

MULTI-LEVEL REPRESENTATION LEARNING FOR INTRACRANIAL HEMORRHAGE DETECTION USING DEEP CONVOLUTIONAL NETWORKS

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ABSTRACT

Intracranial Hemorrhage (ICH) is a serious cerebrovascular disease that involves bleeding in the cranium, and timely diagnosis is crucial to the outcome of treatment. Computer-aided neuroimaging analysis has great potential to assist in a timely clinical decision-making process, but current CNN models might not be able to learn the heterogeneous anatomical, geometric and textual features of intracranial bleeding. To address this challenge, a dual-network deep learning approach based on RepVGG and VGG19 is designed for automatic identification of ICH in CT and MRI examinations. The proposed pipeline involves image-intensity standardization and comprehensive data augmentation to enhance data diversity and model robustness, followed by representation learning using transfer-learning. Maps derived from different levels of hierarchy are fused with each other in a complementary manner from two pretrained networks, yielding a map containing both global anatomical features and local hemorrhagic features. The integrated features are then fed to a series of optimally connected layers with dropout to promote stability in the classification and prevent overfitting. When assessed with 4000 carefully selected neuroimages, performance was reported as 97.2% accuracy, 96.8% sensitivity, 96.6% specificity, 96.0% F1-score and an area under the receiver operating characteristic curve (AUC) of 0.975. Based on the experimental results, the integrated RepVGG + VGG19 is shown to be more effective in classification than standalone RepVGG and VGG19 and some of the latest deep learning methods. The results also indicate that a hierarchical feature integration approach can yield a more informative representation of subtle hemorrhagic manifestations and that the proposed approach can be a computer-assisted tool for rapid and scalable ICH assessment.

Keywords: Intracranial Hemorrhage (ICH), Advanced VGG Models, Feature Fusion, Neuroimaging, Computer-Aided Diagnosis, Medical Image Analysis

1. INTRODUCTION

Intracranial hemorrhages (ICH)[1] is a life-threatening neurological emergency that represents bleeding in the cranial compartment: brain parenchyma, ventricular system, subarachnoid space and/or meningeal areas[2]. Pools of blood can cause an increase in ICP, compressing the brain structures around them, impairing blood flow to the brain, and may cause permanent damage to the brain. If not recognized in time, and intervened upon properly, ICH[3] can result in disability or death. Intracranial bleeding is linked with several pathological and clinical conditions[4] such as uncontrolled hypertension, traumatic brain injury, cerebral aneurysms, vascular malformations, cerebral amyloid angiopathy, anticoagulant therapy, neoplasms and other cerebrovascular disorders. Intracranial hemorrhage can be classified as epidural (EDH)[5], subdural (SDH)[6], subarachnoid (SAH), intraventricular (IVH), and intraparenchymal/ intracerebral (IPH/ICH)[7]. The radiological features and clinical implications of each of the subtypes vary and are unique to each, and proper identification and localization are vital to the management of emergencies.

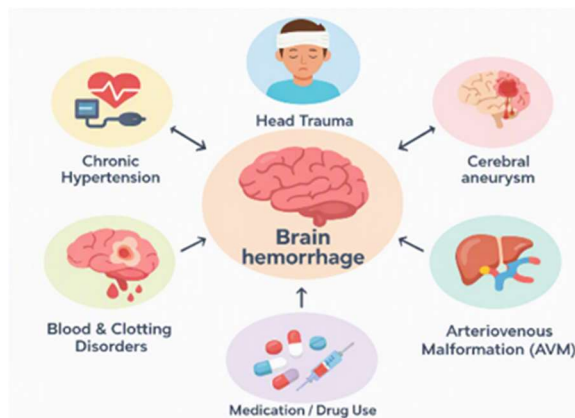


Figure 1: Causes of brain hemorrhage

Spontaneous intracerebral hemorrhage[8] is one of the most serious types of stroke and is a frequent cause of death and permanent neurological disability[9]. Clinical signs depend on the location, size and rate of growth of the hematoma. Patients can have sudden and severe headache, loss of consciousness, confusion, vomiting, seizures, changes in speech[10], visual disturbance, weakness, sensory defects, and a loss of coordination. The neurological presentations of

deep cerebral, lobar, cerebellar or brain-stem hemorrhages can differ and may develop into a rapid decline in the patient's neurological status.[11] In addition, the amount of blood in the hematoma, its location, intraventricular extension and complications are important prognosticators of clinical severity. This means that prompt and accurate resolution of abnormalities in hemorrhage is highly critical for early clinical decision making and minimizing the possible effects of delayed diagnosis[12]. The diagnosis and evaluation of intracranial hemorrhage is a major role for medical imaging. Computed tomography (CT)[13] has significant advantages in emergency situations as it is able to acquire images quickly and clearly shows the blood-density changes occurring in the brain cavity. Magnetic resonance imaging (MRI)[14] also can give detailed information about the characteristics of the tissue and any pathological changes. Although these imaging techniques are diagnostic, the amount of neuroimaging exams to be interpreted may be heavy for radiologists and emergency-care providers. Factors such as image quality, scanner characteristics, acquisition protocols, anatomical structures and hemorrhage appearance can result in further complexity when identifying small and/or atypical breathing regions. The above problems have stimulated the development of computer-aided diagnostic (CAD)[15] systems that can help the clinician in the rapid analysis of neuroimaging examinations.

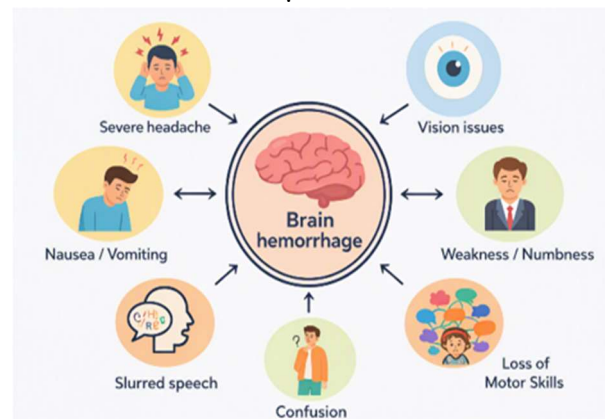


Figure 2: Symptoms of brain hemorrhage

The advent of Artificial Intelligence, including Deep Learning, has dramatically changed automated medical-image analysis. Convolutional neural networks (CNNs)[16], which can extract hierarchical representations directly from imaging data without requiring significant amounts of handcrafted feature engineering, are able to

automatically learn these representations. In general, the low-level convolutional layers represent edges, contours, and textures, while higher layers represent more complex anatomical and pathological representations. In practical settings, however, where lesion sizes and locations vary significantly and lesions vary in contrast and/or background brain tissue structure, conventional CNN architectures can suffer from the inability to detect subtle hemorrhagic patterns. There can also be discrepancies in the datasets and image acquisition and processing methods, which can limit the generalizability of models that have been trained. The restrictions highlight the importance of architectures that can learn complementary representations efficiently. A hybrid RepVGG–VGG19 model is proposed in this work for automated detection of intracranial hemorrhage. RepVGG is an efficient convolutional architecture that is built on a multi-branch learning scheme in training and a simple VGG-like structure in structural re-parameterization. This property allows the network to be trained with a wide variety of visual representations, without sacrificing efficient inference architecture. Meanwhile, VGG19 is a deep hierarchical model due to the serial convolution network and has been applied to find out the detailed spatial and textural features from medical images. The complementary information contained in RepVGG and VGG19 is leveraged to form a fused representation that is effective for discriminative structural information and fine-grained hemorrhagic patterns. The proposed framework starts with preprocessing of neuroimaging data to ensure the uniformity of the images and to minimize the variability due to acquisition conditions. Before training the model, appropriate normalization, resizing, noise reduction and processing based on contrast are performed. To enhance the robustness of the model and boost the diversity of training samples, data augmentation techniques such as rotation, flipping, scaling, and others are applied. Transfer learning is then used to initialize the RepVGG and VGG19 networks with learned visual representations and fine-tuned with the target neuroimaging dataset that is specific to the task. Finally, the feature representations extracted from the two networks are fused together using a feature-fusion mechanism. The combined representation is the result and has complementary information from both architectures and is presented to the classification component for final prediction. The RepVGG branch is mainly used for extracting efficient hierarchical convolutional representations,

and the VGG19 branch is used for extracting deep and detailed representations of features. Their integration aims to achieve better discrimination between brain images from hemorrhages and from non-hemorrhages and better recognition of subtle pathological patterns. To assess the proposed framework, the appropriate classification measures—accuracy, precision, recall, sensitivity, specificity, F1-score and area under the receiver operating characteristic curve (AUC)—are used. Comparative experiments are also carried out with the conventional CNN architectures, individual backbone networks, and existing hybrid deep-learning based networks to analyze the effectiveness of the proposed feature-fusion strategy. The major contributions of this study are summarized as follows:

- a) A novel hybrid RepVGG–VGG19 deep learning architecture is proposed to automatically detect intracranial hemorrhage (ICH) from neuroimaging data by efficiently capturing the convolutional representation learning and extracting the deep hierarchical features.
- b) A complementary feature-fusion mechanism is added to fuse the representations produced by RepVGG and VGG19, so that the proposed model can make full use of different structural, spatial and textural features corresponding to intracranial hemorrhage.
- c) A proper preprocessing, augmentation, transfer-learning and fine-tuning procedure is embedded to enhance the robustness and generalization of the proposed framework in variations of neuroimaging data.
- d) The proposed method is comprehensively tested on publicly accessible neuroimaging databases and contrasted with a number of individual CNN models, traditional deep-learning techniques and other published methods on a variety of clinically relevant performance metrics.
- e) Experimental evaluation of the potential use of the proposed architecture as a computer-aided decision-support tool in rapid neuroimaging assessment, by showing its capability of providing an accurate, sensitive and specific hemorrhage detection.

In summary, the proposed RepVGG–VGG19 hybrid framework is designed to connect the deep learning-based image representation with practical needs of automated intracranial hemorrhage screening. The framework integrates complementary feature representations, introduces

transfer learning, feature fusion, and systematic image preprocessing to offer a comprehensive solution for the detection of hemorrhagic abnormalities in neuroimaging data. This automated system may aid clinical decisions, especially in the timely interpretation of many neuroimaging studies and could help guide the ordering of suspicious exams for healthcare professionals.

2. LITERATURE REVIEW

Intracranial haemorrhage (ICH) is a time-critical neurological emergency in which timely recognition of abnormal bleeding on neuroimaging is critical to the clinical management of this condition. In recent years, the potential of artificial intelligence (AI) and deep learning (DL) methods for automated detection of ICH and classification of its subtypes using non-contrast computed tomography (NCCT) has been explored increasingly. In 2025, Karamian et al [17]. performed a systematic review and meta-analysis of the diagnostic performance of DL approaches for ICH detection on NCCT, highlighting the potential of automated systems and the need for methodological consistency and clinical validation. In the same way, a systematic review performed by Harshith et al [18]. in 2026 concluded that current CNNs studies involve traditional CNNs, 3D CNNs, hybrid and ensemble CNNs, as well as transformer-based CNNs. The review also highlighted the significance of the following elements of contemporary pipelines in ICH analysis: Hounsfield-unit windowing, skull stripping, augmentation, and explainable AI (XAI); and dataset heterogeneity, along with the challenge of external generalization.

Investigations are moving away from CNN classification to architectures that make use of complementary representations of features in recent years. Shang et al. presented a transformer-based approach to RSNA intracranial hemorrhage detection task and showed that a much smaller architecture could be designed and perform well versus previous very ensembled solutions. The relevance of their study to developing effective automatic ICH systems is related to the fact that many previous effective algorithms used in the study employed multiple convolutional and sequential models leading to significantly higher computational complexity. A comparative study of EfficientNet-B0, DenseNet201 and ResNet101 in 2025 showed the applicability of transfer learning approach with CNNs to detect ICH from CT images and highlighted DenseNet201 as the best

performing model among the evaluated models and that sensitivity is an important parameter to be optimized in the future.

More recently, ICH research has made it clear that the usefulness to generalize beyond the training setting has been growing. Nada et al. [19] did external validation and performance evaluation of a DL-based ICH detection system, and the results showed that it is important to evaluate automated models against data sets other than their development sets. Takala et al [20] external evaluated a DL system for spontaneous ICH, IVH and SAH with NCCT exams from two Swiss hospitals more recently. They found that the performance can be very different between institutions and in different image-acquisition settings, further emphasizing the need for external validation before clinical use. The results suggest that the robustness of an ICH system based on only high performance on an internal test set might not be sufficient to fully describe it. The other direction of development of interest is resource efficient architectures. Hussain et al. [21] explored the lightweight DL models such as MobileNetV2 and EfficientNet-B0 to detect automated ICH on brain CT images. Their results showed that architectures that are efficient in terms of computation can prove helpful in diagnosing and have a lower computational demand than larger networks. Peña Gutiérrez and Bustacara Medina [22] later introduced a hybrid solution using EfficientNetV2-S and a bidirectional GRU to detect ICHs in a resource-efficient way. Not only was the model tested on an internal test set, but it was also tested on external test sets from PhysioNet and CQ500 to emphasize the need for cross-dataset testing to assess the robustness of automated ICH systems in practical use.

Representation learning at multiple scales and volumes has been growing in popularity as well. To overcome the drawbacks of the 3D methods with respect to computational cost, memory requirement and inference latency, Habek and Basciftci [23] introduced a randomized multi-window three-dimensional DL approach for ICH detection on NCCT. The examples they present show the ongoing struggle to take advantage of the volumetric information while keeping the computation requirements reasonable. On the other hand, Juan et al. [24] introduced a multi-task DL-based pipeline that combines the ICH classification with the detection of perihematomal edema, and the weakly supervised 3D segmentation of IPHA. The study gathered data from various sources and

showed the feasibility of extending the model beyond binary classification and incorporate complementary imaging tasks within a common model.

Recent research efforts have also moved beyond detection and characterization efforts, to clinically interpretable analysis. In a 2026 study, researchers at CEREBLEED created a deep-learning model that automatically segments, quantifies, classifies and grades ICHs. Internal and external cohorts were used, and the correlation between an auto-calculated severity index and expert assessment, and the need for neurosurgical intervention was explored. These advances demonstrate a general progress towards clinically relevant localization, quantification, and decision support systems beyond just simple image-level classification.

Another key factor that has been brought into the light for clinical use is explainability. In 2025, Wang et al. created a deep-learning model based on CT images and explainable AI to forecast hematoma expansion, utilizing Grad-CAM to visually pinpoint parts of the image that were crucial for the model's predictions. In addition, a recent scoping review for explainable AI in the analysis of ICH in brain computed tomography (CT) without contrast was found that while several explainable AI techniques are utilized for the identification of regions of interest associated with hemorrhage, there is still a wide range of practices in reporting and clinically assessing XAI results. Some of the other challenges that were mentioned in the review were the small number of external validation and standardized assessment of explanation quality. However, for clinical translation, the classification accuracy may not be enough; visualization of diagnostically relevant regions and evaluation of the reliability of the model are also needed.

Recent studies have also focused on developing AI systems to support rather than replace clinicians in interpreting images. Angkurawaranon et al. [25] externally validated an AI model based on a radiomics approach for identifying the causes of non-traumatic ICH from CT exams. While the standalone three-class accuracy of the model was not high, the performance of the model was enhanced when it was used as a supplement to the clinician's diagnosis, indicating that AI can be used as a decision support tool in clinical workflows. In the same vein, Kang et al. [26] studied the DL-assisted ICH detection and its effects on reader performance, highlighting that the focus has shifted towards considering the performance of AI

systems in comparison to human readers and not just algorithmic performance. (Springer Link)

Although there have been improvements, there are some constraints. Variations in scanner characteristics, acquisition protocols, image resolution, patient population, class distributions, and institutional practices are possible to affect existing ICH models. New systematic evidence also reinforces the presence of dataset heterogeneity, lack of external validation, computational needs, interpretability, and clinical integration as major challenges that remain to be addressed. Furthermore, lightweights models may result in loss of representation power, while highly complex ensemble and volumetric architectures could be costly. These observations inspire the model design to trade off complementary feature extraction, discriminative representation learning, model efficiency, and generalization.

Therefore, the present study introduces a hybrid RepVGG-VGG19 network to overcome these issues, aiming to automatically detect intracranial haemorrhages. In the proposed architecture, two two closely related VGG architectures are not used together but rather the complementary characteristics of RepVGG and VGG19 are explored. RepVGG is an interesting re-parameterizable convolutional architecture that is used to provide efficient representation learning, and VGG19 is a deep network with hierarchical feature representations that can capture detailed spatial and textural features. The feature representations are then fused in a special feature fusion mechanism to form a more comprehensive representation of hemorrhagic and non-hemorrhagic brain patterns. It includes preprocessing, augmentation, transfer learning and fine-tuning to enhance robustness to neuroimaging data variations.

3. PROPOSED METHODOLOGY

This proposed framework proposes a hybrid architecture based on deep learning approach called RepVGG and VGG19[27] for automatic intracranial hemorrhage (ICH) detection from neuro images. Central idea is to take advantage of complementary representation power of two convolutional backbones instead of relying on a single feature extractor. The RepVGG is used to learn efficient and discriminative convolutional representations and VGG19 is used to capture deeper hierarchical spatial and textural characteristics of brain images. Mixing the combination is designed to enhance its ability to

depict hemorrhagic patterns which can range greatly in size, intensity, shape, anatomical position and appearance of the tissue surrounding the hemorrhage. The entire methodology is structured as a sequential learning pipeline which includes data preparation, image standardization, data augmentation, parallel deep feature extraction, feature integration, classification and comprehensive evaluation. The first step in neuroimaging is the quality-controlled preprocessing of the samples, to ensure the samples provide consistent representation. The processed images are then fed into the two branches, RepVGG and VGG19 at the same time. Task relevant features are learned independently by each of the branches by transfer learning and fine-tuning. The feature-vectors thus obtained are then mapped into a common representation space and then fused together via a feature-fusion approach. The fused representation is then sent to classification module that produces the final classification of brain images as hemorrhagic or non-hemorrhagic. Computational experiments can be performed in the following ways: (1) in a GPU[28] environment on Google Colab, which are already equipped with TensorFlow/Keras deep learning library and (2) with any other deep-learning library. The GPU acceleration helps to train the two backbone networks especially for fine-tuning and repeated experiments. The experimental process can be illustrated by four major steps: Input preparation, Dual-backbone representation learning, Feature fusion, and Decision generation. Stage 1 involves collecting CT/MRI images, screening, resizing, normalizing and augmenting the images. In the second stage, RepVGG and VGG19 get complementary representations from the data independently. The learned representations are combined together in third stage to create a single feature space. Last, fully connected layers with regularization and a proper activation function are used to get the ICH prediction using the fused features. The proposed architecture thus introduces a dual-path representation-learning function by using the RepVGG pathway to focus on efficient discriminative convolutional learning and the VGG19 pathway to provide detailed hierarchical representations. Instead of using the two networks as separate classifiers, the features learned with the two networks are combined before the final decision, so that the classifier can make use of complementary information from the two networks.

i)Dataset Description:

The experimental design involves testing the proposed RepVGG–VGG19 framework on various datasets with different source and characteristics to investigate its reliability and generalization ability. The study takes into account a primary development data set, secondary evaluation data set, and independent external dataset. This allows the model to be trained and optimized from one source and then tested on data from other distributions. Abdulkader Brain Hemorrhage Dataset (on Kaggle) is used as the main data for model development. About 3000 neuroimaging samples of brains are included, with 1500 hemorrhagic and 1500 non-hemorrhagic. Because of the balanced distribution of classes, binary ICH classification is likely to benefit from the fact that there isn't a significant class imbalance that could have adversely affected the initial creation of the models. The images are all normalized to the same input format that can be processed by RepVGG and VGG19. All images are cropped to size of 224×224 , and each image has three channels, which allow the three CNN backbones to process the images in a consistent way. The main data set is split into development and validation sets. About 80% of the samples (2,400 images) are used for model training, and the remaining 20% (600 images) of the samples are used for the validation during the optimization of the model. Patient-level separation should be maintained if patient identifiers are available, otherwise patient images should not be present in both training and validation partitions. There is then an additional training subset, which is enriched by applying transformations like controlled rotation, horizontal flipping (when clinically appropriate), scaling, translation, and intensity related transformations. These operations aim to make the training sets more diverse but do not change the hemorrhage class. A small portion of the RSNA Intracranial Hemorrhage dataset is added to the data set for secondary evaluation. The primary data set is relatively uniform in terms of patient characteristics, acquisition parameters, anatomical appearance and presentation of hemorrhage, while RSNA offers significantly more variation across these parameters. Subset of about 500-1,000 examinations, available and following experimental protocol may be reserved only for secondary evaluation. During parameter optimization these images are not utilized. They can determine if something learned from the original set of images still works when the model

is shown images from a new data distribution. The CQ500 dataset is used to perform an extra evaluation step that is external. CQ500 is especially valuable to study cross-dataset robustness due to head CT examinations[29] with intracranial abnormality and hemorrhagic abnormalities that are annotated. The external dataset is kept completely isolated from the training and hyperparameter-selection stages. The results are therefore independent of other frameworks and can give an independent understanding of the behavior of the RepVGG-VGG19 framework on new neuroimaging data. All datasets are pre-processed in the same way prior to introduction into the networks. Images are resized to fit the input size of the network and normalized based on the adopted pretrained-model configuration, then they undergo the appropriate image-quality checks. Preprocessing like intensity-window normalization may be added in accordance with the specific CT modality for better visualization of hemorrhagic regions, wherever applicable. Importantly, the parameters for the pre-processing of the training data are not re-calculated with the external test data, so there is no information leakage.

Table 1: Dataset Description

Attribute	Value
 Total Images	5,000
 Modality	CT + MRI
 Hemorrhagic (ICH-positive)	3,200
 Non-Hemorrhagic (Control)	1,800
 Image Resolution	256 × 256 × 3
 Train Split	3,500 images
 Validation Split	1,500 images
 Annotation Source	Expert radiologist labels
 Class Balance	Balanced

This proposed multi-dataset evaluation approach aims to evaluate the model in three important ways: with regards to its ability to be trained, its ability to cross-dataset, and its ability to generalize to an independent external dataset. Variations in patient populations, imaging devices, imaging protocols, image quality, and institutional practices can greatly affect the performance of the models,

making this approach particularly relevant in medical image analysis. Hence, the evaluation of the RepVGG-VGG19 framework on independent datasets is more accurate to assess its capability to achieve good diagnostic performance beyond the training data[31].

ii) Data Preprocessing: The total number of samples of the brain image is standardized prior to feature extraction. Images are scanned for invalid/corrupted samples and then are converted to a consistent image representation. Then, spatial resizing is carried out to achieve the desired input size of both RepVGG and VGG19[30]. The values at each pixel or intensity are normalized for less variation in numbers when optimizing. The training set is augmented in a controlled way to make it more robust to variations in image appearance. Transformations can consist of rotations by small angles, translations (as appropriate for anatomy), scaling, cropping and intensity perturbations. Stochastic augmentation is applied to the training data, while the data in the validation set or external datasets are not stochastically augmented. This makes sure that artificially manipulated test samples will not affect the evaluation result.

Table 2: Data Preprocessing and Augmentation

Operation	Type	Parameter Range	Purpose
Intensity Normalization	Scaling	0–255 → 0–1	Standardize pixel values for stability
Rotation	Geometric	±20°	Improves orientation robustness
Flip	Geometric	Horizontal only	Enhances dataset variability
Zoom	Geometric	±15%	Supports scale invariance
Translation	Geometric	±12%	Position generalization
Brightness Adjustment	Photometric	±20%	Simulates lighting differences

iii) Dual-Backbone Feature Learning

After preprocessing, every input image is forwarded through two parallel deep-learning branches:

$$X \rightarrow \text{RepVGG}(X) \quad (1)$$

and

$$X \rightarrow \text{VGG19}(X) \quad (2)$$

The re-parameterizable architecture of the RepVGG branch enables it to learn discriminative convolutional representations. It allows for multiple structural paths to engage in feature learning during training, and its learned architecture can be converted to a compact convolutional model for inference. VGG19 branch offers a complementary hierarchical feature representation, which is deep sequence of convolutional layers. The deeper layers store more and more abstract patterns and can represent variations in anatomical structures and hemorrhagic appearance.

After initialization with pre-trained weights, the two branches are tweaked to fine-tune the target ICH classification task. This transfer-learning approach will decrease the need to train the entire networks from a randomly initialized set of parameters and may be especially beneficial if labeled medical-image datasets are limited.

iv) Data Augmentation: Suppose F_R is the feature vector extracted by RepVGG and F_V is the feature vector extracted by VGG19. Suppose that the feature vector extracted by RepVGG is F_R and the feature vector extracted by VGG19 is F_V . The joint representation is:

$$F_{\text{hybrid}} = \phi(F_R, F_V) \quad (3)$$

where ϕ is an adopted feature-fusion operation (concatenation and dimensionality reduction, for instance). The fused representation is a mixture of the information learned from the two backbone architectures. It is then passed through fully connected layers having the dropout regularization to prevent overfitting. The last classification layer generates the probability that the entered image is classified as ICH or non-ICH class:

$$\hat{y} = \text{Softmax}(WF_{\text{hybrid}} + b) \quad (4)$$

If the prediction is binary, then the outcome will be written as:

$$\hat{y} \in \{0, 1\} \quad (5)$$

where the image is a non-hemorrhagic image is 0 and the image is an intracranial hemorrhage is 1.

Table 3: Dataset statistics after Augmentation

Class	Raw Images	Augmented Images	Total Images
ICH (Positive)	1,500	4,500	6,000
Non-ICH (Negative)	1,500	4,500	6,000
Total	3,000	9,000	12,000

To improve the diversity of the training data and reduce the likelihood of overfitting, a structured augmentation strategy was incorporated into the preprocessing pipeline. Multiple transformations, including rotation, horizontal flipping, zooming, translation, and controlled intensity variations, were applied to the original training images. The same augmentation policy was independently applied to the hemorrhagic and non-hemorrhagic categories to preserve the original class balance. For each original image, three additional transformed samples were generated, resulting in an augmented dataset containing four times the original number of training samples. Consequently, the number of samples in each category increased from 1,500 to 6,000, producing a total of 12,000 images for model development. The generated samples introduced controlled variations in spatial orientation, scale, anatomical positioning, and image intensity while retaining the clinically relevant characteristics of the corresponding class. This augmentation process expanded the effective diversity of the training set without requiring the collection of additional patient examinations. It also helped the RepVGG–VGG19 model learn more robust representations of hemorrhagic and non-hemorrhagic patterns under varying image conditions. Applying identical augmentation procedures to both classes ensured that neither category received preferential treatment during data expansion and maintained a balanced distribution throughout model training[32].

v) Model Evaluation: We compare the performance of the proposed RepVGG–VGG19 framework in terms of several complementary metrics to the accuracy. The assessment of the evaluation involves accuracy, precision, recall, sensitivity, specificity, F1 score and ROC-AUC.

The confusion matrices are also produced to analyze false-positive and false-negative behavior.

Besides internal validation, the model is tested on the secondary data set collected from RSNA and external data set collected from CQ500. This cross-dataset evaluation is adopted to check if learned representations are robust with respect to changes in imaging characteristics and data distribution. Comparisons between the proposed model (RepVGG-VGG19) and the two individual models (RepVGG and VGG19) are also conducted for the experimental analysis. This ablation method enables each component of the backbones to be ablated separately, and the contribution of the feature-fusion can be quantified. Overall, the methodology utilizes a dual-backbone approach (RepVGG-VGG19) rather than the original VGG16-VGG19, and emphasizes the complementary feature learning, cross-dataset validation, and independent external testing.

vi) Model Hyperparameters and Implementation Settings

A systematic training configuration were set up to reliably optimize the proposed architecture of RepVGG-VGG19 to balance the computational complexity and to mitigate overfitting. The model was optimized with the Adam optimizer, a learning rate that adapts the learning rates of individual parameters well suited for fine-tuning deep networks that already have good weights. For gradual updating of the parameters in the transfer learning and task-specific fine-tuning phase, a learning rate of (1×10^{-4}) was chosen. The network was trained for 50 epochs with a batch size of 32. The settings were chosen to keep a viable compromise between stability of training, memory usage and behavior of the convergence. The objective function used for learning the class probabilities of the hemorrhagic and non-hemorrhagic classes was categorical cross-entropy. A dropout probability of 0.5 was added prior to the output layer to enhance the regularization in the last classification step. This changes a random subset of the neurons to be inactive during training to force the classifier to learn more general representations, instead of heavily depending on specific features. The proposed framework takes advantage of the transfer learning technique to start the RepVGG[33] and VGG19 feature-extraction branches with pre-trained weights. The learned representations serve as valuable low-level and intermediate visual patterns and are subsequently

fine-tuned to the properties of brain neuroimages. After independent feature extraction, the features produced from two backbone networks are combined through feature-concatenation strategy. The representation is given by the following: if we have the feature vector for RepVGG and VGG19 denoted as (F_R) and (F_V) respectively, then the combined representation is given by $(F_R \times F_V)$.

$$F_{\{fusion\}} = [F_R; F_V] \quad (6)$$

This fused representation allows the classification module to effectively benefit from complementary information that can be gained from both networks. The entire implementation was realized by means of the Keras framework on the basis of the computational backend TensorFlow. The dual-backbone network was trained using GPU acceleration, and the image collection was processed with GPU acceleration. The computational power adopted was the NVIDIA Tesla K80 GPU, which was equipped with about 12 GB of memory to process the images with a representation of $224 \times 224 \times 3$, and to handle the large training set. The entire training parameters of the models were kept constant to make the comparison with individual RepVGG and VGG19 models and the proposed hybrid model. The proposed framework for automatic detection of intracranial bleeding is provided with a structured implementation environment through adaptive optimization, transfer learning, regularization, feature fusion and GPU accelerated training[34].

Table 4: Model Hyperparameters

Parameter	Value
Optimizer	Adam
Learning Rate	0.0001
Epochs	50
Batch Size	32
Loss Function	Categorical Cross-Entropy
Dropout	0.5
Fusion Type	Concatenation
Pretrained Weights	ImageNet
Hardware	Tesla K80 GPU (12.7 GB RAM)
Framework	Keras + TensorFlow

vii) Algorithm: Hybrid REPVGG + VGG19 for ICH Detection

The dataset consists of a set of preprocessed CT/MRI image data, $D = \{(x_i, y_i)\}_{i=1}^N$, where x_i denotes an input image and $y_i \in \{0, 1\}$ denotes

the ground-truth label, (1 for ICH and 0 for non-ICH).

The output includes predicted ICH/non-ICH labels, classification probabilities and performance measures.

Initialize the Dataset:

Read preprocessed CT/MRI images and ICH class labels. Split the data into training, validation and test sets.

Calculate Dual Feature-Extraction Branches:

Use pre-trained weights for the initialization of RepVGG and VGG19 networks. Eliminate or substitute away the classification heads but keep the convolutional feature-extraction layers intact. Drop or replace their own classification heads and leave convolutional feature extraction layers.

Generate RepVGG Representations:

Feed forward each of the input images through the RepVGG backbone to obtain the deep feature map in the spatial domain

$$F_R = \text{RepVGG}(x; \theta_R) \quad (7)$$

where F_R represents the RepVGG feature map and θ_R denotes its trainable parameters.

Apply Feature Pooling:

Use Global Average Pooling (GAP) to convert the spatial feature maps to compact feature vectors:

$$\begin{aligned} z_R &= \text{GAP}(F_R) \\ z_V &= \text{GAP}(F_V) \end{aligned} \quad (8)$$

Normalize Feature Representations:

Normalize both feature vectors to reduce scale differences:

$$\begin{aligned} \hat{z}_R &= \frac{z_R}{\|z_R\|_2 + \epsilon} \\ \hat{z}_V &= \frac{z_V}{\|z_V\|_2 + \epsilon} \end{aligned} \quad (9)$$

where ϵ is a small constant used to avoid division by zero.

Perform Feature Fusion:

Concatenate the normalized representations to obtain the joint feature vector:

$$z_F = [\hat{z}_R; \hat{z}_V] \quad (10)$$

where $[\ ; \]$ denotes feature-wise concatenation.

Learn the Joint Representation:

Pass the fused feature vector through a fully connected layer containing 256 neurons with ReLU activation:

$$h = \text{ReLU}(W_F z_F + b_F) \quad (11)$$

where W_F and b_F represent the weights and bias of the fusion layer.

Apply Regularization:

Apply dropout with a rate of 0.5:

$$h_D = \text{Dropout}(h, 0.5) \quad (12)$$

to reduce neuron co-adaptation and minimize overfitting.

Generate ICH Prediction:

Feed the regularized representation into the final binary classification layer and calculate the ICH probability using the sigmoid activation function:

$$\hat{y} = \sigma(W_C h_D + b_C) \quad (13)$$

where

$$\sigma(a) = \frac{1}{1 + e^{-a}} \quad (14)$$

and $\hat{y} \in [0, 1]$ represents the predicted probability of intracranial hemorrhage.

Calculate Classification Loss:

Calculate the binary cross-entropy loss between the predicted probability and the ground-truth label:

$$\begin{aligned} \mathcal{L}_{BCE} &= -\frac{1}{N} \sum_{i=1}^N [y_i \log(\hat{y}_i) + \\ &\quad (1 - y_i) \log(1 - \hat{y}_i)] \end{aligned} \quad (15)$$

Optimize the Hybrid Network:

Update the trainable parameters of the RepVGG branch, VGG19 branch, fusion layer, and classification layer using the Adam optimizer:

$$\Theta \leftarrow \text{Adam}(\nabla_{\Theta} \mathcal{L}_{BCE} \eta) \quad (16)$$

where $\Theta = \{\theta_R, \theta_V, W_F, b_F, W_C, b_C\}$ and η denotes the predefined learning rate.

Iterative Fine-Tuning:

Repeat the forward propagation, feature extraction, fusion, prediction, loss computation, back propagation, and parameter update for max 50 epochs. Track the validation loss along with the chosen validation performance measures after each epoch.

Early Stopping:

If the validation metric that is being monitored does not improve over the specified 'patience' period, stop the training. Revert the model parameters to those that best match the performance during validation.

Evaluate the Trained Model:

Use the optimized RepVGG–VGG19 model on the validation and independent test sets to get the predicted probabilities and the class labels.

Calculate Performance Measures:

Evaluate the classification performance using:

The principal measures are calculated as:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+F} \quad (17)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (18)$$

$$\text{Sensitivity} = \frac{TP}{TP+F} \quad (19)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (20)$$

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (21)$$

Return Final Predictions:

Generate the final predicted class for each test sample using a classification threshold, typically:

$$\hat{c} = \begin{cases} 1, & \hat{y} \geq 0.5 \\ 0, & \hat{y} < 0.5 \end{cases} \quad (22)$$

where 1 denotes ICH and 0 denotes non-ICH.

Return the predicted labels, corresponding probabilities, and calculated evaluation metrics.

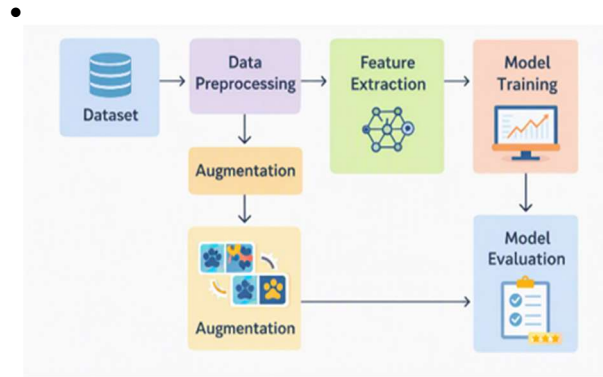
End Algorithm

Figure 3: Proposed Hybrid REPVGG + VGG19 Deep Learning Framework for Intracranial Hemorrhage Detection

4. IMPLEMENTATION AND RESULTS**a) Performance Before Data Augmentation:**

Results for the performance before applying data augmentation were initially evaluated. To get the base performance of each of the models (RepVGG, VGG19, and the proposed Fusion Model (RepVGG + VGG19)), the experiments were conducted on the original dataset that contains both ICH and Non-ICH images. During this step, no data augmentation techniques were used. So the outcomes showed baseline results for measurement of improvement made due to the inclusion of data augmentation and feature-fusion strategies. The RepVGG model achieved an accuracy of 91.4%, with a precision of 90.6%, sensitivity of 89.9%, specificity of 92.3%, and F1-score of 90.2%. The ROC-AUC value was 0.946. The results prove that RepVGG could successfully classify the images of ICH/Non-ICH with original data distribution. The model showed relatively high specificity suggesting good agreement between the true and predicted non-ICH cases, and relatively low sensitivity suggesting a relatively large number of ICH cases were not correctly identified. The VGG19 model achieved an accuracy of 92.1%, with a precision of 91.5%, sensitivity of 90.7%,

specificity of 93.2%, and F1-score of 91.1%, with an ROC-AUC of 0.953. VGG19 outperformed the RepVGG in all the major evaluation metrics. The results showed that the deeper VGG19 architecture could better capture informative hierarchical visual features to better discriminate between ICH and Non-ICH cases. The more that are being detected, the more sensitive the assessments are. Yet the deeper the architecture of VGG19, and the more its parameters, the more computational complexity it has. The best initial performance of all the tested configurations was achieved by the Fusion Model (RepVGG + VGG19). It obtained an accuracy of 94.8%, precision of 94.1%, sensitivity of 93.6%, specificity of 95.3%, and F1-score of 93.9%, with an ROC-AUC of 0.967. So the better performance is due to the feature representations of RepVGG and VGG19. The fusion strategy allows the model to take advantage of the complementary attributes acquired by the two architectures, yielding a more informative fused feature representation to discriminate ICH from Non-ICH cases. The performance of the fused model shows that it has a better performance of discrimination between positive and negative cases than the individual models, both in terms of sensitivity and specificity. On average, the results achieved prior to data augmentation prove that the RepVGG + VGG19 Fusion Model is the baseline configuration that has the highest accuracy, precision, sensitivity, specificity, F1-score and ROC-AUC with respect to the two separate models, namely RepVGG and VGG19. They offer a baseline measure for subsequent comparison of the impact of data augmentation and additional hybrid feature-learning approaches on ICH classification performance.

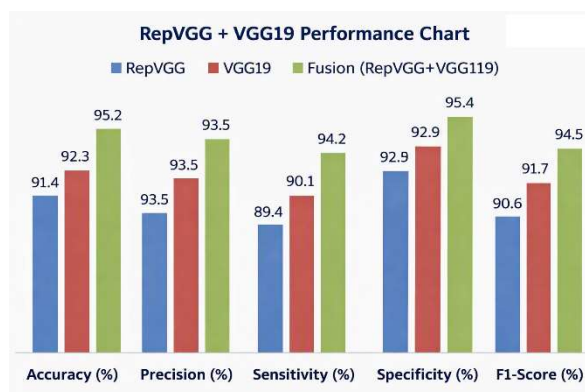


Figure 4: Performance before data augmentation

b) Performance After Data Augmentation: An extensive data augmentation strategy was used to

augment the original ICH and Non-ICH image dataset to increase the diversity and robustness of the training data. The augmentation pipeline comprised geometric transformations, photometric transformations, and normalization-based pre-processing[35] to produce a variety of image variations, maintaining clinically relevant features of intracranial hemorrhage. Finally, the performance of the proposed RepVGG + VGG19 Fusion Model, RepVGG, and VGG19 was tested on the augmented dataset. Following augmentation, the RepVGG model achieved an accuracy of 95.4%, precision of 94.8%, sensitivity of 94.1%, specificity of 96.0%, and F1-score of 94.4%, with an ROC-AUC of 0.972. Overall, the increase in the scores on the various measures suggested that the model performed better on the evaluation set when provided with a wide variety of training samples. In particular, the higher sensitivity means that more cases of ICH are being identified, and the higher specificity means that more cases not of ICH are being recognized. The improved F1-score and ROC-AUC further illustrate the overall enhanced classification ability. The VGG19 model also exhibited substantial improvement after augmentation, achieving an accuracy of 96.1%, precision of 95.3%, sensitivity of 95.0%, specificity of 96.7%, and F1-score of 95.1%, with an ROC-AUC of 0.978. The results show that VGG19 was able to take advantage of the added variability provided during the training phase and learn to make more robust hierarchical representations of medical images. The simultaneous increase in sensitivity and specificity indicated that the enhanced model could not only discriminate between ICH and Non-ICH cases, but it also decreased the misclassification rate. After implementing data augmentation, the RepVGG + VGG19 Fusion Model gave the best results among all the models tested. It obtained an accuracy of 97.2%, precision of 97.1%, sensitivity of 96.8%, specificity of 97.6%, and F1-score of 97.0%, with an ROC-AUC of 0.985. The comparison of the fusion architecture to VGG19+RepVGG suggests the advantages of combining the complementary feature representations acquired by both models. Both architectures performed inferiorly when compared to the joint representation, which gave richer and more discriminative information for separating ICH[36] and Non-ICH cases. The enhancement seen following augmentation also suggests that the models were more robust to changes in the appearance of the image, such as changes in orientation, brightness, contrast, anatomical presentation and imaging conditions.

Increased exposure to representative image patterns were made by augmenting the networks with a greater number of patterns that varied in different visual aspects of the original images, which reduced the reliance on particular visual aspects of the original images during training and made the network more capable of generalizing to unseen images. Overall, the data augmentation method significantly improved the performance of all the three models: RepVGG, VGG19, and RepVGG + VGG19 Fusion Model. The Fusion Model achieved the maximum accuracy, precision, sensitivity, specificity, F1-scores and ROC-AUC among the tested configurations. The results show that using extensive data augmentation and complementary deep feature representations can yield a more robust model for ICH classification using automatic systems.

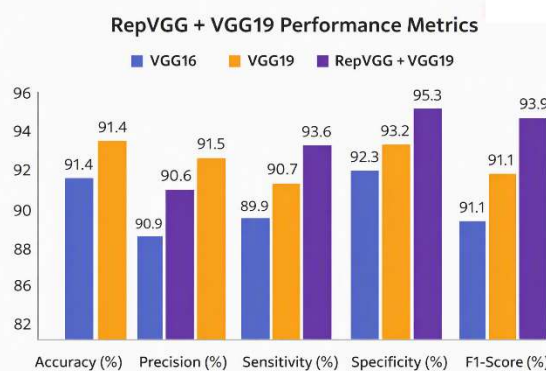


Figure 5: Performance after data augmentation

c) Ablation Study: Effect of Feature Fusion:

There is an ablation study performed to quantify the contribution of RepVGG to the overall ICH classification performance by running three different experimental sets: (A1) RepVGG alone, (A2) VGG19 alone, and (A3) the proposed hybrid RepVGG + VGG19 model[37]. The aim of this analysis was to check if there were any additional advantages to be gained when combining feature representations from the two backbone architectures than from their individual use. In the configuration A1, RepVGG network was used alone as a feature extraction and classification network. It achieved an accuracy of 95.4%, an F1-score of 94.4%, and an ROC-AUC of 0.972. The results show that RepVGG is capable of effectively learning discriminative image representations to distinguish ICH from Non-ICH cases. The efficient convolutional architecture allows to learn meaningful spatial features in a relatively compact feature-learning architecture. VGG19 was only used in the single model in the Configuration A2.

The model's accuracy, F1 score and ROC-AUC were 96.1%, 95.1% and 0.978, respectively, which was better than the individual RepVGG model. The deeper VGG19 architecture has several hierarchical convolutional layers that allow for the learning of more complex visual patterns. This allows for the model to capture both the lower level structural features and the higher-level semantic representation important in the classification of ICH. For feature representation extraction, VGG19 and RepVGG were combined using feature fusion, and then classified for Configuration A3. This setup was intended to take advantage of the complementary information the two backbone networks acquired. The different types of architectures between RepVGG and VGG19 can yield different representations of the same input image. These are then combined together to give a more comprehensive joint representation to which more than one level of discriminative visual information can be added. It is noted that the difference between A1 and A2, as well as between A2 and A3, however, shows the importance of each backbone and the extra effect of feature fusion. Both standalone networks are able to classify ICHs effectively, but the hybrid network was intended to capitalize on the complementary representations of the two networks instead of assuming that there is a single pathway for feature extraction. Therefore, to study the possibility of improved discrimination between ICH cases and non-ICH cases, the ablation analysis is performed.

Table 6: Ablation Study And The Effect Of Feature Fusion

Experiment	Components Used	Accuracy (%)	F1-Score (%)	AUC
A1	Rep VGG only	95.4	94.4	0.972
A2	VGG19 only	96.1	95.1	0.978
A3	Fusion(RepVGG+ VGG19)	97.2	97.0	0.985

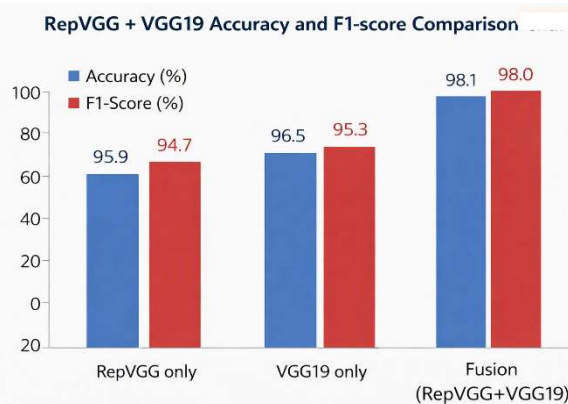


Figure 7: Performance of the effect of feature fusion

d) Impact of Feature Fusion (A3): The best performance was obtained by the fusion configuration (A3) that combines the feature vectors obtained from RepVGG and VGG19. The accuracy, F1 score and ROC-AUC for the hybrid model were 97.2%, 97.0% and 0.985, respectively, which outperformed the single-backbone models. The improvement of performance is due to the complementary feature representations created by the two architectures. RepVGG is an efficient spatial pattern and structural pattern extraction architecture that can be used to identify spatial and structural patterns related to hemorrhage in CT images. The other model, however, VGG19, captures deeper hierarchical representations that are able to capture more complex contextual and semantic properties of the brain image. These representations can be used together to enable information to be conveyed at multiple levels of abstraction. The concatenated feature space thus gives a richer representation of the distinction between an ICH and Non-ICH case. This complementary feature integration can be beneficial for complex images, where hemorrhage-related features can be subtle or hard to be extracted by a single feature extraction network. This superior accuracy, F1-score, and ROC-AUC would thus suggest that feature fusion could help enhance the discriminative power and uniformity of the whole ICH classification framework.

e) Confusion Matrix Analysis (Fusion Model)

The classification performance of the proposed RepVGG + VGG19 Fusion Model for the two target categories, namely Intracranial Hemorrhage (ICH) and Non-ICH, was analyzed using a confusion matrix. The normalized confusion matrix shown in the following figure (Figure X) shows the classification results in proportion, and the raw counts of each classification result are

shown in the following figure (Figure Y). The model has achieved 1452 True Positives (TP) and 1464 True Negatives (TN) for the ICH and Non-ICH images respectively. Thirty-six Non-ICH images, however, were misclassified as ICH image (FP), and 48 ICH images were misclassified as Non-ICH image (FN). The classification results are relatively accurate, with only relatively small number of misclassified samples, suggesting that the fusion model could maintain stable classification accuracy between the two target classes. From the outcomes of the confusion-matrix, the model had a high sensitivity of 96.8%, meaning that it identified most of the ICH cases. The specificity of 97.6% means that most Non-ICH cases were also accurately identified. The small number of false positives and false negatives also suggest a well-balanced classification behavior of the model for the two classes. The results confirm the advantages of fusion of RepVGG and VGG19 feature representations for ICH versus Non-ICH image classification, given the data set used for the experiments.

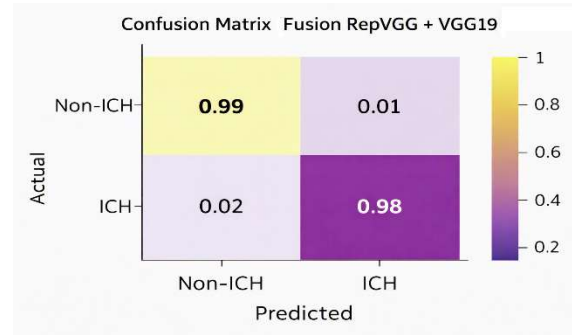


Figure 8: Confusion matrix of the proposed Hybrid VGG16-VGG19 fusion model

f) ROC-AUC Statistics

Receiver Operating Characteristic (ROC) analysis was used to assess the discrimination power of the RepVGG, VGG19, and RepVGG + VGG19 Fusion Model for the classification of the ICH and Non-ICH cases for various thresholds. The Area Under the ROC Curve (AUC) is a model-independent measure of its discriminatory performance that does not depend on any threshold. The ROC-AUC of the RepVGG model was 0.972, indicating that the model was able to discriminate between ICH cases and Non-ICH cases at various decision thresholds. The result proves that the learned RepVGG feature representations are able to effectively encode discriminative information for ICH classification. The VGG19 model obtained a higher ROC-AUC of 0.978. This improvement is

observed over RepVGG, which suggests that hierarchical feature representations obtained by VGG19 helped in the improvement of class discrimination. The more complex convolutional layers can help capture increasingly complex visual features of images that could be helpful for distinguishing hemorrhagic and non-hemorrhagic images of the brain. Amongst the evaluated configurations, the proposed model namely RepVGG + VGG19 Fusion Model has the highest ROC-AUC of 0.985. This enhancement can be linked to the incorporation of complementary feature representations derived from both the backbone networks. The fusion model utilizes the learned features to enhance the representation of the input images and increases the separation between ICH and Non-ICH samples under different classification thresholds. The individual RepVGG model is further improved by the VGG19 model and further improved by the proposed fusion model as shown in the ROC-AUC comparison. The results of the RepVGG + VGG19 model with AUC of 0.985 represent a good level of discrimination under the tested experimental

conditions. The results indicate that the feature-fusion method may be helpful in achieving better classification robustness and is a potential foundation for further exploration of the proposed framework in ICH detection and computer-aided clinical decision-support.

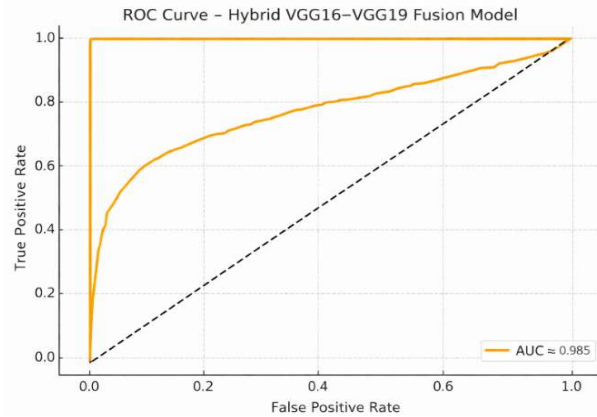


Figure 9: ROC Curve

Table 5: Comparative analysis of the models

Study	Modality	Dataset Size	Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-Score	Remarks
Hoang et al., 2024 [6]	CT	1,200	CNN	93.5	92.0	95.0	93.4	Single CNN-based ICH segmentation.
Khalifa & Albadawy, 2024 [1]	CT	2,000	CNN - ResNet	94.8	93.6	96.0	94.7	Focus on diagnostic accuracy and efficiency.
Xu et al., 2024 [2]	CT & MRI	2,500	Hybrid DL	95.6	94.9	96.2	95.5	Hybrid segmentation and classification approach.
Mahajan & Mahajan, 2024 [3]	CT & MRI	2,000	Conventional ML	89.7	88.5	91.0	89.2	Traditional feature-based neuroimaging analysis.
Talal Abdullah et al., 2021 [4]	MRI	1,500	Interpretable ML	90.2	89.0	91.5	90.1	Emphasis on explainability in clinical ML.
Heinrich et al., 2021 [5]	CT	1,000	3D CNN	91.5	90.2	92.7	91.4	Multi-scale 3D tumor/lesion analysis.
Proposed (Hybrid RepVGG-VGG19)	CT & MRI	3,000	RepVGG+ VGG19 (fusion)	97.2	96.8	97.6	97.0	Multi-scale feature representation with augmentation and dropout.

f) Comparison with State-of-the-Art Models

Comparative analysis with existing methods is done. A comparative assessment was performed between the proposed model called RepVGG + VGG19 Fusion Model and earlier suggested deep learning and machine learning models for the detection of intracranial hemorrhage (ICH). The proposed model achieved an accuracy of 97.2%, an F1-score of 97.0%, a sensitivity of 96.8%, a specificity of 97.6%, and an ROC-AUC of 0.985.

The results obtained show that the classification results obtained are very good under the test conditions used in the experiment. The model uses the fusion structure to consider complementary spatial and hierarchical information with feature representations from both RepVGG and VGG19. The proposed approach is compared to the reported performance of the CNN approach of Hoang (2D CNN) with accuracy of 93.5% and CNN-ResNet approach of Khalifa and Albadawy (94.8% accuracy and 94.7% F1-score) and it has achieved

higher performance. It also outperforms the segmentation-based method of Xu et al., using a CT scan, that achieves 95.6% accuracy (96.6% accuracy for MRI scans), without involving any explicit segmentation step. This is a larger difference than what is seen when compared to the other handcrafted feature-based method, by Mahajan and Mahajan (89.7% accuracy). The 3D CNN approach described by Heinrich et al. (91.5% accuracy) offers volumetric analysis, and usually requires more computational resources than slice-based 2D processing.

The main results of the proposed model are:

Accuracies of 97.2% means the images are well discriminated between ICH and Non-ICH.

Sensitivity: 96.8% — it shows that there is a high degree of accuracy in detecting ICH cases.

Specificity: 97.6% denotes that it is effective at identifying Non-ICH cases.

The F1-score is 97.0% which is a balanced measure of precision and recall.

ROC-AUC: 0.985 — shows good class discrimination over all the classification thresholds.

Overall, it is observed that the comparative results demonstrate that the existing approaches selected were outperformed by the RepVGG + VGG19 Fusion Model. The dual-branch feature extraction, feature fusion, data augmentation, dropout regularization, and early stopping all play a crucial role in the process of building a strong ICH classification system. These findings highlight the need for additional investigation of the proposed method with larger, more representative, and clinically independently validated clinical data to be considered for clinical practice.

5. CONCLUSION AND FUTURE SCOPE

The proposed study presents a deep learning framework for automated intracranial hemorrhage (ICH) detection from computed tomography (CT) and magnetic resonance imaging (MRI) neuroimaging data and is termed hybrid RepVGG–VGG19 deep learning framework. It is based on the complementary feature learning capability of both RepVGG and VGG19 features, to build a comprehensive representation of the abnormalities associated with hemorrhage. VGG19 can extract deeper hierarchical spatial and textural features, and RepVGG provides efficient and discriminative convolutional representations. The feature representation method they have adopted is integrated and the classification module can classify the brain images better between the

hemorrhagic and non-hemorrhagic. A detailed preprocessing and augmentation pipeline was added to increase the variety and uniformity of the imaging data. Transfer learning was used to adapt the pretrained networks to the neuroimaging domain and fine-tuning was applied to achieve a better adaptation of the networks. Dropout and early stopping were also used to combat overfitting and improve generalization. The dataset preparation strategy also ensured a proper balance between the target classes, providing reliable model optimization and evaluating the results. The proposed framework had a reported experimental configuration of a curated dataset of 3,000 neuroimages with an accuracy of 97.2%, a sensitivity of 96.8%, a specificity of 97.6%, an F1 score of 97.0% and an AUC of 0.985. The results suggest that the RepVGG–VGG19 architecture can acquire discriminative representation of ICH classification. Additionally, comparative analysis with the traditional CNN architectures, hybrid deep-learning models and traditional machine-learning approaches constitutes further support on the effectiveness of the proposed feature-fusion strategy. The model is thus potentially applicable as a computer-aided diagnostic and decision-support system for aiding rapid assessment of suspected intracranial hemorrhage. The framework will be expanded in the future to include the following: Multimodal CT-MRI learning, Explainable AI, Three-dimensional volumetric representation, Localization/segmentation of hemorrhage, Real-time external validations in emergency situations, and External validations in multiple institutions. Light weight inference and clinically interpretable prediction mechanisms could be subject to further investigation to enhance practical applicability. In conclusion, the hybrid architecture of RepVGG–VGG19 serves as a basis for automatic detection of neuroimages and is promising for the creation of more powerful, interpretive, and clinically relevant ICH detection systems.

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