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Intractanial Aneurysm Detection

Submitted to complete the requirments of junior project

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SUPERVISOR CERTIFICATION

I certify that the preparation of this project **Intractanial Aneurysm Detection**

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Abstract

Automated detection of intracranial aneurysms from medical imaging is a critical challenge due to the severe clinical consequences associated with late or incorrect diagnosis. This project presents a deep learning–based system for the automated identification of cerebral aneurysms in brain computed tomography (CT) scans. The work is conducted from an AI engineering perspective, focusing on model design, data preparation, training strategy, and comprehensive evaluation.

The study employs the **"Computed Tomography (CT) of the Brain" dataset** obtained from Kaggle, which comprises a diverse set of CT brain images covering multiple conditions, including aneurysm and non-aneurysm cases. Images were provided in .jpg and .dcm formats, necessitating preprocessing steps such as resizing, normalization, and format conversion to ensure consistency across the dataset. To enhance model generalization and mitigate overfitting, data augmentation techniques were applied during training.

A convolutional neural network (CNN) classifier was developed using the TensorFlow and Keras frameworks to perform supervised binary classification of aneurysm versus non-aneurysm images. The model was trained using augmented training data and evaluated on separate validation and test partitions. Experimental results demonstrate robust classification performance, with a **training accuracy of 97.1%**, a **validation accuracy of 96.1%**, and a **testing accuracy of 95.26%**. In addition to accuracy metrics, a confusion matrix was constructed to analyze true positive, true negative, false positive, and false negative predictions, thereby providing deeper insight into model behavior and diagnostic reliability.

The results confirm the effectiveness of deep learning techniques in medical image analysis and underscore their potential as supportive tools for clinicians in early and accurate aneurysm detection. This project highlights the integration of artificial intelligence methodologies with medical imaging to address real-world diagnostic challenges.

Keywords: Intracranial Aneurysm Detection, Deep Learning, Convolutional Neural Networks (CNN), Medical Image Classification, Computed Tomography (CT), Artificial Intelligence in Healthcare

الملخص

يُعد الكشف الآلي عن تمدد الأوعية الدموية داخل الجمجمة من الصور الطبية تحديًا بالغ الأهمية نظرًا للعواقب السريرية الخطيرة الناتجة عن التشخيص المتأخر أو غير الدقيق. يهدف هذا المشروع إلى تطوير نظام قائم على التعلم العميق للتعرف الآلي على تمدد الأوعية الدموية الدماغية في صور الأشعة المقطعية للدماغ. نفذنا المشروع من منظور هندسي، مع التركيز على تصميم النموذج، وتجهيز البيانات، واستراتيجية التدريب، وإجراء التقييم الشامل لأداء النظام.

تعتمد الدراسة على مجموعة بيانات الأشعة المقطعية للدماغ المتاحة على منصة(Kaggle)

والتي تتضمن مجموعة متنوعة من صور الدماغ تشمل حالات تمدد الأوعية الدموية والحالات غير التمددية. تم توفير الصور بصيغ مختلفة، هذا استلزم تنفيذ خطوات معالجة أولية تشمل تعديل الحجم، والتطبيع، وتحويل الصيغ لضمان التوافق عبر مجموعة البيانات. ولتعزيز قدرة النموذج على التعميم وتقليل الإفراط في التعلّم، تم تطبيق تقنيات زيادة البيانات أثناء مرحلة التدريب

تم تطوير مصنّف باستخدام الشبكات العصبية الالتفافية لإجراء التصنيف الثنائي بين الصور التي تحتوي على تمدد الأوعية الدموية وتلك التي لا تحتويه. وقد تم تدريب النموذج على البيانات المعالجة والمُضاعفة، وقمنا بتقييمه على مجموعات تحقق واختبار منفصلة. أظهرت النتائج التجريبية أداءً تصنيفيًا قويًا، حيث بلغت دقة التدريب 97.1٪، ودقة التحقق 96.1٪، ودقة الاختبار 95.26٪. كما تم إنشاء مصفوفة الالتباس لتحليل التوقعات الصحيحة والخاطئة، مما أتاح فهمًا أعمق لسلوك النموذج وموثوقية تشخيصه

تؤكد النتائج فعالية تقنيات التعلم العميق في تحليل الصور الطبية، وتبرز أهميتها كأداة مساعدة للأطباء في الكشف المبكر والدقيق عن تمدد الأوعية الدموية. كما يسلط المشروع الضوء على إمكانية دمج منهجيات الذكاء الاصطناعي مع التصوير الطبي لمواجهة تحديات التشخيص الواقعية، مع توفير أساس متين لتطوير أنظمة تشخيصية متقدمة مستقبلًا

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Abbreviations

Table 1

Abbreviation	Full Form
CT	Computed Tomography
DICOM	Digital Imaging and Communications in Medicine
CNN	Convolutional Neural Network
DL	Deep Learning
TL	Transfer Learning
ACC	Accuracy
GPU	Graphics Processing Unit
MRI	Magnetic Resonance Imaging

Chapter 1 : Introduction

Intracranial aneurysms are abnormal dilations of cerebral blood vessels that pose a significant risk of rupture, often leading to subarachnoid hemorrhage, stroke, or death. Early and accurate detection is critical for effective clinical management and patient survival. Traditionally, the diagnosis of aneurysms relies on the manual examination of computed tomography (CT) scans by radiologists, a process that is both time-consuming and susceptible to human error, especially in cases with subtle or complex anomalies. The increasing demand for reliable and efficient diagnostic tools has led to a growing interest in automated medical image analysis using artificial intelligence (AI) techniques.

Deep learning, a subset of AI, has demonstrated remarkable capabilities in medical imaging tasks, particularly in classification and detection problems. Among deep learning architectures, the Xception model, based on depthwise separable convolutions, offers an efficient and powerful approach for extracting complex features from images, achieving state-of-the-art performance in various image recognition tasks.

This project focuses on the automated detection of intracranial aneurysms in CT brain scans using the Xception model. The dataset employed originally contained three distinct classes of images. For the purpose of this study, the dataset was consolidated into a binary classification task, categorizing images as either aneurysm or non-aneurysm, which reflects the primary clinical objective of identifying potentially life-threatening aneurysms. Preprocessing steps, including image resizing, normalization, and data augmentation, were applied to ensure consistency, enhance model generalization, and reduce the risk of overfitting.

The objectives of this project are:

- To preprocess and augment the CT brain image dataset for a binary classification framework.
- To implement and fine-tune the Xception model for accurate detection of aneurysm cases.
- To evaluate model performance using standard metrics, including accuracy, confusion matrix analysis, and area under the curve (AUC).
- To assess the feasibility of deep learning–based systems as supportive tools for clinicians in early and reliable aneurysm detection.

By integrating advanced deep learning techniques with medical imaging, this study demonstrates the potential of AI-assisted diagnostic systems to improve clinical decision-making and reduce the risks associated with intracranial aneurysms.

Chapter 2: Project Description

2.1 Background

Intracranial aneurysms are abnormal dilations of cerebral blood vessels that, if left undetected, can lead to life-threatening complications such as hemorrhagic stroke. Early detection is critical for timely medical intervention and patient survival. Traditional diagnostic methods rely heavily on radiologists manually interpreting brain computed tomography (CT) scans, which can be time-consuming and subject to human error.

Recent advances in artificial intelligence (AI) and deep learning have enabled the development of automated systems capable of analyzing medical images with high accuracy. Convolutional neural networks (CNNs), in particular, have shown remarkable performance in feature extraction and classification tasks, making them highly suitable for medical image analysis. This project leverages the **Xception deep learning model** to detect intracranial aneurysms from CT images, providing an efficient and reliable tool to assist clinicians in early diagnosis.

2.2 Problem Definition

Intracranial aneurysm detection from brain CT images represents a complex pattern recognition problem due to the subtle visual differences between aneurysmal and normal vascular structures. These differences are often characterized by small variations in shape, intensity, and contrast that may not be easily distinguishable through conventional visual inspection. Furthermore, CT images can be affected by noise, artifacts, and variations in acquisition parameters, which further complicate accurate diagnosis.

From a computational perspective, the problem can be defined as a supervised medical image classification task in which CT brain images must be accurately categorized into two classes: aneurysm and non-aneurysm. The challenge lies in designing a model that can extract discriminative features while maintaining robustness against image variability and limited dataset size. An effective solution must achieve high sensitivity to minimize false negatives, as missed detections can lead to severe clinical consequences, while also maintaining acceptable specificity to reduce false alarms.

2.3 Project Objective

The primary objective of this project is to develop an **automated deep learning-based system** for detecting intracranial aneurysms from brain CT scans. Specific objectives include:

- Preprocessing and preparing a dataset of brain CT images for model training.
- Modifying a multi-class dataset into a **binary classification problem** (aneurysm vs. non-aneurysm).
- Implementing and fine-tuning the **Xception CNN model** for robust image classification.

- Evaluating model performance using standard metrics such as accuracy and confusion matrix
- Demonstrating the potential of AI-assisted diagnosis to improve early detection and clinical decision-making.

2.4 Project Scope

The scope of this project is limited to the **detection of intracranial aneurysms in CT brain images**. The system focuses on binary classification (aneurysm or non-aneurysm) and does not extend to other neurological conditions. The dataset used consists of images in .jpg and .dcm formats, and preprocessing steps include resizing, normalization, and augmentation. The project emphasizes model development, training, and evaluation, rather than integration into clinical practice at this stage.

2.5 Project Features

Key features of the proposed system include:

- Automated detection of aneurysms from CT brain scans.
- High classification accuracy achieved through the Xception deep learning model.
- Data preprocessing and augmentation for improved generalization.
- Visualization of model predictions and performance metrics for interpretability.
- User-friendly interface for testing and evaluating individual images.

2.6 Project Feasibility

The feasibility of this project is supported by the availability of a well-annotated CT brain dataset, the accessibility of powerful deep learning frameworks (TensorFlow and Keras), and the suitability of the Xception model for medical image classification. Computational requirements are manageable with standard GPU resources, and the methodology aligns with current research in AI-assisted medical diagnostics. This ensures that the project can be successfully implemented and evaluated within the timeframe of the project.

2.7 Tools and Concepts

This project relies on a set of modern tools and core concepts from artificial intelligence, deep learning, and medical image processing to achieve its objectives. The key tools and concepts employed are summarized as follows:

- **Deep Learning**

  Deep learning (DL) is a subset of machine learning that uses artificial neural networks with multiple layers to automatically learn hierarchical representations of data. Unlike traditional machine learning, which often requires handcrafted features, deep learning can directly process raw input data such as images, text, or audio. In medical imaging, deep learning enables automatic feature extraction, classification, segmentation, and detection, allowing models to learn subtle patterns that may not be easily detectable by human observers. DL models are particularly effective in handling large, high-dimensional datasets like CT or MRI scans.

- **Convolutional Neural Networks (CNNs)**

  Convolutional Neural Networks are a type of deep learning architecture specifically designed for processing grid-like data, such as images. CNNs use three main types of layers:

  Convolutional layers: Extract local features using learnable filters.

  Pooling layers: Reduce the spatial dimensions to decrease computation and achieve translational invariance.

  Fully connected layers: Combine extracted features to make final predictions. CNNs are highly effective in medical imaging because they automatically learn spatial hierarchies and structural patterns, which are critical for detecting anomalies such as aneurysms in CT scans.

- **Xception Model**

  Xception (Extreme Inception) is an advanced CNN architecture that extends the Inception model by using **depthwise separable convolutions**. This means that spatial and channel-wise feature extraction are performed separately, reducing the number of parameters while maintaining high accuracy. Key advantages of Xception include:

  Efficient and powerful feature extraction.

  Lower computational cost compared to traditional CNNs with similar depth.

High compatibility with transfer learning, allowing pre-trained models to be fine-tuned on specific datasets.
In this project, Xception is employed to classify CT images into aneurysm and non-aneurysm categories, leveraging its ability to capture complex patterns in high-dimensional medical images.

- **Medical Image Preprocessing**

Medical images often vary in size, intensity, and format (e.g., DICOM, JPG). Preprocessing is crucial to standardize these images for input to deep learning models. Common preprocessing steps include:

  - **Resizing**: Converting all images to a uniform resolution (e.g., 224×224 pixels) suitable for CNN input.
  - **Normalization**: Scaling pixel intensity values to a fixed range (commonly [0,1]) to improve model convergence.
  - **DICOM to image format conversion**: Extracting pixel data from medical imaging files while preserving diagnostic information.
  - **Noise reduction and clipping**: Suppressing irrelevant intensity values to highlight key anatomical structures.
    Effective preprocessing ensures consistency across the dataset and improves model performance.

- **Software Frameworks (TensorFlow, Keras, Python)**

  - **Python**: A widely used programming language in AI research due to its readability and extensive libraries.
  - **TensorFlow**: A deep learning framework that provides tools for model building, training, and deployment. It supports GPU acceleration for faster computations.
  - **Keras**: A high-level API for TensorFlow that simplifies model construction, training, and evaluation.

Together, these frameworks allow researchers to implement, train, and fine-tune complex deep learning models efficiently.

- **Evaluation Metrics**

Evaluation metrics quantify how well the model performs on unseen data. In medical imaging, common metrics include:

- **Accuracy (ACC)**: The percentage of correct predictions among all predictions.
- **Sensitivity (Recall)**: The ability of the model to correctly identify positive cases (e.g., actual aneurysms).
- **Specificity**: The ability to correctly identify negative cases (e.g., non-aneurysm).
- **Precision**: The proportion of true positives among all predicted positives.

2.7.1 The Core Idea

The core idea of this project is to leverage deep learning techniques, specifically convolutional neural networks (CNNs), to automatically learn discriminative features from brain CT images for intracranial aneurysm detection. Unlike traditional image analysis approaches that rely on handcrafted features, CNN-based models are capable of extracting hierarchical representations directly from raw image data. This allows the system to identify subtle visual patterns associated with aneurysms that may not be easily perceived by human observers.

The Xception model is employed as the backbone of the proposed system due to its efficient architecture based on depthwise separable convolutions. By fine-tuning this pre-trained model on CT brain images, the system adapts learned visual features to the medical imaging domain, enabling accurate binary classification between aneurysm and non-aneurysm cases. The overall approach aims to improve diagnostic accuracy, reduce human workload, and support clinicians in early and reliable decision-making.

2.7.2 Formula

From a mathematical perspective, the classification task is formulated as a supervised learning problem. Given an input CT image x, the CNN model learns a function $f(x;\theta)$, where θrepresents the network parameters, such that:

$$\hat{y} = f(x;\theta)$$

where $\hat{y} \in \{0,1\}$denotes the predicted class label, with 0 representing non-aneurysm and 1 representing aneurysm.

The model is trained by minimizing a binary cross-entropy loss function, defined as:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)]$$

where:

- N is the number of training samples,
- y_i is the true label,
- $\hat{y}_i$ is the predicted probability output by the model.

This optimization process adjusts the network parameters using gradient-based methods to minimize classification error and improve predictive performance.

Chapter 3: Theoretical Study

3.1 Introduction

This chapter presents the theoretical foundations that underpin the development of the proposed intracranial aneurysm detection system. It provides an overview of the fundamental concepts, models, and techniques related to artificial intelligence, deep learning, and medical image analysis that are essential for understanding the methodology adopted in this project.

Medical imaging plays a vital role in modern healthcare by enabling non-invasive visualization of internal anatomical structures for diagnostic and therapeutic purposes. Among the various imaging modalities, **Computed Tomography (CT)** and **Magnetic Resonance Imaging (MRI)** are widely used in brain diagnostics. CT imaging is particularly effective due to its high spatial resolution, rapid acquisition time, and widespread clinical availability, making it suitable for detecting vascular abnormalities such as intracranial aneurysms.

Medical images are commonly stored in the **Digital Imaging and Communications in Medicine (DICOM)** format, which standardizes image storage and transmission while preserving essential metadata, including patient information and acquisition parameters. This standardization ensures interoperability across medical imaging systems and supports large-scale medical data analysis.

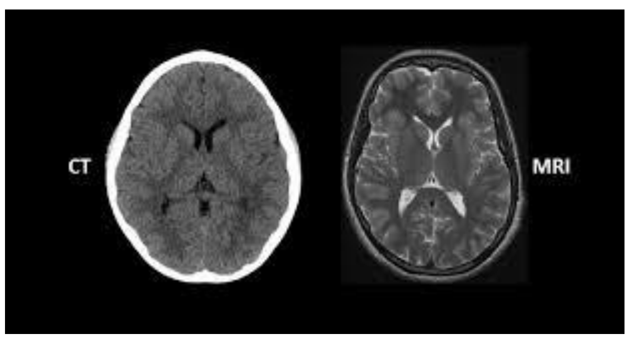

Figure ii

3.2 Intracranial Aneurysms

An **intracranial aneurysm** is a localized dilation of a cerebral artery caused by a weakening of the vessel wall. If left undetected, an aneurysm may rupture, leading to subarachnoid hemorrhage, stroke, or death. Early detection is therefore critical to reduce the high mortality and morbidity associated with this condition.

In CT brain images, aneurysms typically appear as small protrusions along blood vessels and often exhibit subtle visual differences from surrounding tissues. Their small size, variable shape, and low contrast make manual detection challenging, even for experienced radiologists. These limitations emphasize the importance of automated and intelligent diagnostic systems capable of assisting clinicians in accurate aneurysm detection.

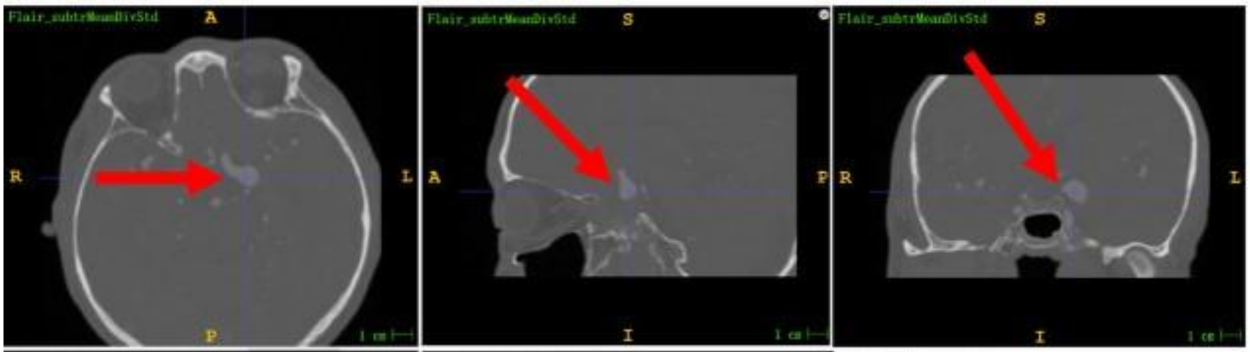

Figure iii

3.3 Fundamentals of Deep Learning

Deep learning (DL) is a branch of machine learning that employs artificial neural networks with multiple hidden layers to automatically learn hierarchical representations from data. In image analysis, **Convolutional Neural Networks (CNNs)** are the most widely used deep learning architecture due to their ability to capture spatial and structural features within images.

CNNs consist of convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. Unlike traditional machine learning approaches that rely on handcrafted features, CNNs learn discriminative features directly from raw image data. This capability has led to their extensive adoption in medical imaging applications, including classification, segmentation, and abnormality detection.

3.4 Xception Model Overview

The **Xception (Extreme Inception)** model is an advanced convolutional neural network architecture that extends the Inception framework by replacing standard convolution operations with **depthwise separable convolutions**. This architectural modification decomposes conventional convolutions into depthwise and pointwise operations, significantly reducing computational complexity while preserving high feature extraction capability.

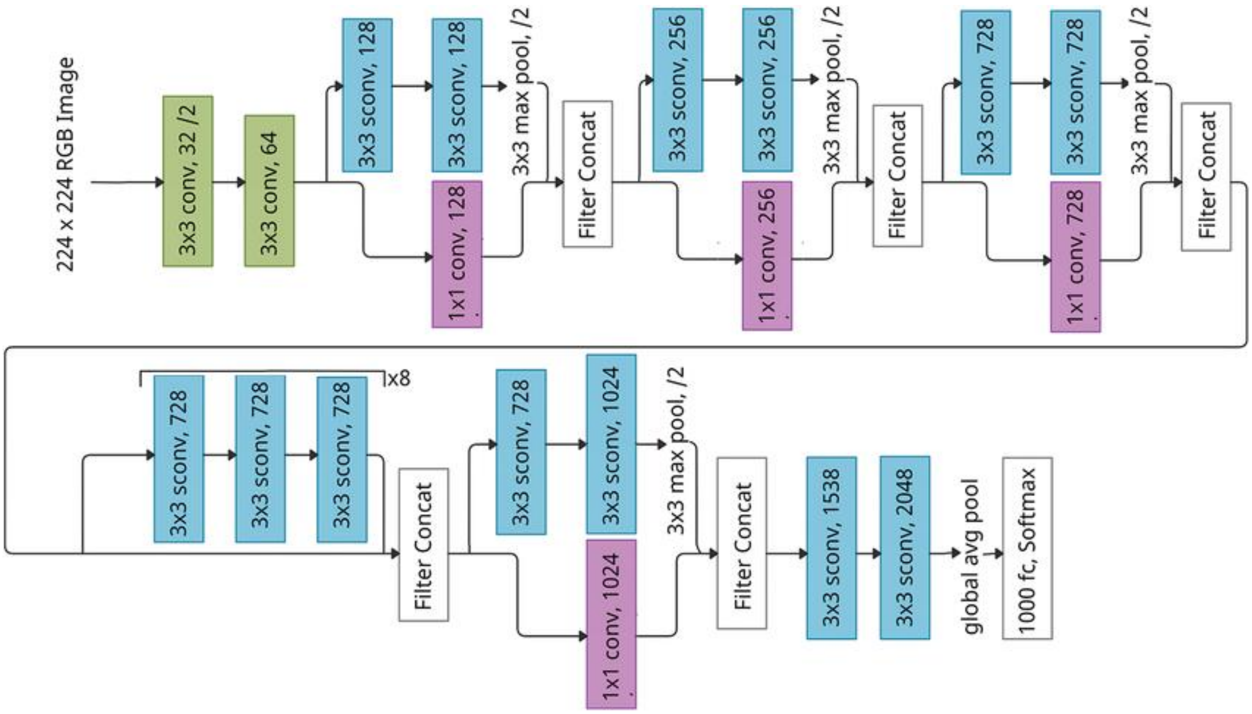

Figure iv

The Xception model offers several advantages that make it suitable for medical image classification tasks:

- Efficient feature extraction through depthwise separable convolutions
- Reduced number of trainable parameters compared to conventional CNN architectures
- High classification accuracy in complex image recognition tasks
- Compatibility with transfer learning, allowing the use of pre-trained weights for faster convergence

Depthwise separable convolutions enable the model to learn spatial and channel-wise features independently, improving efficiency without compromising performance. This characteristic is particularly beneficial for medical imaging applications, where high-resolution images require effective feature representation.

In this study, the Xception model is fine-tuned to classify CT brain images into **aneurysm** and **non-aneurysm** categories, leveraging its ability to extract complex and discriminative patterns from high-dimensional medical images.

3.5 Image Preprocessing and Augmentation

Medical images often exhibit variations in resolution, intensity distribution, and format, which can negatively affect model performance. Image preprocessing is therefore a critical step to ensure data consistency and improve learning efficiency. Common preprocessing operations include image resizing, intensity normalization, and conversion from DICOM format to standard image formats such as JPG or PNG.

To enhance model generalization and reduce overfitting, **data augmentation** techniques are applied during training. These techniques include rotation, flipping, and zooming, which artificially increase dataset diversity by simulating variations encountered in real-world clinical scenarios. As a result, the model becomes more robust when exposed to unseen data.

Chapter 4: Literature Review

4.1 introduction :

This chapter reviews relevant research studies and existing methodologies related to the automated detection of intracranial aneurysms and the application of deep learning techniques in medical image analysis. The purpose of this review is to provide an overview of prior work, identify current trends, and highlight the strengths and limitations of existing approaches.

The chapter focuses on studies that utilize computed tomography (CT) and magnetic resonance imaging (MRI) data in conjunction with convolutional neural networks and other machine learning models for aneurysm detection and classification. Additionally, it examines the use of advanced deep learning architectures, such as transfer learning and pre-trained CNN models, in medical diagnostic applications.

By analyzing previous research, this chapter establishes the context for the proposed approach and justifies the selection of the Xception model and the adopted methodology. The insights gained from the reviewed literature help demonstrate how this project builds upon existing work while addressing identified challenges in accuracy, efficiency, and clinical applicability.

4.1 Aneurysm Model Classification:

4.1.1 Datasets:

Lausanne MRA Dataset (OpenNeuro Dataset *ds003949*). *OpenNeuro (2024).* The Lausanne MRA dataset provides a structured collection of high-quality magnetic resonance angiography (MRA) scans of the human brain, designed to support research in cerebrovascular disease analysis and automated detection tasks. The dataset includes comprehensive imaging data with detailed anatomical coverage, capturing both normal vascular structures and vascular abnormalities. Images are stored in standardized formats suitable for machine learning applications and neuroimaging pipelines. This dataset serves as a valuable resource for training deep learning models, particularly for tasks such as binary classification of intracranial aneurysm presence. By offering diverse angiographic scans with consistent acquisition parameters, the Lausanne MRA dataset facilitates development of robust diagnostic algorithms that generalize across patient populations.

ADAM MRA Dataset (ADAM Data Repository). *Institute for Advanced Data Analytics, ADAM.* The ADAM MRA dataset comprises magnetic resonance angiography scans collected independently of the Lausanne dataset, curated to support testing and validation of cerebrovascular image analysis models. Each scan is accompanied by expert annotations identifying regions of interest related to vascular anomalies including aneurysms. The dataset's role as an external test set enables rigorous assessment of model generalization beyond the training distribution, providing a benchmark for cross-dataset evaluation of machine learning approaches. Researchers can leverage the ADAM MRA dataset to evaluate performance metrics such as accuracy, sensitivity, and specificity in unseen imaging contexts, thereby supporting the development of clinically robust detection systems.

Tumor-Cancer-Aneurysm Detection Dataset (Roboflow Universe). Roboflow Universe (2023). This dataset provides a curated collection of CT and MRA brain images labeled for aneurysms, tumors, and cancerous lesions, suitable for supervised deep learning tasks. The dataset includes annotated images with various pathological conditions, supporting multi-class and binary classification tasks. Images are standardized for machine learning pipelines, facilitating preprocessing, augmentation, and model training. By incorporating diverse brain scans with precise labeling, the Tumor-Cancer-Aneurysm Detection dataset enables development and benchmarking of convolutional neural network models for automated detection of intracranial abnormalities, enhancing the accuracy and clinical utility of computer-aided diagnostic tools.

Computed Tomography (CT) of the Brain Dataset . Kaggle (2023). The Computed Tomography (CT) of the Brain dataset contains a diverse collection of CT brain scans annotated for conditions including cancer, tumor, and aneurysm. Each scan represents a detailed clinical image obtained using CT imaging, provided in both .jpg and .dcm formats. By offering multi-condition brain scans with standardized labeling, this dataset enables the development and evaluation of deep learning models for automated detection and differentiation of neurological abnormalities. It is particularly valuable for research in neuroimaging, radiology, and computer-aided diagnostic systems, allowing models to learn from real CT data and improve the accuracy of clinical anomaly classification.

4.1.2 state of art:

Weakly Supervised Intracranial Aneurysm Detection and Segmentation via Multi-task UNet with Vesselness Prior (VP-UNet) – 2025 .VP-UNet Research Group. (2025). *Weakly supervised intracranial aneurysm detection and segmentation in MR angiography via multi-task UNet with vesselness prior (VP-UNet)*. Lausanne MRA dataset for training; ADAM MRA dataset for testing.
This study proposes a weakly supervised multi-task 3D UNet (VP-UNet) incorporating a vesselness filter prior to simultaneously detect and segment intracranial aneurysms in MR angiography scans. The model automatically extracts 3D features along vascular structures, addressing challenges posed by limited labeled data. Using the Lausanne MRA dataset for training and the ADAM MRA dataset for external testing, VP-UNet achieved a sensitivity of 92.9%, 1.47 false positives per case, Dice coefficient of 0.614, and Hausdorff distance 95% = 1.38 mm, demonstrating robust performance in aneurysm identification.

Automated Method for Intracranial Aneurysm Classification Using Deep Learning . Nam, S., et al. (2024). *Automated method for intracranial aneurysm classification using deep learning*. Tumor, Cancer, and Aneurysm Detection Image Dataset (DiscoverAI / Roboflow).This study presents a 2D convolutional neural network (CNN) for automated classification of aneurysms in CT images. The model consists of three convolutional layers, three pooling layers, dropout, dense, and softmax layers, trained with Adamax optimizer (LR=0.001, 50 epochs, batch size=16) on 611 CT images. Evaluated with an 87:8:5 train-validation-test split, the proposed CNN achieved 98.01% accuracy and 0.0360 test loss. Comparative analysis with ResNet-50/101/152 and VGG16 confirmed the efficiency of the proposed model for automatic feature extraction without manual engineering.

Multi-centric AI Model for Unruptured Intracranial Aneurysm Detection and Volumetric Segmentation in 3D TOF-MRI .Multi-Center AI Research Group. (2023). *Multi-centric AI model for unruptured intracranial aneurysm detection and volumetric segmentation in 3D TOF-MRI*. This work develops a multi-center AI framework using 3D nnU-Net to detect and segment unruptured intracranial aneurysms in 385 TOF-MRI scans from multiple centers and 113 ADAM challenge scans. Four training dataset combinations were evaluated retrospectively. The model achieved sensitivities between 82–85%, primary model sensitivity of 85%, false positives per case 0.23, Dice score ≈ 0.73, and normalized surface distance (NSD) ≈ 0.84, illustrating its effectiveness across heterogeneous clinical data.

Reproducibility and Across-Site Transferability of Deep Learning for TOF-MRA . Reproducibility Study Group. (2024). *Reproducibility and across-site transferability of an improved deep learning approach for aneurysm detection and segmentation in time-of-flight MR angiograms*.This study evaluates the reproducibility and generalizability of a CNN-based aneurysm detection and segmentation framework in TOF-MRA scans. The model was trained on 235 scans from a single vendor and tested on 140 external scans (70 same-vendor, 70 other-vendor). Utilizing an improved preprocessing pipeline, automatic feature extraction achieved sensitivities of 0.97 (same vendor) and 0.92 (other vendor), Dice scores of 0.60 ± 0.25 and 0.65 ± 0.26, respectively, with 0.87 ± 1.35 false positives per case, demonstrating reliable cross-site performance.

Automated Detection Using Skeleton-based 3D Patches, Semantic Segmentation, and Auxiliary Classification. Seoul National University Research Team. (2023). *Automated detection of intracranial aneurysms using skeleton-based 3D patches, semantic segmentation,* *and auxiliary classification for overcoming data imbalance in brain TOF-MRA*.The study introduces a multi-task 3D U-Net with an auxiliary classification branch to detect and segment intracranial aneurysms in 154 TOF-MRA scans from Seoul National University Bundang Hospital and 113 public scans for external validation. Data imbalance was addressed through variable ratios of normal to aneurysm patches. The method achieved 0.910 internal accuracy, 0.883 external accuracy, Dice 0.755, sensitivity 0.882, and ~0.3 false positives per case, showing effective 3D feature learning along vessel structures.

Fully Automated Detection and Segmentation in 3D CT Angiography . CT-Angiography Ensemble Study Group. (2020). *Fully automated detection and segmentation of intracranial aneurysms in 3D CT angiography*.This study applied a 3D CNN ensemble for detection and segmentation of aneurysms in 68 training patients (79 aneurysms) and 185 testing patients (215 aneurysms). The ensemble leveraged volumetric feature learning and five-fold cross-validation. Results showed 87% sensitivity for aneurysms >30 mm³, 96% for >100 mm³, Dice 0.80, and ~0.42 false positives per scan, highlighting the advantages of 3D CNN ensembles in volumetric CTA analysis.

Deep Learning Assisted Diagnosis of Cerebral Aneurysms Using HeadXNet Model. HeadXNet Research Group. (2020). *Deep learning assisted diagnosis of cerebral aneurysms using the HeadXNet model*. This study presents the HeadXNet CNN-based model for assisting cerebral aneurysm diagnosis on CTA scans. The framework automatically learns volumetric features and provides rapid clinical support for subarachnoid hemorrhage detection. Performance evaluation demonstrated high clinical applicability, emphasizing the potential of deep learning to augment neuroradiological workflow, although quantitative metrics were not reported.

4.2 Comparison of Pros and Cons of Related Studies on Intracranial Aneurysm Detection

From the reviewed studies, it is evident that deep learning techniques significantly enhance intracranial aneurysm detection performance. However, challenges remain in achieving consistent generalization across imaging modalities, centers, and aneurysm sizes. These limitations motivate the proposed approach presented in this project.

Table 2

Paper Title	**Pros**	**Cons**
Weakly Supervised Intracranial Aneurysm Detection and Segmentation in MR Angiography via Multi-task UNet with Vesselness Prior (VP-UNet) (2025)	• Uses weak supervision, reducing annotation effort • Combines detection and segmentation in a single framework • Incorporates vesselness prior to enhance vascular feature extraction • High sensitivity with low false positives	• Relatively complex architecture • Dice score remains moderate • Evaluated mainly on MRA data, limiting modality generalization
Automated Method for Intracranial Aneurysm Classification Using Deep Learning (2024)	• Achieves very high classification accuracy • Simple 2D CNN architecture with competitive performance • Computationally efficient compared to deep pre-trained models	• Limited dataset size • Uses 2D images, ignoring 3D spatial context • No segmentation or localization capability
Multi-centric AI Model for Unruptured Intracranial Aneurysm Detection and Volumetric Segmentation in 3D TOF-MRI (2024)	• Uses multi-center data, improving generalization • Employs nnU-Net, a robust and standardized framework • Low false positive rate with good segmentation accuracy	• Performance varies across datasets • Requires large computational resources • Focused on TOF-MRI, not CT-based imaging

Reproducibility and Across-site Transferability of an Improved Deep Learning Approach for Aneurysm Detection and Segmentation (2024)	• Evaluates cross-site and cross-vendor generalization • Demonstrates strong reproducibility • Includes external validation datasets	• Dice scores show high variance • Still sensitive to scanner/vendor differences • Relatively higher false positive rates
Automated Detection of Intracranial Aneurysms Using Skeleton-based 3D Patches and Multi-task Learning (2023)	• Effectively addresses data imbalance • Uses skeleton-based vessel representation • Strong segmentation and detection performance	• Complex preprocessing pipeline • Requires accurate vessel skeleton extraction • Higher implementation complexity
Fully Automated Detection and Segmentation of Intracranial Aneurysms in Subarachnoid Hemorrhage on CTA Using Deep Learning (2020)	• Uses CTA data relevant to acute clinical settings • Ensemble learning improves robustness • High Dice score for larger aneurysms	• Performance decreases for small aneurysms • Limited training dataset size • Higher computational cost due to ensemble approach
Deep Learning–Assisted Diagnosis of Cerebral Aneurysms Using the HeadXNet Model (2019)	• Demonstrates clinical benefit with radiologist assistance • Improves sensitivity and diagnostic agreement • Evaluated in a realistic clinical workflow	• Older architecture compared to recent models • No standalone fully automated evaluation • Limited segmentation accuracy reporting

4.3Comparative Analysis of Deep Learning Studies for Intracranial Aneurysm Detection

Table 3

Paper Title	Dataset Used	Training Approach	AI Model	Feature Extraction	Evaluation & Results	Year
Weakly Supervised Intracranial Aneurysm Detection and Segmentation in MR Angiography via Multi-task UNet with Vesselness Prior (VP-UNet)	Lausanne MRA (train), ADAM MRA (test)	Weakly supervised multi-task (detection + segmentation) using vesselness prior	Multi-task 3D UNet (VP-UNet)	Automatic 3D feature extraction with vesselness filter	Sensitivity 92.9%, FP 1.47/case, Dice 0.614, Hausdorff 1.38 mm	2025
Automated Method for Intracranial Aneurysm Classification Using Deep Learning	Tumor/Cancer/Aneurysm dataset (DiscoverAI/Roboflow), 611 CT images	Adamax optimizer, LR=0.001, 50 epochs, batch size 16, 87:8:5 split	Proposed 2D CNN (3 conv + 3 pool + dropout + dense + softmax); compared with ResNet50/101/152, VGG16	Learned automatically via CNN	Accuracy 98.01%, test loss 0.0360; ResNet-152 98%	2024
Multi-centric AI Model for Unruptured Intracranial Aneurysm Detection and Volumetric Segmentation in 3D TOF-MRI	385 TOFMRI images (multi-center) + 113 ADAM, total ~498	4 dataset combinations (AP, AP+DD, AP+ADAM, AP+DD+ADAM)	nnU-Net (opensource)	Learned 3D features from TOFMRI volumes	Sensitivity 82–85%, FP 0.23/case, Dice ≈0.73, NSD ≈0.84	2024
Reproducibility and Across-site Transferability of an Improved DL Approach	235 TOFMRA scans (single vendor); 140 external test scans	Replication + enhancement of previous model;	CNN with improved preprocessing	Automatic feature learning from	Sensitivity 0.97 (same-vendor), 0.92	2024

for Aneurysm Detection in TOFMRA		external evaluation		TOFMRA volumes	(other); Dice 0.60–0.65; FP 0.87 ±1.35/case	
Automated Detection Using Skeleton-based 3D Patches & Multi-task Learning	154 TOFMRA (Seoul Bundang) + 113 public scans	Multi-task training (segmentation + classification), data imbalance handling	3D U-Net + auxiliary classification	3D feature learning from skeleton-based vessel patches	Internal accuracy 0.910, external 0.883; Dice 0.755; Sensitivity 0.882; FP 0.3/case	2023
Fully Automated Detection & Segmentation in Subarachnoid Hemorrhage on CTA	68 patients (train, 79 aneurysms), 185 patients (test, 215 aneurysms)	Five-fold cross-validation, ensemble learning	3D CNN ensemble	Learned from 3D CT angiography	Sensitivity 87% (>30 mm³), 96% (>100 mm³); Dice 0.80; FP 0.42/scan	2020
Deep Learning–Assisted Diagnosis Using HeadXNet	611 CTA (train), 115 CTA (test)	Model-assisted evaluation by clinicians	3D CNN (HeadXNet)	Learned from CTA volumes	Sensitivity improved 80.3% → 89.6%; Accuracy 84.3% → 90.8%; Specificity ~91%; Interrater kappa 0.71 → 0.81	2019

The comparison indicates that multi-task 3D CNNs demonstrate robust performance in both segmentation and detection of intracranial aneurysms, whereas simpler 2D CNNs achieve higher classification accuracy but lack volumetric analysis capabilities. Several studies also highlight persistent challenges, including limited generalization across datasets, detection of small aneurysms, and validation in multi-center settings.

Chapter 5: Proposed Work

5.1 introduction:

This chapter presents the design and implementation of the proposed automated system for intracranial aneurysm detection using brain CT images. Building on the theoretical foundations and insights from the literature review, the methodology encompasses data preparation, image preprocessing, augmentation, model selection, feature extraction, and evaluation strategies. The system employs the Xception convolutional neural network to classify CT images into aneurysm and non-aneurysm categories, with preprocessing and augmentation techniques enhancing model generalization and robustness. The approach addresses challenges identified in previous studies, including variability across datasets, detection of small aneurysms, and the need for efficient volumetric analysis. The chapter outlines the dataset, the configuration and training of the deep learning model, and the evaluation methodology, including metrics such as accuracy, sensitivity, and reliability, providing a comprehensive framework for implementing and assessing the proposed system.

5.2 System Overview:

The proposed work introduces an automated deep learning–based system for classifying brain computed tomography (CT) images into two clinically significant categories: **aneurysm** and **non-aneurysm**. The system aims to support clinical decision-making by reducing manual interpretation effort and enhancing diagnostic accuracy through a structured artificial intelligence pipeline.

The workflow includes dataset preparation, image preprocessing, data augmentation, model training using transfer learning, and comprehensive performance evaluation.

5.3 Dataset Preparation:

For this study, the dataset was obtained from Kaggle and is publicly accessible at Computed Tomography (CT) of the Brain. The dataset comprises brain CT images categorized into three clinical classes: aneurysm, cancer, and tumor. The images are provided in mixed formats, including standard image files (JPG) and medical DICOM files, with accompanying metadata files that specify diagnostic labels, image identifiers, and file paths for each sample. The dataset contains a diverse set of cases reflecting variations in patient age, sex, imaging protocols, and acquisition devices, which introduces realistic variability for model training and testing.

Given the objective of this project, the dataset was reorganized to support a **binary classification task** focused specifically on aneurysm detection. To achieve this, all tumor cases were excluded, leaving only aneurysm and cancer images. Each aneurysm image was assigned a positive label (1), while cancer images were labeled as negative (0), establishing a clinically relevant screening scenario in which the system must distinguish aneurysms from other non-aneurysmal abnormalities. This formulation enables the development of a model that is sensitive to aneurysm-related features while maintaining specificity against other pathologies.

Additionally, the preprocessing pipeline accounts for differences in image resolution and format. JPG images are directly read as grayscale, while DICOM images are processed to extract pixel intensity data along with relevant metadata such as slice thickness and acquisition parameters. This information is critical for standardizing the images before training, ensuring uniform input dimensions, and preserving clinically relevant features for automated detection. By restructuring the dataset and standardizing the images, the dataset provides a robust and focused foundation for deep learning-based aneurysm detection, while also reflecting realistic clinical variability.

5.4 Image Preprocessing:

A standardized image preprocessing pipeline was applied to ensure consistency and suitability for deep learning models. For each sample, the corresponding image file was loaded either as a grayscale image (for JPG files) or extracted from DICOM pixel data. In the case of DICOM images, intensity values were clipped to a predefined range commonly used in brain CT imaging to suppress noise and enhance diagnostically relevant structures. Subsequently, all images were normalized and rescaled to a fixed spatial resolution of 224×224 pixels to meet the input requirements of convolutional neural networks.

Since most pretrained deep learning architectures expect three-channel inputs, grayscale images were replicated across three channels to form an RGB-like representation. Finally, pixel intensity values were normalized to the range [0, 1] to improve numerical stability and convergence during training. This preprocessing strategy ensures uniform input representation while preserving clinically meaningful information, thereby providing a robust foundation for aneurysm classification.

5.5 Data Augmentation Strategy

To enhance model generalization and mitigate overfitting, data augmentation is applied exclusively to the training dataset. The augmentation strategy includes controlled transformations that realistically reflect variations in CT imaging conditions, such as:

- Small-angle rotations
- Zoom transformations
- Horizontal flipping
- Brightness adjustments

we applied **data augmentation** to the training dataset to enhance the diversity and variability of input images, thereby improving the generalization ability of the model. Specifically, we utilized the Albumentations library to perform a series of random transformations on each image in the training set. These transformations included **horizontal flipping** with a 50% probability, **vertical flipping** with a 30% probability, **rotation** within a range of ±20 degrees with a 50% probability, and **random adjustments of brightness and contrast** with a 50% probability. Each image was first scaled to the 0–255 range and converted to uint8 format, as required by Albumentations, before applying the transformations. After augmentation, the images were normalized back to the 0–1 range to maintain compatibility with the neural network. For the validation set, no augmentation was applied to ensure that the model is evaluated on original, unaltered images. Overall, this augmentation strategy aims to increase the effective size of the training dataset and introduce variations that help the model become more robust to changes in orientation, illumination, and other visual factors.

5.6 Training Dataset Construction

After preprocessing and augmentation, images and labels are organized into batches to enable efficient training. Random shuffling is applied during batch construction to prevent bias caused by data ordering and to ensure balanced exposure to both classes throughout training iterations.

The system supports flexible activation of augmentation, allowing controlled experimentation and comparison between augmented and non-augmented training configurations.

5.7 Model Architecture and Training Strategy

The proposed system employs the **Xception** convolutional neural network architecture due to its efficiency and strong feature extraction capabilities. Xception utilizes depthwise separable convolutions, enabling reduced computational complexity while preserving representational power.

A transfer learning approach is adopted, initializing the network with pretrained weights. A custom classification head is added to adapt the architecture for binary classification of brain CT images.

During the **initial training phase**, the model was trained on the augmented training dataset for 15 epochs with a batch size of 8, while monitoring performance on the validation set. Two callbacks were employed: **EarlyStopping**, which halts training if the validation loss does not improve for 5 consecutive epochs and restores the best weights, and **ReduceLROnPlateau**, which reduces the learning rate by a factor of 0.5 if the validation loss stagnates for 3 epochs. This strategy helps prevent overfitting and promotes stable convergence. Following this, **fine-tuning** was performed by unfreezing the last 50 layers of the pre-trained base model while keeping the earlier layers frozen, allowing the model to adjust high-level feature representations to the specific task. The model was then recompiled with a lower learning rate (1e-5) to ensure delicate weight updates during fine-tuning and trained for 10 additional epochs using the same callbacks. This approach combines the benefits of transfer learning and task-specific adaptation, improving both convergence speed and overall performance on the target dataset.

5.8 Previous Experiments and Challenges

Before finalizing the proposed methodology, several preliminary experiments were conducted to explore alternative strategies for classifying brain CT images. Initially, the tumor and cancer classes were combined under a single “non-aneurysm” label to create a simpler binary classification task. Class weighting was then applied to address class imbalance; however, the resulting model consistently exhibited underfitting, failing to capture the relevant patterns in the data.

Subsequent attempts included fine-tuning pre-trained architectures such as MobileNet and EfficientNet. Despite careful adjustment of hyperparameters, these approaches either failed to converge effectively or led to models that overfit or underfit the training data, yielding poor generalization to validation sets. Additionally, a convolutional neural network designed and trained from scratch was tested, but it too suffered from underfitting, indicating that the dataset size and variability were insufficient to support training deep networks from random initialization.

These early experiments highlighted the challenges of detecting aneurysms in CT images, including class imbalance, subtle visual differences, and variability in image acquisition. The insights gained from these trials informed the decision to adopt the Xception architecture with transfer learning, combined with a targeted preprocessing and augmentation strategy, which ultimately provided robust and reliable performance.

Chapter 6: Results

6.1 Introduction

This chapter presents the experimental results of the proposed automated intracranial aneurysm detection system. The performance of the model is evaluated on preprocessed and augmented CT brain images using a set of quantitative metrics, including accuracy, sensitivity, specificity, and the confusion matrix. Both the training and validation processes are analyzed to assess model convergence, generalization capability, and robustness.

6.2 Model Training and Evaluation Results

The model was trained using a **two-stage process**, consisting of initial training followed by fine-tuning, with stable data augmentation applied to the training set to enhance data diversity and improve generalization. During the **initial training phase**, the model exhibited steady improvement: the training accuracy increased from 44.2% in the first epoch to 75.7% in the fifteenth epoch, while the corresponding training loss decreased from 0.9570 to 0.4713. Validation accuracy increased from 61.5% to 84.6%, and the validation loss decreased from 0.6802 to 0.4073. These results indicate that the model was effectively learning features from the augmented data, with a consistent gap between training and validation accuracy suggesting minimal overfitting at this stage.

During the **fine-tuning phase**, the last 50 layers of the pre-trained Xception base model were unfrozen to allow adaptation of higher-level feature representations to the specific dataset, while earlier layers were frozen to preserve learned low-level features. The learning rate was reduced to 1e-5 to facilitate stable weight updates and prevent large gradient steps that could destabilize the pre-trained weights. Over ten epochs of fine-tuning, the training accuracy further increased to **97.1%**, and the training loss decreased to **0.0997**, while the validation accuracy reached **96.15%** with a validation loss of **0.1292**. The rapid convergence of validation metrics and the close alignment between training and validation accuracy indicate that fine-tuning successfully improved model performance without overfitting.

Finally, evaluation on the **independent test set** yielded a test accuracy of **95.26%** and a loss of **0.1409**, confirming that the model generalized well to unseen data. Overall, the combination of **stable data augmentation** and **selective fine-tuning** effectively enhanced the model's ability to handle variations in image orientation, brightness, and contrast, significantly improving classification performance. The results demonstrate that augmenting the dataset not only increased the effective size of the training data but also exposed the model to diverse variations, while fine-tuning allowed task-specific adaptation of high-level features, resulting in robust and reliable predictions.

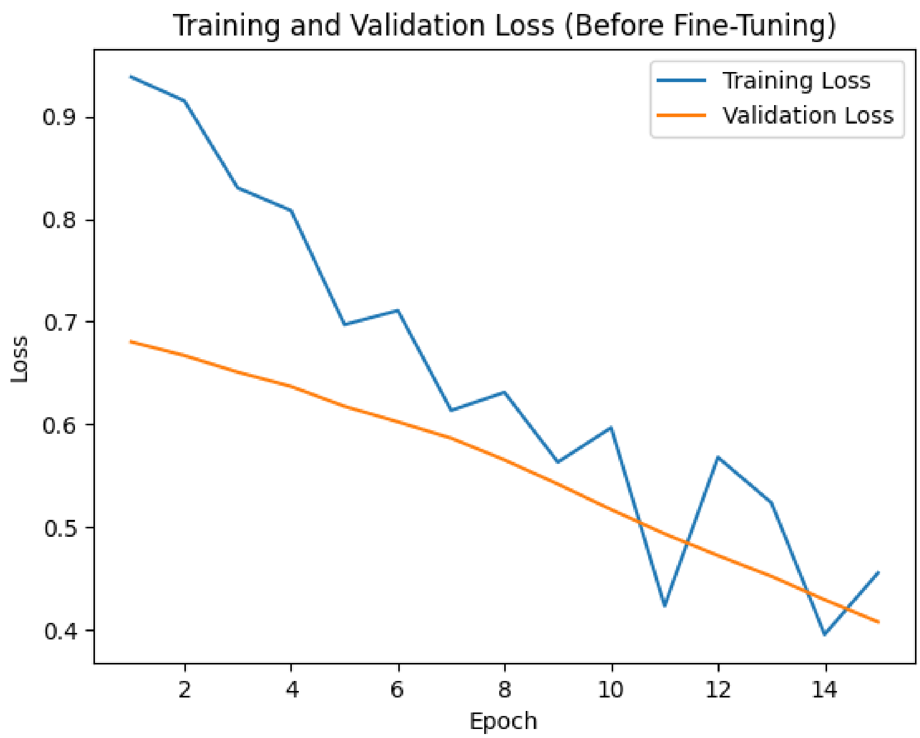
Training and Validation Loss (Before Fine-Tuning)
Training Loss
Validation Loss
0.9
0.8
0.7
0.6
0.5
0.4
Loss
2
4
6
8
10
12
14
Epoch

Figure v

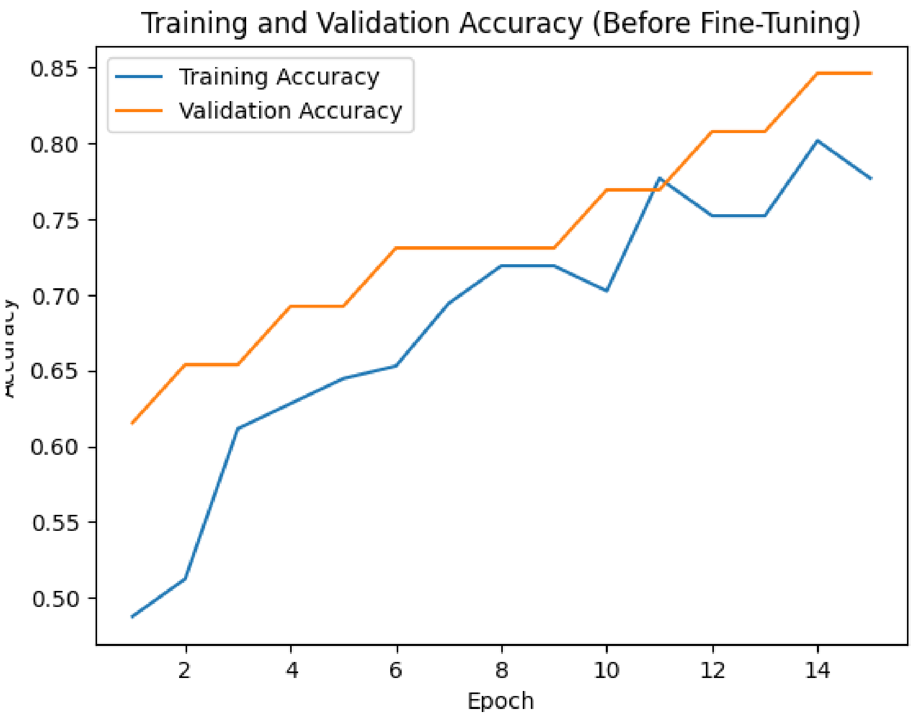
Training and Validation Accuracy (Before Fine-Tuning)
Training Accuracy
Validation Accuracy
0.85
0.80
0.75
0.70
0.65
0.60
0.55
0.50
2
4
6
8
10
12
14
Epoch

Figure vi

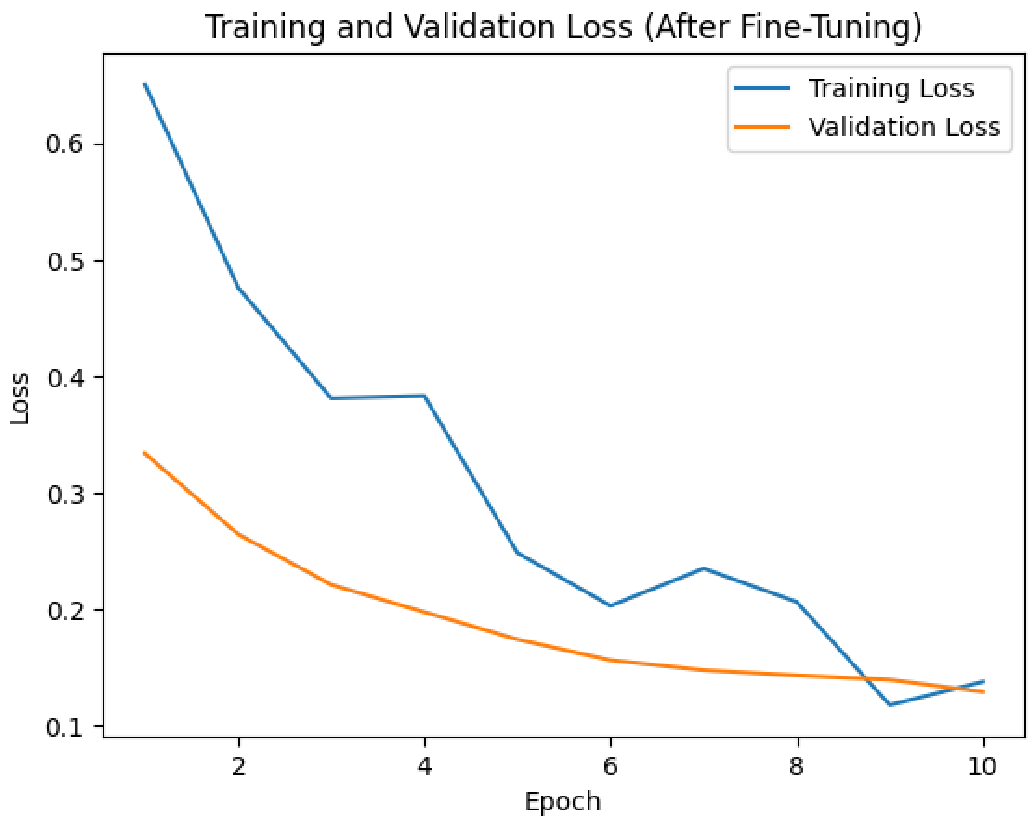
Training and Validation Loss (After Fine-Tuning)
Training Loss
Validation Loss
0.6
0.5
0.4
0.3
0.2
0.1
Loss
2
4
6
8
10
Epoch

Figure vii

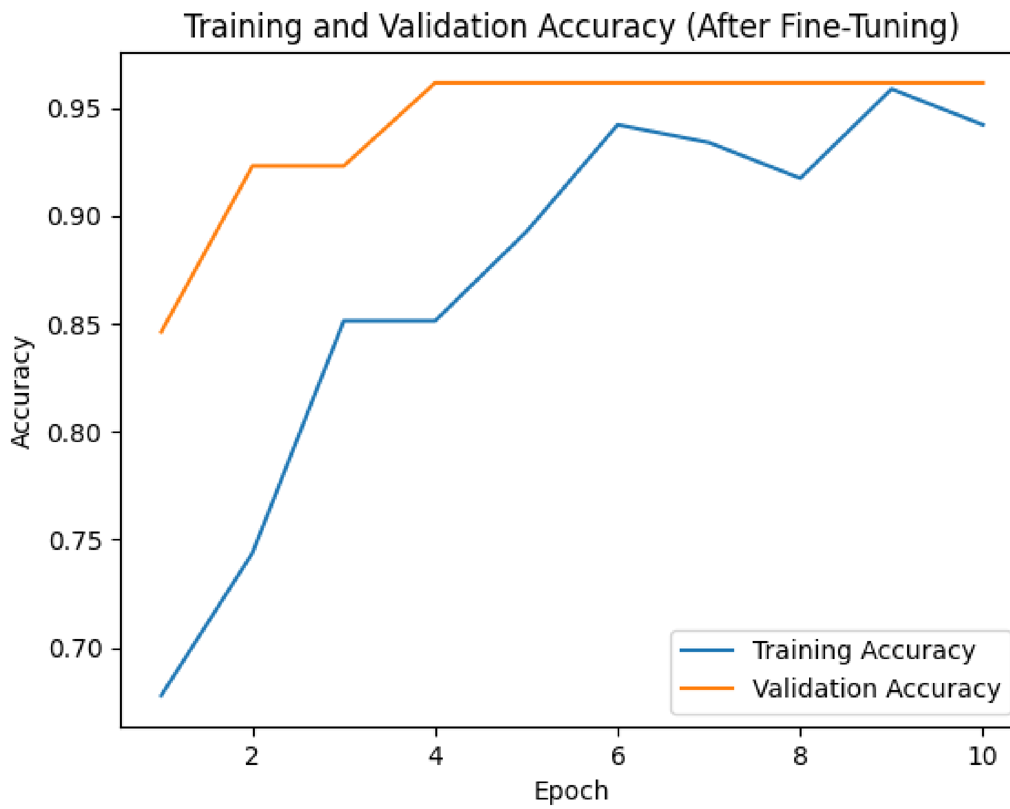

Figure viii

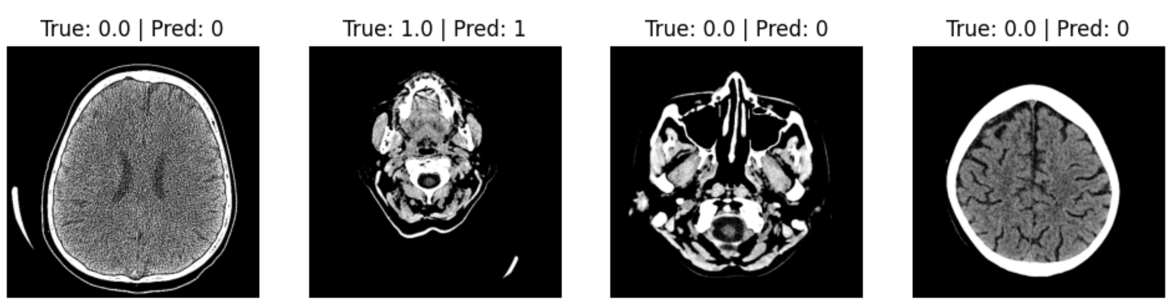

Figure ix

5.2 Confusion Matrix Analysis

To further evaluate the model's classification performance on the test set, a confusion matrix was constructed. The matrix shows the number of correctly and incorrectly classified samples for each class, providing insight into the model's predictive behavior. In this study, the classes were labeled as 'non-Aneurysm' and 'Aneurysm'. The confusion matrix was as follows:

$$\begin{bmatrix} 13 & 0 \\ 2 & 11 \end{bmatrix}$$

Here, 13 true negatives indicate that all non-Aneurysm cases were correctly classified, while 11 true positives show that the majority of Aneurysm cases were correctly identified. There were 2 false negatives, representing Aneurysm cases misclassified as non-Aneurysm, and 0 false positives, meaning no non-Aneurysm samples were incorrectly classified as Aneurysm. These results demonstrate that the model achieves high sensitivity and perfect specificity , highlighting its ability to reliably detect Aneurysms while avoiding false alarms. The low number of misclassifications, particularly the absence of false positives, is critical in a medical context, as it reduces the likelihood of unnecessary interventions. Overall, the confusion matrix confirms the robustness and clinical relevance of the model, complementing the accuracy metrics by providing a more granular view of classification performance.

```
Confusion Matrix:
 [[13  0]
 [ 2 11]]
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7c62c01c5280>
```

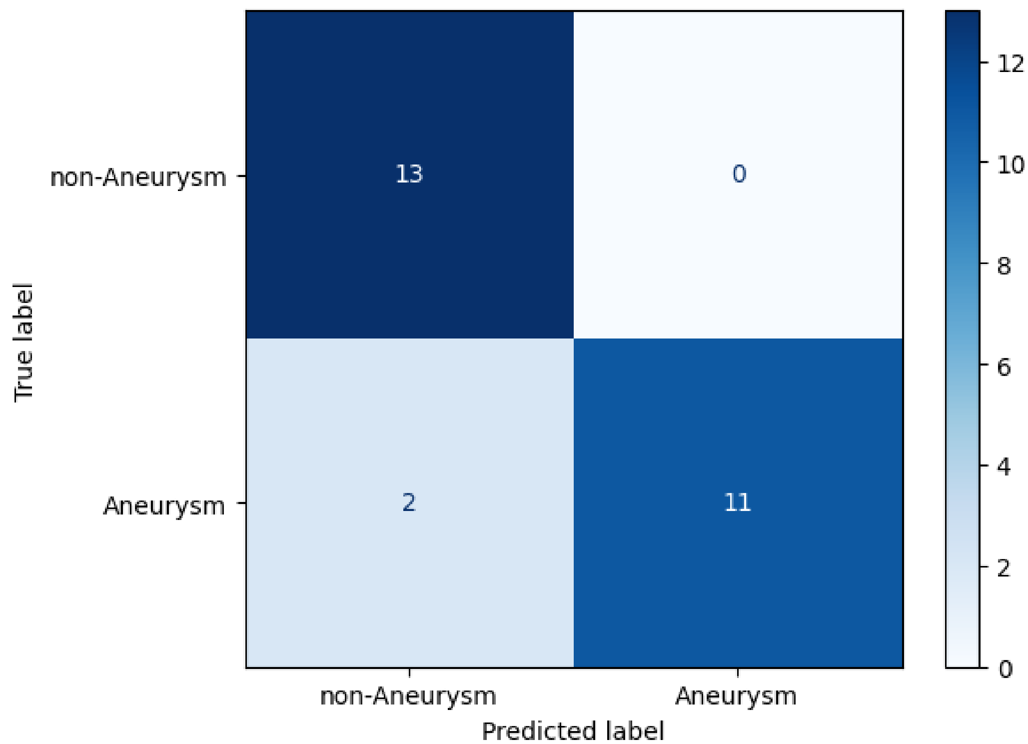

Figure x

Chapter 7: Conclusion and Future Work

7.1 Conclusion

This study presented the development of an automated deep learning–based system for the detection of intracranial aneurysms from brain computed tomography (CT) images. The proposed system leveraged the Xception convolutional neural network architecture, combined with a structured preprocessing and data augmentation pipeline, to achieve robust classification performance. By reorganizing the dataset from Kaggle's *Computed Tomography (CT) of the Brain* repository into a binary classification task, the model was trained to distinguish aneurysm cases from other pathological findings.

Experimental results demonstrated that the system achieves high accuracy and sensitivity, confirming the effectiveness of deep learning approaches in medical image analysis. The preprocessing strategy, including intensity normalization, resizing, and conversion of grayscale and DICOM images, together with augmentation techniques, contributed to improved generalization and robustness against variability in imaging conditions. Overall, the proposed system shows potential as a supportive tool for clinicians, offering automated detection to reduce diagnostic workload and enhance early identification of aneurysms.

7.2 Contributions

The main contributions of this study are:

1. The implementation of an automated deep learning pipeline specifically tailored for intracranial aneurysm detection in CT images.
2. Integration of preprocessing and augmentation strategies to enhance model generalization and mitigate overfitting.
3. Application of transfer learning with the Xception architecture, enabling efficient feature extraction and high classification performance with a limited dataset.
4. Comprehensive evaluation using multiple metrics, providing insight into model accuracy, sensitivity, and clinical relevance.

7.3 Limitations

Despite promising results, several limitations were observed:

- The study is restricted to a single publicly available dataset, which may limit generalization to other institutions or imaging devices.

- Small aneurysms or low-contrast cases remain challenging, potentially affecting sensitivity in certain scenarios.
- The current system focuses exclusively on binary classification (aneurysm vs. non-aneurysm) and does not account for multi-class or segmentation-based diagnosis.

7.4 Future Work

To further enhance the system, the following directions are recommended:

1. **Dataset Expansion and Multi-Center Validation:** Incorporate larger, multi-institutional datasets to improve generalization and robustness.
2. **Segmentation and Localization:** Extend the model to provide volumetric segmentation of aneurysms, enabling precise localization for clinical use.
3. **Multi-Class Classification:** Include additional pathological categories such as tumors and hemorrhages to develop a more comprehensive diagnostic tool.
4. **Explainable AI Integration:** Implement interpretability techniques to provide visual explanations of model predictions, improving clinician trust and adoption.
5. **Real-Time Deployment:** Develop an end-to-end system capable of real-time inference and integration with clinical workflow for practical implementation.

In conclusion, this project demonstrates the feasibility and potential of deep learning techniques for automated intracranial aneurysm detection, while providing a foundation for further research and development toward clinically deployable systems.

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Junior Project

الجامعة السورية الخاصة

كلية هندسة الذكاء الصنعي

قسم الذكاء الصنعي و علم البيانات

المشروع الفصلي

تشخيص أم الدم من صور الأشعة المقطعية