

Integrating CLAHE and Image Enhancement with Deep Learning for Multi-Class Brain CT Analysis

Arda Senyuz[†], Begum Gencer[†], Miray Solmaz[†], Yakup Atici[†], Erdem Okur[†], Ali Salbas[‡], Ali Murat Koc[‡]

[†]Izmir University of Economics, Software Engineering, Izmir, Turkiye

[‡]Izmir Katip Celebi University, Atatürk Training and Research Hospital, Department of Radiology

Abstract—Rapid and accurate detection of brain pathologies such as hemorrhage, infarction, and tumors is crucial in emergency care. Computed tomography is the primary imaging modality for acute cases, yet noise, low contrast, and acquisition variability challenge accurate diagnosis. This study proposes a computer-aided diagnosis framework combining preprocessing, custom enhancement, Contrast Limited Adaptive Histogram Equalization, and deep convolutional neural networks for four-class brain CT classification. Five architectures—InceptionV3, ResNet-50, EfficientNetB0, DenseNet-201, and Xception—were trained under multiple enhancement and transfer learning configurations. DenseNet-201 with transfer learning and combined enhancements achieved the highest accuracy with 88.14%, specificity with 95.78%, and a balanced sensitivity with 86.60%, demonstrating the benefit of multi-enhancement pipelines and pre-trained feature extractors. Results support integrating enhancement-driven CNNs into CAD systems to improve diagnostic accuracy in low-contrast CT imaging.

Keywords—CT classification, hemorrhage detection, infarction detection, brain tumor detection, image enhancement, computer-aided diagnosis.

I. INTRODUCTION

The human brain is the central organ of the nervous system, responsible for regulating voluntary and involuntary bodily functions, cognition, memory, and coordination [1]. Any acute intracranial pathology can have devastating consequences on a patient's health, affecting motor skills, perception, and even personality. Among the most critical and time-sensitive brain abnormalities are hemorrhages, infarction, and tumors [2][3].

A hemorrhage occurs when a blood vessel in the brain ruptures, causing internal bleeding and damaging surrounding tissue. Common causes include trauma and hypertension. Infarctions, typically resulting from ischemic strokes, occur when blood flow to part of the brain is obstructed by a clot or narrowed artery, leading to ischemia, hypoxia, and tissue necrosis. Brain tumors, whether benign or malignant, result from abnormal and uncontrolled cell proliferation within or around brain structures. Primary tumors originate in the brain, whereas secondary (metastatic) tumors spread from other parts of the body [2][3].

The timely diagnosis of these conditions is critical for effective treatment planning. Computed tomography (CT) scans remain the most widely used imaging modality for emergency brain assessments due to their speed, accessibility, and ability

to detect acute bleeding. However, accurate detection can be challenging due to noise, low contrast between normal and pathological tissues, and variability in scanner settings. These limitations can obscure subtle lesions, making diagnosis highly dependent on radiologist expertise and experience.

The evolution of artificial intelligence (AI) and deep learning has resulted in automatic diagnostic tools capable of supplementing a clinician's role by identifying and classifying brain CTs with high specificity. Convolutional neural networks (CNNs) have demonstrated strong results across medical imaging applications, including tumor detection and hemorrhage segmentation [4][5][6][7]. Pre-trained architectures such as ResNet-50, InceptionV3, and DenseNet-201 can be fine-tuned using transfer learning to achieve improved performance on limited medical datasets [8][9][10].

Recent studies have explored various deep learning strategies for classifying brain pathologies from CT images, including tumors, infarcts, and hemorrhages. Transfer learning approaches, as shown in comparative studies, leverage pre-trained weights from natural image datasets to extract relevant features from grayscale CT scans, even with limited data. Other research has explored few-shot learning, volumetric CNNs, slice dependency frameworks, and anatomically-aware data augmentation to address challenges like data scarcity, low contrast, and class imbalance [11][12][13][14].

Among preprocessing techniques, Contrast Limited Adaptive Histogram Equalization (CLAHE) [15] has shown promise in enhancing local contrast and revealing subtle anatomical features [16]. Studies combining CLAHE with augmentation have demonstrated improved classification performance, supporting the integration of enhancement methods into CAD pipelines.

This paper presents a comprehensive classification framework for the detection of hemorrhage, infarction, and tumors on brain CT scans. Our approach integrates preprocessing, enhancement (custom method and CLAHE), augmentation, and deep learning classification, aiming to maximize model performance while maintaining clinical interpretability.

The paper is structured as follows; Section II explains the methodology and the image enhancement technique, Section III lays out the experimental results and discusses the performance of trained models and Section IV concludes the paper.

II. METHODOLOGY

This study employed a structured pipeline comprising pre-processing, enhancement, augmentation, model training, and evaluation for classifying brain CT scans into four categories: Tumor, Hemorrhage, Infarction, and Healthy.

A. Data Collection and Preparation

The dataset was sourced from İzmir Katip Celebi University Atatürk Education and Research Hospital, initially in DICOM format. 108 anonymous patient's various CT scan slices contributed to the dataset. Slices were labeled according to diagnosis and organized into corresponding classes. The dataset also includes the demographic information on patients such as age and gender. Class balance was achieved through random downsampling, resulting in an equal number of samples per class. All scans were converted to JPG using Weasis [17] to enable further processing. The dataset was then, split into 80% training and 20% validation set, with a separate test set reserved for final evaluation.

B. Data Augmentation

In order to achieve a good amount of training data, geometric augmentations, including random rotations ($\pm 15^\circ$), scaling ($\pm 10\%$), and translations (± 10 pixels), were applied to training set which increased the amount and diversity. Reflection-based augmentations, however, avoided due to anatomical constraints.

C. Image Enhancement

Two enhancement techniques were applied to the original dataset with an attempt to improve the image quality to make features more perceivable for network models to be trained.

First, a custom Brightness Map (BRI) method previously used successfully for the detection of melanoma cases by Okur and Turkan [18]. The method consists of creating a "weight map" from the original image and reapplying it back to the image. It employs a specific definition of pixel brightness, where brightness is the absolute difference from the average of a pixel's red, green, and blue values. This brightness value is treated as highlighter for intensity differences to improve feature extraction. A feature map for brightness is generated for each color channel. These feature maps are then normalized to a [0, 1] range, and used to directly weight individual pixels within the original image.

Second, Contrast Limited Adaptive Histogram Equalization (CLAHE) is also used on the original dataset [15]. As it is mentioned in Section I, CLAHE proved its success already in similar tasks. CLAHE is an image processing technique used to improve the local contrast of an image. Unlike traditional histogram equalization, which applies a single, global contrast adjustment to the entire image, CLAHE operates on smaller, individual regions of the image, known as tiles or blocks. This localized approach prevents the algorithm from excessively brightening or darkening large areas of the image, which is sometimes a common problem with global methods. CLAHE is particularly useful for enhancing images with poor or uneven

lighting similar to CT scans, as it can improve the visibility of details in both bright and dark areas simultaneously.

At the end of this image enhancement step, three new datasets were generated which makes total of 4 datasets: original images (R), BRI-enhanced (B), CLAHE-enhanced (C), and BRI+CLAHE-enhanced (BC). Fig. 1 shows an example per class and their enhanced versions from 4 dataset.

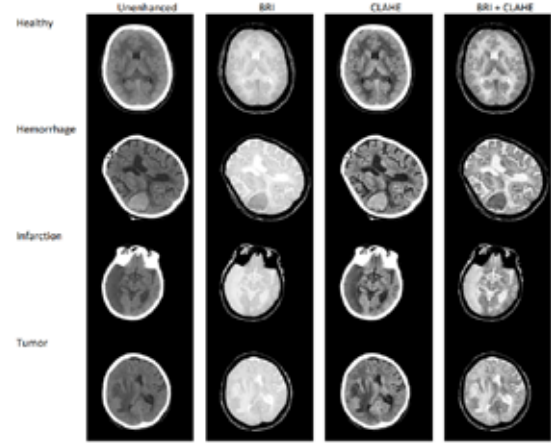


Fig. 1: Example images from 4 datasets prepared from each available class.

D. Model Architectures and Training

Five convolutional neural network (CNN) architectures—InceptionV3, ResNet-50, EfficientNetB0, DenseNet-201, and Xception—were selected for evaluation due to their proven track records in medical image classification and their accessibility through widely used deep learning frameworks [8][9][19][10][20]. These models are readily available with pre-trained weights on large-scale datasets such as ImageNet [21], which makes them ideal for transfer learning in scenarios where collecting large, domain-specific datasets is challenging. Their inclusion was also motivated by ease of integration, as each architecture is well-documented, supported by popular libraries like TensorFlow [22] and PyTorch [23], and benefits from active research communities. Individually, each model offers distinct advantages: InceptionV3's inception modules allow multi-scale feature extraction, which is useful for capturing lesions of varying sizes; ResNet-50's deep residual connections enable effective gradient flow and training stability, making it a robust baseline; EfficientNetB0 strikes a balance between accuracy and computational efficiency, making it suitable for resource-limited environments; DenseNet-201 promotes feature reuse and gradient propagation through dense connectivity, improving learning efficiency; and Xception leverages depthwise separable convolutions for reduced parameter count while maintaining strong representational power. In all experiments, the final classification layers were adapted for the four-class output (tumor, hemorrhage, infarction, and healthy), while training hyperparameters such as learning rate, batch size, and number of epochs were kept constant to ensure a fair comparison across all configurations,

TABLE I: Top 10 Model Performances

Model	Accuracy (%)	Specificity (%)	Sensitivity (%)	NPV (%)	Precision (%)	F1-score (%)
TL DenseNet201+RCB	88.14	95.78	86.60	96.06	89.24	87.48
TL InceptionV3+R	87.71	95.56	87.14	95.78	89.62	88.05
TL Xception+R	87.08	95.50	86.81	95.57	87.48	86.83
TL DenseNet201+CB	86.86	95.32	85.66	95.55	88.26	86.60
TL DenseNet201+B	86.65	95.32	86.07	95.43	87.50	86.49
TL ResNet50+RCB	86.44	95.19	85.20	95.46	87.82	86.06
TL InceptionV3+RCB	86.02	95.11	84.79	95.25	86.08	85.38
TL ResNet50+B	86.02	95.04	84.84	95.23	86.94	85.72
TL EfficientNetB0+R	85.59	94.89	84.78	95.05	86.74	85.53
TL DenseNet201+RB	85.59	94.85	83.73	95.20	87.55	84.97

which varied in transfer learning usage, enhancement methods, and augmentation strategies.

III. EXPERIMENTAL RESULTS AND DISCUSSION

Experiments in this study includes a wide range comparison of the chosen five network model in terms of training type and dataset used. Empty versions of the five models have trained from scratch with four datasets separately and also pretrained versions of them used for transfer learning again with four datasets. With the combinations mentioned above, total of 40 different models are tested in the experiments.

The hardware used in these is a laptop with an Intel Core *i7* 11800H CPU and 16 GB memory accompanied with an NVIDIA RTX 3060 gpu chipset. All experiments are done on MATLAB 2024b [24]. Performance was evaluated using accuracy, sensitivity, specificity, precision, negative predictive value and F1-score to ensure comprehensive assessment of each model's diagnostic capabilities. Table I presents the results acquired with these experiments. To be concise and clear, only top 10 successful models are included in the table.

The top-10 results reveal several important trends regarding the influence of model architecture, enhancement techniques, and transfer learning on classification performance. All models in the top-10 list were trained using transfer learning (TL), underscoring its effectiveness for brain CT classification, especially when datasets are limited. None of the from-scratch (RW) models managed to outperform the TL-based counterparts, highlighting the benefit of leveraging pre-trained weights from large-scale datasets such as ImageNet to extract robust and transferable features, at least when the acquired dataset size is small.

DenseNet-201 appears most frequently among the top-performing configurations, indicating that its densely connected architecture and feature reuse mechanism are particularly effective in capturing the fine-grained structural details present in CT scans. The top-performing model, TL DenseNet201+RCB, which combines original, CLAHE-enhanced, and custom-enhanced images, achieved the highest accuracy (88.14%) and specificity (95.78%), suggesting that integrating multiple enhancement techniques provides complementary benefits. This fusion likely enriches the diversity

of image features, enabling the network to generalize better across different tissue contrast conditions.

InceptionV3 and Xception also appear among the leaders, particularly when trained with original images (R) or a combination of enhancements. InceptionV3's multi-scale feature extraction likely helps capture both localized lesions and global structural abnormalities, while Xception's depthwise separable convolutions may improve efficiency in learning texture variations present in hemorrhage, infarction, and tumor cases.

Interestingly, ResNet-50 appears lower in the top 10, but still with strong performance when trained with multiple enhancements (RCB or B). This suggests that while residual connections help in stable training, ResNet-50's relatively lower representational capacity compared to DenseNet-201 might require the richer feature diversity provided by enhancement combinations to compete effectively.

From an enhancement perspective, models trained with combinations of R, C, and B consistently outperform those trained on a single image type. This indicates that no single enhancement method is optimal for all cases—rather, combining them gives the model a more comprehensive view of the data. CLAHE (C) improves local contrast and structural detail, the custom enhancement (B) amplifies subtle intensity differences, and the original images (R) preserve the natural appearance, all of which complement one another.

Overall, the results suggest that DenseNet-201 with multi-enhancement training and transfer learning provides the best balance of accuracy, specificity, and sensitivity. Other architectures like InceptionV3 and Xception remain competitive, particularly when computational efficiency or multi-scale feature extraction is prioritized.

IV. CONCLUSION

This study demonstrates that integrating targeted image enhancement with modern deep learning architectures significantly improves classification performance in brain CT analysis. Among the evaluated models, DenseNet-201 trained with transfer learning and multi-enhancement data achieved the highest overall accuracy and specificity, underscoring the value of combining complementary preprocessing strategies. Transfer learning consistently outperformed from-scratch



training, reflecting the advantage of leveraging pre-trained feature extractors when working with limited medical datasets. The consistent presence of InceptionV3 and Xception among the top models further highlights the importance of multi-scale feature extraction and efficient convolutional operations in capturing both global and local lesion characteristics. Future work should focus on expanding the dataset, incorporating volumetric and slice-dependency information, and validating the framework in clinical settings to assess real-world diagnostic impact. The findings support the adoption of enhancement-driven, transfer learning-based CNN models in CAD systems to aid radiologists in the rapid and reliable detection of life-threatening brain abnormalities.

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