Syrian Private University

Faculty of AI Engineering

Department of AI & Data Science

Junior Project

الجامعة السورية الخاصة

كلية هندسة الذكاء الصنعي

قسم الذكاء الصنعي و علم البيانات

المشروع الفصلي

Intractanial Aneurysm Detection

Submitted to complete the requirments of junior project

Prepared by :

Enas Saleh

Supervised by :

Dr.Nisreen Sulayman

Eng. Zainab Baghdadi

2025-2026

Figure i

Faculty of Engineering

Department of AI & Data Science

SUPERVISOR CERTIFICATION

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

prepared by Enas Saleh

Was made under my supervision at the Faculty of Engineering in partial fulfillment of the Requirements for the Degree of Bachelor

Name:

Date:

Signature:

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

.

Table of Contents:

Table of tables

Table of figures

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 pathological dilations that occur in the walls of cerebral blood vessels as a result of structural weakness in the arterial layers. These dilations most commonly develop at arterial bifurcations within the circle of Willis, where hemodynamic stress is significantly elevated. Although many intracranial aneurysms remain clinically silent for extended periods, their rupture can lead to devastating neurological outcomes, including subarachnoid hemorrhage, ischemic stroke, permanent disability, or death. Epidemiological studies indicate that the mortality rate following aneurysmal rupture can exceed 40%, while a significant proportion of survivors suffer long-term cognitive and physical impairments. Consequently, early and accurate detection of intracranial aneurysms is of paramount importance in modern neurological care.

Computed tomography (CT) imaging plays a central role in the diagnostic workflow for brain-related conditions due to its rapid acquisition time, high spatial resolution, and widespread availability in both emergency and routine clinical settings. CT scans are particularly effective for visualizing vascular abnormalities, hemorrhages, and structural changes in brain tissue. Despite these advantages, the detection of intracranial aneurysms using CT images remains a challenging task. Aneurysms often present as small, subtle protrusions along blood vessels, with limited contrast relative to surrounding tissues. These characteristics make them difficult to identify, especially when the aneurysm size is small or when image quality is degraded by noise or motion artifacts.

Traditionally, aneurysm detection relies on the manual interpretation of CT scans by experienced radiologists and neurologists. While expert evaluation remains the clinical gold standard, manual diagnosis is inherently time-consuming and subject to human limitations such as fatigue, inter-observer variability, and perceptual bias. In high-volume clinical environments, these factors can increase the risk of missed or delayed diagnoses, potentially leading to severe clinical consequences. The growing demand for medical imaging services further exacerbates this challenge, highlighting the urgent need for automated and intelligent diagnostic tools that can assist clinicians and improve diagnostic reliability.

Recent advances in artificial intelligence (AI), particularly in the domain of deep learning, have transformed the field of medical image analysis. Deep learning models are capable of learning complex, hierarchical representations directly from raw image data, enabling them to identify subtle visual patterns that may not be easily discernible to the human eye. Among these models, convolutional neural networks (CNNs) have demonstrated exceptional performance in tasks such as image classification, segmentation, and object detection. CNN-based approaches have been successfully applied to a wide range of medical imaging applications, including tumor detection, organ segmentation, and disease classification.

This project leverages the capabilities of deep learning to address the challenge of intracranial aneurysm detection from brain CT images. Specifically, the Xception convolutional neural network architecture is employed due to its efficiency and strong feature extraction capabilities. By utilizing depthwise separable convolutions, Xception reduces computational complexity while maintaining high representational power. The proposed system aims to provide an automated, reliable, and efficient tool to support clinicians in the early diagnosis of intracranial aneurysms, thereby improving patient outcomes and reducing diagnostic workload.

2.2 Problem Definition

The detection of intracranial aneurysms from brain CT images represents a complex and multifaceted pattern recognition problem. From a clinical perspective, aneurysms often exhibit subtle morphological and intensity-based differences compared to normal vascular structures. These differences may include slight variations in vessel diameter, localized bulging, or changes in contrast intensity that are difficult to distinguish through conventional visual inspection. The challenge is further compounded by the presence of imaging noise, partial volume effects, and artifacts introduced during image acquisition and reconstruction.

CT images are also characterized by significant variability in acquisition parameters, including slice thickness, scanner type, radiation dose, and patient positioning. Such variability can lead to inconsistencies in image appearance across different datasets, making it difficult to design a robust detection system that generalizes well to unseen data. Additionally, intracranial aneurysms can vary widely in size, shape, and location, ranging from small saccular aneurysms to larger fusiform structures. Small aneurysms, in particular, are prone to misclassification due to their low visibility and resemblance to normal vascular anatomy.

From a computational standpoint, the problem can be formally defined as a supervised binary medical image classification task. Given a set of labeled brain CT images, the objective is to train a model that can accurately classify each image into one of two categories: aneurysm or non-aneurysm. This requires the model to learn discriminative features that capture aneurysm-related characteristics while remaining robust to irrelevant variations in image appearance.

One of the primary challenges in this task is the imbalance between classes, as non-aneurysm images often outnumber aneurysm cases in real-world datasets. This imbalance can bias the learning process and lead to models that achieve high overall accuracy but perform poorly in detecting aneurysm cases. In medical diagnostics, such false negatives are particularly dangerous, as missed detections can delay treatment and increase the risk of fatal outcomes. Therefore, an effective solution must prioritize high sensitivity while maintaining acceptable specificity to avoid excessive false alarms.

2.3 Project Objective

The primary objective of this project is to design, implement, and evaluate an automated deep learning–based system for the detection of intracranial aneurysms from brain CT images. The proposed system aims to serve as a decision-support tool that assists clinicians in identifying aneurysm cases accurately and efficiently.

To achieve this overarching goal, several specific objectives are defined:

- To preprocess and standardize brain CT images obtained from heterogeneous sources, ensuring consistency in resolution, intensity distribution, and format.
- To restructure a multi-class medical imaging dataset into a binary classification problem focused specifically on aneurysm detection.
- To implement and fine-tune the Xception convolutional neural network architecture using transfer learning techniques.
- To evaluate the performance of the proposed system using standard classification metrics such as accuracy, sensitivity, specificity, precision, and confusion matrix analysis.

- To demonstrate the feasibility and effectiveness of AI-assisted diagnosis in improving early detection and supporting clinical decision-making.

These objectives collectively aim to bridge the gap between theoretical advancements in deep learning and practical clinical applications in medical imaging.

2.4 Project Scope

The scope of this project is intentionally constrained to ensure feasibility and focus. The proposed system is limited to the detection of intracranial aneurysms in brain CT images and does not address other neurological conditions such as tumors, hemorrhages, or ischemic lesions. The classification task is restricted to binary outcomes, namely aneurysm and non-aneurysm.

The dataset utilized in this study consists of CT images provided in both standard image formats (JPG) and medical DICOM files. Preprocessing steps include resizing, normalization, intensity clipping, and data augmentation to enhance model robustness. The project emphasizes model development, training, and performance evaluation rather than deployment or integration into clinical workflows. Clinical validation and regulatory considerations are beyond the scope of this work.

2.5 Project Features

The proposed system incorporates several key features designed to enhance its effectiveness and usability:

- Automated detection of intracranial aneurysms from brain CT images.
- Utilization of the Xception deep learning architecture for high-performance feature extraction.
- Comprehensive image preprocessing and data augmentation to improve generalization.
- Quantitative evaluation using clinically relevant performance metrics.
- Visualization of predictions and performance indicators to support interpretability.

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

The successful development of an automated intracranial aneurysm detection system relies on the integration of multiple tools and foundational concepts drawn from artificial intelligence, deep learning, and medical image processing. Each tool and concept plays a critical role in enabling the system to accurately analyze complex medical imaging data and produce reliable diagnostic predictions. This section presents an in-depth discussion of the theoretical principles, computational techniques, and software frameworks employed in this project, providing the necessary background to understand the design and implementation of the proposed system.

2.7.1 Deep Learning

Deep learning (DL) is a specialized subfield of machine learning that focuses on the use of artificial neural networks with multiple hidden layers to learn hierarchical representations of data. Unlike traditional machine learning methods, which often depend on manually engineered features, deep learning models are capable of learning features directly from raw input data through an end-to-end training process. This characteristic makes deep learning particularly well suited for medical imaging applications, where relevant features are often complex, high-dimensional, and difficult to define explicitly.

In the context of medical image analysis, deep learning enables the automatic extraction of spatial, textural, and contextual patterns from imaging data such as CT and MRI scans. These patterns may correspond to subtle anatomical changes or pathological structures that are not easily detectable through visual inspection alone. By stacking multiple layers of nonlinear transformations, deep learning models progressively learn increasingly abstract representations, starting from low-level features such as edges and intensity gradients and advancing toward high-level semantic features associated with disease presence.

Another key advantage of deep learning is its scalability. As the size and diversity of training datasets increase, deep learning models generally improve in performance, provided that appropriate regularization and optimization strategies are applied. This scalability is particularly important in medical imaging, where datasets often include thousands of high-resolution images. Furthermore, advances in hardware acceleration, particularly the use of graphics processing units (GPUs), have made it feasible to train deep neural networks efficiently, even for computationally intensive tasks.

In this project, deep learning serves as the core methodological foundation for automated aneurysm detection. The ability of deep learning models to learn complex and non-linear feature representations enables the system to identify subtle aneurysm-related patterns within CT brain images, thereby supporting accurate and reliable classification.

2.7.2 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a class of deep learning architectures specifically designed for processing grid-structured data, such as images. CNNs have become the dominant approach in computer vision and medical image analysis due to their ability to exploit spatial locality and hierarchical feature structures within images.

A typical CNN architecture consists of three main types of layers:

Convolutional layers:
These layers apply a set of learnable filters (kernels) that convolve across the input image to extract local features. Each filter is trained to detect specific patterns, such as edges, textures, or shapes. In medical images, convolutional layers can learn features related to vessel boundaries, intensity variations, and anatomical structures relevant to aneurysm detection.

Pooling layers:

Pooling layers reduce the spatial resolution of feature maps by aggregating local information, typically using operations such as max pooling or average pooling. This process decreases computational complexity, reduces sensitivity to small spatial variations, and introduces a degree of translational invariance. In medical imaging, pooling helps the model remain robust to minor variations in patient positioning and image acquisition.

Fully connected layers:

Fully connected layers integrate the extracted features and perform high-level reasoning to generate final predictions. These layers map learned features to output classes, such as aneurysm or non-aneurysm.

CNNs are particularly effective for medical imaging tasks because they preserve spatial relationships between pixels and automatically learn hierarchical feature representations. This capability is essential for detecting intracranial aneurysms, which often manifest as localized structural abnormalities within vascular regions. Additionally, CNNs eliminate the need for handcrafted feature extraction, reducing human bias and enabling more objective and data-driven analysis.

2.7.3 Xception Model

The Xception (Extreme Inception) model is an advanced convolutional neural network architecture that builds upon the principles of the Inception family of models. The primary innovation introduced by Xception is the use of **depthwise separable convolutions**, which decompose standard convolution operations into two distinct steps: depthwise convolution and pointwise convolution.

In a standard convolution, spatial and channel-wise feature extraction are performed simultaneously, resulting in high computational cost and a large number of parameters. In contrast, depthwise separable convolutions first apply spatial filtering independently to each input channel (depthwise convolution), followed by a 1×1 convolution (pointwise convolution) to combine information across channels. This decomposition significantly reduces the number of parameters and computational operations while maintaining strong representational power.

The advantages of the Xception model include:

- Efficient feature extraction with reduced computational complexity
- Improved training efficiency and faster convergence
- Strong performance on complex image classification tasks
- Compatibility with transfer learning using pretrained weights

These characteristics make Xception particularly suitable for medical imaging applications, where high-resolution images and limited datasets are common challenges. By employing transfer learning, the model benefits from features learned on large-scale image datasets and adapts them to the medical domain through fine-tuning.

In this project, the Xception model serves as the backbone of the aneurysm detection system. Its ability to capture both spatial and channel-wise information efficiently enables accurate discrimination between aneurysm and non-aneurysm CT images, even when visual differences are subtle.

2.7.4 Medical Image Preprocessing

Medical image preprocessing is a critical step in preparing imaging data for deep learning models. Unlike natural images, medical images often exhibit significant variability in resolution, intensity distribution, format, and acquisition parameters. Without appropriate preprocessing, these inconsistencies can negatively impact model performance and generalization.

Key preprocessing operations employed in this project include:

Image resizing:
All images are resized to a fixed resolution (224 × 224 pixels) to ensure compatibility with the input requirements of CNN architectures. This standardization enables efficient batch processing and consistent feature extraction.

Intensity normalization:
Pixel intensity values are normalized to a fixed range, typically [0, 1], to improve numerical

stability during training and accelerate convergence. Normalization also reduces sensitivity to variations in scanner settings and radiation dose.

DICOM processing:
Medical images stored in DICOM format contain both pixel data and metadata. Extracting pixel data while preserving diagnostically relevant information is essential for accurate analysis. Intensity clipping is often applied to suppress noise and emphasize clinically relevant structures.

Channel replication:
Since many pretrained CNNs expect three-channel (RGB) inputs, grayscale CT images are replicated across three channels to maintain compatibility without altering image content.

Effective preprocessing ensures uniform input representation, enhances learning efficiency, and preserves critical diagnostic information, forming a reliable foundation for deep learning-based aneurysm detection.

2.7.5 Data Augmentation

Data augmentation is a strategy used to artificially increase the size and diversity of training datasets by applying controlled transformations to existing images. In medical imaging, data augmentation is particularly important due to the limited availability of labeled data and the high cost of manual annotation.

Common augmentation techniques include rotation, flipping, scaling, and brightness adjustment. These transformations simulate realistic variations in image acquisition conditions, such as changes in patient orientation or illumination. By exposing the model to a broader range of variations during training, data augmentation improves generalization and reduces the risk of overfitting.

In this project, data augmentation is applied exclusively to the training dataset to ensure that validation and test evaluations reflect real, unaltered clinical data. This strategy enhances model robustness and supports reliable performance on unseen images.

2.7.6 Software Frameworks

The implementation of the proposed system relies on several widely used software frameworks:

Python:
Python is the primary programming language used due to its simplicity, readability, and extensive ecosystem of scientific computing libraries.

TensorFlow:
TensorFlow is an open-source deep learning framework that provides comprehensive tools for model development, training, and evaluation. Its support for GPU acceleration enables efficient processing of large-scale medical image datasets.

Keras:
Keras is a high-level API built on top of TensorFlow that simplifies neural network construction and experimentation. It enables rapid prototyping and facilitates the implementation of complex architectures such as Xception.

Together, these frameworks provide a robust and flexible environment for developing, training, and evaluating deep learning models in medical imaging applications.

2.7.7 Evaluation Metrics

Evaluation metrics play a critical role in assessing model performance, particularly in medical diagnostics where incorrect predictions can have serious consequences. Common metrics used in this project include:

- **Accuracy:** Measures the overall proportion of correct predictions.
- **Sensitivity (Recall):** Measures the ability to correctly identify aneurysm cases.
- **Specificity:** Measures the ability to correctly identify non-aneurysm cases.
- **Precision:** Measures the reliability of positive predictions.

These metrics provide complementary insights into model behavior and diagnostic reliability, ensuring a comprehensive evaluation of system performance.

2.8 The Core Idea

The core idea of this project is to exploit the representational power of deep learning, particularly **convolutional neural networks (CNNs)**, to enable automated and accurate detection of intracranial aneurysms from brain computed tomography (CT) images. The fundamental motivation behind this approach is the limitation of traditional image analysis techniques, which rely heavily on handcrafted features and predefined rules that may fail to capture the complex and subtle visual patterns present in medical images.

Intracranial aneurysms often appear as small, localized dilations in cerebral blood vessels. These abnormalities can vary significantly in shape, size, location, and contrast, making them difficult to identify reliably through manual inspection alone. CNN-based models address this challenge by learning **hierarchical feature representations** directly from raw image data. At early layers, the network captures low-level features such as edges, intensity gradients, and contours. As the data propagate through deeper layers, the network learns increasingly abstract and semantically meaningful representations, including vascular structures, shape irregularities, and textural patterns that are indicative of aneurysmal formations.

A key aspect of the proposed approach is the use of **transfer learning** through the Xception model. Rather than training a deep CNN from scratch—which would require a very large labeled medical dataset—the project leverages a pre-trained Xception network that has already learned rich visual representations from large-scale image datasets. These pretrained features provide a strong initialization, enabling the model to converge faster and generalize better when fine-tuned on a smaller, domain-specific CT brain dataset.

The Xception architecture is selected due to its reliance on **depthwise separable convolutions**, which decouple spatial feature extraction from channel-wise feature learning. This design significantly reduces the number of trainable parameters while preserving high representational capacity. As a result, the model is both computationally efficient and highly effective in capturing fine-grained spatial patterns, which are essential for detecting subtle aneurysmal structures in CT images.

Through fine-tuning, the pretrained Xception model adapts its learned representations to the characteristics of brain CT images, enabling accurate **binary classification** between aneurysm and non-aneurysm cases. The system outputs a probabilistic prediction indicating the likelihood of aneurysm presence, which can be interpreted by clinicians as a decision-support signal rather than a replacement for expert judgment.

Overall, the core idea of this project is to integrate advanced deep learning architectures with medical imaging to create a reliable, efficient, and scalable diagnostic support system. By reducing dependence on manual interpretation and providing consistent, data-driven predictions, the proposed approach aims to enhance diagnostic accuracy, reduce clinician workload, and support early and informed clinical decision-making.

2.9 Mathematical Formulation

From a mathematical standpoint, the intracranial aneurysm detection task is formulated as a **supervised binary classification problem** within the deep learning framework. Let the dataset be defined as:

$$\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}$$

where:

- x_i represents the i-th input CT brain image,
- $y_i \in \{0,1\}$ denotes the corresponding ground-truth label,
- N is the total number of samples in the dataset.

In this formulation, the label $y_i = 1$ indicates the presence of an intracranial aneurysm, while $y_i = 0$ represents a non-aneurysm case.

The convolutional neural network learns a nonlinear mapping function defined as:

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

where:

- $f(\cdot)$denotes the CNN model,
- θrepresents the set of trainable network parameters, including convolutional kernels, biases, and fully connected layer weights,
- $\hat{y} \in [0,1]$is the predicted probability that the input image contains an aneurysm.

The final layer of the network employs a **sigmoid activation function** to map the network output to a probabilistic value:

$$\hat{y} = \sigma(z) = \frac{1}{1 + e^{-z}}$$

where $z$is the output of the last linear transformation.

To optimize the network parameters, the model minimizes the **binary cross-entropy loss function**, which measures the discrepancy between the predicted probabilities and the true class labels. The loss function is 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:

- $\hat{y}_i$is the predicted probability for the i-th sample,
- $y_i$is the corresponding true label.

This loss function penalizes incorrect predictions more severely when the model is confident but wrong, thereby encouraging accurate and well-calibrated probabilistic outputs.

The optimization process is carried out using **gradient-based optimization algorithms**, such as stochastic gradient descent (SGD) or Adam. During training, the gradients of the loss function with respect to the network parameters are computed using **backpropagation**, and the parameters are updated iteratively according to:

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta \mathcal{L}$$

where:

- η is the learning rate,
- $\nabla_\theta \mathcal{L}$ denotes the gradient of the loss function with respect to the parameters.

Through iterative optimization, the network progressively learns parameter values that minimize classification error, improve discrimination between aneurysm and non-aneurysm cases, and enhance overall predictive performance on unseen CT images.

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.

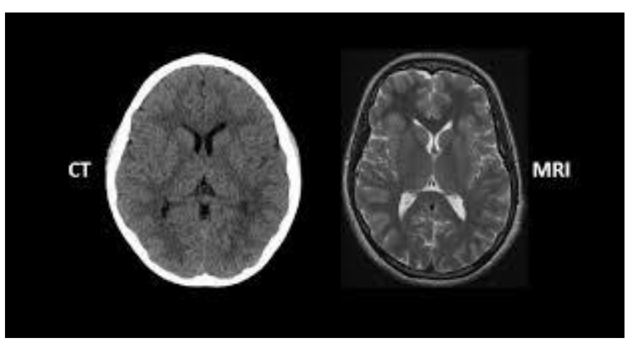

Figure ii

3.2 Intracranial Aneurysms

An intracranial aneurysm is a pathological, localized dilation of a cerebral artery resulting from structural weakening of the vessel wall. This weakening is commonly associated with hemodynamic stress, degenerative changes in the arterial wall, genetic predisposition, and acquired risk factors such as hypertension, smoking, and advanced age. Intracranial aneurysms most frequently develop at arterial bifurcation points within the Circle of Willis, where blood flow turbulence imposes increased mechanical stress on vessel walls. If left undiagnosed and untreated, an aneurysm may progressively enlarge and eventually rupture, leading to subarachnoid hemorrhage (SAH), ischemic stroke, severe neurological deficits, or sudden death. The rupture of an intracranial aneurysm is considered a medical emergency, with reported mortality rates remaining high despite advances in neurosurgical and endovascular treatment techniques.

Early detection of intracranial aneurysms plays a crucial role in reducing associated morbidity and mortality. Identifying aneurysms before rupture allows for timely clinical intervention, including surgical clipping or endovascular coiling, which can significantly improve patient outcomes. However, early diagnosis remains challenging, particularly in asymptomatic patients or in cases involving small aneurysms that do not produce noticeable clinical symptoms. Consequently, imaging-based screening and accurate interpretation of neuroimaging data are essential components of modern diagnostic workflows.

Computed tomography (CT) imaging is widely used in clinical practice due to its availability, rapid acquisition time, and effectiveness in visualizing intracranial structures. In CT brain images, intracranial aneurysms typically manifest as small, rounded or irregular protrusions along cerebral blood vessels. These protrusions often exhibit subtle intensity variations relative to surrounding vascular and soft tissue structures. The visual appearance of aneurysms can vary significantly depending on their size, shape, anatomical location, and the imaging parameters used during acquisition. Small aneurysms, in particular, may be only a few millimeters in diameter and can be easily obscured by image noise, partial volume effects, or overlapping anatomical features.

Manual detection of aneurysms through visual inspection of CT scans is therefore a complex and time-consuming task that relies heavily on the expertise and experience of radiologists. Even skilled clinicians may face difficulties distinguishing aneurysmal structures from normal vascular variations, calcifications, or imaging artifacts. Inter-observer variability and fatigue further contribute to diagnostic uncertainty, increasing the risk of missed or delayed detection. These challenges highlight the inherent limitations of purely manual diagnostic approaches.

Given these constraints, there is a growing need for automated and intelligent diagnostic systems capable of assisting clinicians in the detection of intracranial aneurysms. Artificial intelligence–based methods, particularly those utilizing deep learning and convolutional neural networks, offer the ability to analyze large volumes of CT data and identify subtle patterns that may not be readily apparent to the human eye. By learning discriminative features directly from imaging data, such systems have the potential to enhance diagnostic accuracy, reduce interpretation time, and provide reliable decision support in clinical settings. As a result, automated aneurysm detection represents a critical application of medical image analysis, with significant implications for improving patient safety and clinical outcomes.

Figure iii

3.3 Fundamentals of Deep Learning

Deep learning (DL) is an advanced subfield of machine learning that focuses on the development and application of artificial neural networks with multiple hidden layers capable of learning complex, hierarchical representations from data. Inspired by the structure and function of the human brain, deep learning models are composed of interconnected processing units, known as neurons, that collaboratively transform raw input data into increasingly abstract and informative representations. Unlike traditional machine learning techniques, which often depend on manually engineered features and domain-specific heuristics, deep learning models automatically learn relevant features directly from data, enabling them to handle high-dimensional and unstructured inputs such as images, audio signals, and textual data.

At the core of deep learning lies the concept of representation learning. Lower layers of a neural network typically learn simple and local patterns, while deeper layers progressively capture higher-level and more abstract features. In the context of image analysis, early layers may detect basic visual elements such as edges, corners, and textures, whereas deeper layers learn more complex structures, including shapes, anatomical patterns, and pathological features. This hierarchical learning capability allows deep learning models to achieve superior performance in tasks that require understanding complex visual relationships, making them particularly well suited for medical image analysis.

Among various deep learning architectures, Convolutional Neural Networks (CNNs) have become the dominant paradigm for image-based tasks. CNNs are specifically designed to process grid-like data structures, such as two-dimensional images or three-dimensional volumetric data. Their architectural design exploits spatial locality and parameter sharing, enabling efficient learning of spatial patterns while significantly reducing computational complexity compared to fully connected networks.

A typical CNN architecture is composed of three fundamental types of layers: convolutional layers, pooling layers, and fully connected layers. Convolutional layers serve as the primary feature extractors. They apply a set of learnable filters, also known as kernels, across the input image to generate feature maps that highlight important local patterns. Each filter responds selectively to specific visual characteristics, such as edges, textures, or shapes. Through multiple convolutional layers, the network builds a rich hierarchy of feature representations that capture both local and global image information.

Pooling layers are commonly inserted between convolutional layers to reduce the spatial dimensions of feature maps. This dimensionality reduction decreases computational cost, mitigates overfitting, and introduces a degree of translational invariance, meaning the network becomes less sensitive to small shifts or distortions in the input image. Common pooling operations include max pooling and average pooling, with max pooling being the most widely used in medical imaging applications due to its ability to preserve prominent features.

Fully connected layers are typically positioned toward the end of the CNN architecture and are responsible for high-level reasoning and classification. These layers integrate features extracted by the convolutional layers and produce final predictions through nonlinear transformations. In classification tasks, the final fully connected layer often uses a sigmoid or softmax activation function to output class probabilities, enabling binary or multi-class decision-making.

A key advantage of CNNs over traditional machine learning approaches is their ability to learn discriminative features directly from raw image data. Conventional image analysis pipelines often require handcrafted features such as texture descriptors, edge detectors, or shape-based measurements, which depend heavily on expert knowledge and may not generalize well across datasets. In contrast, CNNs automatically optimize feature extraction during training, adapting to the specific characteristics of the data. This data-driven learning paradigm has led to substantial performance improvements in complex visual tasks.

Deep learning models are trained using supervised, semi-supervised, or unsupervised learning strategies, with supervised learning being the most common in medical image classification. During training, the network parameters are optimized by minimizing a loss function that quantifies the difference between predicted outputs and ground-truth labels. Optimization is typically performed using gradient-based methods such as stochastic gradient descent (SGD) or adaptive optimizers like Adam. The backpropagation algorithm is used to compute gradients efficiently and update network weights iteratively.

In medical imaging, deep learning has demonstrated remarkable success across a wide range of applications, including disease classification, lesion detection, organ segmentation, and image reconstruction. CNN-based models have been applied to modalities such as computed tomography (CT), magnetic resonance imaging (MRI), ultrasound, and X-ray imaging. Their ability to capture subtle visual patterns makes them particularly effective in detecting small or low-contrast abnormalities, such as intracranial aneurysms, that are difficult to identify through manual inspection.

Despite their advantages, deep learning models also face challenges, particularly in medical domains. These include limited availability of labeled data, class imbalance, overfitting, and lack of interpretability. To address these challenges, techniques such as data augmentation, transfer learning, regularization, and explainable AI methods are commonly employed. Transfer learning, in particular, allows models pretrained on large-scale datasets to be adapted to medical imaging tasks with limited data, significantly improving convergence and performance.

In summary, deep learning represents a powerful and flexible framework for automated image analysis. Through the use of convolutional neural networks, deep learning systems can learn rich hierarchical features directly from medical images, enabling accurate and efficient classification and detection of complex pathologies. These capabilities form the theoretical foundation for the automated intracranial aneurysm detection system proposed in this project and justify the selection of CNN-based architectures for medical image analysis.

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.

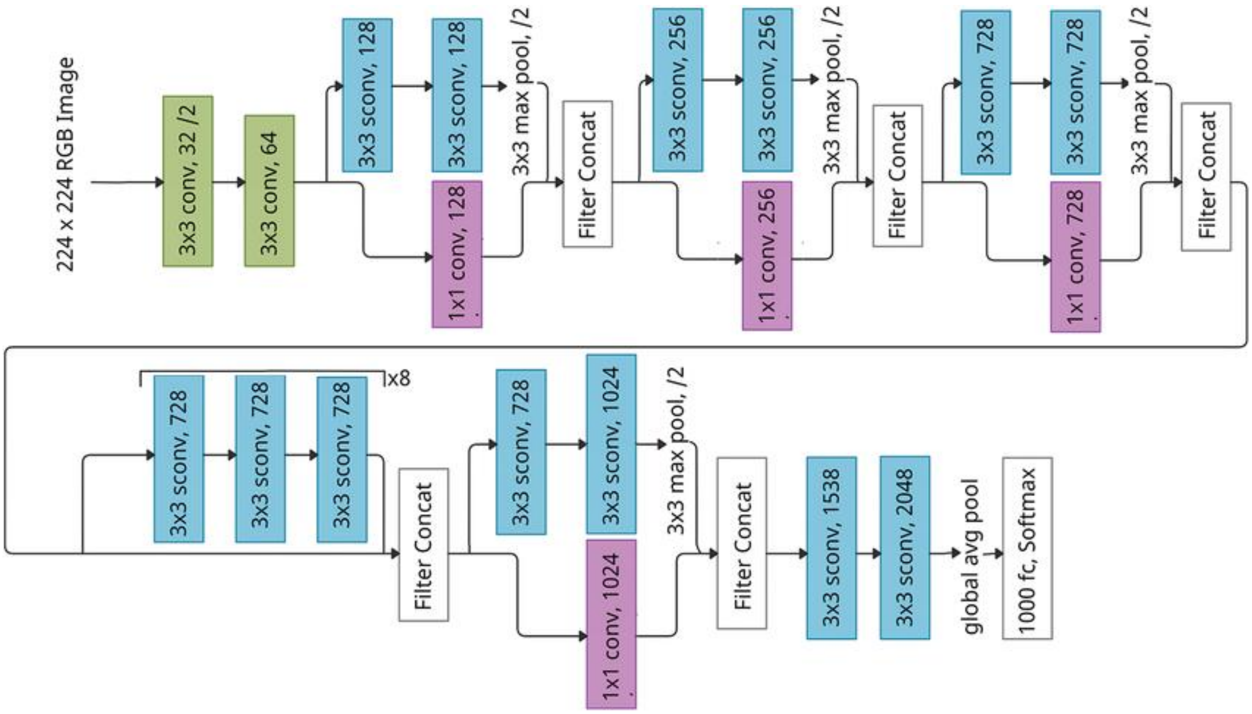

Figure iv

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, particularly those acquired from clinical environments, often exhibit significant variability in terms of spatial resolution, intensity distribution, noise levels, and file formats. These variations arise from differences in imaging devices, acquisition protocols, patient anatomy, and clinical settings. If not properly addressed, such inconsistencies can adversely affect the learning process of deep learning models, leading to poor convergence, reduced accuracy, and limited generalization. Consequently, image preprocessing is a fundamental step in medical image analysis pipelines, aiming to standardize input data and enhance diagnostically relevant features.

One of the primary preprocessing operations is image resizing, which ensures that all images conform to a fixed spatial resolution compatible with the input requirements of convolutional neural networks. Deep learning architectures typically expect images of uniform size; therefore, CT brain images are resized to a standardized dimension, such as 224×224 pixels, while preserving essential anatomical structures. This step facilitates efficient batch processing and ensures consistent feature extraction across the dataset.

Intensity normalization is another critical preprocessing step, as CT images may exhibit wide variations in pixel intensity values due to differences in scanning parameters and patient-specific factors. Normalization scales pixel values to a predefined range, commonly [0, 1] or standardized using z-score normalization. This process improves numerical stability during training, accelerates model convergence, and prevents certain intensity ranges from dominating the learning process. For DICOM images, intensity clipping may also be applied to restrict values to clinically relevant ranges, thereby suppressing noise and enhancing vascular structures.

Medical images are frequently stored in the Digital Imaging and Communications in Medicine (DICOM) format, which contains both pixel data and extensive metadata describing acquisition parameters. To enable compatibility with deep learning frameworks, DICOM images are processed to extract pixel intensity information and converted into standard image formats such as JPG or PNG when necessary. During this conversion, care is taken to preserve diagnostically meaningful information and maintain consistency across the dataset.

In addition to preprocessing, data augmentation plays a vital role in improving model robustness and reducing overfitting, particularly when working with limited medical datasets. Data augmentation artificially increases the effective size of the training dataset by applying realistic transformations to existing images. These transformations simulate variations that may occur in real-world clinical scenarios while preserving the underlying diagnostic labels.

Common augmentation techniques include rotation, which accounts for slight variations in patient head orientation during image acquisition; horizontal or vertical flipping, which improves invariance to spatial orientation; and zooming, which simulates differences in anatomical scale or imaging distance. Additional transformations, such as brightness and contrast adjustments, may also be applied to mimic variations in scanner calibration and image quality. Importantly, augmentation is applied exclusively to the training dataset to prevent data leakage and ensure that validation and test sets accurately reflect real, unseen data.

By combining comprehensive preprocessing with carefully designed augmentation strategies, the system benefits from standardized and diverse input data. This approach enhances feature learning, improves generalization performance, and enables the deep learning model to better handle variability in unseen clinical images. Ultimately, effective preprocessing and augmentation contribute significantly to the reliability and diagnostic accuracy of automated intracranial aneurysm detection systems.

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	• Uses multi-center data, improving generalization	• Performance varies across datasets

Volumetric Segmentation in 3D TOF-MRI (2024)	• Employs nnU-Net, a robust and standardized framework • Low false positive rate with good segmentation accuracy	• 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	• Performance decreases for small aneurysms

	• Ensemble learning improves robustness • High Dice score for larger 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 presents an automated deep learning–based system designed for the classification of brain computed tomography (CT) images into two clinically relevant categories: aneurysm and non-aneurysm. The primary objective of the system is to assist clinicians in the early detection of intracranial aneurysms by reducing reliance on manual image interpretation, minimizing diagnostic subjectivity, and enhancing overall diagnostic accuracy. By leveraging advances in artificial intelligence and medical image analysis, the system provides a reliable and efficient computational framework for supporting clinical decision-making.

The system follows a structured end-to-end pipeline that begins with dataset preparation and standardization. Raw CT images obtained in mixed formats, including standard image files and DICOM medical images, are organized and labeled according to the target classification task. This is followed by an image preprocessing stage, where images are resized, normalized, and converted into a consistent representation suitable for deep learning models. These steps ensure uniformity across the dataset and preserve diagnostically significant anatomical features.

To improve model generalization and reduce overfitting, data augmentation techniques are applied exclusively to the training dataset. Augmentation operations introduce realistic variations in image orientation, scale, and illumination, thereby increasing dataset diversity and enhancing the model's robustness to real-world imaging variability. The augmented data are then used to train a convolutional neural network using a transfer learning strategy.

At the core of the system lies the Xception convolutional neural network architecture, which is initialized with pretrained weights and fine-tuned for the binary classification of CT brain images. This approach enables the system to benefit from learned visual representations while adapting high-level features to the specific characteristics of medical imaging data. The training process incorporates optimization strategies and regularization techniques to ensure stable convergence and prevent overfitting.

Finally, the system's performance is evaluated using standard quantitative metrics, including accuracy and confusion matrix analysis, to assess classification reliability and diagnostic effectiveness. Through this modular and systematic workflow, the proposed system demonstrates a practical and scalable solution for automated intracranial aneurysm detection from brain CT images.

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

Once the preprocessing and augmentation stages were completed, the dataset was organized into a structure suitable for efficient and effective model training. Proper construction of the training dataset is crucial in deep learning workflows, as it ensures that the model receives representative samples from all classes and minimizes potential biases introduced by data ordering or sampling inconsistencies.

5.6.1 Batch Organization

Deep learning models, especially convolutional neural networks, are typically trained using mini-batch gradient descent, wherein subsets of the dataset—called batches—are processed sequentially to update the model's parameters. For this project, images and their corresponding labels were grouped into batches of size 8, chosen after empirical evaluation to balance training stability, memory utilization, and convergence speed. Smaller batch sizes improve generalization by introducing stochasticity in gradient updates, whereas excessively large batches can lead to overfitting and slower learning due to reduced noise in gradient estimation.

Within each batch, the data were paired such that each image retained its corresponding ground-truth label, either aneurysm (1) or non-aneurysm (0). This pairing ensures that the loss function, calculated during each forward pass, accurately reflects the discrepancy between predicted probabilities and true labels, allowing gradient-based optimization to update network weights correctly.

5.6.2 Random Shuffling for Bias Mitigation

To prevent the model from learning spurious patterns related to the order of data presentation, random shuffling of the dataset was applied prior to batch creation at the start of each training epoch. This procedure guarantees that each batch contains a different combination of samples in each epoch, which not only reduces the risk of bias but also improves the generalization capability of the network. Without shuffling, sequential patterns in the dataset—such as clusters of aneurysm or non-aneurysm images—could lead to model overfitting on certain segments while underrepresenting others.

Moreover, random shuffling aids in balancing class exposure throughout the training process. Given the inherent class imbalance between aneurysm and non-aneurysm images, ensuring that each batch contains a representative mix of both classes helps prevent the model from becoming biased toward the majority class. In practice, this was implemented using a shuffling function in the data loader, which randomly reorders the indices of the dataset before batch assignment.

5.6.3 Flexible Augmentation Activation

One of the key design considerations in this study was the ability to flexibly activate or deactivate data augmentation during training. This functionality allows controlled experimentation to assess the impact of augmented images on model performance and generalization. During experiments, augmentation was selectively applied to the training dataset, while the validation and test sets remained unaltered to ensure that evaluation metrics reflected performance on genuine, unmodified images.

The augmentation pipeline, executed before batch construction, generated new variations of each training image through random rotations, flips, zoom transformations, and brightness adjustments. By increasing the diversity of the training set, the model was exposed to a broader range of realistic imaging scenarios, which is particularly important in medical imaging tasks where acquisition conditions, scanner types, and patient anatomy vary significantly.

When augmentation was deactivated, the model trained solely on the original images, providing a baseline for evaluating the contribution of augmented samples. This approach allowed a systematic study of augmentation's effects on convergence speed, overfitting mitigation, and sensitivity to small aneurysms.

5.6.4 Efficient Data Loading and Preprocessing Integration

The training dataset was integrated with a data pipeline capable of on-the-fly preprocessing and augmentation. Images were loaded, normalized, and, when augmentation was activated, randomly transformed just prior to being fed into the network. This dynamic approach reduced memory overhead by avoiding the need to store multiple augmented copies of each image while ensuring that each epoch presented unique variations to the model.

Additionally, this pipeline supported parallelization across multiple CPU cores, which accelerated batch preparation and maintained GPU utilization near its maximum potential. By minimizing idle GPU time, the training process became more efficient and scalable, a critical consideration when working with 3D image data or complex CNN architectures such as Xception.

5.7 Model Architecture and Training Strategy

The proposed system leverages the Xception convolutional neural network (CNN) architecture for the detection of intracranial aneurysms in brain CT images. Xception, short for "Extreme Inception," is an advanced CNN model that extends the Inception architecture by implementing depthwise separable convolutions, where spatial and channel-wise filtering are separated. This design significantly reduces the number of parameters while maintaining high representational power, enabling efficient feature extraction from high-dimensional medical images without incurring excessive computational cost. The architecture is particularly well-suited for detecting subtle patterns such as small aneurysms, which often exhibit low contrast and variable shapes in CT scans.

5.7.1 Rationale for Xception Selection

Several factors informed the decision to use Xception as the backbone model:

1. **Efficient Feature Learning**: Depthwise separable convolutions allow the model to learn spatial and cross-channel correlations independently, enabling more precise detection of fine anatomical structures.

2. **Transfer Learning Compatibility**: Xception has pre-trained weights available on large-scale datasets such as ImageNet, which can be adapted to medical imaging tasks through transfer learning. This reduces the amount of training data required for effective convergence.

3. **Scalability**: The model's modular architecture supports fine-tuning of specific layers, allowing targeted adaptation to the aneurysm classification task while preserving low-level learned features that are relevant across domains.

5.7.2 Network Customization for Binary Classification

The original Xception network is designed for multi-class classification; therefore, a custom classification head was appended to the pre-trained base model to support binary classification (aneurysm vs. non-aneurysm). This classification head consisted of:

- A global average pooling layer to reduce the spatial dimensions of feature maps while retaining the most salient information.

- One or more fully connected (dense) layers with ReLU activation for learning task-specific patterns.
- A dropout layer to prevent overfitting by randomly deactivating neurons during training.
- A final dense layer with sigmoid activation to output a probability score between 0 and 1, representing the likelihood of an aneurysm being present in the input CT image.

This architecture ensures that high-level semantic features extracted from the Xception backbone are effectively translated into a clinically interpretable prediction.

5.7.3 Transfer Learning and Training Strategy

To leverage prior knowledge from large-scale datasets, **transfer learning** was applied by initializing the Xception base model with pre-trained ImageNet weights. This approach provides several advantages:

- Faster convergence due to pre-learned low- and mid-level features.
- Improved generalization on limited medical image datasets.
- Reduction in computational resources required for training from scratch.

Training proceeded in two main phases:

Phase 1: Base Training

- The network was trained on the augmented training dataset for 15 epochs with a batch size of 8.
- **Loss function**: Binary cross-entropy, suitable for the binary classification task.
- **Optimizer**: Adam with a standard learning rate (1e-3) to facilitate stable initial convergence.
- **Callbacks Implemented**:
  - **EarlyStopping**: Monitors validation loss and halts training if no improvement occurs over 5 consecutive epochs, restoring the best-performing weights.

- **ReduceLROnPlateau**: Monitors validation loss and reduces the learning rate by a factor of 0.5 if the loss stagnates for 3 epochs. This helps avoid overshooting local minima and improves convergence stability.

This phase allows the newly added classification head to adapt to the aneurysm detection task while keeping the pre-trained convolutional layers frozen to preserve general visual features.

Phase 2: Fine-Tuning

After the base training stabilized, fine-tuning was performed to adapt high-level features of the pre-trained model to the specific characteristics of CT brain images:

- The last 50 layers of the Xception base were unfrozen while the remaining layers stayed frozen.
- The network was recompiled with a lower learning rate (1e-5) to prevent large gradient updates that could disrupt the pre-trained weights.
- Training continued for 10 additional epochs, again using EarlyStopping and ReduceLROnPlateau callbacks.

Fine-tuning enables the model to learn task-specific patterns, such as subtle variations in vessel morphology and aneurysm appearance, without overfitting the limited dataset.

5.7.4 Model Regularization and Optimization Techniques

Several additional strategies were employed to ensure stable training and reduce overfitting:

1. **Dropout Layers**: Introduced in the custom classification head to reduce neuron co-adaptation and enhance generalization.
2. **Data Augmentation**: During training, random rotations, flips, zooms, and brightness adjustments were applied to increase data variability.
3. **Batch Normalization**: Present in the Xception layers, it normalizes activations to maintain stable learning and accelerate convergence.
4. **Monitoring and Checkpointing**: Model weights were saved at the epoch with the lowest validation loss, ensuring optimal performance during evaluation.

5.7.5 Evaluation Strategy

Model performance was assessed on a **separate validation set** during training and finally on a **test set**. Metrics included:

- **Accuracy (ACC)**: Percentage of correctly classified images.
- **Confusion Matrix**: To evaluate false positives and false negatives, providing insight into clinical reliability.

The combination of a robust architecture, careful training, and systematic evaluation ensures that the model can reliably detect aneurysms while minimizing both false positives and false negatives.

5.8 Previous Experiments and Challenges

Before arriving at the final proposed methodology, a series of preliminary experiments were conducted to explore different modeling strategies and to better understand the characteristics and limitations of the available dataset. These experiments played a crucial role in shaping the final system design by revealing key challenges related to data distribution, model capacity, generalization, and feature learning in the context of intracranial aneurysm detection from brain CT images.

5.8.1 Initial Dataset Formulation and Class Merging

The initial dataset provided three diagnostic classes: aneurysm, tumor, and cancer. As a first experimental step, the tumor and cancer classes were combined into a single category labeled "non-aneurysm," thereby transforming the original multi-class problem into a binary classification task. This formulation was motivated by a clinically relevant screening scenario, where the primary objective is to identify aneurysm cases while grouping other pathological findings into a single negative class.

Although this restructuring simplified the classification problem conceptually, it introduced significant challenges from a machine learning perspective. The resulting dataset exhibited a noticeable class imbalance, with non-aneurysm samples outnumbering aneurysm cases. This imbalance led to biased learning behavior, where early models tended to favor the majority class, achieving superficially high accuracy while failing to correctly identify aneurysm cases. Such behavior is particularly undesirable in medical applications, where false negatives can have severe clinical consequences.

5.8.2 Class Weighting and Underfitting Issues

To address the issue of class imbalance, class weighting was applied during training. Higher weights were assigned to the aneurysm class in the loss function to penalize misclassification of positive cases more heavily. In theory, this approach encourages the model to pay greater attention to minority class samples and improves sensitivity.

However, experimental results demonstrated that the use of class weighting alone was insufficient. While the model showed slight improvements in detecting aneurysm cases, overall learning behavior indicated underfitting. Training and validation accuracies remained low, and loss values plateaued early during training. This suggested that the model was unable to effectively learn discriminative features from the data, despite the adjusted class importance. The underfitting behavior indicated either insufficient model capacity or inadequate feature representation given the complexity of the task.

5.8.3 Experiments with Lightweight Pre-trained Models

In subsequent experiments, attention was shifted toward leveraging lightweight pre-trained convolutional neural network architectures, including MobileNet and EfficientNet. These models are widely recognized for their efficiency and strong performance in image classification tasks, particularly when computational resources are limited.

Both architectures were fine-tuned using transfer learning, with pretrained weights initialized from large-scale natural image datasets. Multiple configurations were tested, including freezing and unfreezing different numbers of layers, adjusting learning rates, modifying batch sizes, and varying training epochs. Despite extensive experimentation, these models failed to deliver stable and reliable performance.

In several cases, the models converged too quickly and exhibited overfitting, achieving high training accuracy while showing poor validation performance. In other cases, especially when stronger regularization was applied, the models suffered from underfitting, failing to learn meaningful representations from the CT images. These outcomes suggested that the feature extraction capabilities of these architectures were either insufficiently expressive for the subtle vascular patterns associated with aneurysms or poorly aligned with the grayscale and medical nature of CT imaging data.

5.8.4 Limitations of Training a CNN from Scratch

To further investigate the feasibility of alternative approaches, a custom convolutional neural network was designed and trained from scratch. The architecture consisted of multiple convolutional and pooling layers followed by fully connected layers, with the goal of learning task-specific features directly from the CT images without relying on pretrained weights.

Despite careful architectural design and hyperparameter tuning, this approach consistently resulted in underfitting. The model struggled to learn meaningful patterns, as evidenced by low training accuracy and minimal improvement over successive epochs. This outcome can be attributed to several factors, including the relatively limited size of the dataset, the high dimensionality of image data, and the complexity of aneurysm-related visual features. Training deep networks from random initialization typically requires large-scale datasets, which were not available in this project.

5.8.5 Data Variability and Imaging Challenges

Across all preliminary experiments, additional challenges were observed related to the inherent variability of CT imaging data. Differences in image resolution, acquisition protocols, scanner types, and contrast levels introduced inconsistencies that negatively affected model learning. Furthermore, aneurysms often occupy a very small region of the image and may exhibit low contrast relative to surrounding tissues, making them difficult to distinguish even for deep learning models.

The experiments also highlighted the difficulty of detecting small aneurysms, which are more likely to be misclassified as non-aneurysm cases. These challenges underscored the importance of robust preprocessing, normalization, and augmentation strategies to reduce variability and emphasize diagnostically relevant features.

5.8.6 Lessons Learned and Methodological Refinement

The collective insights gained from these early experiments were instrumental in guiding the final methodological choices. The repeated issues of underfitting and overfitting demonstrated that a balance between model complexity and dataset size was essential. Lightweight models lacked sufficient representational power, while training from scratch was not feasible given data limitations.

These findings ultimately motivated the selection of the Xception architecture as the backbone of the proposed system. Xception's depthwise separable convolutions offer a strong balance between efficiency and expressive feature learning, making it well-suited for medical image classification tasks. Combined with transfer learning, targeted preprocessing, and a carefully designed augmentation strategy, the final approach addressed many of the shortcomings observed in earlier experiments.

In summary, the preliminary experiments revealed critical challenges related to class imbalance, data variability, model generalization, and feature learning. By systematically evaluating and analyzing these challenges, the project evolved toward a robust and reliable solution that effectively leverages deep learning for intracranial aneurysm detection from brain CT images.

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.

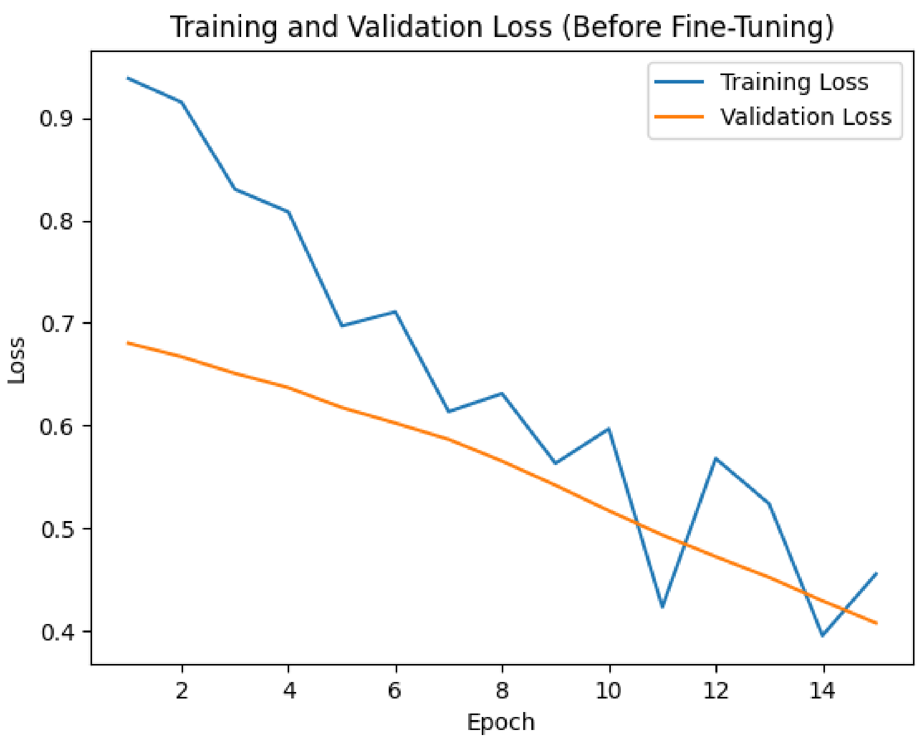

Figure v

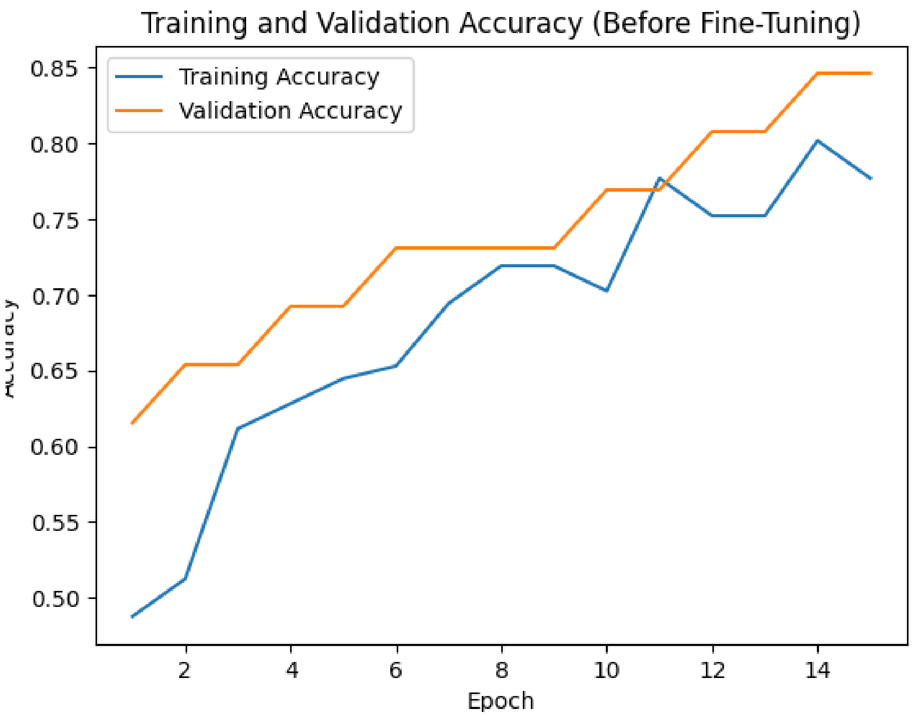
Training and Validation Accuracy (Before Fine-Tuning)
Training Accuracy
Validation Accuracy
0.85
0.80
0.75
0.70
0.65
0.60
0.55
0.50
2
4
6
8
10
12
14
Epoch

Figure vi

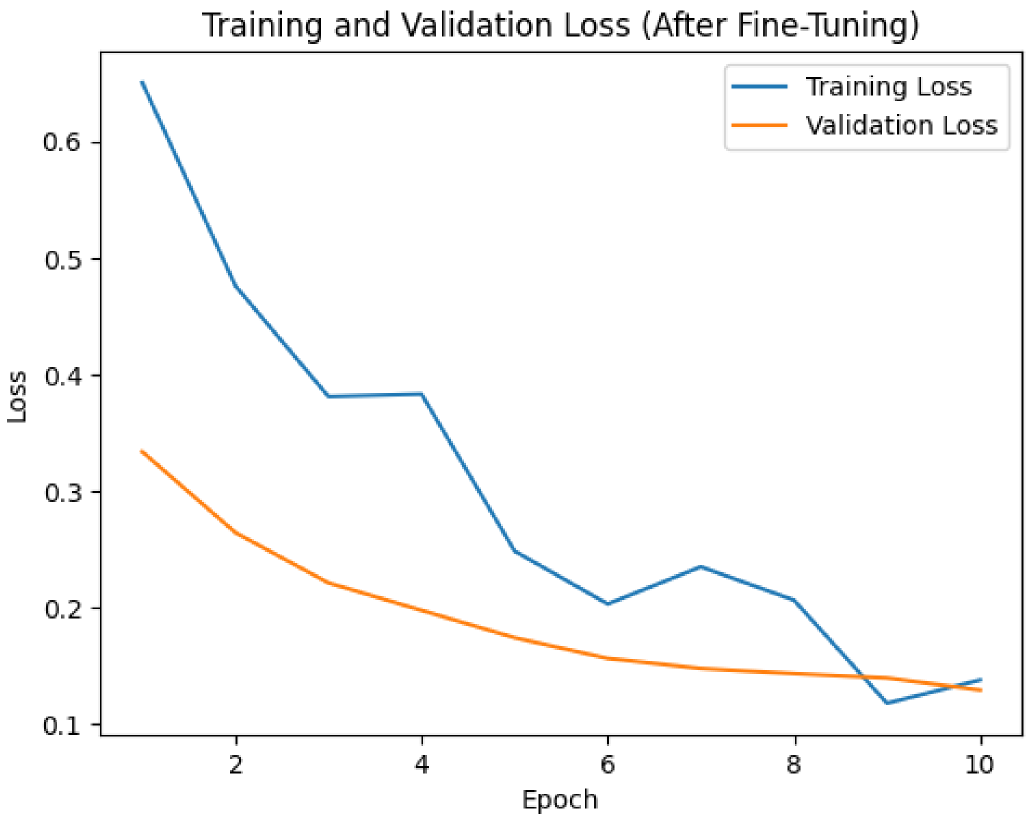
Training and Validation Loss (After Fine-Tuning)
Training Loss
Validation Loss
0.6
0.5
0.4
0.3
0.2
0.1
Loss
2
4
6
8
10
Epoch

Figure vii

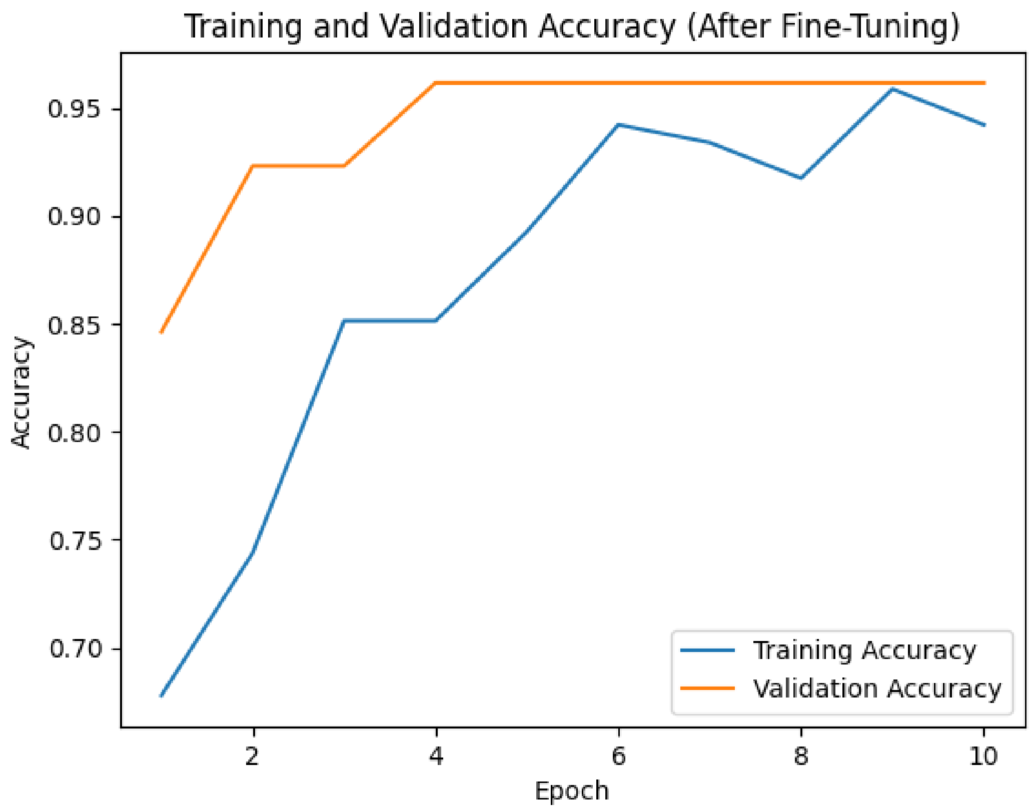
Training and Validation Accuracy (After Fine-Tuning)
Accuracy
0.95
0.90
0.85
0.80
0.75
0.70
2
4
6
8
10
Epoch
Training Accuracy
Validation Accuracy

Figure viii

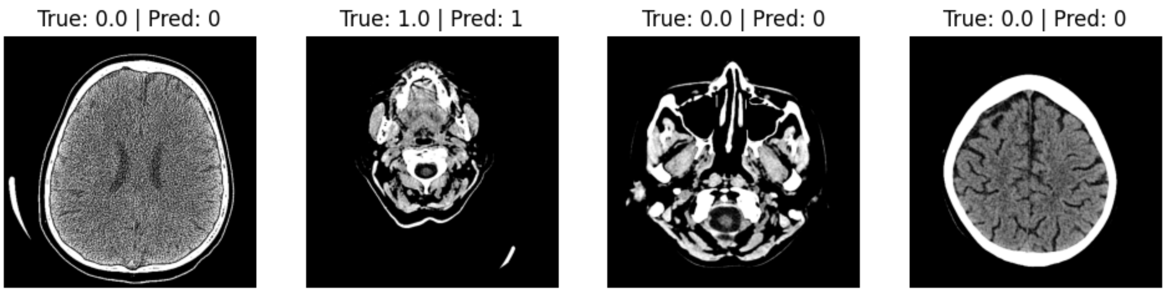

Figure ix

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>
```

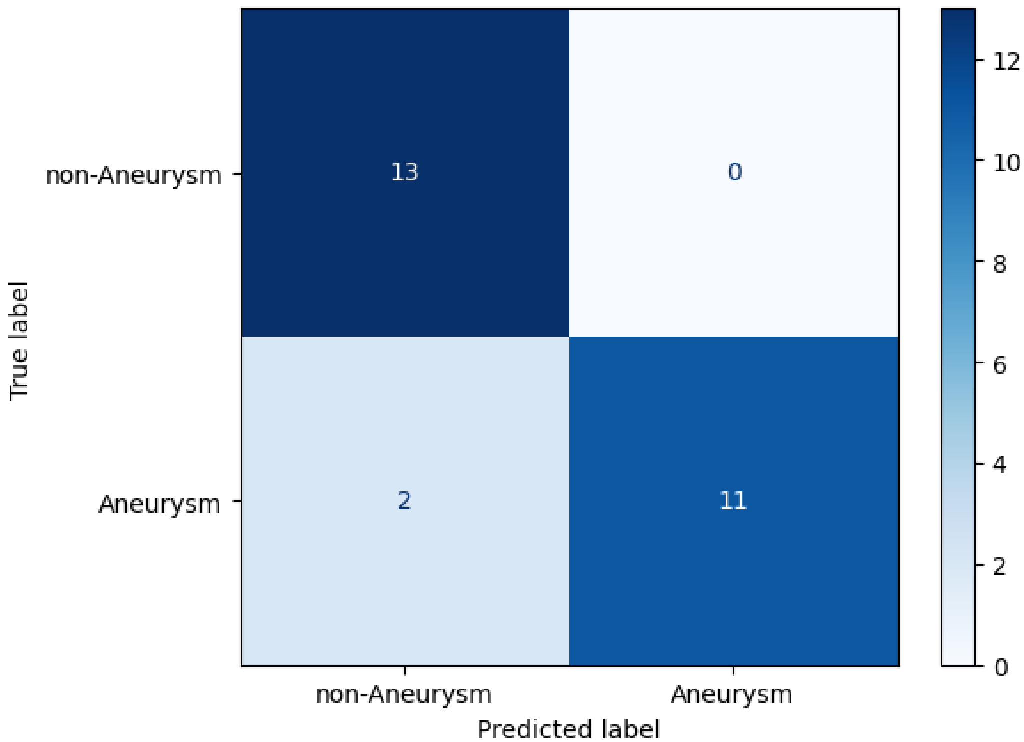

Figure x

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.

Chapter 8: References

References

1. Ham, S., Seo, J., Yun, J., Bae, Y. J., Kim, T., Sunwoo, L., … & Kim, N. (2023). *Automated detection of intracranial aneurysms using skeleton-based 3D patches, semantic segmentation, and auxiliary classification for overcoming data imbalance in brain TOF-MRA*. *Scientific Reports*. https://www.nature.com/articles/s41598-023-38586-9

2. DiscoverAI. (n.d.). *Tumor, cancer, aneurysm detection (dataset and model)*. Roboflow Universe. https://universe.roboflow.com/discoverai/tumor-cancer-aneurysm-detection Roboflow

3. OpenNeuro. (n.d.). *ds003949: Brain imaging data*. OpenNeuro. https://openneuro.org/datasets/ds003949/versions/1.0.1

4. ResearchGate. (n.d.). *Architecture of the Xception deep CNN model*. https://www.researchgate.net/figure/Architecture-of-the-Xception-deep-CNN-model_fig2_351371226

5. Kaggle. (n.d.). *Computed Tomography (CT) of the Brain dataset*. Kaggle. https://www.kaggle.com/datasets/trainingdatapro/computed-tomography-ct-of-the-brain

6. MDPI. (2023). *Title not available* [Article]. *Journal of Clinical Medicine and Biosciences*. https://www.mdpi.com/2227-9059/11/3/760?utm_source=chatgpt.com

7. Chollet, F. (2017). *Xception: Deep learning with depthwise separable convolutions*. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*

(CVPR) (pp. 1251–1258). IEEE. https://doi.org/10.1109/CVPR.2017.195

8. Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., van der Laak, J. A. W. M., van Ginneken, B., & Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. *Medical Image Analysis, 42*, 60–88. https://doi.org/10.1016/j.media.2017.07.005

9. Tajbakhsh, N., Shin, J. Y., Gurudu, S. R., Hurst, R. T., Kendall, C. B., Gotway, M. B., & Liang, J. (2016). Convolutional neural networks for medical image analysis: Full training or fine tuning? *IEEE Transactions on Medical Imaging, 35*(5), 1299–1312. https://doi.org/10.1109/TMI.2016.2535302
10. Shen, D., Wu, G., & Suk, H. I. (2017). Deep learning in medical image analysis. *Annual Review of Biomedical Engineering, 19*, 221–248. https://doi.org/10.1146/annurev-bioeng-071516-044442

11. Shorten, C., & Khoshgoftaar, T. M. (2019). A survey on image data augmentation for deep learning. *Journal of Big Data, 6*(1), 60. https://doi.org/10.1186/s40537-019-0197-0

12. Greenspan, H., van Ginneken, B., & Summers, R. M. (2016). Deep learning in medical imaging: Overview and future promise of an exciting new technique. *IEEE Transactions on Medical Imaging, 35*(5), 1153–1159. https://doi.org/10.1109/TMI.2016.2553401

13. Pereira, S., Pinto, A., Alves, V., & Silva, C. A. (2016). Brain tumor segmentation using convolutional neural networks in MRI images. *IEEE Transactions on Medical Imaging, 35*(5), 1240–1251. https://doi.org/10.1109/TMI.2016.2522270

14. Abdar, M., Pourpanah, F., Hussain, S., Rezazadegan, D., Liu, L., Acharya, U. R., Khosravi, A., & Makarenkov, V. (2021). A review of uncertainty quantification in deep learning: Techniques, applications and challenges. *Information Fusion, 76*, 243–297. https://doi.org/10.1016/j.inffus.2021.05.008

Syrian Private University

Factuly of Artificial Intelligence Engineering

Department Artificial Intelligence and Data science

Junior Project

الجامعة السورية الخاصة

كلية هندسة الذكاء الصنعي

قسم الذكاء الصنعي و علم البيانات

المشروع الفصلي

تشخيص أم الدم من صور الأشعة المقطعية