures are useful for certain periods of analysis and model structure.

- **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.

Skimage: The skimage library is used for additional processing, such as sharpening contrast and identifying particular features.



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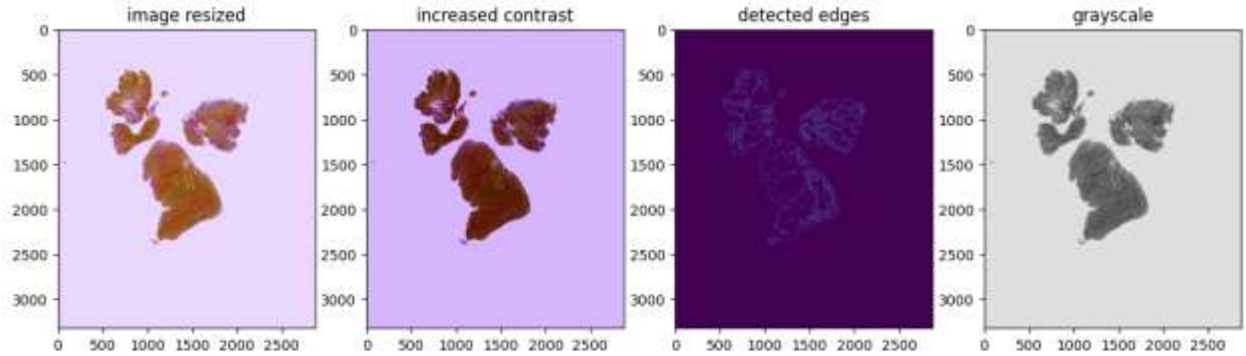

Figure 1: Resizing

3.3 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.

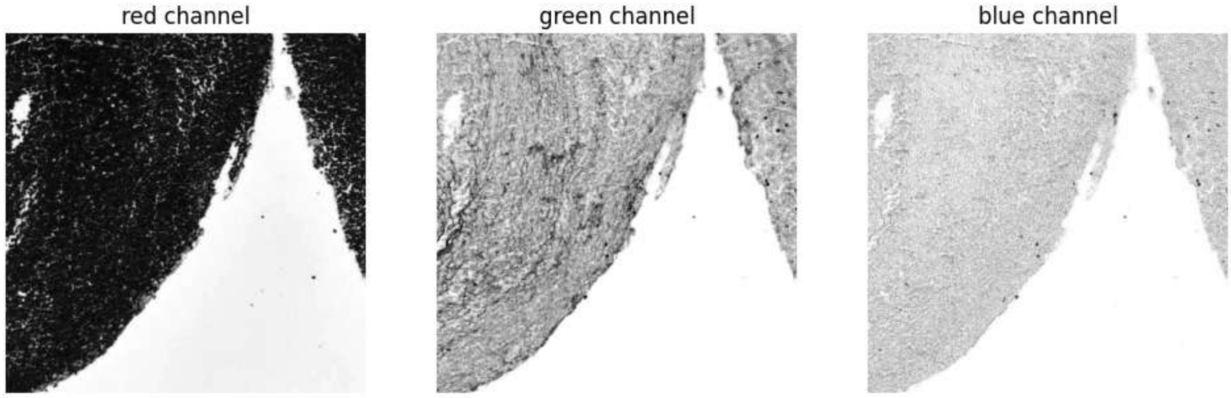

Figure 2: Channels

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

4 EXPERIMENTAL SETUP

4.1 Architecture of the Enhanced Siamese Network with Multi-Scale Feature Fusion

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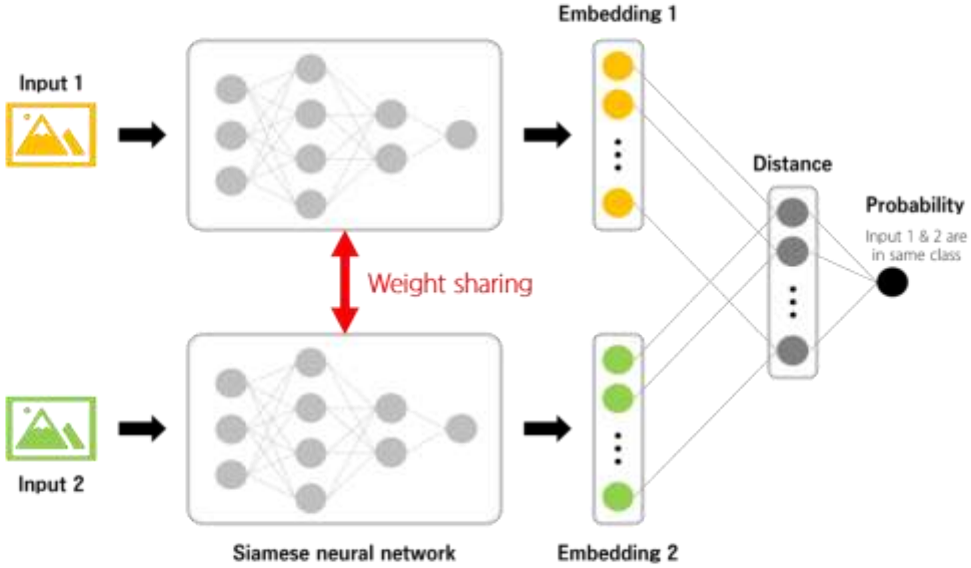

Figure 3: Enhanced Siamese Network with Multi-Scale Feature Fusion architecture.

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 characterisation. 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.

4.2 Input Layer

The initial two information layers of the plan each get an image from the pair that must be looked at. Typically, preprocessing is finished on these photographs to work on model execution. Preprocessing incorporate data augmentation methods including rotation, flipping, and zooming to improve the model's strength and generalizability, as well as standardization to normalize pixel values. In clinical imaging datasets, for example, those utilized for ischemic stroke analysis, the info images are regularly scaled to a predefined shape appropriate for deep learning models, for example, 224x224 pixels with three color channels (RGB), empowering the network to deal with the high resolution and changeability run of the mill of these datasets.

4.3 Feature Extraction Layers

Multiple convolutional layers in every one of the twin sub-networks of the Siamese architecture extract hierarchical characteristics from the information images. The reason for these layers is to advance progressively complicated and unique visual portrayals step by step.

Convolutional layers apply various channels to the information image in each convolutional block to catch various properties including edges, surfaces, and examples. The network presents non-linearity by applying a Rectified Linear Unit (ReLU) initiation capability after every convolution, permitting the network to learn more complex examples. Cluster standardization, which normalizes the result of each layer to speed up learning, is utilized to guarantee consistent and viable training. Starting there forward, max pooling layers are used

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to down model the data and back off the computational load by cutting down the spatial dimensions of the component maps while keeping the most dire characteristics.

4.4 Multi-Scale Feature Fusion

Multi-scale feature fusion is one of the main enhancements made to our network. This method aims to productively learn both fine-grained details and more thorough context oriented knowledge by catching features at many scales. In genuine use, this is achieved by utilizing convolutional layers inside a single network block that have changing kernel sizes. To gather more exhaustive relevant data, one layer might utilize a bigger kernel (e.g., 3x3 or 5x5), while another layer might utilize a more modest kernel (1x1) to catch better details.

The information image is then completely addressed by linking these multi-scale features. The network can now break down various perspectives immediately on account of this feature fusion, which works on its ability to recognize comparative and different images. This capacity is particularly valuable for the complicated undertaking of lesion characterisation in stroke analysis.

4.5 Feature Comparison

The recuperated feature vectors are contrasted with decide how comparative the images are after the twin networks have independently handled their individual information images. A distance metric that actions how intently practically identical the feature portrayals are — like Euclidean distance or cosine similarity — is typically utilized for this correlation.

With regards to stroke analysis, the network figures this distance to assess assuming the pair of pictures are similar or unique, which aids in distinguishing matching or non-matching lesion patterns. The network successfully recognizes various sorts of ischemia lesions by learning to limit the distance between feature vectors of comparative images and maximize the distance between those of disparate images.

4.6 Output Layer

A similarity score is produced by the network's last step using the calculated distance metric. The similarity between the two input photos is indicated by this score. Greater similarity is indicated by a higher score, and greater dissimilarity is shown by a lower score. The photos can be categorized using this output by determining whether or not they show the same kinds of lesions or distinct situations.

5 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 underneath:

5.1 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.

5.2 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:

$$Binary\ Cross - Entropy\ Loss = -\frac{1}{N}\sum_{i=1}^{N}[\mathcal{Y}_i \log(\mathcal{P}_i) + (1 - \mathcal{Y}_i)\log(1 - \mathcal{P}_i)]$$

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.

6 RESULTS AND DISCUSSION

Through various training and approval standards, the effectiveness of our Enhanced Siamese Network with Multi-Scale Feature Fusion for ischemic stroke analysis was assessed. These metrics offer a thorough understanding of the model's prescient and speculation capabilities, which is essential for its use in clinical diagnosis.

6.1 Model Performance

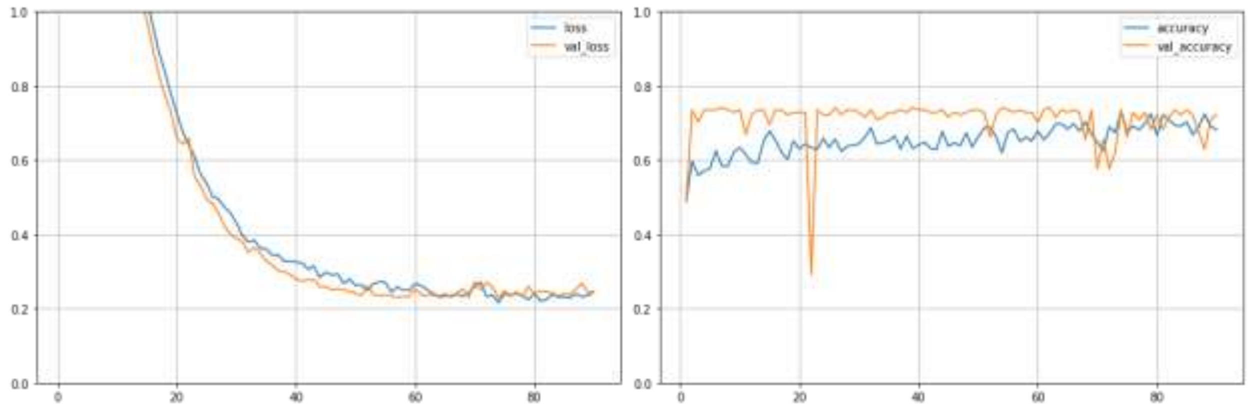

Figure 4: Model accuracy and loss

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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%)
Training Loss	0.2456
Validation Loss	0.2457

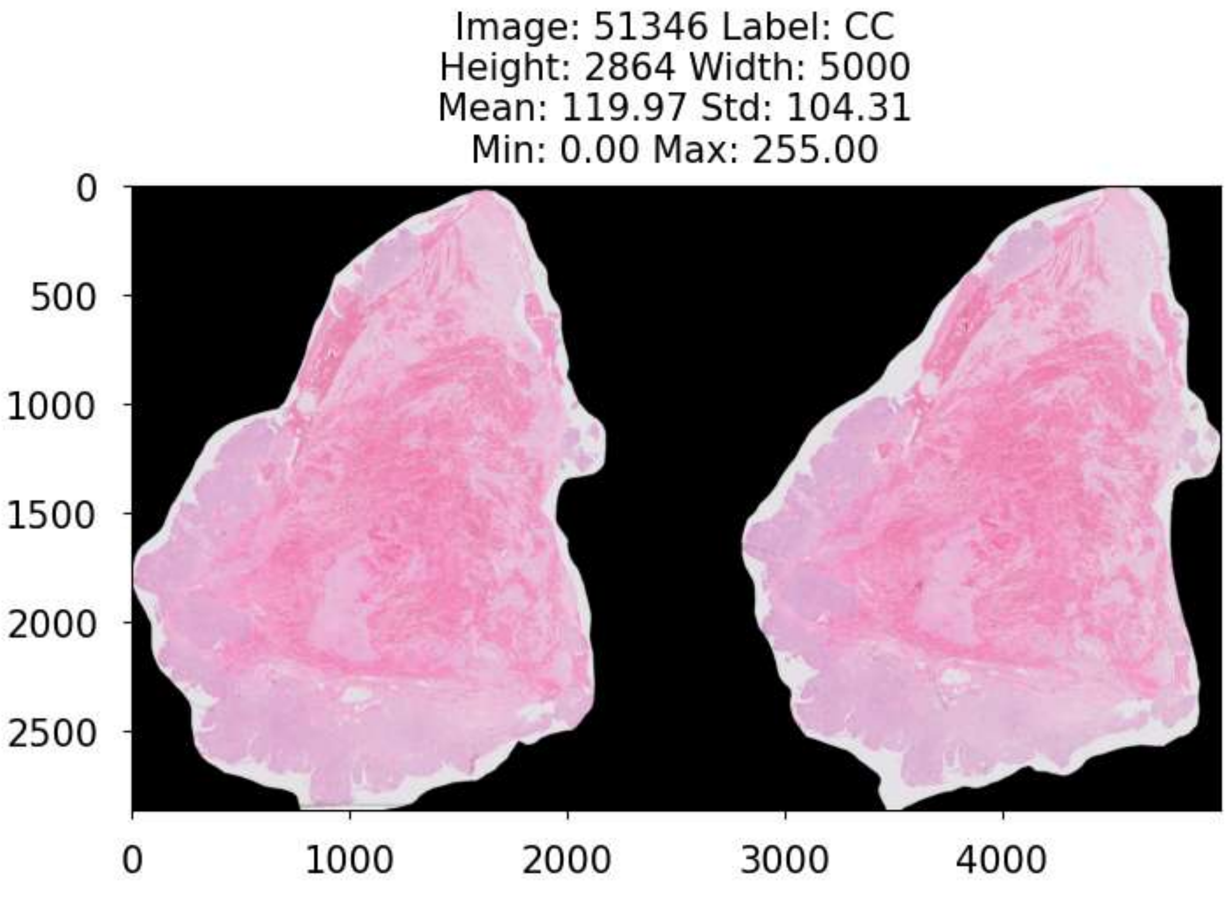

Figure 5: Predicted Image with Lesion Detection and segmentation

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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.

6.2 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.

6.3 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 in order 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.

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

6.4 Summary of Model Performance

1. **Convolutional Neural Network (CNN)**:

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.

2. **Random Forest**:

Popular ensemble learning technique Random Forests performed mediocrely, with a validation accuracy of 0.6304. Although this model's capacity to manage non-linear interactions is advantageous, in this particular situation, its accuracy and loss values were less than those of the Siamese Network.

3. **Support Vector Machine (SVM)**:

SVMs are renowned for their superior performance in tasks involving binary classification. In this high-dimensional image analysis job, they were unable to reach high accuracy (0.6103) and showed higher loss values (training loss of 0.3791 and validation loss of 0.3842). This suggests that without extensive feature engineering, SVMs might not be the best choice for complicated image data.

4. **k-Nearest Neighbors (k-NN)**:

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Despite being easy to understand and straightforward, the k-NN method had restricted effectiveness, with a validation accuracy of 0.6002 and greater loss values (0.3903 for training and 0.3995 for validation). In comparison to our suggested network, this result demonstrates its susceptibility to high-dimensional and noisy data, which reduces its effectiveness for ischemic stroke analysis.

5. **Decision Tree**:

Although decision trees offer a simple method of categorization, their performance in this case shows that they frequently overfit. Compared to our Enhanced Siamese Network, which successfully balanced fitting and generalization, the Decision Tree model performed much worse, with a validation accuracy of 0.5920 and larger losses (0.4152 for training and 0.4217 for validation).

7 CONCLUSION

These conventional and traditional machine learning models are clearly outperformed by our Enhanced Siamese Network with Multi-Scale Feature Fusion. Its ability to capture and generalize from the intricate patterns seen in ischemic stroke lesion images was demonstrated by its superior accuracy and reduced loss metrics. Its result highlights its true capacity as a strong diagnostic tool for medication and its clinical setting application for exact ischemic stroke analysis and lesion characterisation. Subsequent research endeavors might focus on refining and expanding this network to increase its functionalities and expand its scope of uses within the field of clinical image analysis.

8 DISCUSSION

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 among 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.

REFERENCES

1. Huang, X., Mao, L., Wang, X., Teng, Z., Shao, M., Gao, J., ... & Shao, Z. (2021). Multi-Sequence MRI Registration of Atherosclerotic Carotid Arteries Based on Cross-Scale Siamese Network. Frontiers in cardiovascular medicine, 8, 785523.
2. Samak, Z. A. (2023). Automatic Prediction of Functional Outcome of Patients with Ischaemic Stroke (Doctoral dissertation, University of Bristol).
3. Liang, J., Feng, J., Lin, Z., Wei, J., Luo, X., Wang, Q. M., ... & Ye, Y. (2023). Research on prognostic risk assessment model for acute ischemic stroke based on imaging and multidimensional data. Frontiers in Neurology, 14, 1294723.
4. Aktar, M. (2023). Automatic Evaluation of Collaterals in Ischemic Stroke (Doctoral dissertation, Concordia University).
5. Yousif, A. S., Omar, Z., & Sheikh, U. U. (2022). An improved approach for medical image fusion using sparse representation and Siamese convolutional neural network. Biomedical Signal Processing and Control, 72, 103357.
6. Barman, A., Inam, M. E., Lee, S., Savitz, S., Sheth, S., &Giancardo, L. (2019, April). Determining ischemic stroke from CT-angiography imaging using symmetry-sensitive convolutional networks. In 2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019) (pp. 1873-1877). IEEE.
7. Soun, J. E., Chow, D. S., Nagamine, M., Takhtawala, R. S., Filippi, C. G., Yu, W., & Chang, P. D. (2021). Artificial intelligence and acute stroke imaging. American Journal of Neuroradiology, 42(1), 2-11.
8. Boehme, A. K., Esenwa, C., & Elkind, M. S. (2017). Stroke risk factors, genetics, and prevention. Circulation research, 120(3), 472-495.
9. Lee, E. J., Kim, Y. H., Kim, N., & Kang, D. W. (2017). Deep into the brain: artificial intelligence in stroke imaging. Journal of stroke, 19(3), 277.
10. Valliani, A. A. A., Ranti, D., & Oermann, E. K. (2019). Deep learning and neurology: a systematic review. Neurology and therapy, 8(2), 351-365.
11. Murray, N. M., Unberath, M., Hager, G. D., & Hui, F. K. (2020). Artificial intelligence to diagnose ischemic stroke and identify large vessel occlusions: a systematic review. Journal of neurointerventional surgery, 12(2), 156-164.
12. Krittanawong, C., Zhang, H., Wang, Z., Aydar, M., & Kitai, T. (2017). Artificial intelligence in precision cardiovascular medicine. Journal of the American College of Cardiology, 69(21), 2657-2664.
13. Xanthopoulos, P., Pardalos, P. M., &Trafalis, T. B. (2012). Robust data mining. Springer Science & Business Media.
14. Castaneda-Vega, S., Katiyar, P., Russo, F., Patzwaldt, K., Schnabel, L., Mathes, S., ... & Poli, S. (2021). Machine learning identifies stroke features between species. Theranostics, 11(6), 3017.
15. Thornhill, R. E., Lum, C., Jaberi, A., Stefanski, P., Torres, C. H., Momoli, F., ... & Dowlatshahi, D. (2014). Can shape analysis differentiate free-floating internal carotid

artery thrombus from atherosclerotic plaque in patients evaluated with CTA for stroke or transient ischemic attack?. Academic radiology, 21(3), 345-354.

16. Ge Y, Wang Q, Wang L, Wu H, Peng C, Wang J, et al. (2019) Predicting post-stroke pneumonia using deep neural network approaches. Int J Med Inform. 132:103986. doi: 10.1016/j.ijmedinf.2019.103986
17. Strong K, Mathers C, Bonita R. (2007) Preventing stroke: saving lives around the world. Lancet Neurol.6:182–7. doi: 10.1016/S1474-4422(07)70031-5
18. Lin, Z., He, Z., Xie, S., Wang, X., Tan, J., Lu, J., et al. (2021). AANet: Adaptive attention network for COVID-19 detection from chest X-ray images. IEEE Transactions on Neural Networks and Learning Systems, 32, 4781–4792. https://doi.org/10.1109/TNNLS.2021.3114747
19. Wang, H., Sun, Y., Ge, Y., Wu, P. Y., Lin, J., Zhao, J., et al. (2021). A clinical-radiomics nomogram for functional outcome predictions in ischemic stroke. Neurology and Therapy, 10, 819–832. https://doi.org/10.1007/s40120-021-00263-2
20. Sun, Y., Zhuang, Y., Zhu, J., Song, B., & Wang, H. (2023). Texture analysis of apparent diffusion coefficient maps in predicting the clinical functional outcomes of acute ischemic stroke. Frontiers in Neurology, 11, 1132318. https://doi.org/10.3389/fneur.2023.1132318