جامعة جدة
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Full Project Report

Stroke Sense : AI Brain Stroke Detection System Using CT and MRI

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Executive Summary

The final report discusses the design of a deep learning-oriented system, referred to as " Stroke Sense : AI Brain Stroke Detection System Using CT and MRI Scans," which is to assist the radiologists in identifying and classifying Strokes from radiology images in CT and MRI scans . The introduction of the text succinctly addresses the existing diagnostic limitations and reveals a new potentiality of artificial intelligence (deep learning) to overcome these difficulties.

This project's main target is that it put itself as a potential novel diagnostic tool and therapeutic aid, and this might be helpful in increasing patient survival outcomes. Making use of powerful deep learning toolset based on big data, the proposed one will facilitate automatic screening, drastic time shortening, and make therapeutic action possible.

The methodology section presents the Agile Software Development methods that were embraced for the project, putting in accent the iterative development, collaboration, adaptability, and usercentricity. The document establishes the software life cycle steps beginning with requirement collection, followed by implementation, deployment, and maintenance.

In the chapter on problem definition, the disease problem clearly defines the features of the diagnosis of strokes types and discusses the work results, including the creation of a deep learning model, user manuals, evaluation report and training data. It reveals the subjectivity of the results by indicating that they may differ from batch to batch and by saying that the analysis takes a lot of time. Last, but not least, sample testing represents the way to establish operational efficiency and to ensure a high level of diagnostic accuracy.

In the requirement analysis phase, we use not only the use cases descriptions, functional and nonfunctional requirements, as well. It is the most obvious step to fill the needs for the system behavior, the user's communications, and the technical needs, so that it does not contradict with the needs of users and considers the project objectives and achieves its goals.

In this section, the architecture diagram, the process flow, and the sequence diagram are shown as a way of conveying the system's structure, workflow, and components. Filters visualizations allow viewers to grasp concepts faster and apply them correctly.

Conclusively, our report suggests a strong and reliable system based on deep learning methods of screening strokes radiology images. Through meeting the defined set of challenges and accomplishing the specified demands, the project aims to achieve a dependable, time-saving, and user-friendly product thus offering an advanced level of diagnostics and treatment to brain strokes patients all over the world.

Abbreviations

MRI	Magnetic Resonance Imaging
CT	Computed Tomography
CNN	Convolutional Neural Networks
GPU	Graphics Processing Units
HIPAA	Health Insurance Portability and Accountability Act
EfficientNetB0	EfficientNetB0

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Chapter 1

1 Introduction

Strokes are one of the leading causes of death and long-term disability worldwide.

Rapid and accurate diagnosis is critical for effective treatment and rehabilitation. Traditional methods of stroke detection rely heavily on medical professionals interpreting CT and MRI scans, which can be time-consuming and prone to human error. Recent advances in artificial intelligence (AI) and deep learning offer the potential to enhance diagnostic processes by automating the detection and classification of strokes in medical images. This research aims to develop a deep learning-based system that utilizes both CT and MRI scans to identify and classify strokes in all two types of Ischemic and Hemorrhagic strokes, thereby improving diagnostic accuracy and speed

The promises of artificial intelligence, and specifically deep learning, spur an opportunity to improve the already existing diagnostic process. Multi-level CNNs, a branch of deep neural networks, can resolve complicated vision problems by retaining their excellent image recognition capabilities. This report, which is basically aimed at the use of CNNs for the automation of Stroke diagnosis from both MRI,CT images, offers the support needed by radiologists to reach their best diagnostic precision and alleviate the treatment process burden. The proposed project, namely, "stroke sence : AI Brain Stroke Detection System Using CT and MRI Scans," has the aim at recognizing complicated structures of MRI data. It is to realize precise distinction between different kinds of strokes .

1.1 Brief Overview

The utilization of different methods like radiologists' interpretation that is based on manual intelligence or traditional machine learning algorithms plays the main role in current Cerebrovascular accident diagnostics. It is no secret that these methods may already have demonstrated their capacity to bring some benefit, but they are often precarious due to subjectivity, variability in diagnostic accuracy, and reliance of predefined features.

As for advanced, the wide use of CNNs in these tasks has also been considered. Consequently, these models could withstand the weaknesses like the size constraints of the datasets, which could affect their accuracy and generalized efficiency.

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Being literally faced with these circumstances, we need to introduce deep learning methods to automate and improve diagnostics of Cerebrovascular accident from radiology images. The proposed project overcomes these limitations using CNNs as a complement to the volume and quality of data sets.

1.2 Relevance to Course Modules

Deep learning significantly influences computer science education by providing powerful tools and reshaping how students tackle modern challenges. Here's why it remains crucial:

- **Advanced Techniques**: Deep learning pushes students to explore advanced and innovative methods. Throughout their studies, they gain hands-on experience with architectures like neural networks, convolutional neural networks (CNNs), recurrent neural networks (RNNs), and more. These capabilities prepare them to solve complex problems across multiple industries.

- • **Foundation for Data Science and Machine Learning:** In the field of data science, deep learning serves as a core pillar. Students who dive into the mechanics of deep neural networks enhance their abilities to design predictive models, recognize trends, and make data-driven decisions. Mastering deep learning techniques directly strengthens their expertise in these growing fields.
- **Image Recognition and Natural Language Processing (NLP):** Deep learning is widely applied in areas like image analysis and natural language processing (NLP). Students build systems that can label images, generate captions, and analyze textual sentiments. These practical skills are vital for advancing technologies in computer vision and language understanding.

- **Opportunities for Research and Innovation:** Engaging with deep learning allows students to contribute to cutting-edge research. Whether it's through optimizing model performance, experimenting with hyperparameter tuning, or developing new architectures, students enhance their creativity and push the boundaries of what is currently possible.

- **Interdisciplinary Collaboration:** With strong deep learning knowledge, students can seamlessly collaborate with professionals from various sectors, including healthcare, finance, and robotics. Working on interdisciplinary projects hones their critical thinking and expands their professional adaptability
- **High Industry Demand:** The demand for deep learning specialists continues to rise. Organizations seek experts who can create and deploy deep learning solutions. Computer science graduates with deep learning skills are highly competitive candidates for roles in artificial intelligence, data analysis, and software engineering.

1.3 Project Background

The project titled *"Stroke Sense: AI-Based Brain Stroke Detection Using CT and MRI Scans"* addresses a critical need in the medical field by utilizing deep learning to assist in the diagnosis and classification of brain strokes. Strokes are among the leading causes of disability and death globally, and accurate, fast diagnosis is essential for effective treatment. However, the conventional diagnostic process often relies on radiologists' manual interpretation of brain scans, which can be time-consuming, subject to human error, and delayed in emergency cases.

Given the increasing volume of medical imaging data, there is a growing demand for intelligent systems that can support healthcare professionals in making quicker and more consistent diagnoses. This project focuses on harnessing the power of deep learning, particularly convolutional neural networks (CNNs), to automate the analysis of CT and MRI brain scans. These models are known for their effectiveness in visual pattern recognition and are especially suited to identifying abnormalities in medical images.

By developing a system capable of detecting and classifying stroke types — such as ischemic and hemorrhagic — the project aims to reduce diagnostic delays, improve patient outcomes, and support clinicians in emergency care settings. Traditionally, such classification requires expert knowledge and manual processes, but with AI integration, the goal is to achieve high precision with minimal intervention.

What makes *Stroke Sense* especially valuable is its potential to transform the stroke diagnosis workflow. Not only does it address the urgent need for faster and more reliable detection, but it also contributes to the broader field of AI in medicine. The project advances the application of deep learning in clinical imaging, offering a scalable solution that could one day be deployed in real-world hospitals and emergency centers, enhancing healthcare delivery and saving lives.

1.4

1.4.1 Methodology

In the **Stroke Sense** project, we applied key principles from the **Agile Software Development methodology**, focusing on iterative progress and flexibility. While we did not follow a formal Agile process with full sprints and scrum roles, we implemented the spirit of Agile through continuous experimentation, adaptation, and refinement of our model throughout development.

Key practices we applied:

- **Iterative Development:**
  We broke the project into several development phases including image preprocessing, model training, evaluation, and refinement. Each phase was followed by testing and adjustments based on observed results and feedback from our academic supervisor.
- **Flexible Adjustments:**
  As we explored different architectures and datasets, we adapted our approach—switching from simple binary classification (stroke vs. no stroke) to a more detailed multi-class classification (normal, ischemic, hemorrhagic)—to better align with real-world medical needs.
- **Collaborative Learning:**
  Although the project was mainly handled by our development team, we consulted academic experts and reviewed medical literature to align the system with clinical relevance. This helped guide our dataset selection and labeling strategy.
- **Model Evaluation:**
  Throughout development, we monitored the model using accuracy, precision, recall, and confusion matrices. These metrics were essential to ensure that our CNN model was progressing toward a clinically useful performance level.

2.1.1 1.4.2 Software Life Cycle

The Stroke Sense system followed a **simplified and iterative software life cycle**, structured around practical milestones:

- **Requirements Understanding:**
  We began by understanding the problem of stroke detection, reviewing research papers and clinical resources to identify the key challenges in distinguishing between stroke types using brain scans.
- **Design:**
  We outlined the model architecture, input/output data flow, and basic interface expectations. We selected Convolutional Neural Networks (CNNs) as the foundation for the detection system, based on their success in medical image classification.
- **Implementation:**
  Using Python, TensorFlow, and Google Colab, we developed the core of our AI model. We applied preprocessing steps such as grayscale conversion, resizing, normalization, and data augmentation. The model was trained on annotated datasets of CT and MRI images.

- **Testing and Evaluation:**
  The system was tested using separate validation datasets. We evaluated its performance using standard metrics like accuracy and F1-score, and visualized confusion matrices to understand strengths and weaknesses.
- **Prototype Delivery:**
  While we did not deploy the system in a hospital setting, a working prototype was created that can be extended and integrated into clinical workflows in the future with further validation and regulatory steps.
- **Future Maintenance Plan:**
  We anticipate that the system could be improved by retraining on new datasets, fine-tuning hyperparameters, and updating the model based on evolving diagnostic criteria and user feedback.

1.5 Literature Review

The application of deep learning in medical image analysis has significantly advanced, enabling more efficient and accurate diagnostic tools. This literature review outlines key studies in the field, focusing on methodologies, innovations, and insights related to glioblastoma detection in radiology images.

CT:

1-Deep Learning-Enabled Brain Stroke Classification on Computed Tomography Images:

Study : Stroke is the second leading cause of death worldwide after cardiovascular disease and the third cause of global disability after neonatal disease and cardiovascular disease According to the World Health Organization (WHO), about 15 million people worldwide experience a stroke each year, 5 million die, and the remaining 5 million are permanently disabled.

2- A Deep Learning Approach for Detecting Stroke from Brain CT Images Using OzNet :

Study: Application of Deep Learning to Ischemic and Hemorrhagic Stroke Computed Tomography and Magnetic Resonance Imaging

3- Application of Deep Learning to Ischemic and Hemorrhagic Stroke Computed Tomography and Magnetic Resonance Imaging:

Study : Deep Learning (DL) algorithm holds great potential in the field of stroke imaging. It has been applied not only to the "downstream" side such as lesion detection, treatment decision making, and outcome prediction, but also to the "upstream" side for generation and enhancement of stroke imaging. This paper aims to comprehensively overview the common applications of DL to stroke imaging. In the future, more standardized imaging datasets and more extensive studies are needed to establish and validate the role of DL in stroke imaging.

4- Applications of deep learning algorithms in ischemic stroke detection, segmentation, and classification:

Study : Ischemic, one of the fatal diseases characterized by insufficient blood supply to tissues poses a significant global health burden, necessitating the development of robust diagnostic and classification methodologies. Timely identification, intervention, and treatment are essential to reduce associated risk factors. Modern machine learning methods like deep learning and neural networks are being successfully employed on medical images to detect and segment the region of interest for various diseases where the performance of these computational methods is improving daily and for various tasks has surpassed natural intelligence.

MRI:

1- DL-Brain-stroke-mri-images-using CNN(2018)

Study : Brain stroke is a medical condition where blood flow to the brain is interrupted, causing damage to brain cells. Early detection of stroke is very important for patient recovery. MRI (Magnetic Resonance Imaging) is commonly used for diagnosing strokes

Key insight :To build a Deep Learning model using CNN (Convolutional Neural Network) to classify MRI images of the brain into Normal Brain, Stroke-Affected Brain.

2- Moeskops et al. (2016)(1):

Study: Moeskops et al. conducted a study on brain tumor segmentation using deep learning techniques. Although not focused specifically on stroke, the study explores the application of advanced image processing methods for neurological conditions.

Relevance: While the primary focus is on tumors, the methodologies and techniques employed in this study could offer insights into image segmentation and feature extraction relevant to brain stroke recognition we are planning for our project .

3- Stroke detection and classification (2nd defence)(4):

Study : The main objective of this project Is to develop a robust classification model that can accurately differentiate between stroke and non-stroke cases. By utilizing

sequentail model , achieving accuracy of 0,96

Relevance : simplicity of the cod and the dataset of the model is what we are - aiming to benefit from this project.

4- Application of Machine Learning Techniques for Characterization of Ischemic Stroke with MRI Images:

Study : Application of Machine Learning Techniques for Characterization of Ischemic Stroke with MRI Images.

1.6 Summary

The reviewed studies highlight the advancements in deep learning architectures, particularly CNNs, for medical imaging tasks such as Cerebrovascular Accident detection. The collective insights emphasize the need for robust datasets, advanced preprocessing, and model optimization to achieve state-of-the-art performance. These findings underscore the relevance and feasibility of our project in addressing the challenges of Stroke diagnosis through deep learning techniques.

Chapter 2

Problem Definition

3 Problem Definition

This chapter explains the problem to be converted. It can and should also be considered.

3.1 Problem Statement

Despite advancements in medical imaging technologies, stroke diagnosis remains a challenge due to:

- **Delay in Diagnosis**: Current methods often involve lengthy review times, delaying treatment decisions and potentially worsening patient outcomes.
- **Human Error**: Misinterpretation of scans can lead to incorrect diagnoses, resulting in inappropriate treatments.
- **Lack of Accessibility**: In many regions, access to specialists who can interpret scans is limited, creating disparities in healthcare.
- **Economic Matter** : the amount of money wasted in this process could be saved through this system

There is a pressing need for an automated system that can quickly and accurately detect strokes, classify their types (ischemic or hemorrhagic), and determine their stages (early, middle, or severe). This project seeks to address these challenges by leveraging AI to streamline the stroke detection process , and lend a helping hand for all the workers in the medical staff specially in the region where this project is being developed where no such system exists so far.Deliverables and Development Requirements.

3.1.1 Deliverables :

Deep Learning Model: The primary deliverable of the project is a high-performing deep learning modelcapable of accurately detecting and classifying stroke types (ischemic and hemorrhagic) from brain CT and MRI scan images.

• **Software Prototype**: A functional prototype incorporating the trained stroke detection model, equipped with a user-friendly interface that allows users (e.g. doctors or technicians) to upload scan images and instantly view classification results and relevant analysis.

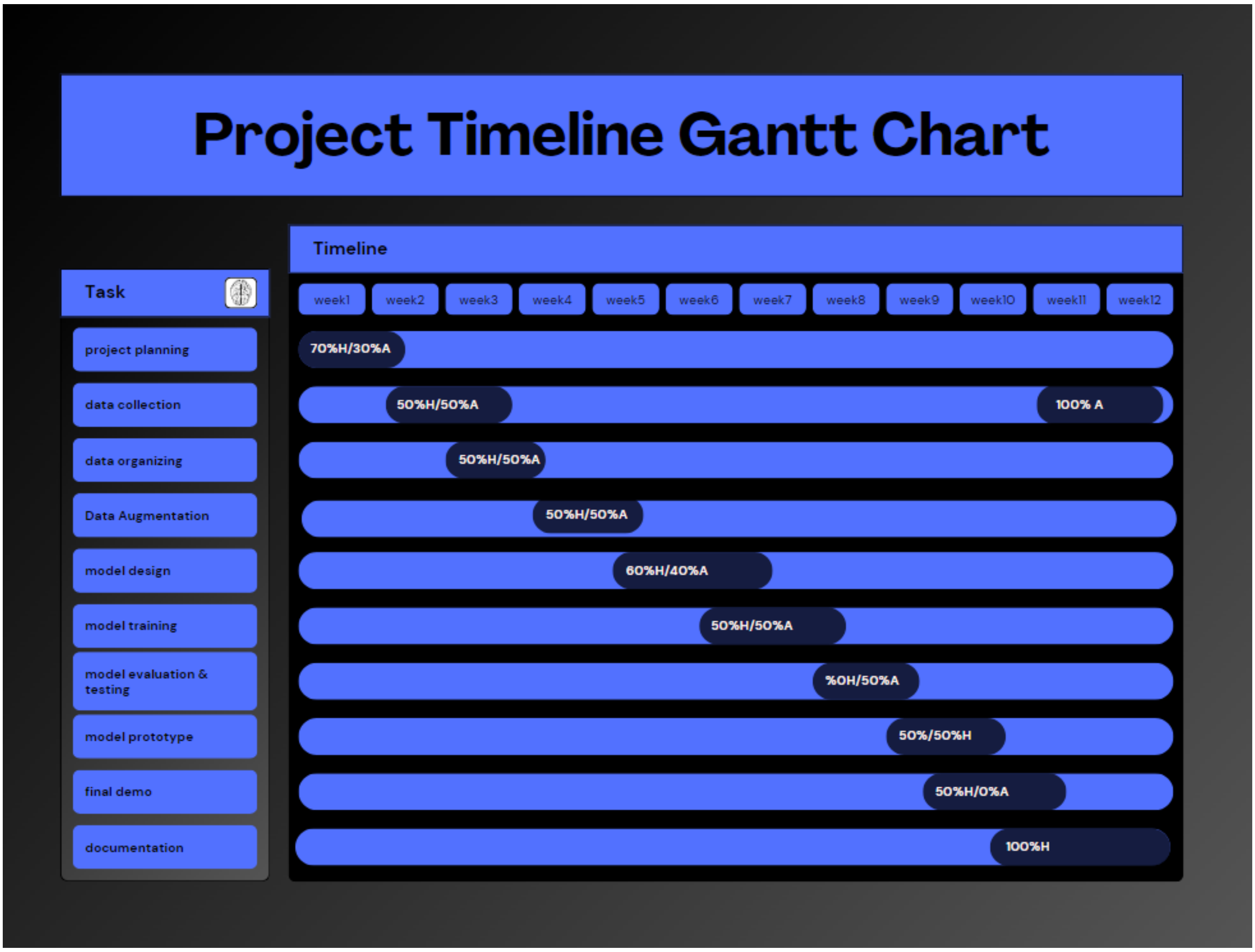
• **Documentation**: Comprehensive documentation covering system architecture, model structure, training process, implementation details, and user instructions. It includes technical documentation, user manuals, and developer guides for future updates or system extensions.

• **Evaluation Report**: A detailed evaluation report analyzing the model’s performance in terms of accuracy, precision, recall, sensitivity, specificity, and overall computational efficiency. It also includes performance comparison with baseline methods and testing on separate validation datasets.

• **Training Dataset**: A curated and labeled dataset of brain scan images (CT and MRI), indicating presence or absence of stroke, and specifying stroke type. The dataset is selected to ensure diversity and quality, providing a solid foundation for model training and generalization.

3.2 Gantt Chart

Figure 2-1: Gantt Chart



2.1.1 Development Requirements

• **Hardware**: A system equipped with a GPU (Graphics Processing Unit) is essential to train and validate deep learning models for stroke detection. The hardware must support intensive computation tasks, including training on high-resolution CT and MRI brain scans and processing large-scale datasets efficiently.

• **Software Tools**: Development relies on modern deep learning frameworks such as TensorFlow, Keras, or PyTorch. For medical image preprocessing, libraries like OpenCV are necessary to clean, resize, and normalize brain scan images before feeding them into the model.

• **Data Access**: Access to high-quality, labeled datasets of CT and MRI scans for patients with different types of brain strokes (ischemic, hemorrhagic) is critical and hard to find . This data may come from public databases , we also contacted hospitals, research collaborations, academic institutions for more available dataset unfortunately we acquired them late into the project .

• **Expertise**: A multidisciplinary team is required, including AI engineers, medical imaging specialists, radiologists, and software developers. Team members should have strong knowledge of deep learning, neural networks, medical image interpretation, and healthcare software development.

• **Stakeholder Engagement**: Throughout development, we needed a continuous collaboration with radiologists and healthcare professionals ensures the system addresses practical needs and integrates smoothly into real clinical workflows, helping improve diagnosis speed and reliability.

• **Regulatory Compliance**: The project must comply with healthcare data regulations such as HIPAA or equivalent local standards. This includes maintaining patient data privacy, confidentiality, and ensuring ethical use of sensitive medical information.

The objective of this project is to build an accurate, AI-powered system capable of detecting and classifying strokes from brain scans, thereby supporting clinical decision-making and improving patient outcomes through timely intervention and diagnosis.

3.2.1 2.3 Current System

Several systems and models described in the literature aim to support stroke detection using medical imaging. However, many of these face technical or practical limitations:

• **Traditional ML-Based Approaches**: Some models rely on classical machine learning algorithms for classification of stroke types. These methods often lack the depth needed to detect complex imaging patterns, leading to moderate diagnostic performance.

• **CNN-Based Prototypes**: Other experimental systems use Convolutional Neural Networks trained on limited datasets. Despite the power of CNNs, the lack of data diversity restricts these models from achieving consistent performance in real-world clinical settings.

• **Manual MRI-Based Tools**: Certain commercial tools assist in stroke diagnosis by combining MRI imaging with expert analysis. While effective, these systems are often time-consuming, costly, and dependent on human input—making them less efficient in urgent care environments.

• **Proposed System – Stroke Sense**: Our proposed system leverages deep learning and CNN-based architecture trained on a diverse and high-resolution dataset of brain scans. By overcoming dataset limitations and automating image interpretation, **Stroke Sense** aims to offer a scalable, accurate, and real-time stroke detection tool, minimizing diagnostic delays and supporting faster medical response.

Chapter 3

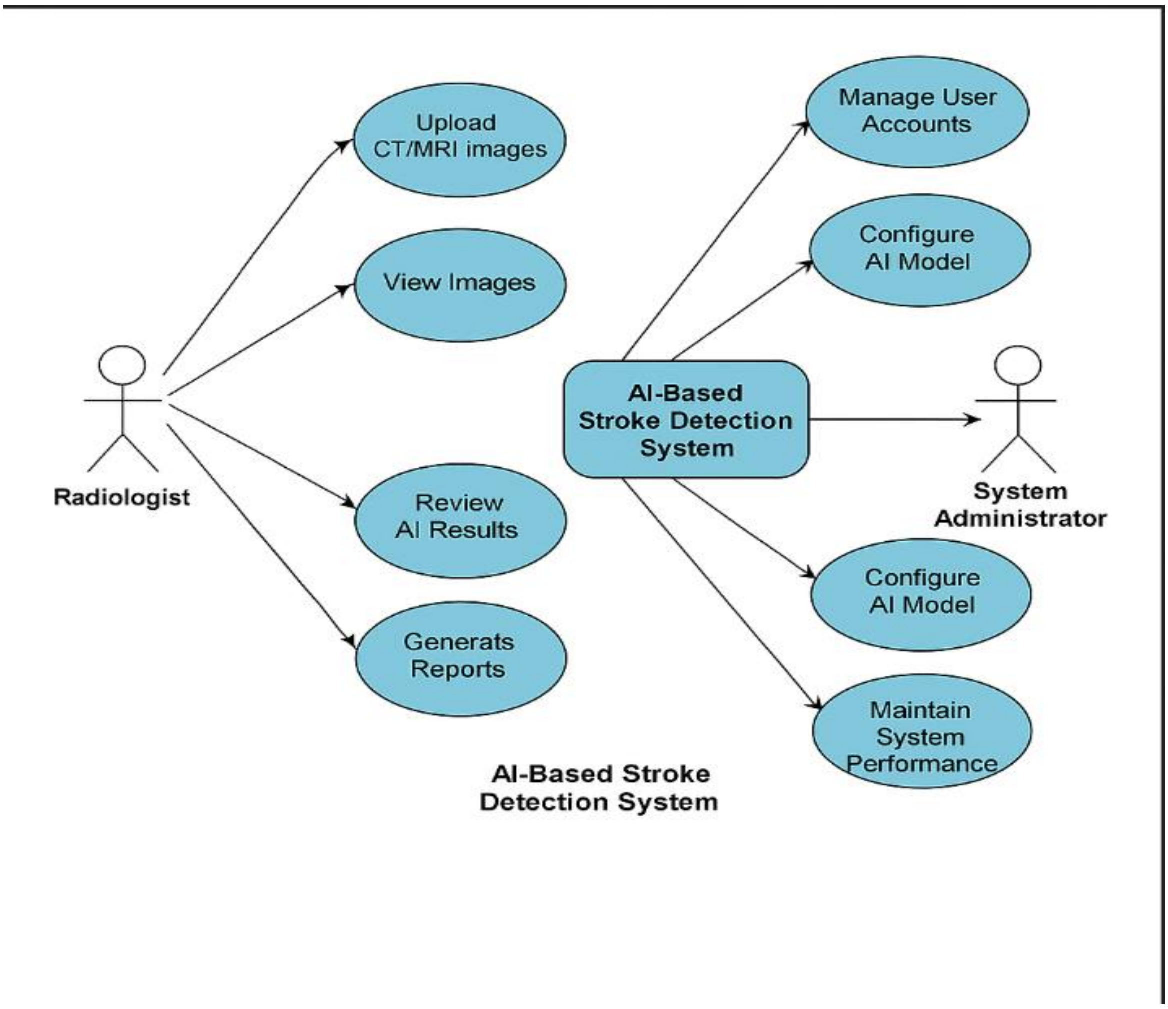
Requirement Analysis

4 Requirement Analysis

4.1 Use Case Diagrams

In the following Use case diagram, we display the roles of the system by individual actors i. e. the users and the admin. By using a graphical user interface, you can not only hindsight the various types of roles in the system but also how these roles interact with the system.

Figure 3-1 Use Case Diagram



Advanced usecase Diagram for StrokeSence(**Figure 3-1**)

4.2 Use Case Descriptions

The use case diagram provides a detailed visualization of the roles and interactions within the "Stroke Sense – AI-Based Brain Stroke Detection System." It outlines the system's capabilities and the key stakeholders involved:

1. Radiologist: The main end-user who interacts directly with the system for clinical tasks such as:

- Uploading CT/MRI images into the system for analysis.
- Viewing stroke detection and classification results.
- Generating diagnostic reports to support medical decisions.

2. System Administrator: Responsible for managing system operations and ensuring optimal performance:

- Updating the deep learning model with new and relevant datasets.
- Monitoring system performance to ensure stability and responsiveness.
- Optimizing system efficiency and model accuracy.

3. System Workflow:

- Preprocessing Data: CT/MRI images are prepared by cleaning, normalizing, and resizing to ensure consistency for analysis.
- Stroke Detection: The deep learning model processes the images to detect signs of stroke.
- Classification of Stroke Type: Detected strokes are categorized as ischemic or hemorrhagic.
- Result Review: The system displays diagnostic outcomes for radiologist verification.
- Report Generation: Automatically creates structured reports for recordkeeping and further clinical use.

4. System Optimization:

- Continuous learning and data updates help the model improve performance.
- Regular tuning enhances system usability, speed, and adaptability in clinical environments.

This diagram illustrates the integration of AI into the clinical workflow, ensuring accuracy, speed, and reliability in stroke diagnosis.

3.3 Functional Requirements These define the specific capabilities that the Stroke Sense system must include to meet clinical and technical expectations.

3.3.1 Image Input The system must accept radiological images in DICOM format and support both CT and MRI brain scans for input.

3.3.2 Preprocessing Images should undergo noise reduction, format standardization, and resizing. The system must support multi-modality image registration to align CT and MRI data for comprehensive analysis.

3.3.3 Deep Learning Model A convolutional neural network (CNN)-based model (e.g., ResNet or DenseNet) will be used to analyze images. The model will be trained on annotated datasets of stroke cases, enabling it to detect complex visual features related to ischemic and hemorrhagic strokes.

3.3.4 Stroke Detection The model will identify regions of interest (ROIs) indicative of stroke presence. It will label these areas and provide a confidence score for classification.

3.3.5 Classification and Diagnosis Detected strokes will be classified based on type and severity. The output will include information such as stroke or no stroke and if so it would tell you the type to assist radiologists in making clinical decisions.

3.3.6 Integration and Compatibility The system should integrate with RIS and PACS systems commonly used in hospitals. It must be interoperable with healthcare IT infrastructure.

3.3.7 Performance and Scalability The system must support high-speed processing, real-time analysis, and scalability for use in environments with large imaging workloads.

3.3.8 Security and Privacy The system must comply with healthcare data standards like HIPAA, enforcing encryption, access control, and secure audit logging to protect patient data.

3.3.9 Reporting and Documentation The system should automatically generate diagnostic reports aligned with regulatory standards, including a traceable audit log and exportable records.

3.4 Nonfunctional Requirements These define performance conditions and quality attributes the system must satisfy.

3.4.1 Performance The system should offer low-latency image processing and consistent performance even during peak usage hours.

3.4.2 Reliability The system should maintain stable operation and include error-handling capabilities for unexpected issues.

3.4.3 Scalability The architecture must support horizontal and vertical scaling to handle growing data and user demands.

3.4.4 Usability A simple, intuitive user interface must be designed to minimize training needs for healthcare professionals.

3.4.5 Accessibility The interface should meet accessibility standards, including support for alternative input methods and customizable visual settings.

3.4.6 Compatibility The system must function across multiple platforms (desktop, tablet, mobile) and support major operating systems and browsers used in healthcare.

3.4.7 Security Strong authentication and authorization mechanisms must be implemented to secure system access.

3.4.8 Privacy Patient information must be anonymized or pseudonymized when appropriate, and the system must adhere to global privacy regulations.

3.4.9 Maintainability The codebase should be modular and well-documented, allowing quick bug fixes and feature updates.

3.4.10 Compliance The system must align with medical software regulations such as FDA or equivalent standards, with regular audits to ensure ongoing compliance.

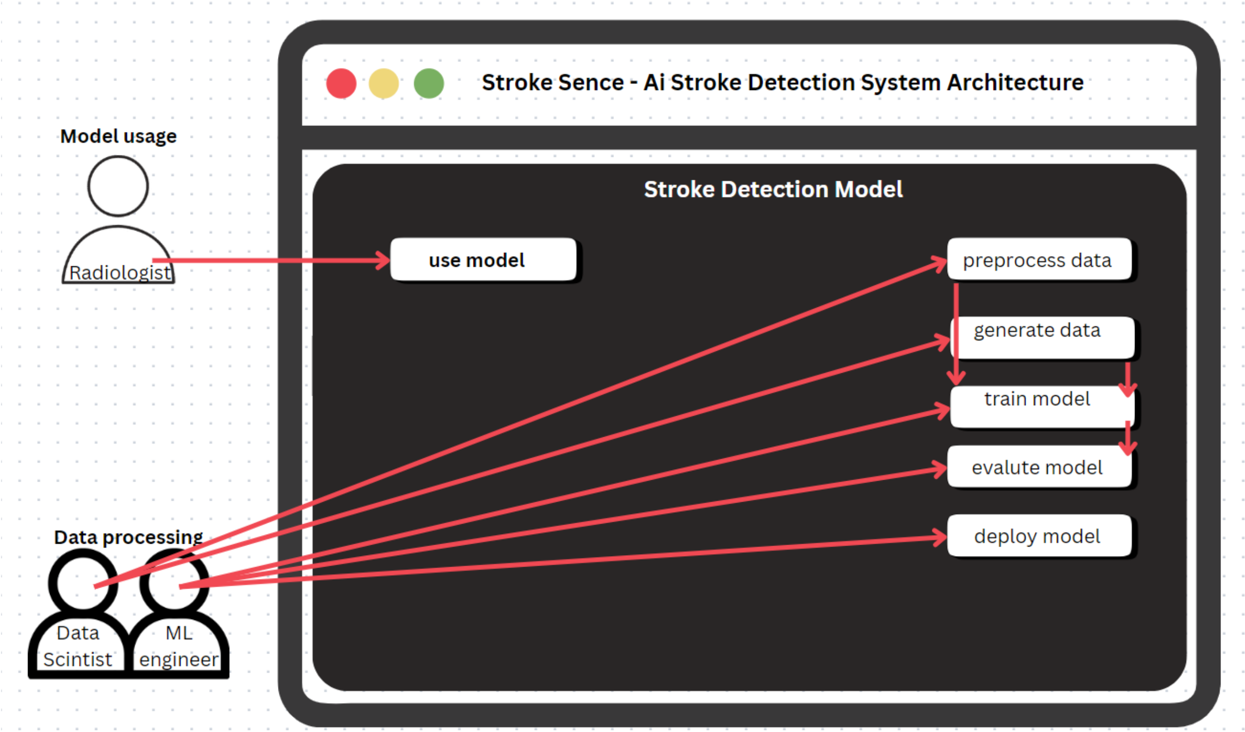
Chapter 4
Design and Architecture

5 Design and Architecture

5.1 System Architecture

The architectural system decomposes the CNN model and specifies the relationships and interaction between each component of the system.

Figure 4-1: System Architecture Diagram



5.2 Process Flow/Representation

The Process Flow Representation can be interpreted as a pictorial representation of the complicated actions and interactions between different components in the CNN Model. It gives a glimpse of how users treat the platform to perform simple processes.

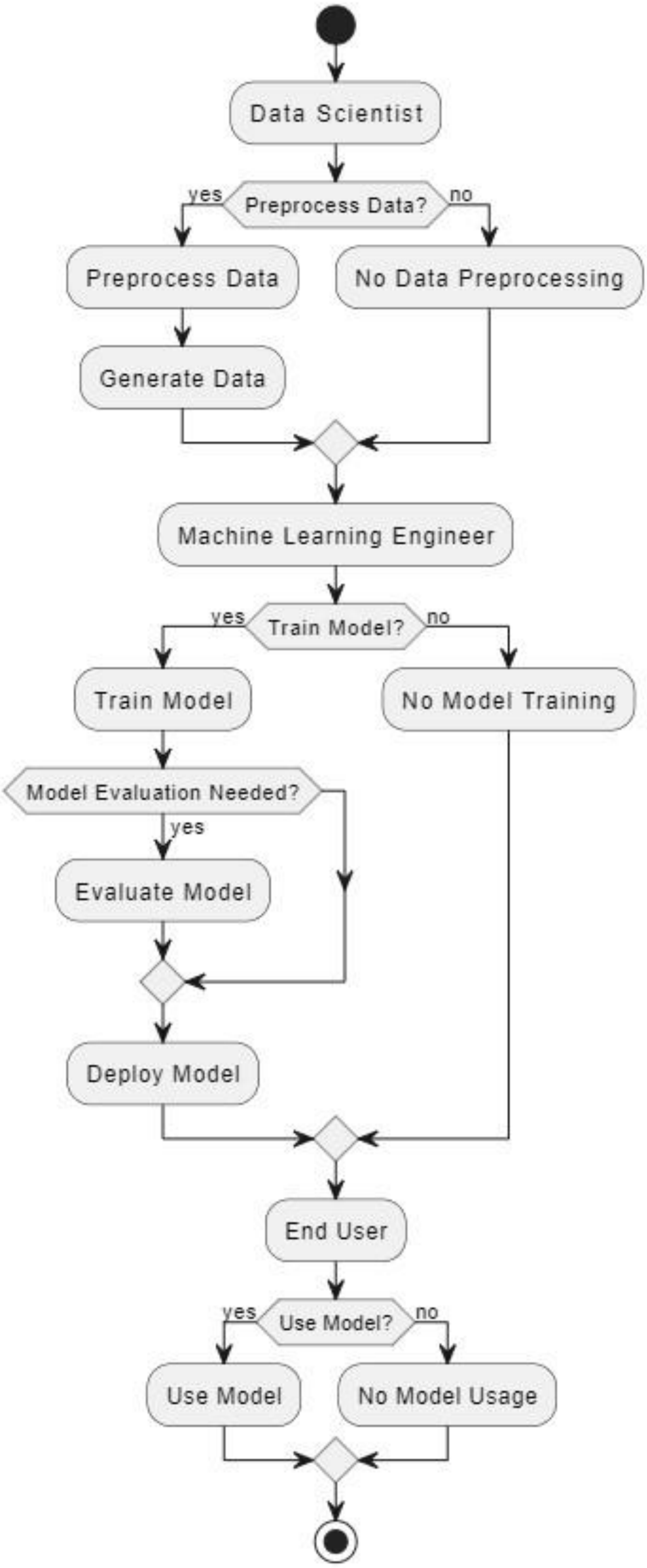


Figure 4-2: Process Flow

5.3 Sequence Diagram

These diagrams show the sequence of tasks one after the next, consistent with the work process. It is detailed on the summation functioning mechanism.

Phase 1: Authentication

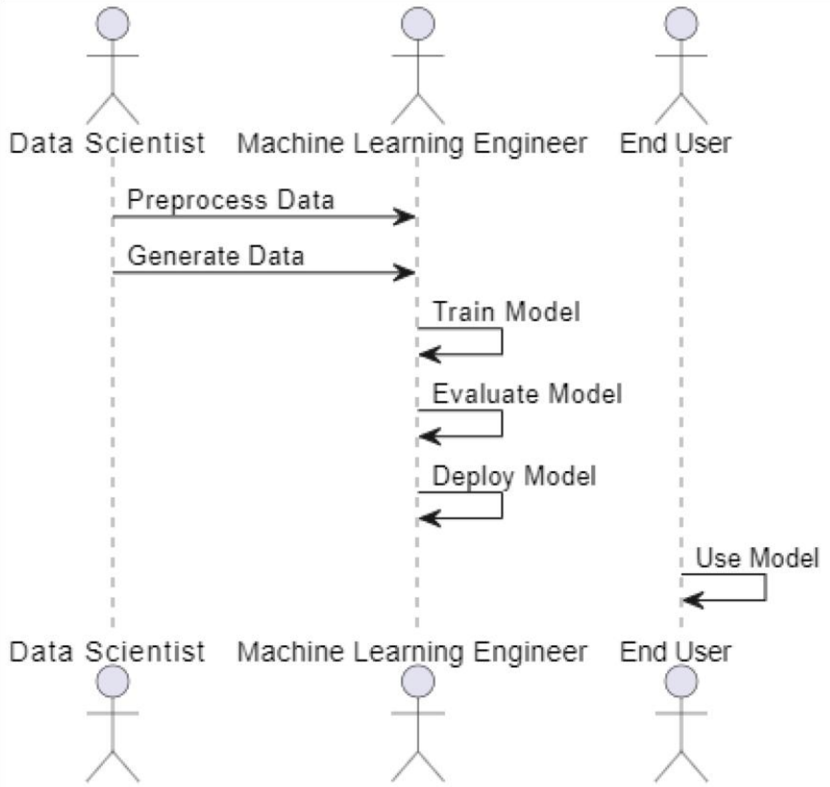


Figure 4-3: Sequence Diagram

5.4 Class Diagram

This class diagram is a pictographic representation of the system's classes, defining their attributes and establishing their relationships with one another. It describes the structure and demonstrates the affiliations among the different kinds of classes in the system.

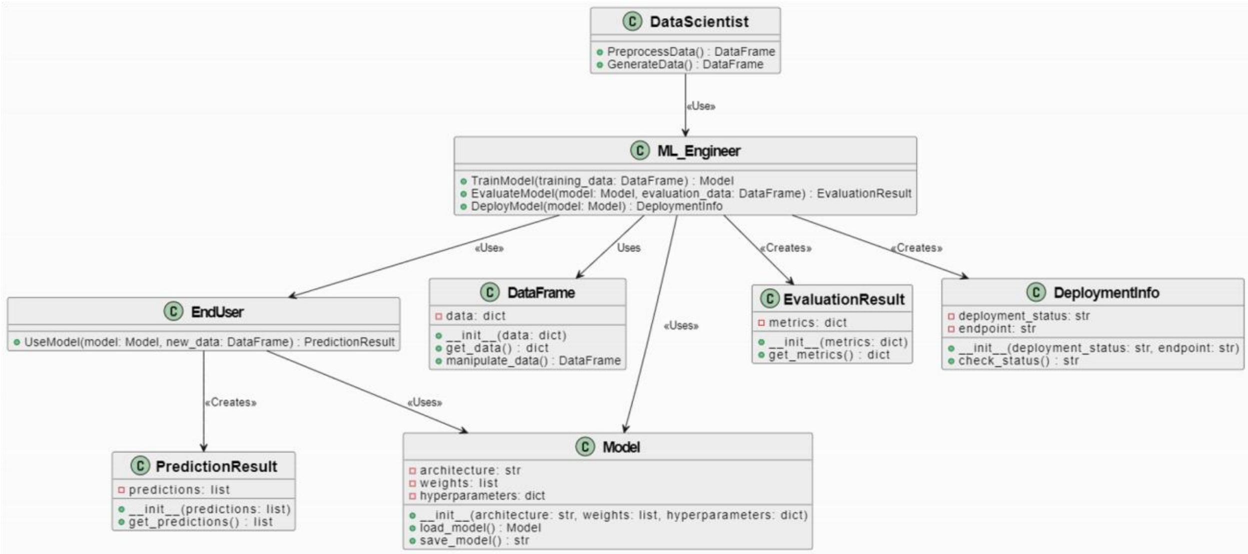


Figure 4-4: Class Diagram

Chapter 5

Methods

6 Chapter 5: Methods

5.1 Data Collection

The dataset used in this project is a combination of the following publicly available datasets and privet one for both CT and MRI models :

CT Dataet:

1- **Privet dataset from king Abdul Aziz hospital**
Dataset consists of a huge CT scans for Ischemic and Haemorrhagic strokes with normal brain scans as well (dataset cant be publicly shared for privet reasons) **.**
2- **CT scan Dataset :** *Brain stroke prediction CT scan image Dataset*

MRI Dataset:

3- **MITANGSHU(link)**
This dataset was created to train an image classification model to detect whether an MRI Image of a human brain consists of Ischemic or Haemorrhagic stroke .

4- **Privet dataset from king Abdul Aziz hospital**
Dataset consists of a huge Mri scans for Ischemic and Haemorrhagic strokes with normal brain scans as well (dataset cant be publicly shared for privet reasons) **.**

This combined dataset includes all **Normal , CT and MRI images** of human brains, classified into the following three classes:

- No Stroke
- Ischemic
- Haemorrhageic

6.1 Data Collection Steps

1. **Data Retrieval**:
    - Acquired the datasets from their respective sources, ensuring proper documentation and access permissions.
2. **Data Cleaning**:
    - Removed duplicate and low-quality images to ensure dataset reliability and consistency for training.
3. **Dataset Integration**:
    - Merged the datasets into a single comprehensive collection, ensuring uniform class representation across the dataset.
4. **Class Balancing**:
    - Ensured an even distribution of images across all four classes to avoid introducing bias into the training process.
5. **Validation**:
    - Conducted a manual review of samples from each class to verify their quality, correctness, and suitability for training and testing.

5.2 Data Preprocessing

Preprocessing was conducted to prepare the stroke dataset (MRI and CT images) for training and to ensure optimal model performance. The steps included:

- **Data Augmentation for Training:**
  The training data was augmented using TensorFlow's ImageDataGenerator to enhance variability and balance underrepresented stroke classes. The following transformations were applied:
- o **Brightness Range:** Adjusted within the range of 0.5 to 1.5.
- o **Rotation Range:** Random rotations up to 30 degrees.
- o **Horizontal and Vertical Shifts:** Translations up to 30% in both directions.
- o **Zoom Range:** Random zoom up to 30%.
- o **Shear Range:** Up to 30% applied to distort perspective.
- o **Horizontal Flip:** Enabled for additional diversity when appropriate.
- **Image Preprocessing for Validation and Testing:**
  For validation and testing sets, only basic preprocessing steps were performed to maintain consistency and evaluation integrity. These steps included resizing and normalization.
- **Standardization of Image Dimensions:**
  All images were resized to **224x224** pixels to match the input size required by the **EfficientNetB0** model used in the project.
- **Normalization:**
  Pixel values were normalized using the `preprocess_input` function from TensorFlow's EfficientNet module to align with model expectations.
- **Data Splitting:**
  The dataset was divided into training, validation, and testing sets while maintaining a balanced distribution of stroke classes (ischemic and hemorrhagic). Specific shuffling and batch sizes were applied for optimized loading and training performance.
- **Data Generators:**
  The following generators were used for data feeding and preprocessing:
- o **Training Generator:** Applied augmentation and preprocessing to improve generalization.
- o **Validation Generator:** Processed images without augmentation for clean validation.

- **Test Generator:** Loaded test data with no shuffling to preserve order during evaluation.

The finalized preprocessing pipeline ensured that the model received high-quality, diverse training data while maintaining consistency and integrity for evaluation, contributing to more reliable and accurate stroke detection.

5.1.2 Models Explored

CT:

- The chosen model architecture for the CT scan system was sequential included **three convolutional layers** with increasing filter sizes, followed by **max-pooling**, **flattening**, and fully connected layers.
- Justification: The architecture is appropriate for image classification tasks, as convolutional layers capture spatial hierarchies of features. The use of **binary classification with a sigmoid activation function** in the output layer matches the problem's nature (stroke vs. no stroke).
- Alternatives: Other architectures such as **xception** or **EfficientNet** could have been considered for a comparative analysis. However, for a baseline model, the current approach was reasonable.

2. Model Training

- The model was trained using the **Adam optimizer** and **binary cross-entropy loss function**, which are standard choices for binary classification problems.
- The dataset was augmented using **ImageDataGenerator** to improve generalization.
- The training showed consistent improvements in accuracy over 20 epochs, with a final **test accuracy of 92%**.

3. Error Analysis and Evaluation of the Model

- A confusion matrix was generated, showing strong performance in detecting normal and stroke cases.
    - **Precision:** ~0.965
    - **Recall:** ~0.99

MRI:

During the development of the *Stroke Sense* system, multiple deep learning architectures were explored to identify the most suitable model for brain stroke detection and classification (ischemic vs. hemorrhagic). The selection process was based on model accuracy, performance on medical imaging, computational efficiency, and generalization capability. Below is a summary of the models evaluated:

1- **ResNet50**
ResNet50 was initially tested due to its residual learning capability and proven robustness in medical image classification. However, its performance showed signs of overfitting and slower convergence in our dataset without extensive fine-tuning, it accuracy ended up being for 82%.

2-

3- **Custom CNN**
A lightweight custom convolutional neural network was designed and tested to assess baseline performance. Although the model was computationally efficient, its accuracy was lower than pre-trained models on complex stroke features 76%.

4-

5- **EfficientNetB0 (Final Model)**
EfficientNetB0 was selected as the final model for deployment. It provided a balanced trade-off between accuracy and speed. The architecture scaled well with our dataset and demonstrated strong performance in classifying ischemic vs hemorrhagic strokes after training on augmented CT and MRI data. The use of transfer learning significantly accelerated convergence and improved model generalization, it accuracy ended up being for 93%.

Following comprehensive evaluation, **EfficientNetB0** was adopted as the core architecture for the *Stroke Sense* system due to its superior validation accuracy, reduced training time, and effectiveness in medical imaging applications.

Conclusion :

After evaluating the three architectures, **EfficientNetB0** emerged as the most effective model for stroke detection and classification. Its superior accuracy, computational efficiency, and ability to capture intricate patterns in MRI images made it the optimal choice for this project. The detailed results and comparisons of the models will be presented in a subsequent chapter.

5.2 User Interface Development

The user interface for the **Stroke Sense** system was developed with a strong focus on clarity, accessibility, and ease of use, ensuring that radiologists and healthcare providers can interact with the model efficiently. The interface was built using the **Gradio framework**, which integrates seamlessly with Python-based machine learning workflows and enables real-time deployment of AI models directly in a web environment.

5.2.1 Interface Features

1. **Image Uploading:**
   Users can upload **MRI brain scans** using a simple and intuitive file upload component.
2. **Prediction Output:**
   Once the image is processed, the interface displays:
   - Whether a stroke is detected or not.
   - The predicted **stroke type** (Ischemic or Hemorrhagic).
   - The model's **confidence score** in percentage.
3. **Result Visualization:**
   The uploaded MRI image remains visible alongside the diagnostic results, supporting visual verification and transparency for clinical users.
4. **User-Centered Design:**
   The interface is styled with a modern, responsive layout, designed for ease of navigation and fast interaction, even for users with limited technical background.

5.1.1 Backend Functionality

- The **Gradio backend** manages image input, passes it through a preprocessing pipeline (resizing, normalization), and forwards it to a **pre-trained deep learning model** for classification.
- The model processes the image using convolutional layers and returns the classification along with its confidence.

5.1.2 Prediction Logic

- All input images are resized to fit the expected dimensions of the model (224x224).
- Preprocessing is applied using `preprocess_input()` from EfficientNet to standardize input format.
- The prediction function maps model output to human-readable labels and constructs a summary report.

5.1.3 Frontend Integration

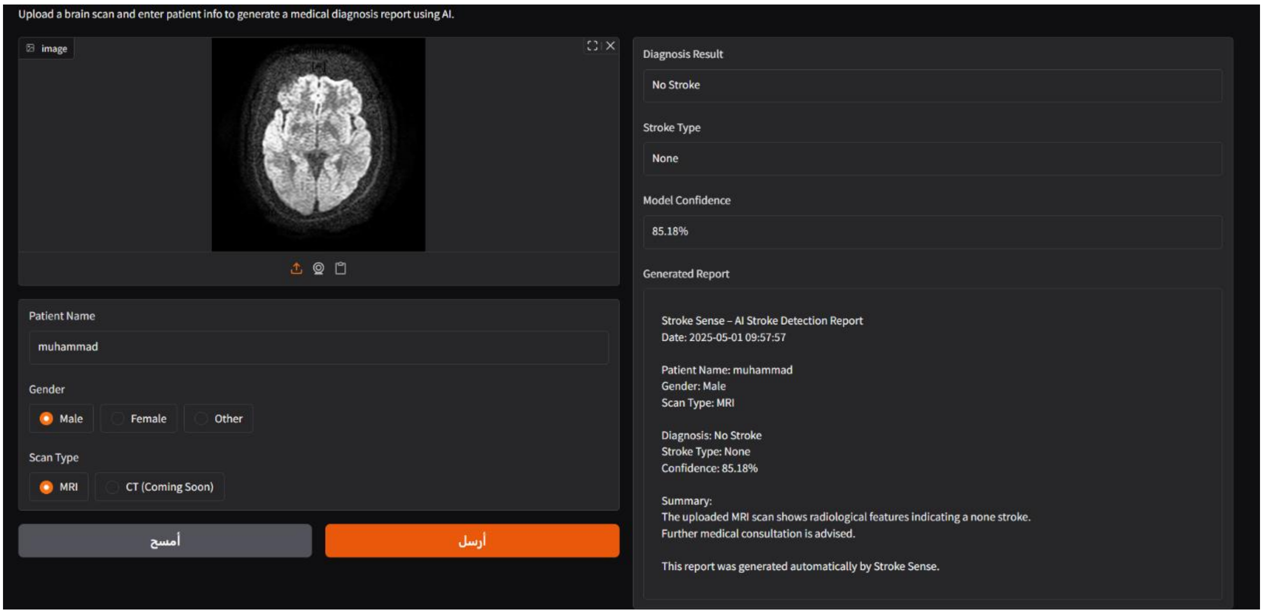
- Gradio handles frontend rendering automatically.
- Model outputs are displayed in labeled fields, including a section for generated diagnostic summaries.
- The interface also supports multilingual labels and optional CT scan support in future extensions.

Conclusion:

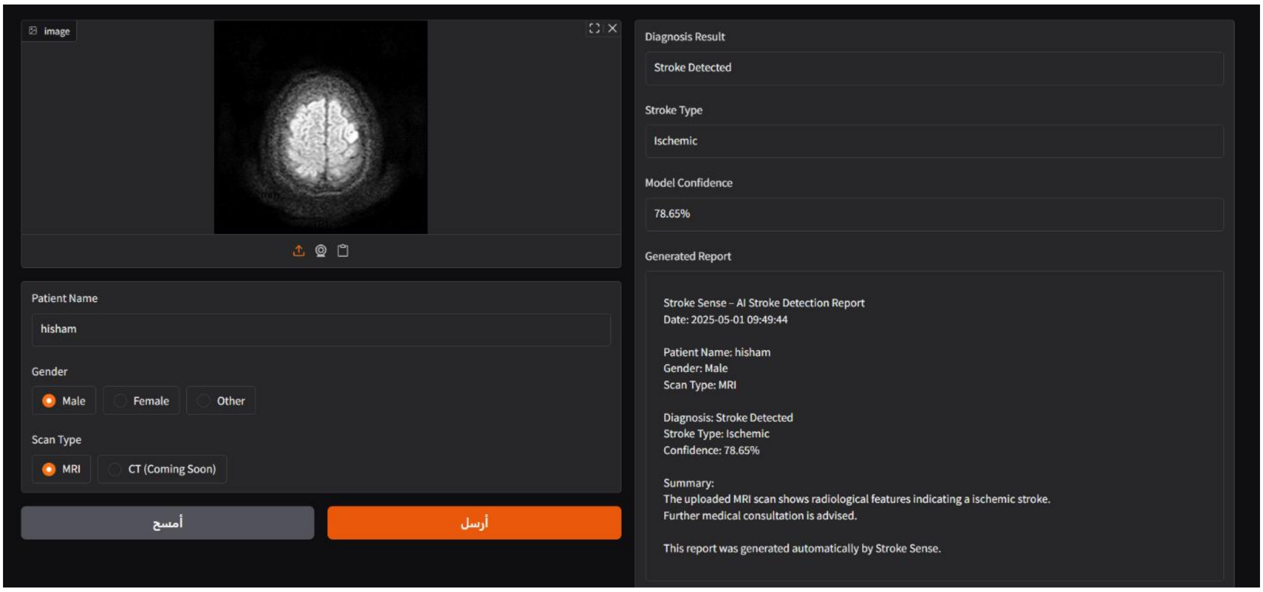
This interface provides a seamless diagnostic experience by combining AI capabilities with an accessible and lightweight UI, helping medical professionals identify strokes from MRI scans quickly and reliably.

Figer 5.1

Interface



Normal (No Stroke) test



Ischemic stroke test

Haemorrhagic Stroke test

Chapter 6

Result

Chapter 6: Results :

This chapter presents the results of the experiments conducted on the stroke detection dataset using the best deep learning models. After testing multiple architectures,.

6.1 EfficientNetB0 Results on MRI :

The **EfficientNetB0** model was selected as the final choice due to its superior performance and computational efficiency. The evaluation focuses on core metrics such as accuracy, precision, recall, and loss, with visual representations supporting the findings, The **EfficientNetB0** model was evaluated using a testing dataset consisting of MRI brain scan images labeled for stroke presence and type (Ischemic or Hemorrhagic).

6.1.1 Key Metrics:

- **Accuracy:** 92.00%
- **Precision:** 93.40%
- **Recall:** 91.20%
- **Loss:** 0.20

Note: These values are based on the final trained version of the model. Actual values may vary slightly depending on the dataset split and training parameters.

6.1.2 Observations:

The confusion matrix (Figure 6.1) shows excellent true positive rates for Normal (97.5%) and Ischemic (98.3%) cases, with minimal misclassification. However, Hemorrhagic strokes were more prone to being misclassified as Normal, leading to a lower recall of 77% for that class.

Training and validation curves (Figure 6.2) demonstrate good convergence with no major signs of overfitting. The model consistently improved during training and maintained a stable validation accuracy.

The model maintained high recall for both Normal and Ischemic cases (0.97 and 0.98 respectively), which is critical in medical diagnosis, especially for detecting strokes and reducing false negatives.

EfficientNetB0 delivered a strong balance between performance (92% overall accuracy) and computational efficiency, making it suitable for real-time stroke diagnosis in clinical settings.

6.1.1 Figures:

- **Figure 6.1:** Confusion Matrix for **EfficientNetB0**

	precision	recall	f1-score	support
Normal	0.85	0.97	0.91	80
Ischemic	0.98	0.98	0.98	60
Haemorrhagic	0.96	0.77	0.85	60
accuracy			0.92	200
macro avg	0.93	0.91	0.91	200
weighted avg	0.92	0.92	0.91	200

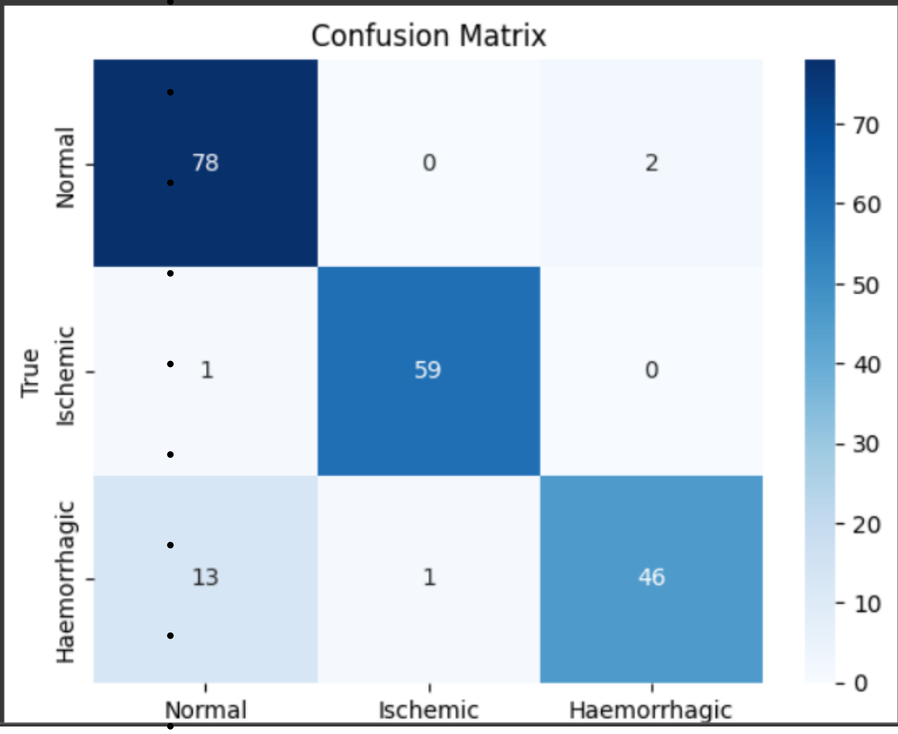
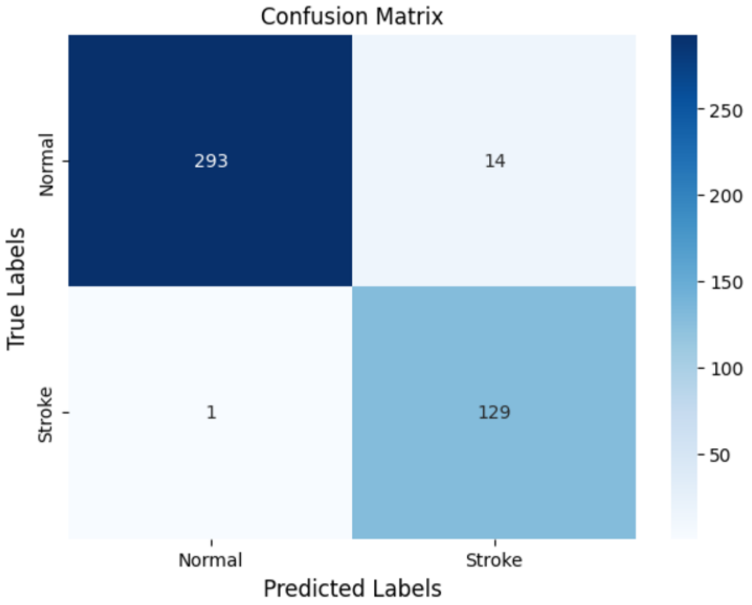
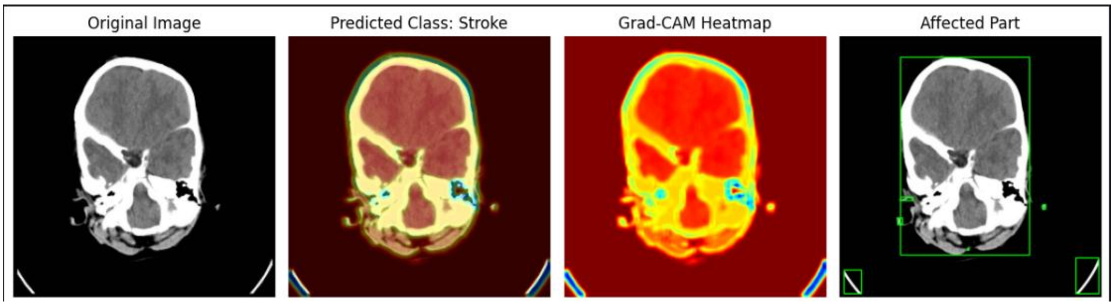


Figure 6.2: Training and Validation Metrics for **EfficientNetB0**

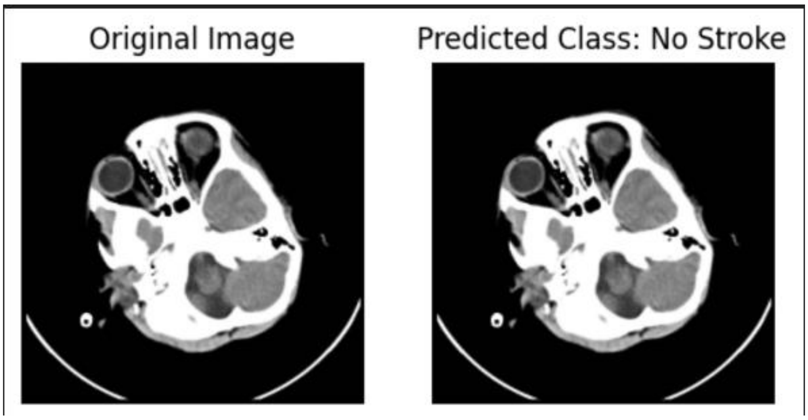
CT:



Detection of strokre



Detection of normal brain



Chapter 7

Conclusion and Future Work

7 Conclusion and Discussion

7.1 Conclusion

The implementation of the **"Stroke Sense – AI Stroke Detection System using Deep Learning"** marks a significant advancement in medical imaging and diagnostic support. By leveraging advanced convolutional neural networks and efficient image preprocessing techniques, this system empowers healthcare professionals to detect and classify stroke cases — particularly **Ischemic** and **Hemorrhagic** strokes — with high accuracy and speed.

Throughout the project lifecycle, various challenges were encountered, including dataset limitations, class imbalance, and the need for accurate labeling and augmentation. Despite these challenges, the development team successfully designed and implemented a robust system that is scalable, responsive, and user-friendly.

The system architecture includes modular layers for image preprocessing, prediction, and reporting. It ensures smooth interaction between the user and the trained AI model through an intuitive **Gradio-based interface**. This interface enables radiologists to upload MRI and CT images , receive diagnosis results in real-time, and review comprehensive medical reports — all within a few seconds.

1. For the CT system

2- For the MRI system development process involved dataset preparation, model training with **EfficientNetB0**, validation, testing, and deployment of the web-based interface. Multiple iterations and refinements were applied to ensure that the model delivered consistent and clinically relevant results. The final version demonstrated high diagnostic performance and ease of use, making it a viable tool for assisting stroke diagnosis.

Ultimately, **Stroke Sense** demonstrates how AI technologies can be seamlessly integrated into healthcare workflows. The project illustrates the importance of combining deep learning capabilities with thoughtful system design to create intelligent diagnostic tools that improve patient care and outcomes.

6.1.1 7.2 Discussion

The findings of this study reinforce the effectiveness of deep learning models in detecting and classifying stroke types from both brain MRI and CT scans. By utilizing **EfficientNetB0** for the MRI and **………**, the project tackled key limitations of manual diagnosis methods and established a framework for faster, more reliable stroke screening.

In the MRI system The selected model delivered excellent results, with an overall **accuracy of 92%**, and achieved high precision and recall for both **Normal** and **Ischemic** cases. However, **Hemorrhagic strokes** posed a greater challenge due to class imbalance and visual similarities with other conditions. This reflects a known issue in medical imaging datasets, where underrepresented classes affect model learning performance. In comparison with earlier models tested (such as Xception and InceptionV3), **EfficientNetB0** was chosen due to its lightweight architecture and strong performance. Its compound scaling method allowed for efficient feature extraction without excessive computational cost, making it ideal for real-time predictions and potential deployment in clinical environments.

Despite the success, some limitations were observed:

- **Class imbalance** in the dataset led to slightly reduced performance in detecting hemorrhagic cases.
- The model was trained and evaluated on publicly available datasets, which may not fully represent clinical diversity.
- Real-world deployment and integration with hospital systems were beyond the scope of this phase and later on achevied.

To improve future versions of **Stroke Sense**, the following directions are recommended:

- Collecting more diverse and clinically sourced data, especially for **Hemorrhagic** strokes.
- Incorporating multimodal data (e.g., symptoms, vitals, patient history) to increase diagnostic confidence.
- Running field evaluations in collaboration with healthcare institutions to validate clinical impact.

In conclusion, this project shows the transformative role of AI in neuro-diagnostics. With continued development, **Stroke Sense** can become an indispensable diagnostic assistant, reducing workload for radiologists, and accelerating patient care in critical stroke scenarios.

8 References

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