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A COMPREHENSIVE STUDY: INTRACRANIAL ANEURYSM DETECTION VIA VGG16-DENSENET HYBRID DEEP LEARNING ON DSA IMAGES

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Abstract. *An intracranial aneurysm is a swelling in a weak area of a brain artery. The main cause of aneurysm is high blood pressure, smoking, and head injury. A ruptured aneurysm is a serious medical emergency that can lead to coma and then death. A digital subtraction angiogram (DSA) is used to detect a brain aneurysm. A neurosurgeon carefully examines the scan to find the exact location of the aneurysm. A hybrid model has been proposed to detect these aneurysms accurately and quickly. Visual Geometry Group 16 (VGG16) and DenseNet are two deep-learning architectures used for image classification. Ensembling both models opens the possibility of using diversity in a robust and stable feature extraction. The model results assist in identifying the location of aneurysms, which are much less prone to false positives or false negatives. This integration of a deep learning-based architecture into medical practice holds great promise for the timely and accurate detection of aneurysms. The study encompasses 1654 DSA images from distinct patients, partitioned into 70% for training (1157 images) and 30% for testing (496 images). The ensembled model manifests an impressive accuracy of 95.38%, outperforming the respective accuracies of VGG16 (94.38%) and DenseNet (93.57%). Additionally, the ensembled model achieves a recall value of 0.8657, indicating its ability to correctly identify approximately 86.57% of true aneurysm cases out of all actual positive cases present in the dataset. Furthermore, when considering DenseNet individually, it attains a recall value of 0.8209, while VGG16 attains a recall value of 0.8642. These values demonstrate the sensitivity of each model to detecting aneurysms, with the ensemble model showcasing superior performance compared to its individual components.*

Keywords: DenseNet, DSA, hybrid model, intracranial aneurysm, VGG16

KOMPLEKSOWE BADANIE: WYKRYWANIE TĘTNIAKA WEWNĄTRZCZASZKOWEGO ZA POMOCĄ HYBRYDOWEGO GŁĘBOKIEGO UCZENIA SIĘ VGG16-DENSENET NA OBRAZACH DSA

Streszczenie. *Tętniak wewnątrzczaszkowy to obrzęk w słabym obszarze tętnicy mózgowej. Główną przyczyną tętniaka jest wysokie ciśnienie krwi, palenie tytoniu i uraz głowy. Pęknięcie tętniaka jest poważnym stanem nagłym, który może prowadzić do śpiączki, a następnie śmierci. W celu wykrycia tętniaka mózgu stosuje się cyfrową angiografię subtrakcyjną (DSA). Neurochirurg dokładnie bada skan, aby znaleźć dokładną lokalizację tętniaka. Zaproponowano model hybrydowy do dokładnego i szybkiego wykrywania tych tętniaków. Visual Geometry Group 16 (VGG16) i DenseNet to dwie architektury głębokiego uczenia wykorzystywane do klasyfikacji obrazów. Połączenie obu modeli otwiera możliwość wykorzystania różnorodności w solidnej i stabilnej ekstrakcji cech. Wyniki modelu pomagają w identyfikacji lokalizacji tętniaków, które są znacznie mniej podatne na fałszywie dodatnie lub fałszywie ujemne. Ta integracja architektury opartej na głębokim uczeniu się z praktyką medyczną jest bardzo obiecująca dla szybkiego i dokładnego wykrywania tętniaków. Badanie obejmuje 1654 obrazów DSA od różnych pacjentów, podzielonych na 70% do treningu (1157 obrazów) i 30% do testowania (496 obrazów). Złożony model wykazuje imponującą dokładność 95,38%, przewyższając odpowiednie dokładności VGG16 (94,38%) i DenseNet (93,57%). Dodatkowo, złożony model osiąga wartość pełności 0,8657, co wskazuje na jego zdolność do prawidłowej identyfikacji około 86,57% prawdziwych przypadków tętniaka spośród wszystkich rzeczywistych pozytywnych przypadków obecnych w zbiorze danych. Ponadto, biorąc pod uwagę DenseNet indywidualnie, osiąga on wartość pełności 0,8209, podczas gdy VGG16 osiąga wartość pełności 0,8642. Wartości te pokazują czułość każdego modelu w wykrywaniu tętniaków, przy czym model zespołowy wykazuje lepszą wydajność w porównaniu z jego poszczególnymi komponentami.*

Słowa kluczowe: DenseNet, DSA, model hybrydowy, tętniak wewnątrzczaszkowy, VGG16

Introduction

An enormous weak spot in the brain artery causes an intracranial aneurysm, which is a dangerous condition. Weakness of the artery walls in some areas can lead to aneurysm formation, posing a great risk to those affected. When an intracranial aneurysm ruptures, it causes a medical emergency that can lead to serious damage, including the possibility of coma and death. For prompt intervention and improved patient outcomes, intracranial aneurysms must be accurately and quickly detected. Among the major risk factors for the development of an intracranial aneurysm are head trauma, smoking, and high blood pressure. These factors can lead to wall disruption, highlighting the need to identify and monitor aneurysms in individuals with these conditions. The identification of intracranial aneurysms was made meticulously and precisely possible through the utilization of Cutting-edge imaging techniques like magnetic resonance imaging (MRI), computed tomography (CT) scans, and exceptionally accurate digital subtraction angiography (DSA). However, these methods may not always provide the accuracy or speed required to diagnose aneurysms, especially in emergencies. In recent years, the intersection of medical imaging and artificial intelligence (AI) has opened the door to better and more effective diagnoses. Deep learning-based designs attract attention due to their ability to analyse medical images accurately and quickly. Among these models, the two main options are Visual Geometry Group 16 (VGG16) and DenseNet [5], which are widely used in image classification [1]. VGG16 and DenseNet have been successful in many types of image classification. However, accurate and timely detection of intracranial aneurysms is a unique challenge that can be solved by combining the advantages of these two methods. This study leverages the power of deep learning by providing composite models that leverage diversity inference provided by VGG16 and DenseNet [8].

The main objective is to implement a model that can quickly and accurately detect intracranial aneurysms in DSA images while minimizing negative-related risks. The integration of deep learning-based architectures into the realm of medical practice offers significant potential to reshape the landscape of aneurysm diagnosis, emphasizing the importance of early detection and precise localization. This study offers a comprehensive exploration of the proposed hybrid model, delving into the methodology, evaluation, and results. Furthermore, it highlights the potential implications of this discovery in clinical practice, underscoring the significance of early detection. The ensuing sections of this study will provide detailed insights into the methods, evaluations, and outcomes, shedding light on how this hybrid model can significantly enhance the precise identification of intracranial aneurysms, particularly in DSA images, thereby advancing the field of medical imaging and patient care.

1. Literature review

Cheol Kim et al. [12] utilized the Alexnet_v2 architecture, achieving superior accuracy over human assessors in a computer-aided system. Despite this success, limitations such as a small dataset and variability from user-selected ROIs were acknowledged, signaling the need for broader studies to enhance model robustness and generalization.

Gurunathan et al. [10] proposed CNN-based models, boasting high accuracy rates of 98.6% for normal and 98% for abnormal cases. However, the challenges associated with demanding data requirements and complexities in model interpretation underscore the ongoing efforts required for optimization and practical application.

Hossain et al. [11] presented a deep CNN architecture for brain tumor detection, emphasizing its accuracy advantages. Yet, they acknowledged the complexity and resource requirements as significant drawbacks. The study's comprehensive assessment, utilizing F1 scores and balanced statistics, highlighted the need for a nuanced evaluation approach.

Stember et al. [20] employed U-net and CNN for Magnetic Resonance Angiography. However, the study revealed challenges, particularly in achieving a lower F1 score, pointing to the importance of dataset quality in model performance.

Xinke Liu et al. [14] introduced a modified UNet-based 3D CNN with excellent segmentation accuracy, particularly in handling 3D DSA pictures. Despite its strengths, challenges such as lower accuracy for smaller aneurysms were noted. The evaluation, encompassing F1 scores and error analysis, identified specific areas for improvement.

Haihan Duan et al. [7] implemented cascade CNNs for intracranial aneurysm identification, highlighting their precision but acknowledging computational complexity and extended training cycles as drawbacks. The study emphasized the critical role of the dataset in ensuring model robustness and generalization.

Chen et al. [6] introduced a system for early detection using contrast-unenhanced magnetic resonance angiography, showcasing high sensitivity and low false positive rates. This suggests practical applicability for automated screening in routine examinations, addressing the need for efficient identification of suspected aneurysm areas.

Takahiro Nakao et al. [17] proposed a deep neural network model for diagnosing cerebral aneurysms, emphasizing the high accuracy achieved. However, challenges such as the model's limitations in detecting tiny aneurysms underscore the importance of broader datasets for increased generalizability and therapeutic effectiveness.

Yuan et al. [22] introduced DCAU-Net for segmenting intracranial aneurysms, showcasing superior accuracy and efficiency. The model's utilization of dense blocks and Convolution Block Attention Module (CBAM) contributed to enhanced segmentation performance. Comparative experiments highlighted its advantages over other models, emphasizing its potential in clinical applications.

Jun Hyong Ahn et al. [2] introduced a Multiview CNN-ResNet50 model for classifying rupture risk in tiny intracranial aneurysms. The algorithm demonstrated high sensitivity, specificity, accuracy, and F1 score, suggesting its utility in assessing rupture likelihood.

Daiju Ueda, MD et al. [21] developed a deep-learning framework for detecting brain aneurysms using time-of-flight MRI, achieving improved detection rates. The focus on avoiding misses, though resulting in lower specificity, prompted suggestions for further improvements, including incorporating additional imaging data for comprehensive evaluations.

Agus Eko Minarno et al. [15] applied SVM and DenseNet to MRI images for brain tumor categorization and achieved an impressive 99.65% accuracy. This study underscores the effectiveness of deep learning strategies in accurately identifying brain tumor categories.

Bincy Chellapandi et al. [5] discussed plant disease detection using a self-built CNN model and achieved superior performance with over 93% accuracy. This study also explored the application of transfer learning to enhance the accuracy of plant disorder detection.

Zeng et al. [23] proposed a method for enhancing detection accuracy using successive image fusion (SIF), achieving an impressive 98.89% accuracy with 3D-RA projection images. The study demonstrated the robustness and effectiveness of the proposed framework.

Belaid et al. [4] presented a model that combines VGG16 CNN and GLCM features for brain tumor classification and achieved a 96% accuracy. This study highlighted the potential of this approach for accurate tumor categorization.

Sourodip et al. [9] utilized an enhanced U-Net architecture with VGG-16 for brain tumor categorization via MRI, outperforming basic U-Net and other CNNs with pixel accuracies of 0.997. The study highlighted the superior performance of the enhanced U-Net architecture.

Wufeng Liu et al. [13] achieved a 96% accuracy rate for rice leaf disease identification using a hybrid neural network model with enhanced attention. The study demonstrated the model's efficiency in identifying and classifying diverse types of rice leaf diseases.

Yufan Zhou et al. [24] proposed a method for diagnosing brain tumors using composite 3D MR images, achieving accurate tumor diagnosis without detailed annotations. The study emphasized the potential of dense convolutional neural networks and recurrent neural networks for accurate diagnosis and categorization.

Martinson Ofori et al. [18] presented an approach for reducing DL model complexity in precision agriculture systems by combining ensemble learning, model compression, and transfer learning for sustainability and cost-effectiveness. This study addressed the limitations of DL models in precision agriculture.

Muhammad Mujahid et al. [16] utilized machine learning and signal processing for early-stage Alzheimer's disease detection, achieving promising accuracies of 97.35% and 99.64%, respectively, in terms of the area under the curve (AUC). The study explored different datasets and techniques, demonstrating the potential for improving the accuracy of diagnosing Alzheimer's disease.

Rahil Shahzad et al. [19] employed a deep learning system to identify active aneurysms in aSAH patients via CT angiography; the system was effective and had high sensitivity for detecting aneurysms of unusual sizes. The study demonstrated the model's accuracy in detecting and classifying large arteries.

Al Okashis et al. [3] developed an autonomous model for hemorrhage detection via MRI, achieving 89.2% accuracy and 100% sensitivity. The study evaluated the impacted brain area by applying segmentation-based feature extraction for efficient detection.

2. Proposed methodology

The intended system architecture strives to guarantee accurate and fast detection of intracranial aneurysms. The system is designed by ensembling two widely used pre-trained models, VGG16 (Visual Geometry Group 16) and DenseNet, which are commonly employed for image classification. By concatenating the outputs of both models, the system leverages feature extraction from both networks. Fig.1 illustrates the process flow diagram of the methodology. Integrating these advanced CNN models for analyzing medical images results in robust, error-free, and timely detection of aneurysms in the intracranial section.

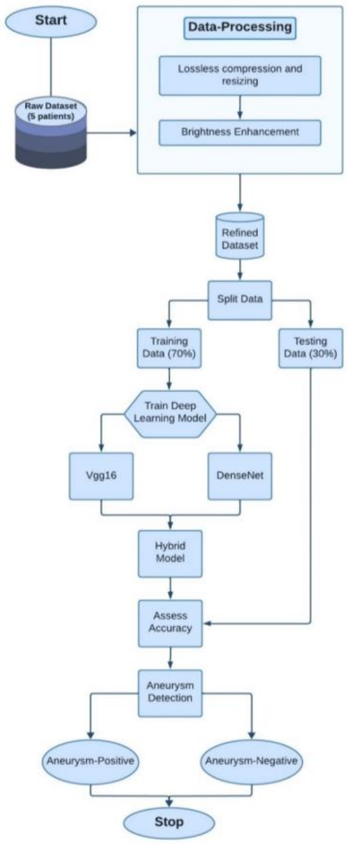

Fig. 1. Process flow model

2.1. Raw dataset

The dataset utilized in this study was gathered from various hospitals. It contains images of the Vascular system of the intracranial section of the Brain. These images are captured using the Digital Subtraction Angiographic Technique which incorporates advanced X-ray Technology, Contrast dye, and monitoring equipment that ensures safe imaging of Brain Vascularity. The dataset contains 1654 DSA images composed from the unique cases of 5 patients. The dataset consists of two classes: the positive class, comprising 446 images containing aneurysms, and the negative class, comprising 1208 images that do not contain aneurysms. Fig. 2 represents the sample images of raw dataset.

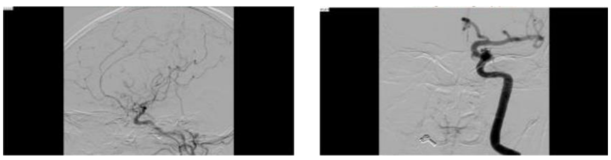

Fig. 2. Raw dataset

2.2. Data preprocessing

The collected DSA images have varying dimensions, contrasts, and levels of sharpness. To standardize the dataset, it has undergone two preprocessing steps.

2.2.1. Lossless compression and resizing

The initial step involves standardizing all the images to a uniform size. Within this dataset, the images include details such as scan layer numbers, which must be eliminated through cropping. After the cropping process, all the images are resized to dimensions of 512×512 using the Lanczos filter. The Lanczos filter is employed for resizing the images to the specified dimensions while also preserving image quality and minimizing aliasing effects. This is achieved through a weighted convolution filter that calculates new pixel values by considering a limited number of neighboring pixel values, resulting in smoother images.

2.2.2. Brightness enhancement

The DSA images exhibit low contrast and variations in brightness due to the different diameters of blood vessels. Additionally, smaller structures are hardly visible in these images. These issues can be addressed by applying a CLAHE (Contrast Limited Adaptive Histogram Equalization) filter. An excessive brightness ratio of 1.2 has been employed to overcome this problem, enhancing visibility without over-amplifying the blood vessels. This technique improves contrast and visibility by dividing the image into tiny blocks and equalizing the histogram of each block. Fig. 3 represents a sample of refined dataset.

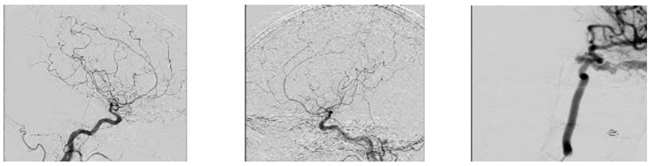

Fig. 3. Processed images

2.3. Split data

The preprocessed and refined images have been split into training data and testing data. In total, there are 1,654 images. Out of these, 70% of the data, which amounts to 1,158 images, is designated as the training dataset, while the remaining 30%, comprising 496 images, is assigned to the test dataset. This division ensures a robust evaluation of the model's performance and allows for effective training on a diverse range of examples. By carefully partitioning the dataset in this manner, we aim to optimize the model's ability to generalize to unseen data, thereby enhancing its overall efficacy in real-world applications.

2.4. Train deep learning models

To assess the accuracy of various deep learning models, multiple models were trained with the same dataset to compare their performance and select the one with the highest accuracy. The preprocessed data was trained by choosing diverse model architectures. The trained models were evaluated on the test data by comparing key metrics. After comparing the results, the model with higher performance is selected. This rigorous evaluation process ensures that the chosen model not only performs well on the training data but also generalizes effectively to unseen test data, enhancing its reliability for real-world applications. By systematically testing different architectures and comparing their performance, we aim to identify the most suitable model for the given task, thereby maximizing the accuracy and efficiency of our deep learning system.

2.4.1. DenseNet

The data was trained utilizing a pre-existing Deep Learning model DenseNet-121 [8]. To initiate model training, the pre-trained DenseNet-121 model was loaded with pre-trained weights from the ImageNet dataset. Data augmentation was implemented through the `ImageDataGenerator`, introduces variations to the training images. Techniques such as rotation, shifting, shearing, zooming, and flipping, coupled with rescaling, contribute to a more diverse dataset. The setup involved excluding the upper classification layers and configuring it to accept input images with specific dimensions. The layers of the DenseNet-121 model were locked, ensuring that they would not be modified during the training process. Custom classification layers were added above the pre-trained model. To reduce the spatial dimensions of the feature maps, GlobalAveragePooling2D was applied. Following that, dense layers incorporated with Rectified Linear Unit (ReLU) Trigger purposes, and a final dense layer with a sigmoid activation function was added to produce binary classification results. The model was compiled using the Adam optimizer employing a learning rate of 0.0001. For binary classification, the binary cross entropy loss function was utilized, and precision was chosen as the evaluation metric. After completing the training process, the model demonstrated a success rate of 93.57%.

Algorithm 1: Image Classification using DenseNet121.

Input: train_ dir: Training data directory; test_dir:Testing data directory;img_width, img_height:Image dimensions; batch_size: Batch size;
Output: Trained DenseNet121-based model;
Step 1: Import Libraries;Load TensorFlow and the required modules;
Step 2: Data and Parameters:Specify the data directories, image parameters, and batch size;
Step 3: Data Augmentation;Prepare the data generators with data augmentation;
Step 4: Load the DenseNet121 Model;The DenseNet121 model is loaded with pretrained weights;
Step 5: Customize the top layers;Add custom classification layers;
Step 6: Compile the model;Compile the model with the specified optimizer and loss function;
Step 7: Callbacks;Define the model checkpoint and early stopping callbacks;
Step 8: Train Model;Train the model with specified settings;
Step 9: Assess Model;The model's performance was assessed on the test dataset;

2.4.2. VGG16

The data were trained utilizing a pre-existing deep learning model VGG16. The training process commenced by loading the pretrained VGG16 model with weights initially trained on the ImageNet dataset. Data augmentation was implemented through the `ImageDataGenerator`, introduces variations to the training images. Techniques such as rotation, shifting, shearing, zooming, and flipping, coupled with rescaling, contribute to a more diverse dataset. The model's configuration excluded the top classification layers and allowed input images with specified dimensions. The layers of the VGG16 model were frozen to prevent updates during training, and the model deliberately excluded the uppermost classification layers. Additional custom classification layers were placed on the pretrained model. A flattening layer was applied to the base model's output. Subsequently, two dense layers with ReLU activation functions were introduced, and a final dense layer with a sigmoid activation function was included to produce binary classification results. The model was constructed with the Adam optimizer using a designated learning rate of 0.0001. Binary cross entropy served as the loss function for binary classification, and accuracy was chosen as the evaluation metric. Following the training process, the model achieved an accuracy of 94.38%.

Algorithm 2: Image Classification Using VGG16

Input: train_ dir: Training data directory; test_dir:Testing data directory;img_width, img_height:Image dimensions; batch_size: Batch size;
Output: Trained VGG16-based model;
Step 1: Import Libraries;Load necessary TensorFlow libraries;
Step 2: Data and Parameters:Specify the data directories and image parameters;
Step 3: Data Augmentation;Prepare the data generators with augmentation;
Step 4: Load the VGG16 Model;The VGG16 model is loaded with pretrained weights;
Step 5: Customize the top layers; add custom classification layers;
Step 6: Compile the model;Compile the model with the specified optimizer and loss function;
Step 7: Callbacks;Define the model checkpoint and early stopping callbacks;
Step 8: Train Model;Train the model with specified settings;
Step 9: Assess Model;The model's performance was assessed on the test dataset;

2.4.3. Hybrid model

After training the two models, DenseNet121 and VGG16, respectively, achieved accuracies of 93.17% and 92.32%. To create a hybrid model, both pretrained models, DenseNet121 and VGG16, are loaded with weights from the ImageNet dataset. Both models are connected to exclude their top classification layers and to accept input from the previously defined input layer. For transfer learning, all the layers of both models are frozen so that they cannot be changed during the training process. Global average pooling layers are added to both the DenseNet121 and VGG16 models [22], which diminishes the spatial dimensions of the feature maps. Now, the outputs of the global average pooling of both models are concatenated into a single 1×1 tensor. Two custom dense layers are added to it: the first is ReLU, with 256 units. Each unit computes a weighted sum of input features, allowing nonlinearity in the model and the ability to learn complex relationships. The final layer is the sigmoid layer with a single unit, which is typically used for binary classification tasks. The hybrid model is prepared by using pretrained models as input layers and custom dense layers as output layers. The model is assembled in combination with. The Adam optimizer, incorporating a designated learning rate of 0.0001. The accuracy of the hybrid model was evaluated. It achieved an accuracy of 95.38%.

Algorithm3: CombinedModel: DenseNet121 and VGG16

Input: train_ dir: Train datadir; test_dir: Test data dir;img_width,img_height:Img dimensions; batch_ size: Batch size;
Output: Combined model for binary classification;
Step 1: Import Libraries; Load TensorFlow and modules;
Step 2: Define the input and layers; define the input shape and create layers;
Step 3: Load the pretrained models;
The DenseNet121 and VGG16 models are loaded with pretrained weights;
Step 4: Freeze layers: Freeze layers in both models;
Step 5: Combine the outputs;
Combined_output = Concatenate ([GlobalAvgPool (DenseNet121 output), GlobalAvgPool (VGG16 output)])
Step 6: Custom dense layers;
x = Dense (combined output, 256; activation =' *relu*')output = Dense (x, 1; activation =' *sigmoid*');
Step 7: Create the combined model; Create the combined model with input and output;
Step 8: Compile the model; Compile the model with the specified optimizer and loss function;
Step 9: Data generators; Define the data generators for the training and test data;
Step 10: ModelCheckpoint; Define a ModelCheckpoint to save the best model;
Step 11: Train and evaluate; Train the model with data generators and evaluate the best model;

3. Results and comparitive analysis

The dedicated test dataset is subsequently used to assess the trained models. This stage facilitates a detailed evaluation of each model's performance. Various crucial performance indicators, such as the ROC-AUC, precision, accuracy, F1 score, and recall curve, were computed to provide a comprehensive assessment of each model's capabilities. Analyzing these metrics helps identify the model that excels in our specific task, simplifying the decision-making process for further deployment or analysis. Table 1 shows the comparison of the various models on the above-mentioned parameters. By meticulously examining these metrics, we gain insights into the strengths and weaknesses of each model, enabling us to make informed decisions regarding their suitability for practical implementation in real-world scenarios.

Table 1. Performance metrics

Model	Accuracy	Precision	Recall	F1 SCORE	ROC-AUC
Hybrid	0.9538	0.9587	0.8657	0.9098	0.9712
DenseNet	0.9357	0.9322	0.8209	0.8730	0.9675
VGG16	0.9438	0.9206	0.8642	0.8923	0.9650

Figures 4a, b, and c show the confusion matrices, which represent the performances of VGG16, DenseNet, and the hybrid model, respectively. These matrices offer insights into the models' classification accuracy by illustrating the distribution of true positive, true negative, false positive, and false negative predictions across different classes. Additionally, in figures 5a, b, and c, the ROC-AUC curves are shown for VGG16, DenseNet, and the hybrid model, respectively. These curves provide a graphical representation of the models' performance in terms of true positive rate against false positive rate across different threshold values. Analyzing both confusion matrices and ROC-AUC curves aids in understanding the strengths and weaknesses of each model's classification capabilities, facilitating informed decision-making for model selection and further optimization.

Table 2 illustrates a comparison of the accuracies of architectures proposed in various studies previously discussed. Upon examination, it is evident that the ensembled model of VGG16 and DenseNet exhibits higher accuracy compared to the others. The hybrid model benefits from the complementary strengths of both VGG16 and DenseNet, leveraging VGG16's robust feature extraction capabilities and DenseNet's dense connectivity to achieve superior performance.

By combining the strengths of these two architectures, the hybrid model achieves enhanced accuracy, demonstrating the effectiveness of ensemble methods in deep learning.

By combining the strengths of these two architectures, the hybrid model achieves enhanced accuracy, demonstrating the effectiveness of ensemble methods in deep learning. Ensemble methods leverage the diverse perspectives and capabilities of multiple models to create a more robust and reliable system. In this case, integrating features from both DenseNet and VGG16 allows the hybrid model to capture a wider range of image characteristics and patterns, leading to improved performance in detecting intracranial aneurysms. This approach not only increases accuracy but also enhances the model's resilience to noise and variability in the data, making it more suitable for real-world applications where robustness is critical.

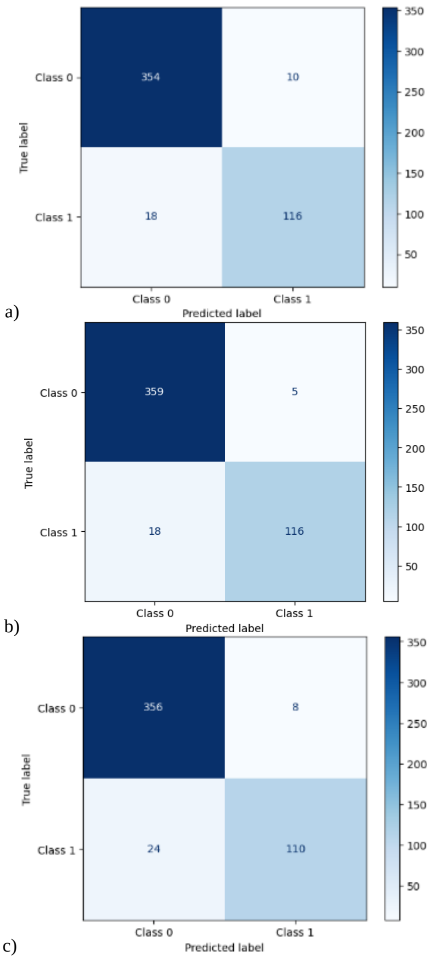

Fig. 4. Confusion matrices of: a) DenseNet, b)VGG16, c) hybrid model

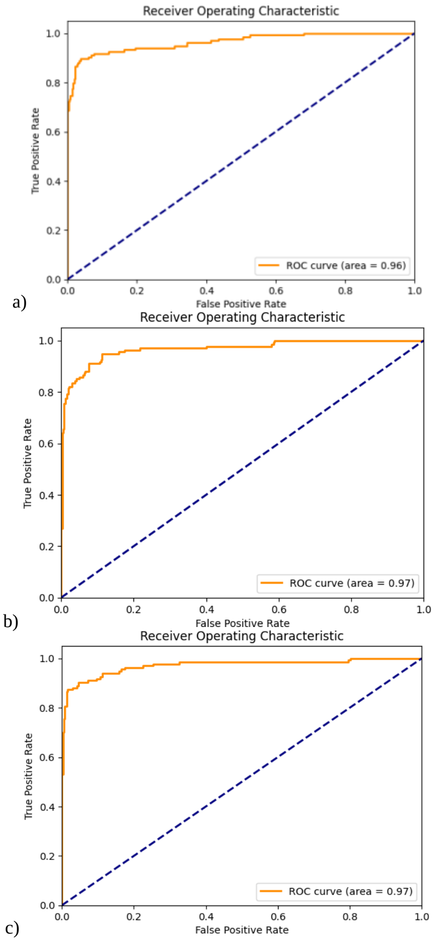

Fig. 5. ROC-AUC Curves of: a) DenseNet, b) VGG16, c) hybrid model

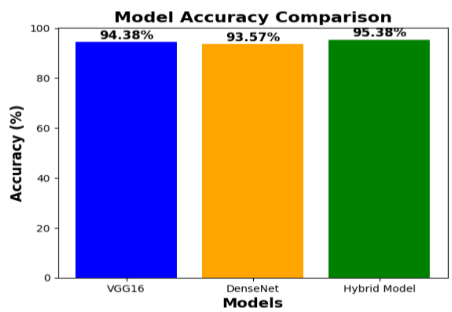

Fig. 6. Bar Graph representing accuracy comparison

Table 2. Comparative analysis

Reference number	Architecture	Accuracy
[18]	Ensembled model (VGG, Resnet, DenseNet)	91.2%
[2]	A multi-view CNN-ResNet50	81.72%
[12]	CNN	76.84%
[14]	CNN and MIP	94.2%
[7]	Cascade CNN	93.5
	Ensembled Model (VGG16, DenseNet)	95.38%

4. Conclusion

DenseNet and VGG16 stand out as prominent deep learning models widely employed for image classification, with this study focusing on the detection of intracranial aneurysms in DSA images. Remarkably, the DenseNet and VGG16 models showcased outstanding performance, achieving accuracies of 93.57% and 94.38%, respectively. DenseNet's proficiency in feature extraction, facilitated by its deep network architecture, and VGG16's high efficiency due to its straightforward design contributed to their respective successes. Specifically, for recall values, VGG16 demonstrated a recall of 0.8642, while DenseNet exhibited a slightly lower but still commendable recall of 0.8209. Combining the strengths of both models in a hybrid approach yielded a significantly higher accuracy of 95.38%. Notably, the hybrid model, with a recall value of 0.8657, not only surpassed individual model performances but also showcased enhanced robustness and superior generalizability to previously unseen data. In conclusion, the hybrid model successfully fulfil all the objectives of detecting aneurysms in DSA images with remarkable efficiency, demonstrating the synergistic power of leveraging diverse deep learning architectures. The ensembled model, by combining the strengths of DenseNet and VGG16, achieves a level of performance that exceeds what either model can achieve individually. Ensembling is a useful technique for improving model performance by leveraging the complementary strengths of multiple models, in this case, enhancing feature extraction and detection sensitivity for more effective identification of intracranial aneurysms in DSA images.

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