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PAPER

Ischemic Stroke Classification Using VGG-16 Convolutional Neural Networks: A Study on Moroccan MRI Scans

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ABSTRACT

This study presents a comprehensive exploration of deep learning models for precise brain ischemic stroke classification using medical data from Morocco. Following the OSEMN approach, our methodology leverages transfer learning with the VGG-16 architecture and employs data augmentation techniques to enhance model performance. Our developed model achieved a remarkable validation accuracy of 90%, surpassing alternative state-of-the-art models (ResNet50: 87.0%, InceptionV3: 82.0%, VGG-19: 81.0%). Notably, all models were rigorously evaluated on the same meticulously curated dataset, ensuring fair and consistent comparisons. The investigation underscores VGG-16's superior performance in distinguishing stroke cases, highlighting its potential as a robust tool for accurate diagnosis. Comparative analyses among popular deep learning architectures not only demonstrate our model's efficacy but also emphasize the importance of selecting the right architecture for medical image classification tasks. These findings contribute to the growing evidence supporting advanced deep learning techniques in medical imaging. Achieving a validation accuracy of 90%, our model holds significant promise for real-world healthcare applications, showcasing the critical role of cutting-edge technologies in advancing diagnostic accuracy and the transformative potential of deep learning in the medical field.

KEYWORDS

ischemic stroke, deep learning, transfer learning, VGG-16, data augmentation

1 INTRODUCTION

Stroke stands among the second leading causes of death worldwide [1]–[3], affecting over 100 million people annually [4]. It ranks as the third major cause of premature death, resulting in approximately 6.2 million deaths each year [5]. This alarming trend extends to the African continent, including the North African region, where stroke poses a significant health burden.

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Stroke is a medical condition characterized by the loss of neurological function due to a range of underlying causes. The predominant cause of stroke is ischemia, often resulting from atherosclerosis. Contributing risk factors include hypertension, diabetes mellitus, and hyperlipidemia. Other etiologies encompass cardioembolism and vasculopathies [6]. Stroke is broadly categorized into two primary types: ischemic stroke and hemorrhagic stroke. Ischemic stroke occurs when there is a blockage or impairment in the blood supply to a part of the brain, leading to the deprivation of oxygen and nutrients, ultimately causing brain tissue damage [6]–[8]. On the other hand, hemorrhagic stroke is caused by the rupture of a blood vessel in the brain, resulting in bleeding and subsequent damage to the surrounding brain tissue [9]. Figure 1 likely illustrates the difference between these two types of strokes.

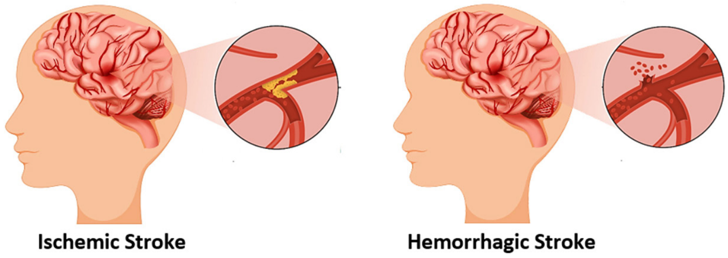

Fig. 1. Ischemic and hemorrhagic brain stroke

In the realm of medical image analysis, artificial intelligence (AI) and deep learning [10] have garnered immense interest due to their potential to enhance accuracy, efficiency, and speed. With the exponential growth of digital medical imaging data, these technologies can swiftly analyze and interpret vast amounts of information, aiding healthcare professionals in making timely and accurate diagnoses. Deep learning models, such as convolutional neural networks (CNNs), excel at extracting intricate features from medical images, allowing them to identify subtle anomalies that may go unnoticed by the human eye [11].

The integration of AI and deep learning in medical imaging has revolutionized the early detection and classification of brain ischemic strokes, addressing the critical need for swift and precise identification. Through training on diverse magnetic resonance imaging (MRI) scans, AI models distinguish between healthy and affected brain tissues, enabling expedited diagnoses for timely interventions. In the context of Morocco, an epidemiological survey in urban areas of Casablanca and Rabat revealed that ischemic stroke accounts for a significant 70.9% of all stroke cases [12]. This underscores the growing impact of ischemic stroke on public health, particularly in North Africa and Morocco, warranting specific attention.

In this sense, the present study adopts an approach centered around the visual geometry group 16 (VGG-16) architecture for accurately identifying ischemic stroke cases in MRI scans. Our emphasis on VGG-16 is grounded in its robust transfer learning capabilities and proven success across various image classification tasks. To validate the efficacy of our approach, we meticulously compared results obtained from VGG-16 with those from alternative deep learning architectures, including ResNet50, InceptionV3, and VGG-19, all evaluated on the same database. This comparative analysis not only reaffirms the validity of our results but also underscores the superior performance of VGG-16 in distinguishing cases of ischemic stroke. The integration of deep learning and the VGG-16 architecture holds great promise for advancing medical image analysis and elevating the diagnosis and treatment of stroke to new heights.

The article is organized as follows: Section 2 provides an overview of related works in the studied field. In Section 3, we explain the research methodology adopted for this study. Section 4 presents the results and discussion, combining the findings and their analysis. Finally, Section 5 presents the conclusions drawn from the study. The article additionally includes Section 6, which outlines future directions for research.

2 RELATED WORK

In this section, we explore several articles in the field of medical image analysis utilizing transfer learning [14] based on the powerful VGG-16 [13] architecture. In a study by Mohanty et al. [15], the primary focus is on addressing diabetic retinopathy (DR), a common complication of long-term diabetes that may lead to permanent blindness. The authors harness the potential of deep learning and specifically leverage the VGG-16 architecture to achieve early detection and precise classification of DR. Given the time-consuming and error-prone nature of manually grading retinal images, their proposed DL architectures, which include a hybrid network combining VGG-16 and XGBoost Classifier, along with the DenseNet 121 network, have proven to be invaluable tools in this domain.

Moreover, another notable study by [16] presents a novel convolutional neural networks (CNN) algorithm for brain tumor classification in MRI. Manual diagnosis of brain tumors can be complex and time-consuming, but the advancements in deep learning, particularly with the use of VGG-16, have revolutionized the automated process of medical image analysis, benefiting the healthcare sector. The proposed CNN algorithm demonstrates exceptional performance in classifying brain tumor types, such as glioma, meningioma, and pituitary tumors. This study highlights the effectiveness of VGG-16 in medical image classification tasks, showcasing its potential to aid doctors in making prompt and accurate decisions in brain tumor diagnosis.

In line with the research trend, CNN models have been increasingly utilized for medical image classification. Gaur et al. address the need for automatic COVID-19 detection from chest X-rays, utilizing deep convolution neural networks (DCNN) to differentiate between normal cases and those affected by viral pneumonia. The authors evaluate three pre-trained DCNN models, including VGG-16, through transfer learning, considering their balance of accuracy and efficiency, especially for mobile applications. This study highlights the potential of computer vision design for effective COVID-19 detection and screening measures [17].

Nijaguna et al. explore the challenges of handling large medical data in diagnosis and propose the quantum fruit fly algorithm (QFFA) for feature selection, addressing imbalanced data and overfitting. Utilizing the Min-Max Normalization technique enhances image quality. Deep learning models, ResNet50 and VGG-16 are employed for feature extraction. QFFA's unique features enable overcoming local optima and support vector machine (SVM) achieves effective disease classification. The approach outperforms existing models in sensitivity and accuracy, highlighting VGG-16's significance in medical image analysis [18].

Sujatha et al. focus on utilizing deep learning concepts, including VGG-16, for grading breast invasive ductal carcinoma using transfer learning. Five transfer learning approaches, namely VGG-16, VGG-19, InceptionReNetV2, DenseNet121, and DenseNet201, were evaluated. The study highlights the potential of deep learning and transfer learning for early detection and classification of breast carcinoma, offering valuable insights for improved patient outcomes and healthcare management [19].

The research conducted by Al-Zoghby et al. [20] addresses the classification of tumors in MRI images, with a specific emphasis on meningioma, glioma, and pituitary tumors. At the heart of this investigation lies the innovative dual convolutional tumor network (DCTN), leveraging the robust capabilities of the VGG-16 architecture, complemented by custom CNN designs.

In the domain of dental radiology, a groundbreaking approach emerged for automated feature detection in periapical radiographs. Leveraging AI-driven CNN models, specifically VGG-16 and U-Net architectures, this study focuses on diverse periodontal factors. These include tooth position, shape detection, interproximal bone levels, and radiographic bone loss [21].

In summary, the application of VGG-16 in healthcare showcases its efficacy in medical image analysis, with studies highlighting its potential for accurate disease classification.

Turning our focus to the realm of ischemic stroke and AI, the following articles delve into innovative approaches for accurate detection and assessment, showcasing the growing potential of AI in enhancing ischemic stroke diagnosis and management.

One notable study conducted by Gurunath Bharathi et al. [22] presents an automatic method for detecting acute ischemic stroke lesions from MRI volumes. This novel approach leverages textural and unsupervised learned features, harnessing a patch-based methodology to exploit 3D contextual evidence. By combining textural feature extraction using gray level co-occurrence matrix (GLCM) and unsupervised feature learning based on k-means clustering, their hybrid approach achieves a significant boost in discriminative feature sets. Through evaluation of the ischemic stroke lesion segmentation (ISLES) 2015 training dataset, the proposed method achieves remarkable results, with an accuracy of 82.01%.

In pursuit of enhancing anomaly detection, Tursynova et al. [23] apply deep learning to categorize brain CT images of normal, surviving ischemia, or cerebral hemorrhage cases. Utilizing a CNN, a computer-aided diagnostic system (CAD) is developed, incorporating data augmentation techniques and an early stopping method. The proposed approach enhances accuracy and recall compared to other methods, achieving a commendable 79% accuracy in identifying normal cases.

With the aim of enhancing TOAST (Trial of Org 10172 in Acute Stroke Treatment) subtype classification for ischemic stroke, Zhang et al. [24] present a novel active deep learning architecture. The proposed methodology incorporates XGB-based feature selection, a distinctive causal CNN, and an active sample selection criterion, strengthened by KL-focal loss. Upon evaluation using a dataset of 2310 patients, the approach achieves an accuracy of 60.2%, underscoring its potential applicability in stroke medicine.

Concluding our review of related works, the studies by Gurunath Bharathi et al. [22], Tursynova et al. [23], and Zhang et al. [24] offer valuable insights into deep learning's role in stroke diagnosis. Nonetheless, they exhibit significant limitations such as time-consuming training, dataset size affecting accuracy, and insufficient exploration of feature combinations. Future research endeavors should focus on further adaptation and diverse datasets to enable wider stroke classifications.

3 METHODOLOGY

In this research, the OSEMN (Obtain, Scrub, Explore, Model, and iNterpret) process was employed as the methodology. The OSEMN process is a widely recognized and standardized model for organizing research in the field of Data Science, addressing challenges, and improving efficiency in Data Science/Analytics [25] on a large scale.

To ensure the organized and well-prepared retrieval and manipulation of beehive data, it is crucial to follow a structured approach. The OSEMN process offers a systematic sequence of activities, as depicted in Figure 2: Obtaining the data, scrubbing it, exploring the data, modeling the data, and interpreting the findings. This process facilitates a clear and logical framework for conducting the research.

Fig. 2. OSEMN workflow

In this study, a dataset consisting of MRI of the brain of Moroccan patients was employed as the input data for analysis. The dataset comprises a total of 342 MRI images, collected from 22 patients. These images vary in dimensions, with the vast majority having sizes of either 512×512 or 256×256 pixels.

To ensure appropriate evaluation and validation of the developed model, the dataset was divided into three distinct subsets. Specifically, 77% of the images were allocated for training the models, 3% for testing their performance, and 20% for validating the results. The partitioning percentages were selected based on best practices. This approach ensures balanced training, robust evaluation, and optimized model generalization.

3.1 Analyzing the study context

When it comes to ischemic strokes, the prevalence of this condition and the complex nature of its treatment underscore the need for appropriate diagnostic and therapeutic resources that can provide optimal solutions for patients.

The primary objective of this project is to develop a deep learning-based model specifically designed to accurately classify the presence of brain ischemic stroke based on MRI scans. The model's performance was evaluated using accuracy as a metric, which provided a measure of its effectiveness in accurately distinguishing between subjects with and without a stroke. Continuous efforts were made to refine and optimize the model's capabilities, ensuring that it consistently achieved high accuracy and reliability in detecting brain ischemic strokes using MRI technology.

Our success criterion is to construct a model with performance values exceeding 80%.

3.2 Computational environment and tooling

- **Hardware and Software Setup:** The deep learning model was developed and trained using an Intel(R) Core(TM) i5-6300U CPU @ 2.40GHz with a clock speed of 2.50 GHz. The training process was conducted within a Jupyter Notebook environment, providing an interactive and efficient platform for model development and experimentation.
- **Libraries and Dependencies:** The implementation of the deep learning model was facilitated through the utilization of several essential Python libraries and dependencies (summarized in Table 1).

Table 1. Python libraries and dependencies utilized in the implemented model

Library	Purpose
imutils	Image processing and manipulation for data augmentation
numpy	Efficient array operations and mathematical computations
cv2 (OpenCV)	Computer vision tasks: image loading, resizing, etc.
scikit-learn	Data preprocessing, splitting, and performance evaluation
matplotlib.pyplot	Generating visualizations for analyzing experimental results
keras	Deep learning framework for model construction and training
ImageDataGenerator	Data augmentation and preprocessing for model generalization
VGG-16	Pre-trained CNN architecture for feature extraction
Other keras components	Including layers, models, optimizers, and callbacks

While the above-cited libraries are essential to the study, it's worth noting that additional libraries and dependencies were used as required throughout the research process. The selected libraries contributed significantly to data preparation, model development, and performance evaluation.

3.3 Data collection and preprocessing

We set forth on the OSEMN approach to detail the comprehensive process of data collection and the preprocessing steps employed for MRI scan images in the development of a deep learning-based model aimed at classifying brain ischemic stroke. By adhering to this structured methodology, we ensure the data is efficiently obtained, thoroughly cleaned, explored for insights, and appropriately prepared to feed into the model. The resulting analysis and interpretation empower us to build a robust classification system for accurate identification of brain ischemic stroke from MRI scans.

Data collection. The MRI scan images were sourced from the Mohammed VI University of Sciences and Health (UM6SS), a Moroccan dataset containing samples related to brain ischemic stroke cases. The dataset was organized into distinct sets, including the training set, validation set, and test set. Each set was further categorized based on the presence or absence of a stroke, represented as 'YES' and 'NO' classes, respectively. Notably, the dataset comprises a balanced gender distribution, with 55% female and 45% male patients, ensuring a comprehensive representation of patient profiles (Figure 3).

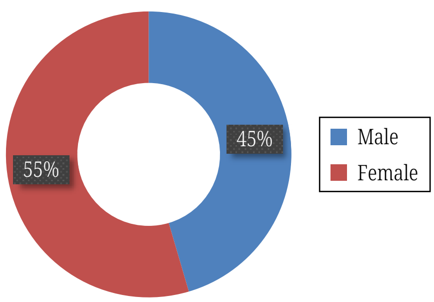

Fig. 3. Gender distribution in the dataset

Additionally, we explored the distribution of classes in each set to gain insights into the dataset's balance. Figure 4 visually represents the number of samples for each class (presence and absence of a stroke) across the training, validation, and test sets.

This valuable visualization allows us to assess potential class imbalances and ensure the dataset's representativeness for training our brain ischemic stroke classification model.

Fig. 4. Distribution of classes in dataset

Data preprocessing.

– **Image Loading and Resizing:** The image data was skillfully loaded and processed with a dedicated function called 'load_data'. This custom function exhibits proficiency in both loading the images and skillfully resizing them to a standardized dimension of (100,100). Through this meticulous process, the image dimensions are normalized, fostering uniformity across the dataset and paving the way for seamless data preparation and analysis. The resultant standardized images are now optimally primed for the subsequent stages of data processing and modeling (Figure 5).

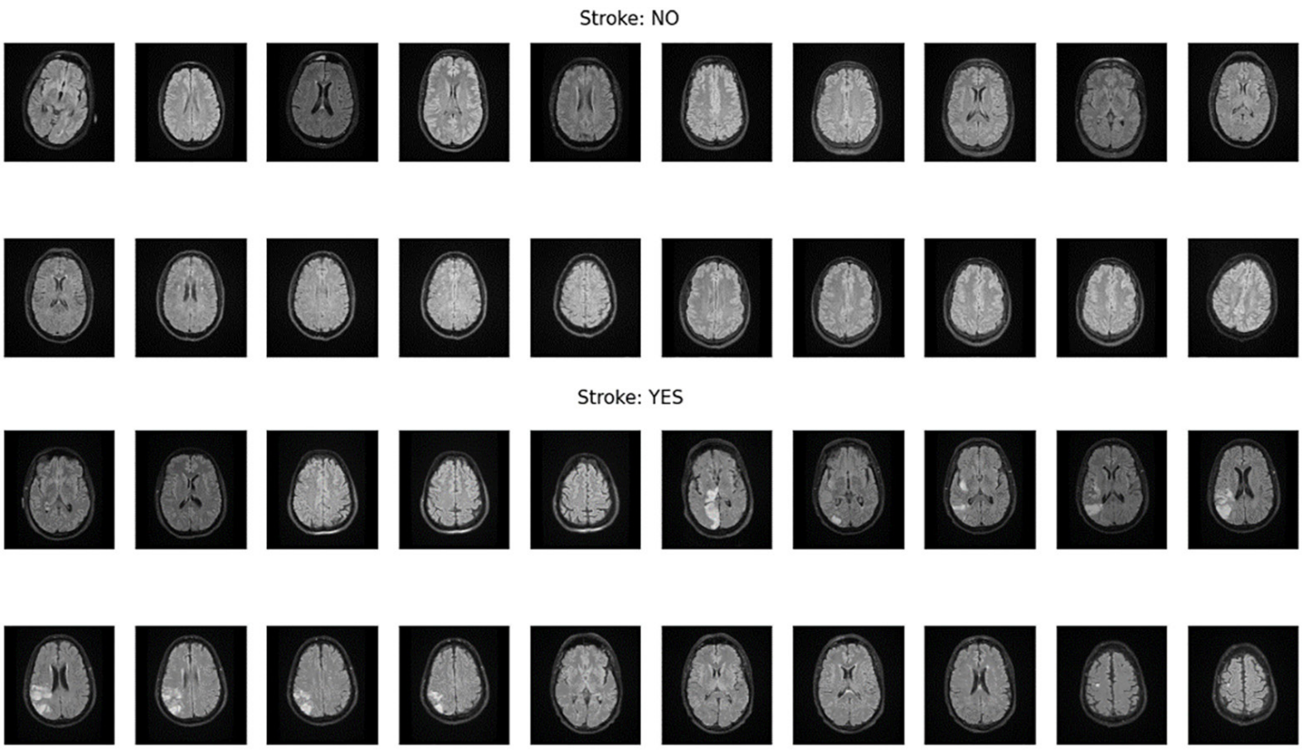

Fig. 5. Simple MRI scans

– **Exploring Data Imbalance:** During the initial exploration of the MRI scan images dataset, we observed variations in the width and height of the images, along with different sizes of 'black corners' present in some images. Considering that the input layer size for the VGG-16 model is fixed at (224,224), resizing wide images might lead to distortions and suboptimal representation.

$$ratio = \frac{width}{height} \tag{1}$$

The aspect ratio (1) analysis allowed us to identify potential issues related to image dimensions and resizing. By carefully considering these insights, we aim to optimize the preprocessing steps and ensure the accurate representation of brain ischemic stroke patterns in the classification model. The objective is to strike a balance between normalization and preserving image details, ultimately contributing to the effectiveness of the classification model.

– **Crop and Normalize:** Utilizing the brain cropping technique (Figure 6), as described in the renowned pyimagesearch blog, we accurately isolate the brain region within each image, removing background noise and focusing solely on the brain's central area. The applied function extracted the brain region from the MRI scans by identifying extreme points and cropping the images accordingly. This process enhances dataset quality and ensures consistent alignment of brain regions, essential for subsequent normalization.

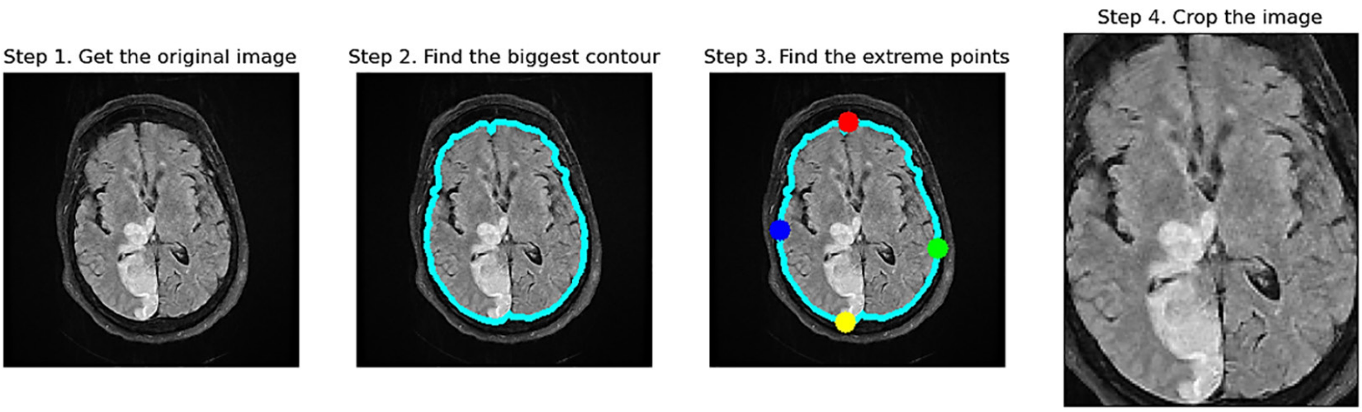

Fig. 6. Cropping process

– **Resizing and Preprocessing for VGG-16 Model:** To ensure compatibility with the VGG-16 model's input requirements, the MRI scan images were resized to (224, 224). This standardized size facilitates seamless integration with the VGG-16 architecture and allows for efficient model training and evaluation.

3.4 Model architecture selection: Transfer learning with VGG-16

For our brain ischemic stroke classification task, we employ transfer learning with the VGG-16 architecture to expedite model development and enhance accuracy. Leveraging the pre-trained VGG-16 model, originally designed for image classification tasks, we adapt it to our specific medical imaging dataset for precise brain ischemic stroke identification.

The VGG-16 model is first loaded with pre-trained weights from the ImageNet dataset, and we exclude its fully connected layers by setting 'include_top' to False, making it suitable for our binary classification task.

Next, we design a custom model on top of the VGG-16 base, consisting of a Flatten layer, a Dropout layer to mitigate overfitting, and a Dense layer with a sigmoid activation function for binary classification.

To finetune the VGG-16 model for our task, we freeze the pre-trained weights by setting the base model's trainable parameter to False, preserving the knowledge learned from ImageNet while adapting it to our medical imaging dataset.

The model is compiled with binary cross-entropy loss and RMSprop optimizer, using a learning rate of 1e-4, and evaluated based on accuracy.

– **Illustration of Transfer Learning with VGG-16:** Table 2 presents a summary of the layers and parameters of our custom VGG-16 based model, highlighting its architecture. Furthermore, Figure 7 visually illustrates the transfer learning process, showcasing how the pre-trained VGG-16 model, initially trained on ImageNet, is fine-tuned for brain ischemic stroke classification using our medical imaging dataset. This powerful combination enables effective brain ischemic stroke classification in MRI scan images.

Table 2. Model Architecture Summary

Layer (Type)	Output Shape	Param #
VGG-16 (Functional)	(None, 7, 7, 512)	14,714,688
flatten (Flatten)	(None, 25088)	0
dropout (Dropout)	(None, 25088)	0
dense (Dense)	(None, 1)	25,089

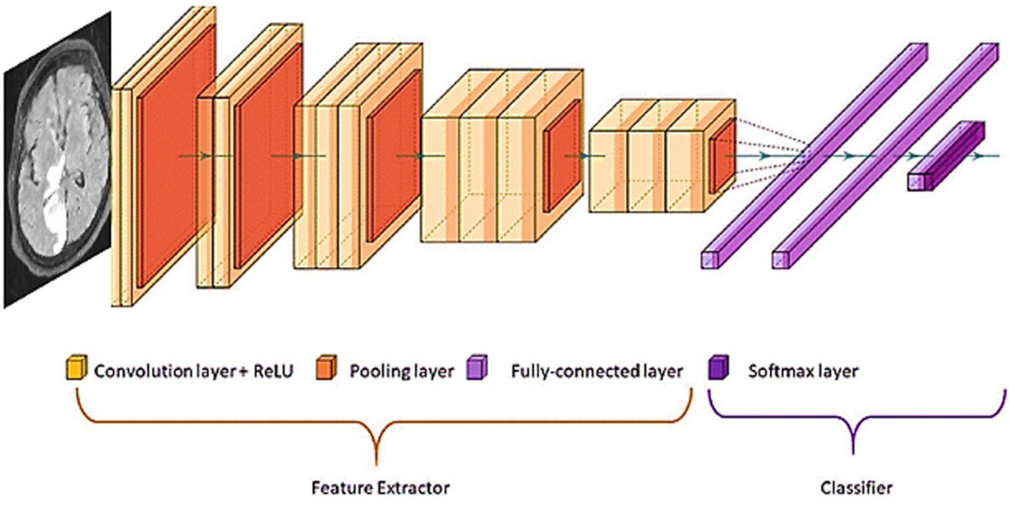

Fig. 7. Illustration of transfer learning with VGG-16

3.5 Training procedure

– **Data Augmentation Techniques:** To enhance the model's ability to generalize and improve performance, we applied various data augmentation techniques during training. These included random rotation, width and height

shifts, rescaling, shear transformation, brightness adjustment, and horizontal and vertical flipping. Data augmentation enriched the training dataset with diverse variations of the images, making the model more robust and less prone to overfitting.
- **Data Generator Setup:** To efficiently load and preprocess data during training, we utilized data generators for the training and validation datasets. Data generators managed memory resources effectively and facilitated data augmentation, ensuring the model was exposed to augmented images during training.
- **Early Stopping:** To optimize model performance and prevent overfitting, we implemented early stopping during training. The model's training progress was monitored using the validation accuracy metric. If no improvement was observed after six epochs, the training process was halted, preserving the best-performing model.
- **Fine-Tuning VGG-16:** We employed the pre-trained VGG-16 model, initially trained on the ImageNet dataset, as the base model. To adapt it for brain ischemic stroke classification, we added custom layers and fine-tuned the model's weights using our specific medical imaging dataset. The architecture of the final model was composed of the VGG-16 base model, a flatten layer, dropout layer, and a dense layer with a sigmoid activation function for binary classification.
- **Hyperparameter Tuning:** During training, we iteratively fine-tuned hyperparameters, including the learning rate, dropout rate, and batch size. The learning rate, set at 0.001, governs the step size in the optimization process, influencing the convergence of the model. The dropout rate, a regularization technique, was fine-tuned to 0.3 to strike a balance between preventing overfitting and preserving valuable features. The batch size, defined at 32, determined the number of samples processed in each iteration, impacting both computational efficiency and the stability of the training process. This iterative process optimized the model's performance and ensured the best possible results for brain ischemic stroke classification.

The model's performance and evaluation will be presented in the dedicated subsection, providing a thorough assessment of its classification capabilities.

3.6 Evaluation

To evaluate the model's performance further, we applied it to the validation set and calculated the accuracy (2). The model achieved an impressive validation accuracy of 90%. This high accuracy underscores the potential of the deep learning-based model to aid in the early and accurate detection of brain ischemic stroke from MRI scans.

$$Accuracy = \frac{Number\ of\ correclty\ predicted\ images}{Total\ number\ of\ tested\ images} \times 100\% \tag{2}$$

The confusion matrix shown in Figure 8 reveals the detailed performance of the model, presenting a detailed breakdown of the model's predictions. It achieved 19 true positives (TP) and 42 true negatives (TN) predictions, demonstrating its ability to accurately identify both stroke and non-stroke cases. The model exhibited high sensitivity and specificity, with only 3 false positives (FP) and 4 false negatives (FN) predictions. This indicates its robustness and potential clinical utility for accurate stroke diagnosis.

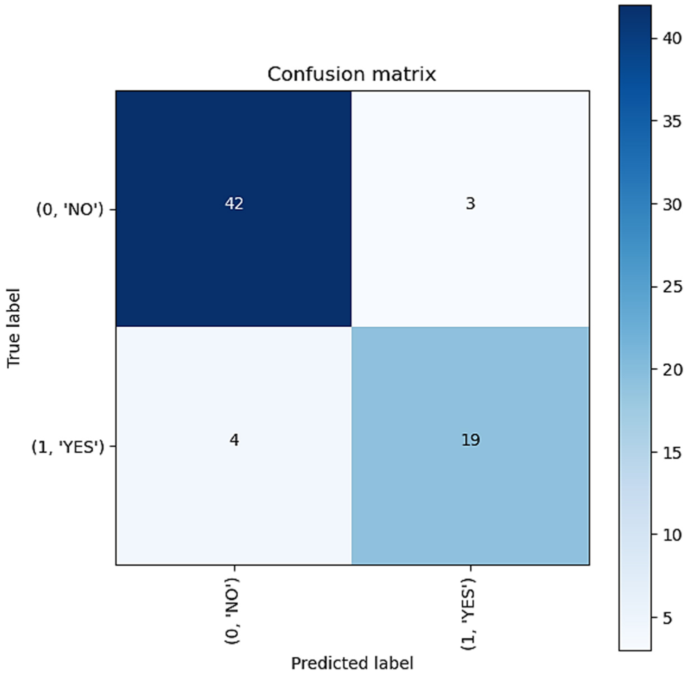

Fig. 8. Confusion matrix of the model in the detection of ischemic stroke

In addition to evaluating our model's performance, we conducted a comparative evaluation with other established deep learning architectures, namely VGG-19, ResNet50, and InceptionV3, using the same dataset. The objective was to determine the most effective model for accurately classifying ischemic strokes from medical images.

Table 3. Evaluation of deep learning architectures for ischemic stroke classification

Model	Accuracy
VGG-16	90.0%
ResNet50	87.0%
InceptionV3	82.0%
VGG-19	81.0%

The results of our evaluation revealed distinct differences in the performance of these architectures (Table 3). Notably, VGG-16 demonstrated superior accuracy compared to the other three models. Specifically, the accuracy achieved by VGG-16 was 90%, while ResNet50 achieved 87%, InceptionV3 achieved 82%, and VGG-19 achieved 81%. This outcome underscores the effectiveness of VGG-16 in our specific application of ischemic stroke classification.

The comparison emphasizes the significance of selecting an appropriate deep learning architecture, and our findings indicate that VGG-16 is a promising choice for accurate ischemic stroke diagnosis.

4 DISCUSSION AND RESULTS

– **Model Performance:** Firstly, let us analyze the model's performance during the training process. As shown in Figure 9, the accuracy of the model on both the training and validation sets steadily increased with each epoch, reaching a validation accuracy of approximately 90%. This signifies that the model successfully learned to classify brain ischemic stroke cases from MRI scans and generalized well to unseen data.

The model's loss, as depicted in Figure 10, demonstrates a decreasing trend over the epochs. This indicates that the model's predictions gradually improved, minimizing the difference between predicted and actual outcomes.

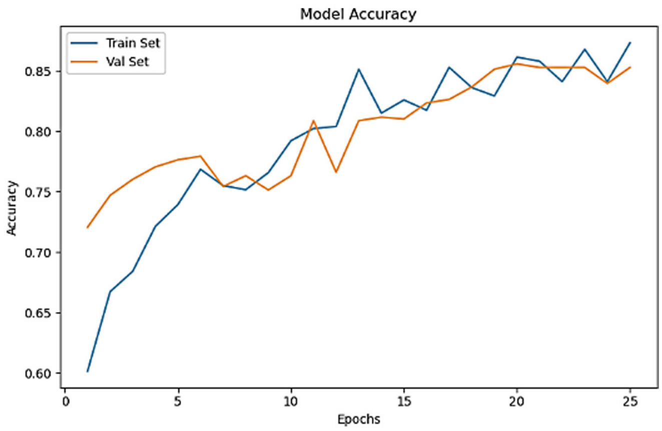

Fig. 9. Model accuracy

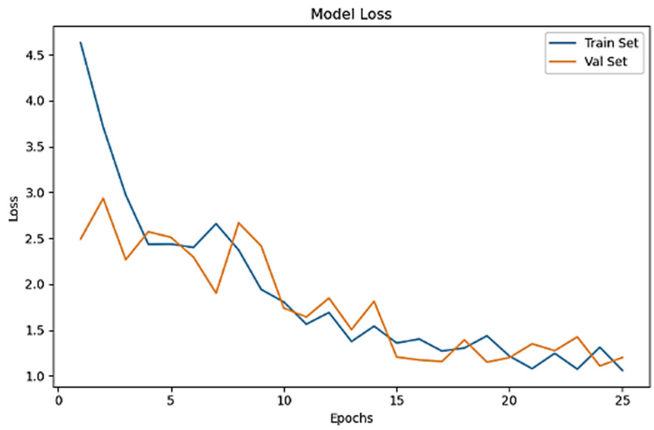

Fig. 10. Model loss

– **Comparison with Other Algorithms:** In this subsection, we provide a comprehensive comparison of our developed brain ischemic stroke classification model using the VGG-16 architecture with three other prominent deep learning algorithms: ResNet50, InceptionV3, and VGG-19. The comparison is based on the same dataset and experimental setup, ensuring a meaningful assessment of their performance.

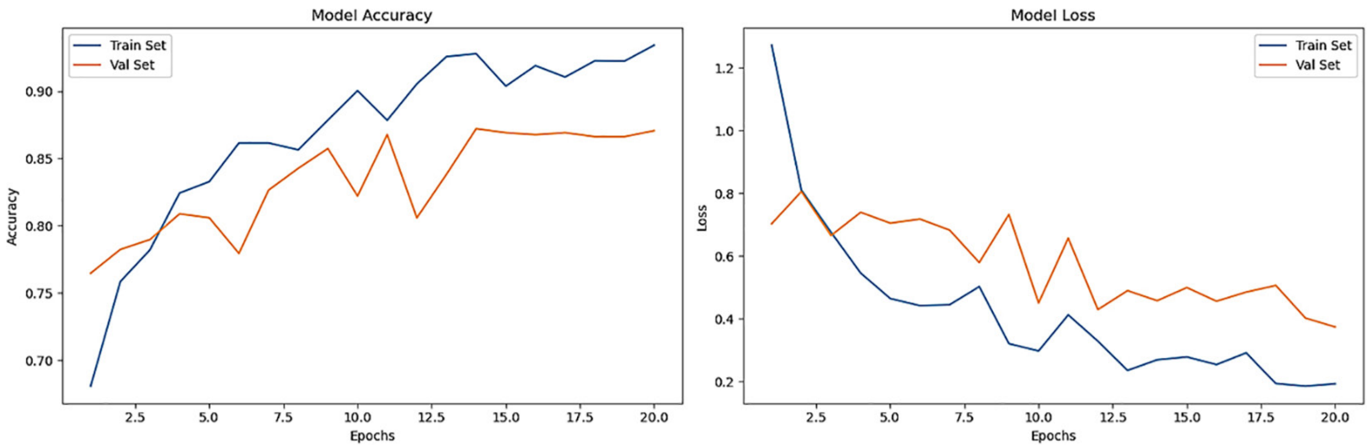

Fig. 11. ResNet50 Model Performance

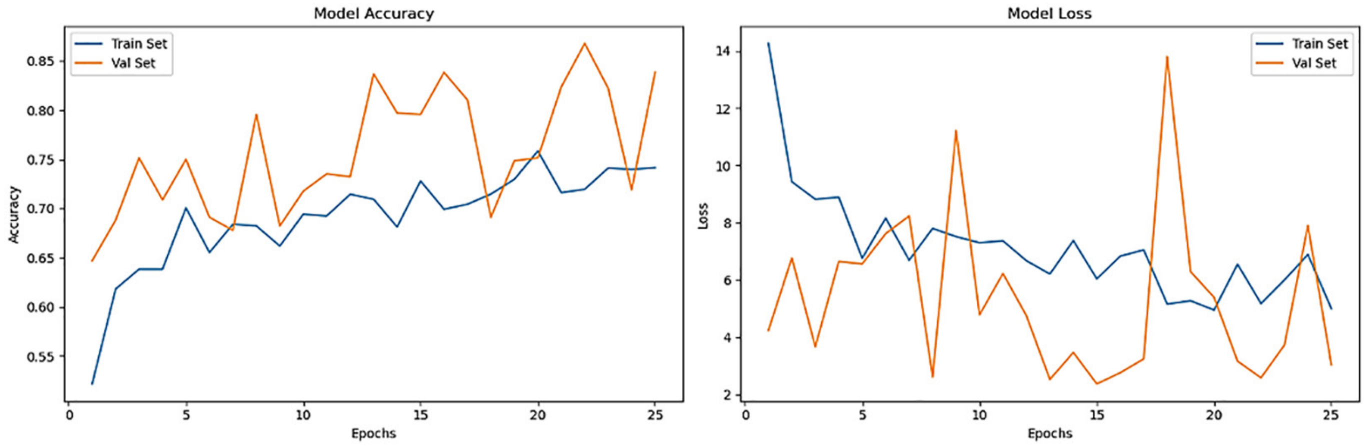

Fig. 12. InceptionV3 Model Performance

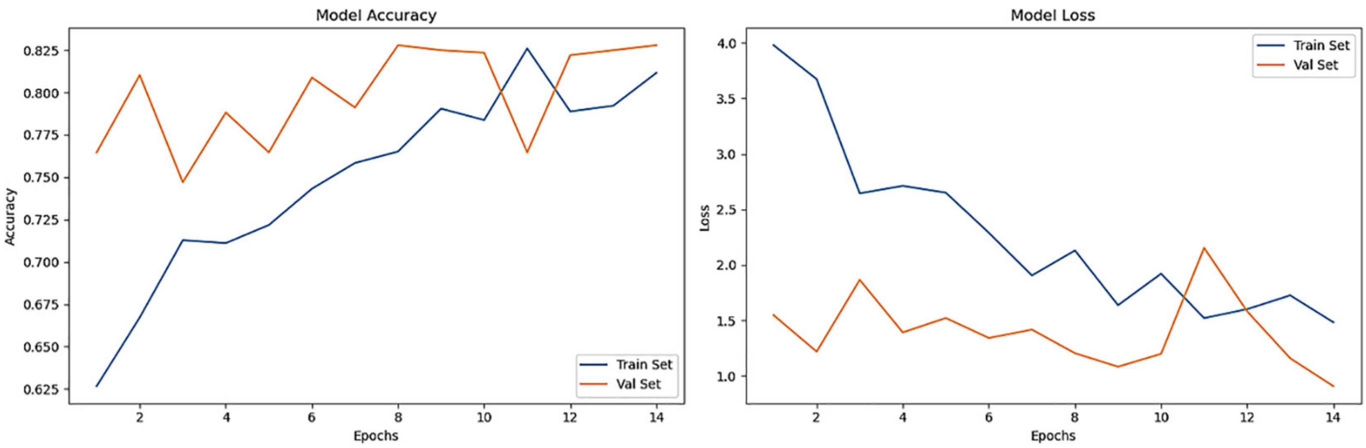

Fig. 13. VGG-19 Model Performance

Figures 11–13 showcase the progression of model accuracy and model loss for each algorithm. Specifically, Figures 9 and 10 illustrate the accuracy and loss trends for our VGG-16 model, while Figures 11–13 display the corresponding trends for ResNet50, InceptionV3, and VGG-19, respectively. These graphs provide a visual representation of how each algorithm's accuracy improves and loss decreases over epochs during training.

The performance comparison underscores the significant influence of the selected deep learning architecture on the accuracy and convergence speed of the model. Notably, our VGG-16-based model exhibits the highest accuracy among all algorithms, effectively distinguishing between brain ischemic stroke and non-stroke cases. This outcome highlights the VGG-16 architecture's adeptness in capturing intricate features within medical images, contributing to superior classification results.

While ResNet50 exhibits a competitive accuracy rate, InceptionV3 and VGG-19 show relatively lower performance in terms of accuracy. These findings highlight the critical role of architecture choice in medical image analysis, further emphasizing the importance of leveraging advanced neural network design for improved diagnostics.

In conclusion, the comparative analysis demonstrates the superior accuracy of our VGG-16-based model in classifying brain ischemic stroke from MRI images. The performance hierarchy, with VGG-16 leading, followed by ResNet50, InceptionV3, and VGG-19, validates the effectiveness of deep learning approaches in medical diagnostics. These findings hold the promise of transforming the landscape of stroke diagnosis and contributing to the advancement of healthcare through innovative technological solutions.

– **Limitations:** While the model shows promising results, it is essential to acknowledge its limitations. One potential limitation is the dataset's size and diversity, which can affect the model's ability to generalize to a broader patient population. Additionally, the model's reliance on a single modality (MRI scans) may limit its performance in cases where additional imaging data is required for accurate diagnosis.
– **Discussion:** The successful implementation of the transfer learning approach with the VGG-16 architecture has demonstrated the model's capacity for brain ischemic stroke classification. The high accuracy and strong performance in detecting stroke cases highlight its potential clinical relevance. Nevertheless, further research and testing with larger and more diverse datasets are necessary to validate and improve the model's robustness and generalization capabilities.

5 CONCLUSION

In summary, this study successfully applied the OSEMN approach to developing a deep learning model for classifying ischemic strokes using medical data from Morocco. The use of transfer learning with the VGG-16 architecture and data augmentation resulted in an effective model with a validation accuracy of 90%, capable of accurately distinguishing stroke cases. The detailed confusion matrix confirms the model's effectiveness. Moreover, through a comparative study with alternative algorithms including ResNet50, InceptionV3, and VGG-19, our findings highlight the superior performance of the VGG-16 model. The research underscores the significance of employing advanced techniques in medical imaging data for enhanced stroke diagnosis, while also highlighting the vast potential of deep learning in healthcare applications. The developed model holds promise for assisting medical professionals in early and accurate stroke detection, thereby contributing to better patient outcomes and healthcare management.

6 FUTURE WORK

In the context of future research directions, several avenues hold promise for advancing our current study on ischemic stroke classification. Firstly, the exploration of ensemble models, combining the strengths of multiple classifiers, could enhance overall predictive performance and robustness. Additionally, the integration of more diverse and comprehensive datasets from different medical institutions can contribute to the generalizability of our model. The investigation of transfer learning approaches, where knowledge gained from one medical imaging task is leveraged to improve performance in ischemic stroke classification, represents another intriguing avenue. Moreover, refining the interpretability of the model outputs and understanding the key features contributing to classifications is vital for building trust in AI-assisted medical diagnoses. Lastly, the potential integration of explainable AI techniques, such as attention mechanisms or saliency maps, could provide valuable insights into the decision-making process of the model, fostering increased confidence among healthcare practitioners.

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