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Optimized transfer learning for detection susceptibility vessel sign in stroke using gorilla troops optimizer

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ABSTRACT

The blockage of blood vessels causes ischemic stroke due to clots. The susceptibility vessel sign (SVS), observed through susceptibility-weighted imaging (SWI) via magnetic resonance imaging (MRI), is a key indicator that reveals clots within brain vessels. Early detection of these clots is crucial for timely and effective treatment. Image-based detection methods, particularly non-invasive techniques like MRI, offer a superior approach compared to other modalities. This study proposes an optimized method using transfer learning to classify SVS. The deep convolutional neural network (DCNN) residual network 50 version 2 (ResNet50V2) was applied for classification, with hyperparameters fine-tuned using the gorilla troops optimizer (GTO). The optimized proposed model achieved an accuracy of 94%, sensitivity of 100%, specificity of 88%, and an F1-score of 93%. This significantly outperforms the standard ResNet50V2 model using the default parameter, which achieved an accuracy of 91%, sensitivity of 82%, specificity of 100%, and an F1-score of 77%. These results demonstrate that the proposed method significantly enhances the detection of SVS, offering a promising tool for early ischemic stroke diagnosis.

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1. INTRODUCTION

The early and accurate detection of acute ischemic stroke is crucial for timely medical intervention and improved patient outcomes. In stroke diagnosis, the susceptibility vessel sign (SVS) in susceptibility-weighted imaging (SWI) via magnetic resonance imaging (MRI) scans serves as a critical biomarker indicating the presence of thrombi in cerebral arteries. The manual detection of SVS by radiologists is time-consuming and highly subjective, leading to inconsistencies in diagnosis. Meanwhile, automated detection techniques have been widely explored for the hyperdense middle cerebral artery sign (HMCAS) using computed tomography (CT) imaging. However, limited research has focused on developing robust deep learning-based methodologies for SVS detection in MRI scans. This gap underscores the necessity of developing an automated approach tailored specifically for SVS identification.

The HMCAS is a key radiological indicator observed on non-contrast CT scans, characterized by increased attenuation within the middle cerebral artery (MCA) due to an acute thrombus [1], [2]. However, HMCAS detection can be complicated by artifacts such as beam hardening and conditions like polycythemia, leading to false-positive interpretations [3], [4]. Furthermore, detecting HMCAS can be subjective and may vary between radiologists. Although objective measurements, such as hounsfield units (HU) and MCA ratio, can improve sensitivity, they still present challenges in standardizing the detection process [5]. Diffusion-weighted imaging (DWI) in MRI is another widely used technique for ischemic stroke evaluation, as it detects acute ischemic changes based on water molecule diffusion within tissues [6]. Despite its sensitivity to early ischemic changes, DWI does not directly visualize clot composition, limiting its effectiveness in identifying thrombus burden [6]. In contrast, SVS observed on SWI-MRI provides direct visualization of thrombi due to their paramagnetic properties [7], [8]. SVS offers a more specific indication of clot presence and burden compared to HMCAS and DWI [9]. Nonetheless, manual detection of SVS by neuroradiologists is time-consuming and prone to inter-observer variability, necessitating automated detection techniques. Thus, integrating deep learning models into SVS detection can enhance accuracy, speed up diagnosis, and reduce variability, addressing a critical gap in ischemic stroke imaging.

Automated approaches, including deep learning models such as convolutional neural networks (CNNs), have been explored to improve accuracy and speed. Some methods focus on detecting the HMCAS using CT imaging [10], [11], while others utilize DWI in MRI scans to identify ischemic regions [12]. At the same time, machine learning algorithms, including support vector machines (SVMs) and random forests, have also been implemented for stroke diagnosis and outcome prediction [13]. Nevertheless, challenges remain in adapting existing techniques for SVS detection due to the subtle appearance of clots in SWI-MRI scans.

Furthermore, hyperparameter tuning remains a critical challenge in transfer learning, affecting model performance and generalization ability. Several studies have explored hyperparameter optimization techniques such as Bayesian optimization, grid search, and genetic algorithms to enhance model efficiency [14], [15]. Metaheuristic algorithms, including particle swarm optimization (PSO) and gorilla troops optimizer (GTO), have recently gained attention for their ability to improve deep learning performance in medical imaging [16]–[18]. Accordingly, the increasing stroke burden necessitates automated, accurate, and efficient detection tools specifically designed for SVS identification.

The primary challenges in SVS detection include the lack of automated tools tailored for MRI-based SVS identification, the suboptimal performance of deep learning models due to ineffective hyperparameter tuning, and the limited comparability of SVS detection methods to existing HMCAS-based techniques. To address these challenges, this study introduces an optimized transfer learning approach for SVS detection using the GTO for hyperparameter tuning. Unlike conventional tuning methods, GTO efficiently navigates complex search spaces to improve model generalization and classification accuracy.

This study makes three key contributions. First, it presents the development of an automated SVS detection model leveraging transfer learning techniques. Second, it integrates the GTO for hyperparameter fine-tuning to enhance classification performance. Third, it conducts a comprehensive evaluation of the optimized model against manual tuning and default parameter settings. The remainder of this manuscript is structured as follows: section 2 provides a detailed literature review, highlighting prior studies on stroke detection and deep learning applications. Section 3 describes the methodology, including data pre-processing, model architecture, and optimization. Section 4 presents experimental results and performance comparisons. Section 5 discusses the findings and their implications. Section 6 concludes the study with future research directions.

2. RELATED WORK

The literature on stroke detection and classification using deep learning and machine learning techniques has expanded significantly in recent years. Notably, various studies have demonstrated the potential of automated systems in improving the speed and accuracy of stroke diagnosis, addressing key challenges such as long diagnosis times, lack of specialist availability, and the limitations of traditional methods on unseen data. For instance, several studies employed CNNs applied to CT imaging, such as one that achieved a 99.9% accuracy in ischemic stroke detection. This highlights the effectiveness of deep learning in predicting the functional outcome of ischemia using DWI-MRI images [19].

Another notable work utilized retinal photographs with the DeepRETStroke architecture, achieving a 91% area under the curve in detecting silent brain infarctions [20]. Additionally, advanced architectures such as MobileNetV2 and EfficientNet-B0 have been explored for classifying vascular territories, reporting accuracies of 96 and 93%, respectively, when applied to DWI-MRI data [21]. However, overfitting remains a common issue when applying deep learning models to medical imaging. To address this, some researchers have carefully fine-tuned pre-trained models. The application of deep learning for detecting acute ischemic stroke using CT scans [22] has also shown promise, with models such as CNNs and Transformers achieving a Dice similarity score of 73.58%. These studies collectively illustrate the growing role of deep learning in medical image analysis, offering significant improvements in diagnostic accuracy and efficiency, though challenges such as overfitting, model generalization, and time-consuming processes remain areas for further research and optimization. The summary of the literature review is provided in Table 1.

Table 1. Summary of literature review

References	Modality	Accuracy	Sample Size
[19]	Diffusion-weighted MRI	97.5%	1,482 cases
[20]	Retinal photographs	Area under the curve (AUC) 0.901	218 cases
[21]	Diffusion-weighted MRI	96% (MobileNetV2), 93% (EfficientNet-B0)	421 cases (271 stroke patients, 150 without ischemia)
[22]	CT	Dice score coefficient is 73.58%	11 cases

3. RESEARCH METHODOLOGY

An automated method is proposed to predict the SVS from SWI, as illustrated in Figure 1. This method aims to assist radiologists and other medical professionals in making quick, accurate decisions. Considering the challenge of identifying SVS with small datasets, transfer learning has been selected as it has demonstrated high performance in various medical imaging studies.

3.1. Dataset

The dataset used in this study was obtained from Hospital Pengajar Universiti Putra Malaysia (HUPM). Note that the SVS was identified by a neuroradiologist from HUPM. The data consists of 27 patients, of which only nine exhibit the SVS. Each patient has SWI-MRI scans with 60 slices of 2D images. For the training dataset, 30 cropped images display the presence of SVS, while 30 cropped images do not. Meanwhile, the validation dataset consists of 19 cropped images with SVS and 19 cropped images without SVS. Moreover, the testing dataset includes 17 cropped images with SVS and 17 cropped images without SVS. The summary of the data allocation is presented in Table 2. To prepare the data for the experiment, the images, originally in digital imaging and communications in medicine (DICOM) format, were converted to JPEG format. The region of interest (ROI) was cropped into squares of varying sizes, depending on the area of the SVS. This approach maximized the information related to the SVS while minimizing the background content.

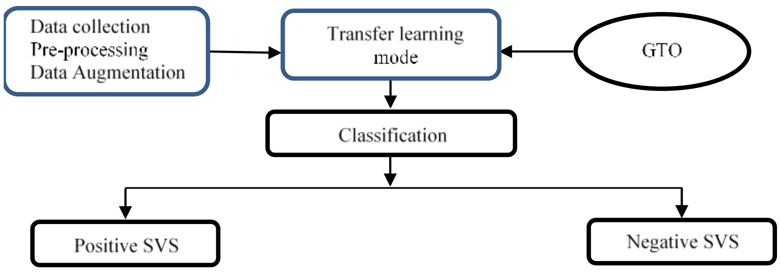


Figure 1. Methodology

Table 2. Number of cropped images based on a different folder

Dataset	With SVS	Without SVS
Training	30	30
Validation	19	19
Testing	17	17

3.2. Pre-processing and data augmentation

To enhance the quality of the images and remove noise, median filtering (kernel size 5) and Gaussian filtering (kernel size 5, σ=0) were applied. The images were resized to 224×224 pixels to match the input requirements of residual network 50 version 2 (ResNet50V2). Furthermore, augmentation techniques were applied to the training dataset to improve model generalization. This includes rotation (±15°), width and height shifts (0.2), shear transformation (0.2), zoom scaling (0.2), horizontal and vertical flipping, and brightness adjustment (0.8-1.2). The training and validation datasets were normalized by rescaling pixel values to [0, 1].

3.3. Residual network 50 version 2

ResNet50V2 is a part of the ResNet model, which can manage gradient problems through the use of residual connections. Many applications using this model have been made, such as detecting respiratory diseases using X-ray images, demonstrating superior performance with an accuracy of 95% [23].

In coronary artery disease detection, it also outperforms when combined with EfficientNetV2B0, with an accuracy of 95% [24].

The key architecture for ResNet50V2 employs residual connection, which allows gradients to flow through the network more effectively during backpropagation. Furthermore, it also consists of 50 layers, including the convolution layer, batch normalization layers, and activation function. This depth helps the model to learn complex features [25], [26]. ResNet50 is compared with ResNet50V2 within the residual blocks, which enhances training stability and performance. Another special mechanism in ResNet50V2 is the skip connection mechanism [27]. In addition, this mechanism helps in preserving the norm gradient, which stabilizes backpropagation and prevents the vanishing gradient problem. Simultaneously, skip connection provides a direct pathway for the gradient to flow, which minimizes computational cost and is very efficient in the training process [28]. It also helps the network to learn effectively without having a problem with gradient issues.

This study used a pre-trained ResNet50V2 model (trained on ImageNet) as the backbone for feature extraction. To adapt the model for binary classification, the top layers were removed, and a custom classification head was added. The classification head consists of a global average pooling (GAP) layer, followed by two fully connected (Dense) layers with 256 and 128 neurons, respectively, each using rectified linear unit (ReLU) activation and L2 regularization (λ =0.05). Batch normalization was applied after each Dense layer to stabilize training, followed by a Dropout layer to prevent overfitting. The final output layer consists of a single neuron with a sigmoid activation function for binary classification. During training, only the top 20 layers of the ResNet50V2 model were unfrozen to allow fine-tuning, while the lower layers remained frozen to retain pre-trained feature representations.

3.4. Optimization method using gorilla troop's optimization

GTO is one of the metaheuristics algorithms inspired by the social behaviors and lifestyle of gorillas [29]. It was introduced in 2021 and mimics various gorillas' activities, such as migration, following the silverback, and competing for mates. In particular, GTO consists of two stages: exploration and exploitation. The exploration stage is described by (1), where X(t+1) denotes the future position of the gorilla and X(t) represents its current position. In each iteration, three different options are considered based on the value of a randomly generated number. The first option is preferred when the random number is less than the p-value. The second option is when the random value is greater than or equal to 0.5, and the last option is when the random value is less than 0.5. The value of p ranges between 0 and 1 and is also known as the probability of migration. The value of rand_1, rand_2, and rand_3 is a random number between 0 and 1.

$$X(t+1) = \begin{Bmatrix} (UL - LL\ x\ rand_1 + LL\ , \quad rand < p \\ (rand_2 - c1)\ \times\ X_r\ (t) + c2\ \times\ c3, \quad rand \geq 0.5 \\ X(i) - c2 \times \left(c2 \times \left(X(t) - SX_r(t)\right) + rand_3 \times \left(X(t) - SX_r(t)\right)\right), \\ rand < 0.5 \end{Bmatrix} \tag{1}$$

The coefficient of c1, c2, and c3 is computed as (2)-(6).

$$C1 = F \times 1 - (\tfrac{1}{MaxIt}) \tag{2}$$

$$F = cos(2 \times rand4) + 1 \tag{3}$$

$$C2 = C1 \times l \tag{4}$$

$$C3 = Z \times X(t) \tag{5}$$

$$Z = [-C1, C1] \tag{6}$$

Where l is a random value between -1 and 1, the maximum iteration is denoted as MaxIt. For the exploitation stages, there are two essential behaviors: the silverback gorilla and the mating process. Note that the silverback gorilla is the group leader who makes all the choices for survival. The mathematical operation for the following silverback gorilla is (7)-(9).

$$SX(t+1) = c1 \times T \times (X(t) - X_{silverback}) + X(t) \tag{7}$$

$$T = \left(\left|\tfrac{1}{N}\textstyle\sum_{i=1}^{N} SX_{i(t)}\right|^{g}\right)^{1/g} \tag{8}$$

$$g = 2^L \tag{9}$$

Where N is the number of gorillas. For the mating process, which has to compete for adult females, the mathematical equation can be observed as in (10)-(12).

$$SX(i) = X_{silverback} - (X_{silverback} \times U - X(t) \times U) \times K \tag{10}$$

$$U = 2 \times r_5 - 1 \tag{11}$$

$$K = \beta \times D \tag{12}$$
$$\mathrm{D} = \begin{cases} N_{1,} \ rand \geq 0.5 \\ N_2, rand < 0.5 \end{cases}$$

Where r5 is the random value between 0 and 1, the value of β is a pre-defined variable, and this experiment β is 0.9. The advantages of this method are straightforward structure, simplicity, and ease of use, making it suitable for various optimization tasks without requiring complex parameter settings [29]. It is also highly adaptable and capable of overseeing constrained and unconstrained optimization problems. The GTO competes in benchmark tests and real-world applications such as power generation scheduling and load frequency control. In this study, we employed GTO to optimize the model performance and fine-tuned the learning and dropout rates. Note that the optimization process involves evaluating different combinations of learning rates (ranging from 1e-6 to 1e-2) and dropout rates (ranging from 0.2 to 0.5), as shown in Algorithm 1. The fitness of each solution was measured based on validation accuracy over three training epochs, and the best-performing hyperparameters were selected after ten iterations with ten gorillas (solution candidates).

Algorithm 1. GTO hyperparameter optimization
Input: Preprocessed MRI images (training and validation sets)
Output: Optimized model with best hyperparameters
1. Start
2. Apply image preprocessing and data augmentation
3. Normalize images to range [0, 1]
4. Load pre-trained ResNet50V2 model and modify for binary classification
5. Define hyperparameter search space:
    a. Learning rate range [1e-6, 1e-2]
    b. Dropout rate range [0.2, 0.5]
6. Initialize GTO algorithm:
    a. Generate initial population of hyperparameter sets (random selection)
    b. Compute fitness of each solution based on validation accuracy
7. Repeat until stopping criteria (max iterations or convergence):
    a. Perform **exploration phase** (random search for better solutions)
    b. Perform **exploitation phase** (refinement using best solutions)
    c. Update hyperparameters dynamically based on gorilla movement rules
    d. Evaluate fitness of new solutions (validation accuracy)
8. Select best hyperparameter combination
9. Retrain final model using optimized hyperparameters
10. Evaluate final model on validation dataset
11. Test final model on unseen dataset
12. Report final accuracy, sensitivity, specificity, and F1-score
13. End

3.5. Manual hyperparameter

To identify the optimal model configuration, a manual hyperparameter tuning strategy was employed (see Algorithm 2). The model was trained using three different learning rates (0.001, 0.0001, and 0.000001) and three dropout rates (0.1, 0.5, and 0.9), resulting in nine different training configurations. Consequently, each model was trained using the Adam optimizer, with binary cross-entropy loss and accuracy as the primary evaluation metric. The training process was conducted using a mini-batch size of 16 for better generalization. Early stopping (patience=5) was applied based on validation loss to prevent overfitting and reduce unnecessary training epochs. Each possible combination of these hyperparameters was systematically tested to identify the best-performing configuration.

3.6. Evaluation metrics

The performance of the proposed approach is analyzed using accuracy, sensitivity, specificity, and F1-score. The mathematical equation for each of the evaluation metrics is presented in (13)-(15).

$$Accuracy = \frac{TP+FN}{Tp+FP+TN+FN} \tag{13}$$

$$Specificity = \frac{TN}{FP+TN} \tag{14}$$

$$Sensitivity = \frac{TP}{TP+FN} \tag{15}$$

Algorithm 2. Manual hyperparameter tuning
Input: Preprocessed MRI images (training and validation sets)
Output: Trained model with best hyperparameters and performance metrics

1. Start
2. Apply image preprocessing and data augmentation (same as Algorithm 1)
3. Normalize images to range [0, 1]
4. Load pre-trained ResNet50V2 model and modify for binary classification (same as Algorithm 1)
5. Define hyperparameter search space:
    a. Learning rate {0.001, 0.0001, 0.000001}
    b. Dropout rate {0.1, 0.5, 0.9}
6. For each (learning rate, dropout rate) combination:
    a. Update model with selected hyperparameters
    b. Compile model using Adam optimizer with chosen learning rate
    c. Train model and monitor validation accuracy
    d. Evaluate model performance (accuracy, sensitivity, specificity, F1-score)
7. Select best hyperparameter combination based on validation accuracy
8. Retrain final model using best hyperparameters
9. Evaluate final model on validation dataset
10. Test final model on unseen dataset
11. Report final accuracy, sensitivity, specificity, and F1-score
12. End

4. RESULT AND DISCUSSION

This study investigated the effect of hyperparameter tuning using GTO with ResNet50V2. While previous studies have explored the impact of pre-trained models in identifying HMCAS [11] as indicators of clotting in CT images, our study focused on SVS detection in MRI scans, an area with limited prior research. By employing the GTO to fine-tune hyperparameters, specifically the learning and dropout rates, the model demonstrated significant performance improvements. In particular, the optimized ResNet50V2+GTO model achieved an accuracy of 0.94, a perfect sensitivity of 1.0, a specificity of 0.88, and an F1-score of 0.93, which outperforms the standard ResNet50V2 model and ResNet50V2 with manual hyperparameter tuning. The best parameter obtained using GTO for the learning rate is 0.0001, and the dropout rate is 0.3.

From the result provided in Table 3, manual hyperparameter tuning, the best configuration was a learning rate of 0.0001 and a dropout rate of 0.5. Under this configuration, the model achieved an accuracy of 0.91, specificity of 1.0, sensitivity of 0.82, and F1-score of 0.91. Additionally, as summarized in Table 4, manual hyperparameter tuning improved the sensitivity from 0.82 to 1 and the F1-score from 0.77 to 0.93. Moreover, Figure 2 shows the training and validation accuracy and loss, Figure 2(a) illustrates the training and validation accuracy for proposed method, and Figure 2(b) illustrates for the manual hyperparameter tuning, while Figure 3 shows the training and validation accuracy and loss, Figure 3(a) is training and validation loss for proposed model, and Figure 3(b) present the trend for the manually tuned model. The graph trend indicates that the proposed model exhibits better generalizability compared to manual tuning, which is prone to overfitting.

The performance improvements obtained in this study highlight the importance of systematic hyperparameter tuning in deep-learning applications for medical imaging. In contrast to manually tuning hyperparameters, which is often time-consuming and prone to local optima, GTO provides more efficient exploration of the hyperparameter space, leading to better generalization and model robustness. Compared to previous studies, HMCAS detection using CT scans has demonstrated that pre-trained models can achieve accuracies ranging from 0.80 to 0.90 [11]. However, due to fundamental differences in imaging modalities, these models are not directly transferable to SVS detection. In kidney stones, ensemble models with optimization techniques exhibit performance improvement, yet overfitting remains a challenge [30].

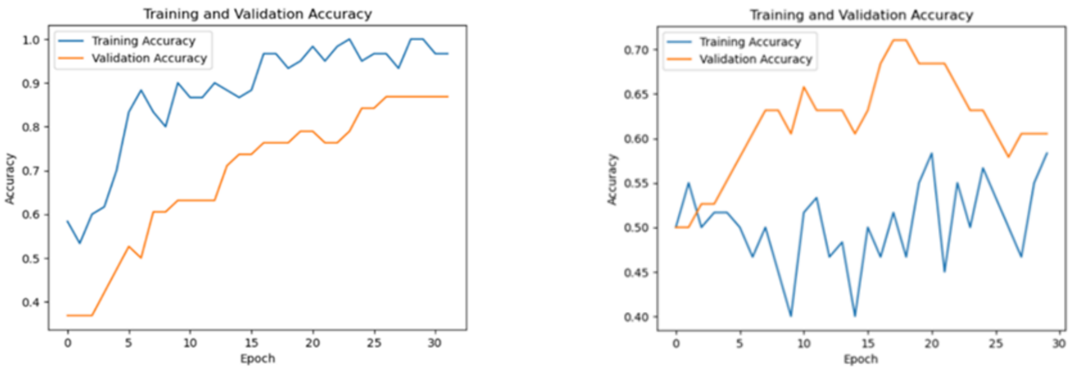
Similarly, transfer learning in Alzheimer's disease classification has demonstrated that model fine-tuning significantly impacts sensitivity and specificity [31]. Our results further reinforce these findings, indicating that deep learning models for SVS detection may suffer from suboptimal performance without proper hyperparameter optimization, including lower sensitivity and overfitting issues.

Table 3. Result based on validation dataset for manual hyperparameter

Learning rate	Dropout rate	Accuracy	Sensitivity	Specificity	F1-score
0.000001	0.1	0.3684	0.7368	0	0.5385
0.000001	0.5	0.5789	0.7368	0.4211	0.6364
0.000001	0.9	0.6053	0.8947	0.3158	0.6939
0.0001	0.1	0.7632	0.7368	0.7895	0.7568
0.0001	0.5	0.8947	0.8947	0.8947	0.8947
0.0001	0.9	0.5	0	1	0
0.001	0.1	0.5526	1	0.1053	0.609
0.001	0.5	0.5	1	0	0.6667
0.001	0.9	0.5	0	1	0

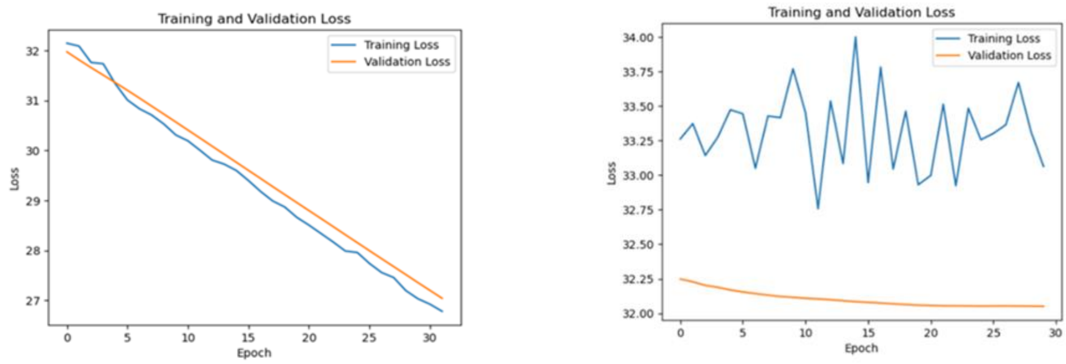
Table 4. Result based on evaluation metrics on unseen dataset

Model	Accuracy	Sensitivity	Specificity	F1-score
ResNet50V2+GTO	0.94	1.0	0.88	0.93
ResNet50V2 (Manual)	0.91	1.0	0.82	0.91
ResNet50V2 (Default)	0.91	0.82	1.00	0.77



(a) (b)

Figure 2. Training and validation accuracy and loss of (a) proposed method and (b) manual hyperparameter tuning



(a) (b)

Figure 3. Training and validation accuracy and loss of (a) proposed method and (b) manually tuned model

The perfect sensitivity (1.00) achieved by the optimized model is critical in clinical applications. A model with high sensitivity ensures that no true SVS-positive cases are missed, which is crucial. Notably, missing an SVS in an ischemic stroke patient could delay appropriate treatment, worsening patient outcomes.

Additionally, the improved specificity (0.88) indicates that the model reduces false positives, making it more reliable for radiologists by minimizing unnecessary follow-up scans or interventions.

This finding demonstrates that hyperparameter tuning is a technical enhancement and a crucial step in improving artificial intelligence-based diagnostic tools for real-world clinical applications. Without proper optimization, the deep learning model either fails to detect all stroke cases (low sensitivity) or leads to misdiagnosis (low specificity), limiting their practical use. In summary, integrating GTO with transfer learning models presents a promising approach for improving the automated detection of SVS in ischemic stroke patients. This study demonstrated that optimized hyperparameter tuning enhances model performance, offering an effective tool for clinical decision-making and improving patient care.

5. CONCLUSION

This study demonstrated that integrating the GTO with ResNet50V2 significantly improves the detection of SVS in ischemic stroke patients. The optimized model achieved perfect sensitivity and improved overall performance by fine-tuning key hyperparameters like learning rate and dropout rate. Compared to baseline and manually tuned models, the GTO-enhanced approach showed superior accuracy and robustness, highlighting the importance of hyperparameter optimization in detecting subtle clinical markers such as SVS in MRI scans. Despite promising results, challenges remain regarding model generalizability and clinical validation. Future work should focus on evaluating performance with larger, diverse datasets and refining optimization strategies, including hybrid or adaptive methods. Additionally, enhancing model interpretability through techniques like gradient-weighted class activation mapping (Grad-CAM) can increase trust among clinicians. Beyond stroke, the proposed method could be applied to other vascular conditions and oncology diagnostics, underscoring its broader potential in medical image analysis.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author [NLSA] on request.

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