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RESEARCH ARTICLE

Ischemia and Hemorrhage detection in CT images with Hyperparameter optimization of classification models and Improved UNet Segmentation Model

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ABSTRACT

Deep learning is a powerful technique that has been applied to stroke detection using medical imaging. Stroke is a medical condition that occurs when the blood supply to the brain is interrupted, which can cause brain damage and other serious complications. Stroke detection is important to minimize damage and improve patient outcomes. One of the most common imaging modalities for stroke detection is CT (Computed Tomography). CT can provide detailed images of the brain and can be used to identify the presence and location of a stroke. Deep learning models, particularly convolutional neural networks (CNNs), have shown promise for stroke detection using CT images. These models can learn to automatically identify patterns in the images that are indicative of a stroke, such as the presence of an infarct or hemorrhage. Some examples of deep learning models used for stroke detection in CT images are U-Net, which is commonly used for medical image segmentation tasks, and CNNs, which have been trained to classify brain CT images into normal or abnormal. The purpose of this study is to identify the type of stroke from brain CT images taken without the administration of a contrast agent, i.e., occlusive (ischemic) or hemorrhagic (hemorrhagic). Stroke images were collected, and a dataset was constructed with medical specialists. Deep learning classification models were evaluated with hyperparameter optimization techniques. And the result is segmented with an improved Unet model to visualize the stroke in CT images. Classification models were compared and VGG16 achieved %94 success. Unet model achieved %60 IOU and detected the ischemia and hemorrhage differences.

Keywords: stroke detection; CT image; Deep learning; medical image processing; segmentation

1. Introduction

Stroke detection is a critical area of research in medical artificial intelligence. In recent studies, deep learning algorithms have been explored to predict hematoma expansion from non-contrast computed tomography (NCCT) scans through external validation [1]. One novel CNN, SkullNetV1, uses CNN for feature extraction and a lazy learning approach to classify five types of skull fractures from brain CT images [2]. Another study formulated intracranial hemorrhage (ICH) detection as a problem of multiple instance learning (MIL), which enables training with only scan-level annotations [3]. Deep learning-based automated analysis of CT scan slices has been proposed for detecting various levels of brain hemorrhages [4]. A combination of deep learning and machine learning classification algorithms has been used to establish an explainable COVID-19 detection system using CT scans and chest X-rays [5]. The proposed research focuses on several deep transfers learning-based CNN approaches for detecting COVID-19 in chest CT images, using foundation models such as VGG16, VGG19, Densenet121, InceptionV3, Xception, and Resnet50 [7]. A method for detecting pulmonary nodules based on multiscale fusion has been shown to have a higher detection rate for small nodules and improve the classification performance of true and false-positive nodules [8,9], with competitive performance in terms of sensitivity compared to state-of-the-art methods [10].

There are also studies proposing deep learning-based methods for CT [11,12], proposing fully automated lesion detection and segmentation systems on whole-body PET/CT scans [13,14], and developing effective segmentation techniques based on deep learning algorithms for optimal identification of regions of interest and segmentation [15-17]. Other influential work includes developing a deep learning model capable of segmenting IVCF from CT scan slices along the axial plane [18] and showing a deep learning model that segments acute ischemic stroke on NCCT at a level comparable to neuroradiologists [19]. Medical images differ from natural images in many ways, and a domain expert should be consulted to assess the model's performance. Detecting stroke in CT images is a challenging task due to its nature. It is important to verify the outcomes of deep learning models on different datasets and with different preprocessing methods, as the models' performance may vary depending on these factors.

The purpose of this study is to identify the type of stroke from brain CT images taken without the administration of a contrast agent, i.e., occlusive (ischemic) or hemorrhagic (hemorrhagic). A deep learning model was used to visualize the important area (ischemia and/or bleeding site) on the CT image, and classification algorithms were used. In addition, a study was carried out on determining the stroke region with the segmentation structure. The most successful classification model accuracy was 94 % and the improved UNET segmentation model IOU metric accuracy was 60 %. The paper is organized as follows, Materials and Methods, Transfer learning, Data Augmentation, Segmentation Mode, Results and Discussion and Conclusion.

2. Materials and Methods

The quantity of the training dataset and the variability of the data are key factors in the network's success. For deep learning models to function well, large datasets are required. Data augmentation and transfer learning techniques were applied. The data was used from Kaggle (Brain MRI dataset) and collected from the hospitals and labeled with the medical professionals.

Due to its structure, learning transfer removes the requirement for additional data and improves model performance by cutting down on learning time. As pre-trained networks already modify weights by learning from many data, they are known to need less input than networks trained from the start.

To create a project on stroke detection using deep learning classification and segmentation models, several steps need to be taken:

- Assembling a database of medical CT scans including unaffected and photos showing the effects of a stroke. Having a varied dataset that encompasses various stroke types and imaging circumstances is crucial.
- Images need to be resized or normalized, and the dataset might be divided into training, validation, and test sets.
- Training the model on a custom dataset, the training needs to be adjusted to the model's parameters to accurately classify and segment the images.
- Evaluating the model's performance using the validation and test sets. To observe how well the model can classify and segment new images that have not been seen before.
- For the model to correctly categorize and segment the images, the parameters need to be adjusted using the training set (Hyperparameter optimization).

2.1 Transfer learning

Transfer learning is a technique in machine learning that allows a model trained on one task to be used for a different but related task. In the context of medical imaging, transfer learning can be used to apply a model trained on a large dataset of general images to a smaller dataset of medical images.

There are two main ways to use transfer learning for medical imaging:

- Feature extraction: In this approach, a pre-trained model extracts features from the medical images. The extracted features are then used as input to a separate classifier to recognize specific medical conditions. This allows the model to take advantage of the pre-trained model's ability to detect low-level features, while still allowing the classifier to learn the specific characteristics of the medical images.

- Fine-tuning: In this approach, a pre-trained model is used as a starting point and is further trained on a medical imaging dataset. This allows the model to adapt to the specific characteristics of the medical images, while still taking advantage of the knowledge learned from the pre-trained model.

Transfer learning can be useful in medical imaging because it allows for the training of models with a smaller amount of data, which is often a limitation in the medical field. Additionally, transfer learning can also help to improve the performance of models by leveraging the knowledge learned from pre-trained models on large datasets.

Even with transfer learning, it's still important to have a diverse and high-quality dataset, as well as to evaluate the model's performance and ensure that it generalizes well to new cases. In this study, classification models combined the feature extraction and fine-tuning methods.

2.2. Data augmentation

Furthermore, a study evaluated various methodologies, deep learning architectures, approaches, bioinformatics, specified function requirements, monitoring tools, artificial neural network (ANN) algorithms, data labeling, and annotation algorithms that control data validation, modeling, and diagnosis of different diseases using smart monitoring health informatics applications [23]. Another study proposed an end-to-end Generative Adversarial Network (GAN) architecture capable of generating high-resolution 3D images [24].

Additionally, an Extreme Gradient Boosting (XGBoost) algorithm was developed to classify four subtypes of brain tumors: normal, gliomas, meningiomas, and pituitary tumors [25]. Tumor segmentation is a specific task that requires clinicians to label every slice of volumetric scans for each patient, which can become impractical for training neural networks with a large dataset. To address this issue, a novel semi-supervised framework was proposed to train any segmentation model using only the presence of a tumor in the image, as well as a few annotated images [26]. The training pipeline of the dataset included histogram equalization and data augmentation [29,30]. Data augmentation is a machine learning technique that applies various transformations to existing data, such as flipping, rotation, scaling, and cropping, to artificially increase the size of the dataset. In medical imaging, data augmentation can be used to increase the training data available for a model, and thus improve its performance.

There are several reasons why data augmentation is important in medical imaging:

- Small datasets: Medical imaging datasets are often small in size due to the high cost and complexity of acquiring medical images. Data augmentation can help to overcome this limitation by artificially increasing the size of the dataset.
- Variability: Medical images can vary greatly depending on the imaging modality, patient population, and imaging conditions. Data augmentation can help to increase the diversity of the dataset and make the model more robust to these variations.
- Overfitting: Deep learning models can easily be overfit to the training data, resulting in poor performance on new data. Data augmentation can help to reduce overfitting by introducing additional variations in the training data.

Common data augmentation techniques used in medical imaging include flipping, rotation, scaling, translation, shearing, and adding noise. Additionally, it is important to keep in mind that data augmentation should be applied carefully and with consideration of the specific characteristics of the medical images, as well as the medical condition being analyzed, to avoid creating unrealistic or misleading images.

The data augmentation techniques applied should be chosen carefully and considering the specific characteristics of the medical images, as well as the medical condition being analyzed, to avoid creating unrealistic or misleading images. Additionally, it is important to consider the regulatory requirements for your project, such as HIPAA compliance, as well as ethical considerations.

2.3. Classification model

Using pre-trained models such as VGG16, InceptionV3, DenseNet, and Xception for medical image classification is a common approach in deep learning. These models have already been trained on large image datasets and can be fine-tuned for a specific medical imaging task. Here is a general outline of the process:

- First, a dataset of medical images labeled with the appropriate class labels.
- Fully connected layers need to be removed, which is used for the original image classification task the model was trained on.
- Then, a fully connected layer with the number of neurons corresponding to the number of classes was added for our study.
- Fine-tune the model by training on a medical image dataset. This can be done by "freezing" the weights of the pre-trained layers and only training the added fully connected layer.

A big, diversified dataset with high-quality photos might be challenging to get in the field of medical imaging. Additionally, it is preferable to have a domain specialist assess the model's performance because medical images differ from natural photos in many ways. Therefore, the dataset was constructed with radiologists.

2.4. Segmentation model

U-Net style convolutional neural networks (CNNs) are a popular choice for the segmentation of medical images. The U-Net architecture is designed specifically for image segmentation, with a contracting path (downsampling) and an expansive path (upsampling). The contracting path is based on a traditional CNN, while the expansive path uses a transposed CNN (deconvolution) to increase the spatial resolution of the feature maps. The two paths are connected via skip connections, which concatenate feature maps from the contracting path with corresponding feature maps from the expansive path. By leveraging information from earlier layers in the contracting path, the U-Net architecture can achieve more precise segmentation results.

Improved UNet is an enhanced version of the original UNet architecture. It aims to improve the performance of the original UNet by incorporating some novel techniques such as:

- Attention Mechanism
- Multi-Scale Feature Fusion
- Residual Connection
- Spatial Dropout
- Batch Normalization
- Weighted Cross-Entropy Loss

These changes help to improve the accuracy and stability of the model. In this study, improved UNet was trained and tested with parameter optimizations.

2.5. Hyperparameter optimization

Hyperparameter optimization is the process of finding the best set of hyperparameters for a given model and dataset. Hyperparameters are parameters that are not learned during the training process, but rather set before the training process begins. Examples of hyperparameters in the UNET model include learning rate, batch size, and number of filters in each layer.

One possible approach to hyperparameter optimization is grid search, which involves evaluating the model's performance for all possible combinations of hyperparameters in a predefined range. Another approach is random search, which involves sampling hyperparameters from a distribution. In practice, it is often useful to use a combination of these methods, along with techniques such as early stopping and cross-validation, to find the best set of hyperparameters for a given task. Pixel-level thresholding is a post-processing technique used in image segmentation tasks to improve the accuracy of the segmentation. In this technique, a threshold value is applied to the predicted probabilities to binarize the output image. The threshold value can be set based on the distribution of the predicted probabilities, or it can be optimized using a validation set. By setting an appropriate threshold value, the output image can be refined to better separate the foreground and background.

In addition to the weighted cross-entropy loss function, there are several other loss functions that can be used in the UNET model for image segmentation tasks. These include Dice Loss: This loss function measures the overlap between the predicted and true segmentation masks using the Dice coefficient. Jaccard Loss: This loss function measures the similarity between the predicted and true segmentation masks using the Jaccard coefficient. Focal Loss: This loss function is designed to give more weight to hard examples in the training data by down-weighting easy examples. Lovasz Softmax Loss: This loss function is based on the Lovasz extension of submodular functions and is designed to optimize the intersection-over-union (IoU) metric directly. The choice of loss function depends on the specific task and the performance metric of interest. In practice, it is often useful to experiment with different loss functions and compare their performance on a validation set. Therefore, Dice loss was used in the dataset to compare very similar stroke types.

Multi-scale feature fusion is a technique used to combine features from different scales to improve the accuracy of the model. In the UNET model, multi-scale feature fusion is typically achieved by concatenating feature maps from different layers of the encoder and decoder networks. This allows the model to capture both high-level and low-level features, which can be particularly useful in tasks where objects of different sizes need to be segmented. Mathematically, the multi-scale feature fusion operation can be represented as follows:

$$F_i = \text{Concatenate}\ (F_i\ \text{-}1,\ G_i) \qquad (1)$$

Where F_i is the i-th feature map in the decoder network, F_i -1 is the corresponding feature map in the encoder network, and G_i is the i-th feature map in the corresponding decoder layer. The resulting feature map is then processed further in the decoder network to refine the segmentation output.

A residual connection is a technique used to improve the training of deep neural networks by allowing gradients to flow more easily through the network. In the UNET model, residual connections are typically used to connect layers in the encoder and decoder networks. Mathematically, a residual connection can be represented as follows:

$$F_i = G_i + Conv\ (F_i -1) \quad (2)$$

Where F_i is the i-th feature map, G_i is the corresponding feature map in the same layer, Conv is a convolutional layer, and the '+' operator denotes element-wise addition. The resulting feature map is then processed further in the decoder network to refine the segmentation output.

Spatial dropout is a variant of the standard dropout technique used in deep learning to prevent overfitting. In the UNET model, spatial dropout is typically applied to the input feature maps to the decoder network. Mathematically, spatial dropout can be represented as follows:

$$F_i = Dropout\ (F_i -1) \quad (3)$$

Where F_i-1 is the input feature map, Dropout is the spatial dropout layer, and F_i is the resulting feature map with some of its elements set to zero. The resulting feature map is then processed further in the decoder network to refine the segmentation output.

Batch normalization is a technique used in deep learning to normalize the inputs to each network layer. In the UNET model, batch normalization is typically applied to the convolutional layers in both the encoder and decoder networks. Mathematically, batch normalization can be represented as follows:

$$F_i = BatchNorm\ (Conv\ (F_i -1)) \quad (4)$$

Where F_i-1 is the input feature map, Conv is the convolutional layer, BatchNorm is the batch normalization layer, and F_i is the resulting feature map with normalized values. The resulting feature map is then processed further in the decoder network to refine the segmentation output.

In the UNET model, the weighted cross-entropy loss function can be used to improve the accuracy of segmentation tasks by giving more weight to certain classes or regions of interest in the image.

The Dice loss is a commonly used loss function in deep learning models for image segmentation tasks. It is named after the Dice coefficient, which is a statistical metric used to measure the similarity between two sets.

The Dice coefficient is defined as follows:

$$\text{Dice coefficient} = (2 * |A \cap B|) / (|A| + |B|) \quad (5)$$

where A and B are two sets, and |A| and |B| represents the number of elements in each set. $|A \cap B|$ represents the number of common elements between A and B.

The Dice loss is derived from the Dice coefficient and is used to measure the dissimilarity between the predicted segmentation mask and the ground truth segmentation mask. The Dice loss is defined as follows:

$$\text{Dice loss} = 1 - (2 * |P \cap G|) / (|P| + |G|) \quad (6)$$

where P and G represent the predicted and ground truth segmentation masks, respectively, and |P| and |G| represent the number of pixels in each mask. $|P \cap G|$ represents the number of common pixels between the predicted and ground truth masks.

The Dice loss ranges from 0 to 1, with a value of 0 indicating complete dissimilarity between the predicted and ground truth masks, and a value of 1 indicating perfect similarity.

In the UNET model, the Dice loss is commonly used as the loss function to optimize the model during training. The UNET architecture is designed for image segmentation tasks. The Dice loss is well-suited for this type of problem because it penalizes false positives and false negatives equally, making it a more balanced loss function than other options like binary cross-entropy.

During training, the UNET model updates its weights to minimize the Dice loss between the predicted and ground truth segmentation masks. By minimizing this loss, the model learns to produce more accurate segmentation masks, which is more effective for medical imaging.

Intersection over Union (IOU) is a common evaluation metric used in image segmentation tasks to measure the accuracy of the segmentation output. It measures the overlap between the predicted segmentation mask and the ground truth mask.

In conclusion, hyperparameter optimization techniques such as grid search, random search, and Bayesian optimization is used to optimize hyperparameters in a UNET model for image segmentation tasks to maximize IOU metrics. These techniques involve exhaustively searching through all possible combinations, randomly sampling from a predefined distribution, or using a probabilistic model to predict performance, respectively.

3. Results and Discussion

In this study, VGG16, InceptionV3, DenseNet, Xception and InceptionResnetV2 were compared with data augmentation, fine-tuning and transfer learning methods. Also, the hyperparameter-optimized UNet model was trained to segment the stroke type and region from the CT scan. The Dice loss optimization, multiscale feature optimization, batch normalization, learning rate optimization, Residual Connection, and Spatial Dropout Loss were used in our study.

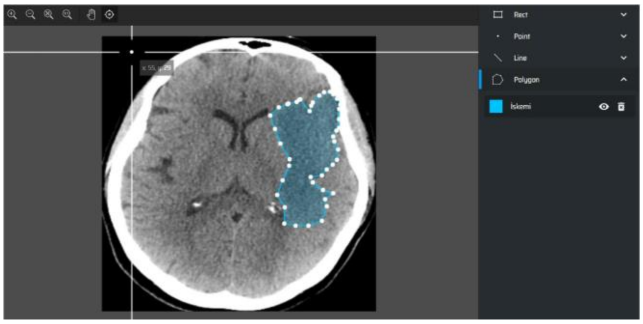

Figure 1 Labeled data example of CT image.

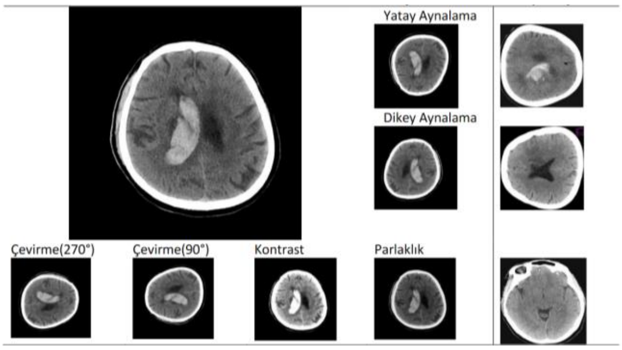

Figure 2 Rotate, contrast, brightness, mirror, and ROI example of data augmentation.

Data augmentation was performed to evaluate the performance of the CT scan. The critical point of the augmentation is that every augmentation type needs to have a reason to add to the dataset. For example, in CT the images can rotate, contrast can change, brightness can change, and the images can be mirrored depending on the application. Therefore, in the study, these parameters were made accordingly. Table 1 shows the augmentation of the data and Table 2 shows split size of the model data for training and test purposes.

Table 1 Dataset size after augmentation, 5-fold of original dataset

Class	**Dataset size**
Positive	8892
Negative	8854

Table 2 Training, validation, and test data size for comparison

Model Data	**Data Size**
Training	12422
Test	3550
Validation	1774

As shown in Table 3, the preprocessed data were prepared for training as ischemia and hemorrhage for the segmentation model. Additionally, data augmentation procedures are shown in Figure 11.

Table 3 The segmentation model data size for ischemia and hemorrhage

Class	**Dataset size**
Ischemia	6780
Hemorrhage	6558

Table 4 Classification model training results for stroke detection

Model	**Accuracy**	**Val_acc**	**Loss**	**Val_Loss**
VGG16	0.9189	0.9336	0.193	0.227
Inceptionv3	0.8793	0.9152	0.277	0.266
DenseNet	0.8025	0.8863	0.454	0.399
Xception	0.9235	0.9256	0.190	0.198
InceptionResnetV2	0.9052	0.9262	0.211	0.234

Table 5 Classification result parameters for detecting the stroke.

Model	**Class**	**Accuracy**	**Precision-Recall**	**F1 score**
VGG16	Negative	0.92	0.96	0.94
	Positive	0.95	0.94	0.92
Inceptionv3	Negative	0.81	0.92	0.87
	Positive	0.97	0.83	0.85
DenseNet	Negative	0.72	0.93	0.86
	Positive	0.98	0.72	0.80
Xception	Negative	0.91	0.91	0.90
	Positive	0.96	0.90	0.92
Inception ResnetV2	Negative	0.92	0.92	0.95
	Positive	0.94	0.88	0.94

Table 6 Improved UNet segmentation results for IOU metric to detect ischemia and hemorrhage.

Model	**Accuracy**	**Val_acc**	**IOU**	**Loss**	**Val_Loss**
U-Net	0.8825	0.8125	0.6505	0.2125	0.2397

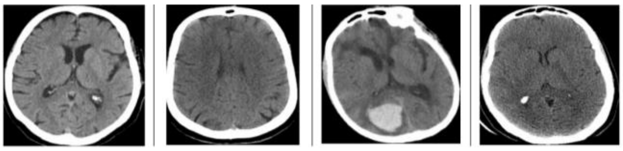

Figure 3. Ischemia and hemorrhage data examples

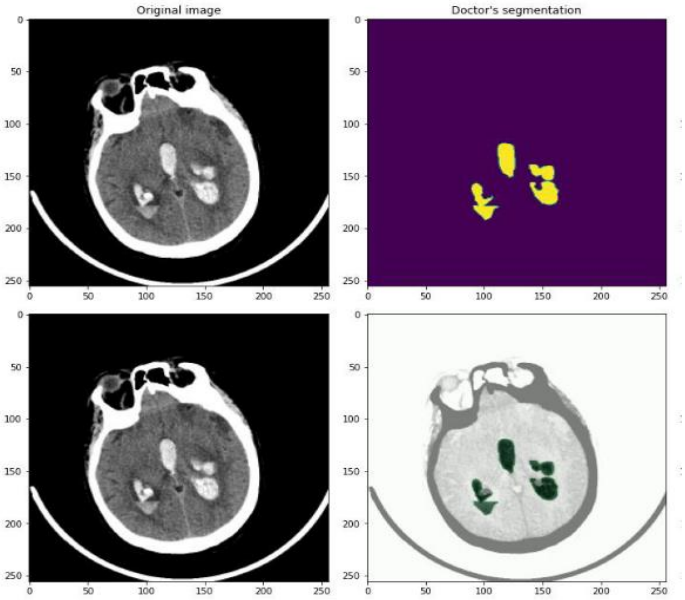

Figure 4 Improved Unet Segmentation results compared to the ground truth.

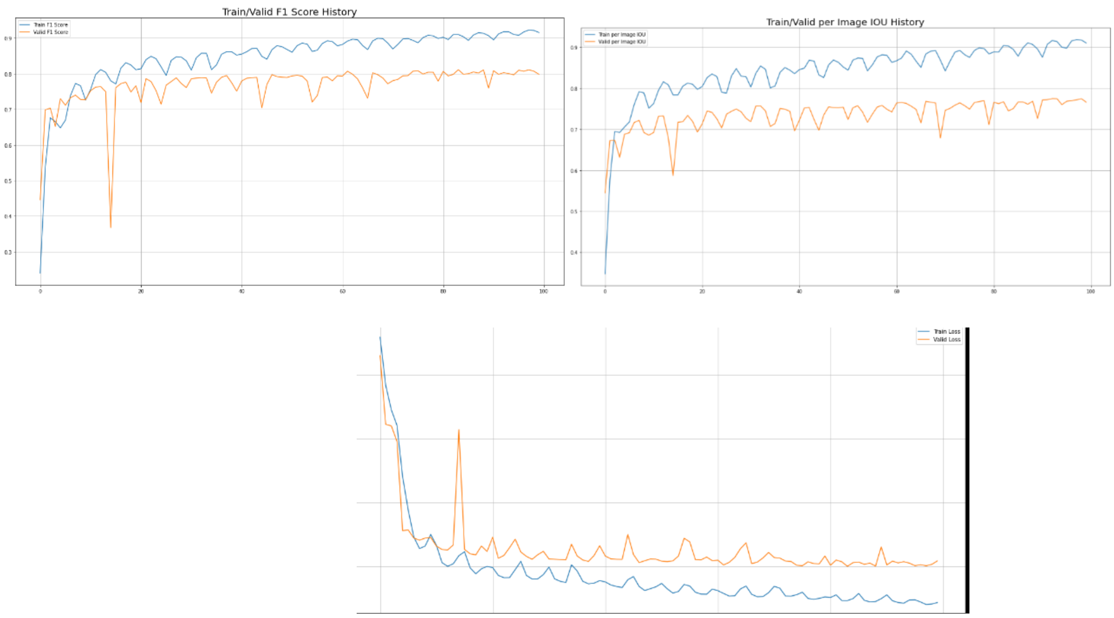

Figure 5 F1, IOU and Loss graphics.

We have demonstrated how classification models can be used to detect strokes in CT images. These models can be trained to recognize patterns in the images that are indicative of a stroke and can provide a more accurate and efficient way to detect stroke compared to traditional image analysis methods.

One of the benefits of using classification models for stroke detection in CT images is that they can provide a binary output, indicating whether a stroke is present in the image. This can help physicians quickly and easily identify patients who require further examination or treatment.

Another benefit is that these models can be trained with a large dataset of CT images, which can improve their accuracy and generalizability. Additionally, these models can be implemented with different architectures such as CNNs, RNNs and others, which can further improve their performance.

Also, in our study segmentation model was used. Segmentation models can be used to detect ischemia and hemorrhage in medical images. These models can segment or label specific regions of an image, such as the brain or blood vessels. They can be trained to identify patterns in the images that are indicative of ischemia or hemorrhage.

One of the benefits of using segmentation models for ischemia and hemorrhage detection is that they can provide more specific information about the location and extent of the condition within the image. This can help physicians to make more accurate diagnoses and treatment decisions. Additionally, these models can be used to automatically segment the regions of interest in an image, which can save time and reduce the need for manual annotation.

4. Conclusion

Ischemia and hemorrhage detection in CT images with deep learning can be challenging for a few reasons:

- Variability in imaging protocols: Different imaging protocols can result in variations in the appearance of ischemia and hemorrhage in CT images. This can make it difficult for deep learning models to learn to recognize patterns that are indicative of these conditions.
- Limited annotated data: Obtaining a large dataset of annotated CT images that contain ischemia and hemorrhage can be difficult. This can make it challenging to train deep learning models that are able to accurately detect these conditions.
- High dimensionality: CT images are high-dimensional, making it difficult for deep-learning models to learn to recognize patterns in the images.
- Overlapping features: Ischemia and hemorrhage can have similar features, making it difficult for deep learning models to differentiate between them.
- Class imbalance: Ischemia and hemorrhage may be rare in some datasets, making it difficult for deep learning models to learn to detect these conditions.

All these challenges could be addressed by using more sophisticated models, more data, and more advanced pre-processing techniques. In our work classification and segmentation models were used to challenge the task of detecting the stroke type automatically. The IOU metric is a very difficult metric to improve given the ischemia and hemorrhage similarities on CT images. Therefore pixel-wise accurate models must be evaluated and given to the medical professional for usage.

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It is declared that during the preparation process of this study, scientific and ethical principles were followed, and all the studies benefited from are stated in the bibliography.

Availability of data and material
Not applicable.

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