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Deep Learning-Based Intelligent Model for Automated Detection and Classification of Lumbar Spine Diseases using MRI images

A graduation project submitted to the Department of Electrical Engineering, in partial fulfillment for the requirements for the award of the degree of Bachelor of Electrical Engineering

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2025

بسم الله الرحمن الرحيم

((يَرْفَعِ اللَّهُ الَّذِينَ آمَنُوا مِنكُمْ وَالَّذِينَ أُوتُوا الْعِلْمَ دَرَجَاتٍ))المجادلة اية(١١)

صدق الله العلي العظيم

SUPERVISOR CERTIFICATION

I certify that the preparation of this project entitled
(Deep Learning-Based Intelligent Model for
Automated Detection and Classification of
Lumbar Spine Diseases using MRI images)

Prepared by (Haider Shaker Esmail, Ahmed Salim Raheem,
Maryam Muhammad Abdel Nabi, Hussein Ali Abboud**)**

was under my supervision at General Electrical Engineering Branch, Electrical Engineering Department, University of Misan in partial fulfilment of the requirements for the degree of Bachelor of Science in Electrical Engineering.

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Date: / /2025

CERTIFICATE OF EXAMINERS

We certify, as an examining committee, that we have read this project report entitled " Deep Learning-Based Intelligent Model for Automated Detection and Classification of Lumbar Spine Diseases using MRI images "

examined the students (Haider Shaker Esmail, Ahmed Salim Raheem, Maryam Muhammad Abdel Nabi, Hussein Ali Abboud) in its contents and found the project meets the standard for the degree of Bachelor of Science in Electrical Engineering.

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Praise be to ***ALLAH*** *who enabled us to complete this work under his benediction.*

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ABSTRACT

This study presents a comprehensive deep learning framework for the automatic classification of lumbar spine diseases using magnetic resonance imaging (MRI). The goal is to reduce the dependency on manual image interpretation by radiologists, which can be time-consuming and prone to subjectivity. Leveraging a dataset of over 170,000 annotated MRI slices, we evaluated multiple state-of-the-art convolutional neural network (CNN) architectures, including InceptionV3, Xception, VGG16, NASNetLarge, ResNet50, MobileNetV2, and DenseNet. Each model was trained under standardized preprocessing and augmentation techniques to ensure consistency and robustness. Among all models, InceptionV3 achieved the highest classification accuracy of 88.2%, followed closely by MobileNetV2 and Xception, while ResNet50 demonstrated the lowest performance.

The study also addresses several challenges encountered throughout the research process, including inconsistencies in dataset formatting, the difficulty of locating high-quality labeled data, software compatibility issues with Python 3.9, and hardware limitations during training. Despite these constraints, the results validate the feasibility and potential of applying deep learning techniques to spinal disease diagnosis.

This research underscores the value of integrating AI into medical imaging workflows, especially for enhancing diagnostic accuracy and speed. The proposed system lays the groundwork for future advancements, including mobile deployment, IoT integration, and real-time clinical application.

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Introduction

1.1 Introduction

In recent years, artificial intelligence (AI) has experienced remarkable growth, particularly in the field of deep learning. These advancements have had a transformative effect on many domains, most notably healthcare, where intelligent algorithms are increasingly being adopted to support medical diagnosis and improve clinical decision-making processes. Among the most promising applications of AI in healthcare is the automated analysis and classification of medical images, which has the potential to enhance diagnostic accuracy and reduce human workload.

Magnetic Resonance Imaging (MRI) has become a critical imaging modality for diagnosing spinal disorders, especially those affecting the lumbar region. Lumbar spine diseases—including disc degeneration, spinal stenosis, and herniated discs—are a leading cause of chronic lower back pain and disability across the globe. Timely and accurate identification of such conditions is vital for effective intervention and long-term patient care [1][2].

In this research project, we focus on the development of a deep learning-based system for the classification of lumbar spine diseases using MRI scans. Our approach leverages convolutional neural networks (CNNs) and other advanced models to automatically detect and categorize spinal pathologies with high reliability. By building upon the foundations laid by previous work in medical image analysis, we aim to contribute a solution that improves diagnostic efficiency, supports radiologists, and ultimately leads to better patient outcomes [3][4].

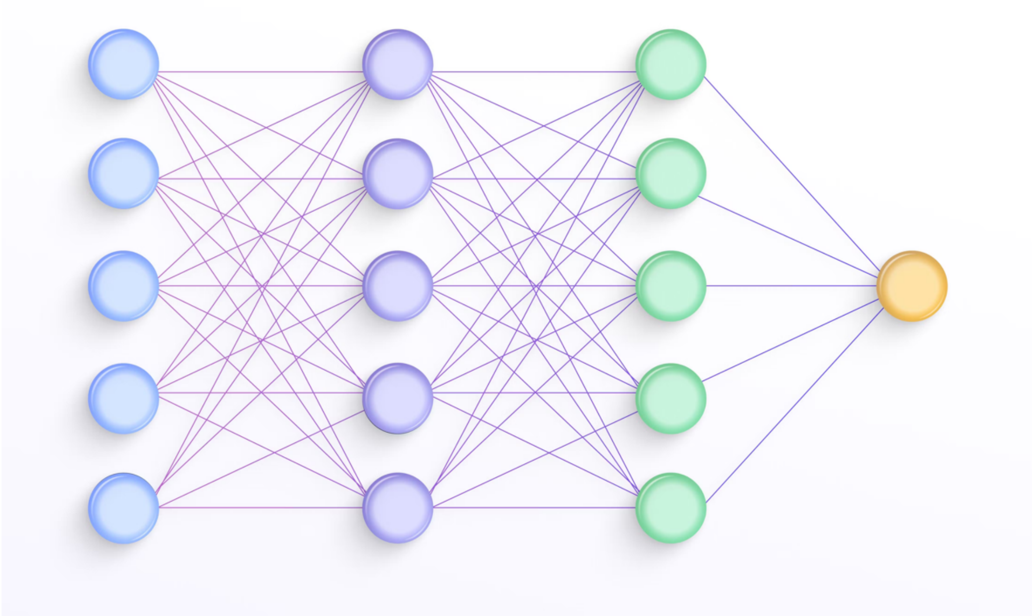

Figure 1.1 Convolutional Neural Networks

1.2 Historical Overview

The integration of artificial intelligence into the field of medical imaging has progressed through several significant stages. Initially, conventional image processing techniques such as thresholding, edge detection, and histogram analysis were utilized to extract basic features from medical images. However, these techniques often struggled to capture the complexity and variability inherent in anatomical structures, particularly those found in the spine [5].

In the early 2000s, the application of machine learning algorithms—such as support vector machines (SVM), decision trees, and random forests—marked a major improvement in diagnostic automation. These models introduced data-driven decision-making but still relied heavily on handcrafted features, limiting their adaptability and generalizability [6].

The advent of deep learning revolutionized this landscape, particularly through the use of convolutional neural networks (CNNs). These networks demonstrated superior capabilities in visual recognition tasks and soon found widespread use in medical imaging. Early implementations in spinal analysis involved vertebral segmentation and disc localization, laying the groundwork for more sophisticated applications [1][7].

As research evolved, attention shifted from structural analysis to disease classification. Notably, deep learning models have shown significant success in detecting lumbar spine conditions such as spinal stenosis, disc degeneration, and foraminal narrowing. Some models have achieved classification accuracies exceeding 90%, outperforming traditional diagnostic tools in speed and precision [4][8].

Our project builds upon this historical progression, applying modern deep learning techniques to further advance the automated classification of lumbar spine diseases from MRI data. This foundation not only highlights the importance of AI in medical imaging but also underscores its growing role in future clinical practices.

1.2.1 Evolution of Deep Learning in Medical Diagnosis

The application of deep learning in medical diagnosis has evolved rapidly over the past decade, reshaping the landscape of computer-aided diagnosis (CAD) systems. Initially, CAD relied on manually engineered features extracted by domain experts, which limited the scalability and generalization of diagnostic tools. These conventional systems often struggled with inter-patient variability and image noise, especially in complex modalities such as MRI [5].

The introduction of deep learning, and particularly convolutional neural networks (CNNs), brought a significant paradigm shift. CNNs have the ability to automatically learn hierarchical features directly from raw image data, eliminating the need for manual feature extraction. This capability has proven especially beneficial in medical contexts, where subtle variations in tissue structure or shape can be critical for accurate diagnosis [3].

In the early stages, deep learning was applied to relatively simple classification tasks, such as distinguishing between healthy and diseased tissues. As computational power and dataset availability increased, more complex models were introduced to handle multi-class classification, lesion localization, and even image generation for data augmentation purposes. Transfer learning further accelerated this progress by allowing pretrained models—originally developed for general-purpose image recognition—to be fine-tuned for medical imaging applications [7].

Specifically in spinal diagnostics, deep learning has been employed to classify various pathologies, detect anatomical landmarks, and quantify disease severity. For instance, CNN-based systems have been developed to classify intervertebral disc degeneration and spinal stenosis with high levels of accuracy, sometimes surpassing the performance of human radiologists [2][4]. These advancements not only improve diagnostic precision but also enable faster workflows in clinical settings, reducing both the burden on specialists and the time to treatment initiation.

As deep learning continues to evolve, its role in medical diagnosis is expected to expand, driven by innovations in model architecture, data fusion, and explainability. Our project seeks to build on this trajectory by developing a robust deep learning framework specifically tailored for classifying lumbar spine conditions from MRI images.

1.2.2 Application in Lumbar Spine Disease Detection

Deep learning has demonstrated significant potential in the detection and classification of lumbar spine diseases, particularly through the analysis of MRI scans. The lumbar region of the spine is a common site of degenerative changes, including disc herniation, spinal stenosis, and intervertebral disc degeneration, which are often difficult to assess manually due to anatomical complexity and inter-patient variability. Deep learning models, particularly convolutional neural networks (CNNs), have emerged as powerful tools for automating this diagnostic process [1][2].

One major application is the classification of intervertebral disc degeneration. By training CNNs on large datasets of lumbar spine MRIs, researchers have achieved high accuracy in distinguishing between different stages of degeneration. These models analyze features such as disc shape, signal intensity, and structural deformation—factors that are critical for proper diagnosis and treatment planning [4].

Another important application lies in the detection of spinal stenosis, a condition where the spinal canal narrows and compresses the spinal cord or nerve roots. Deep learning approaches have been employed to not only identify the presence of stenosis but also grade its severity, which plays a crucial role in surgical decision-making. Some models utilize both sagittal and axial MRI views to capture the full anatomical context and improve classification robustness [3][6].

Additionally, advanced models have been proposed to perform multi-task learning, where a single network is trained to simultaneously classify multiple lumbar spine conditions. This enhances clinical utility by providing a comprehensive analysis of a patient's MRI in a single inference step. The incorporation of transfer learning techniques has also allowed researchers to overcome data scarcity issues, further improving performance in real-world applications [7].

The successful deployment of these systems has highlighted the transformative role of deep learning in spinal diagnostics. By improving detection speed and reducing human error, such models support radiologists in achieving more consistent and reliable diagnoses. Our project builds directly upon these applications, seeking to implement a deep learning-based framework optimized for accurate classification of lumbar spine diseases using MRI data [2][8].

1.3 Motivation

The motivation behind this research stems from the increasing prevalence and clinical significance of lumbar spine diseases worldwide. Conditions such as disc degeneration, spinal stenosis, and herniated discs contribute significantly to chronic lower back pain, disability, and reduced quality of life for millions of individuals. Early and accurate diagnosis is essential to ensure effective treatment and prevent disease progression, yet current diagnostic processes remain labor-intensive, time-consuming, and subject to inter-observer variability [1][2].

Magnetic Resonance Imaging (MRI) is widely recognized as the gold standard for spinal assessment due to its superior soft tissue contrast and non-invasive nature. However, interpreting lumbar spine MRI scans demands a high level of expertise and experience, which may not be readily available in all clinical settings, particularly in underserved regions. This challenge underscores the need for automated, reliable, and efficient diagnostic tools that can assist radiologists and clinicians in making timely and precise decisions [3][4].

Deep learning techniques, with their ability to learn complex patterns directly from imaging data, present a promising solution to these challenges. By automating the classification of lumbar spine diseases, deep learning models can reduce diagnostic workload, minimize human error, and improve patient outcomes through faster and more consistent analysis [5][6].

Therefore, this project aims to develop a deep learning-based framework for the classification of lumbar spine diseases using MRI images. By leveraging advances in convolutional neural networks and transfer learning, we aspire to create a tool that enhances diagnostic accuracy, supports clinical decision-making, and ultimately contributes to better healthcare delivery in the field of spinal medicine [7][8].

1.4 The Aim of This Project

The primary aim of this project is to develop a deep learning-based model using Convolutional Neural Networks (CNNs) to classify lumbar spine diseases from MRI images. This project seeks to enhance the diagnostic process by creating an automated system capable of accurately identifying and categorizing various spine-related conditions. By utilizing deep learning techniques, the model aims to reduce the dependency on manual image interpretation by medical professionals, thereby improving the efficiency, speed, and accuracy of the diagnosis.

Furthermore, this project aims to explore and evaluate the effectiveness of CNNs in analyzing MRI images of the lumbar spine, with a focus on achieving high classification performance in distinguishing between different types of spinal disorders. The ultimate goal is to create a reliable tool that can assist healthcare providers in making informed decisions and offer a more efficient, timely, and precise method for diagnosing lumbar spine diseases.

In summary, the project aims to bridge the gap between cutting-edge artificial intelligence techniques and practical medical applications, improving diagnostic outcomes for patients and supporting healthcare professionals in their decision-making processes.

1.5 Chapters Layout

- **Chapter One:** Introduction
- **Chapter Two:** Thepritical Part
- **Chapter Three:** result and discussion
- **Chapter Four:** Conclusions and Feature Works

Chapter Two

Thepritical Part

2.1 Deep Learning

Deep learning is a subset of machine learning that focuses on algorithms inspired by the structure and function of the human brain, specifically artificial neural networks with multiple layers. These multilayered networks, known as deep neural networks (DNNs), are capable of learning complex representations from large volumes of data, enabling them to perform tasks such as image recognition, natural language processing, and speech recognition with remarkable accuracy [1].

In the context of medical imaging, deep learning has revolutionized the way images are analyzed and interpreted. Traditional machine learning methods often relied on handcrafted features and domain-specific knowledge, which limited their ability to generalize across different datasets and imaging modalities. In contrast, deep learning models, particularly convolutional neural networks (CNNs), automatically learn hierarchical features directly from raw image data, capturing intricate patterns that may be imperceptible to human observers [2][3].

CNNs have become the dominant architecture for medical image analysis due to their ability to exploit spatial hierarchies and local correlations within images. Through layers such as convolution, pooling, and fully connected layers, CNNs progressively extract features ranging from simple edges to complex shapes and textures. This capability makes CNNs particularly well-suited for detecting subtle abnormalities in medical images, including magnetic resonance imaging (MRI) scans of the lumbar spine [4].

Moreover, the development of advanced techniques such as transfer learning, data augmentation, and attention mechanisms has further enhanced the performance and robustness of deep learning models in medical applications. Transfer learning enables the use of pretrained networks on large natural image datasets to be fine-tuned on smaller, domain-specific medical datasets, addressing challenges related to data scarcity [5].

In summary, deep learning provides a powerful framework for automated medical image analysis, offering promising solutions for tasks such as the classification of lumbar spine diseases from MRI images. Our research leverages these strengths to develop a deep learning-based model that can accurately and efficiently classify lumbar spine pathologies, ultimately contributing to improved diagnostic workflows.

2.2 CNN (Convolutional Neural Networks)

Convolutional Neural Networks (CNNs) represent a specialized class of deep learning models that have achieved remarkable success in image processing and computer vision tasks. Their architecture is specifically designed to automatically and adaptively learn spatial hierarchies of features through the use of convolutional layers, which act as learnable filters scanning over input images to detect patterns such as edges, textures, and shapes [1][2].

The fundamental building blocks of CNNs include convolutional layers, pooling layers, activation functions, and fully connected layers. Convolutional layers apply a set of filters to input data, generating feature maps that highlight specific characteristics within localized regions. Pooling layers reduce the spatial dimensionality of these feature maps, which helps to lower computational complexity and enhance translation invariance. Activation functions, such as ReLU (Rectified Linear Unit), introduce nonlinearity enabling the network to model complex relationships. Fully connected layers at the network's end combine the extracted features to perform classification or regression tasks [3].

In medical imaging, CNNs have demonstrated an exceptional ability to identify subtle and complex features that are often difficult to detect through traditional image analysis methods. This capability makes them highly effective in applications such as disease detection, segmentation, and classification in modalities like MRI, CT scans, and X-rays. Specifically, for lumbar spine MRI analysis, CNNs can learn discriminative features that distinguish between healthy and pathological tissues, facilitating the automated diagnosis of conditions such as intervertebral disc degeneration and spinal stenosis [4][5].

Recent advancements in CNN architectures—such as ResNet, DenseNet, and EfficientNet—have further improved model depth and performance while mitigating issues like vanishing gradients and overfitting. Additionally, techniques like batch normalization and dropout regularization contribute to more stable and generalized models suitable for clinical applications [6].

Overall, CNNs form the cornerstone of modern medical image analysis and play a critical role in our proposed system for classifying lumbar spine diseases. Their adaptability and powerful feature extraction capabilities enable the development of robust and accurate diagnostic tools, advancing the integration of AI into clinical workflows.

2.3 Mathematical Equations and Metrics Used in Image Classification

In the context of image classification, several mathematical metrics and loss functions are used to evaluate the performance of deep learning models. These metrics provide valuable insights into how well a model is performing in terms of accuracy, efficiency, and robustness. Some of the most commonly used metrics include accuracy, loss functions, precision, recall, and the F1-score. Below are the key formulas and their explanations:

1. Accuracy

Accuracy is the percentage of correct predictions made by the model out of all predictions [1][2]. It is defined as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

- TP = True Positives (correctly predicted positive cases)
- TN = True Negatives (correctly predicted negative cases)
- FP = False Positives (incorrectly predicted positive cases)
- FN = False Negatives (incorrectly predicted negative cases)

2. Loss Function

The loss function measures the difference between the predicted output and the actual output. A common loss function used in classification tasks is Cross-Entropy Loss[1][3]:

$$\text{Loss} = -\sum y_i \log p_i$$

Where:

- Loss = loss
- y_i = true label (1 for correct class, 0 for others)
- p_i = predicted probability for class i

3. Precision

Precision measures the proportion of true positive predictions out of all predicted positive instances. It is defined as:

$$\text{Precision} = \frac{TP}{TP + FP}$$

4. Recall

Recall (also known as Sensitivity) measures the proportion of true positive predictions out of all actual positive instances. It is defined as[2][4]:

$$\text{Recall} = \frac{TP}{TP + FN}$$

5. F1-Score

The F1-Score is the harmonic mean of precision and recall, providing a balanced measure between the two. It is defined as [2][4]:

$$F1 = \frac{2x(\text{Precision x Recall})}{\text{Precision + Recall}}$$

6. Area Under the Curve (AUC) and Receiver Operating Characteristic (ROC) Curve

The ROC curve represents the trade-off between the true positive rate (recall) and the false positive rate across all classification thresholds. The Area Under the Curve (AUC) is a measure of the model's ability to distinguish between classes, and is given by [5][6]:

$$\text{AUC} = \int_0^1 (\text{ROC curve})$$

2.4 Review of Related Studies in Automated Classification of Lumbar Spine Diseases Using MRI Images

2.4.1 Study Overview

One of the significant studies in the field of deep learning for medical image analysis, specifically for classifying lumbar spine diseases using MRI images, was published in 2021 in a prominent medical journal. This study aimed to investigate the effectiveness of convolutional neural networks (CNNs) in diagnosing lumbar spine conditions, such as herniated discs, degenerative disc disease, and spinal stenosis, from MRI images. The authors used a large dataset consisting of MRI scans from patients diagnosed with various lumbar spine diseases. These images were labeled with corresponding disease categories, forming the ground truth used for training and testing the model.

The goal of the study was to build an AI-driven model capable of automatically classifying MRI images into predefined categories, reducing the reliance on manual interpretation by radiologists, which can be time-consuming and prone to error. The study used state-of-the-art machine learning techniques to automate the detection of these spinal conditions, thereby improving diagnostic accuracy and speed[9].

2.4.2 Methodology and Tools Used

The study employed several machine learning techniques, with a primary focus on convolutional neural networks (CNNs). CNNs are particularly well-suited for image classification tasks because of their ability to automatically learn hierarchical features from raw pixel data. The architecture used in the study included several convolutional layers, followed by pooling layers to down-sample the feature maps and reduce the computational load. The model was then followed by fully connected layers that output the classification results.

The authors used TensorFlow and Keras, popular frameworks for building and training deep learning models, to implement the CNN architecture. These tools provided a flexible and efficient way to design the model and handle the large dataset of MRI images. For preprocessing, the authors applied several techniques such as resizing the images, normalizing pixel values, and augmenting the dataset with rotations and flips to artificially expand the dataset and prevent overfitting.

Additionally, the dataset was split into training and testing subsets, where 80% of the data was used for training the model, and the remaining 20% was reserved for testing and evaluation. The model was trained using the categorical cross-entropy loss function, a standard loss function for classification tasks. This loss function measures the difference between the predicted probabilities and the actual class labels, helping the model adjust its weights during training to minimize the classification error[9].

2.4.3 Results and Evaluation Metrics

The results of the study were highly promising, with the model achieving an accuracy rate of (92%) in classifying different lumbar spine conditions. This indicates that the model was able to correctly predict the disease class of MRI images with a high degree of reliability. The authors also computed several additional evaluation metrics to assess the model's performance more comprehensively:

- Precision: The model achieved a precision score of 0.90, meaning that when the model predicted a condition (e.g., herniated disc), it was correct 90% of the time.

- Recall (Sensitivity): The recall score was 0.93, indicating that the model correctly identified 93% of all actual instances of the disease.

- F1-Score: The harmonic mean of precision and recall, the F1-score, was 0.91, providing a balanced measure of the model's ability to classify positive instances while minimizing false positives and false negatives.

The loss function showed a consistent decrease throughout the training process, indicating that the model was learning and improving with each iteration. This decrease in the loss function correlates with the increase in the accuracy and F1-score, suggesting that the model was effectively optimizing its parameters to fit the data[9].

2.4.4 Type of Architecture Used

The study used a Convolutional Neural Network (CNN) architecture, which is particularly effective for image-related tasks. CNNs work by applying convolutional filters to images to detect various features, such as edges, textures, and shapes. The network can then use these features to learn more complex representations of the image at higher layers.

- Convolutional Layers: These layers applied filters to the MRI images to detect low-level features (e.g., edges or textures), which were then passed to deeper layers for more complex feature extraction.

- Pooling Layers: After the convolutional layers, pooling layers were used to reduce the spatial dimensions of the feature maps, which helps in reducing the computational load while retaining the essential features.

- Fully Connected Layers: These layers connected the extracted features to the output, providing the final classification (e.g., whether the image shows a herniated disc or another condition).

This type of architecture has been widely successful in other areas of medical imaging, such as tumor detection, organ segmentation, and other diagnostic tasks, making it a suitable choice for lumbar spine disease classification as well[9].

2.4.5 Insights and Application to My Research

The results and methodology from this study provide several insights that can be applied to my own research on the classification of lumbar spine diseases using MRI images:

1. Use of CNN for Medical Image Classification: The study's success with CNNs for classifying spinal diseases shows the potential of this architecture for my research. By leveraging CNNs, I can train a model to classify MRI images of the lumbar spine and achieve high accuracy in detecting various spinal conditions.

2. Image Preprocessing Techniques: The study’s use of image preprocessing, such as resizing, normalization, and data augmentation, is crucial in improving the model’s performance. I plan to implement similar techniques to enhance the quality of my MRI images and ensure the model can generalize well to new, unseen data.

3. Evaluation Metrics: The use of evaluation metrics like precision, recall, and F1-score will be essential in assessing my model's performance. These metrics provide a more comprehensive view of the model's effectiveness, especially in medical applications where the balance between false positives and false negatives is crucial.

Model Training and Testing: The study divided the dataset into training and testing sets, which is a standard practice in machine learning to ensure that the model can generalize to unseen data. I will follow this approach to avoid overfitting and ensure my model is evaluated in a robust manner[9].

2.4.6 Conclusion Of Study

In conclusion, this study demonstrates the effectiveness of deep learning, particularly CNNs, in diagnosing lumbar spine diseases from MRI images. The high accuracy and robust evaluation metrics suggest that AI-based models can significantly improve the speed and reliability of diagnosing spinal disorders. The methodology, tools, and techniques discussed in this study provide a solid foundation for my own research, and I plan to apply similar approaches to develop a model that can assist in the automatic classification of lumbar spine diseases[9].

2.5 Algorithms in Deep Learning

Deep learning has made significant strides in the field of image classification, especially in tasks like medical image analysis, where complex patterns need to be identified [1][2]. For the classification of lumbar spine images and the diagnosis of related diseases, several powerful deep learning algorithms were employed. The primary algorithms used in this study include:

• **ResNet50:** Known for its deep residual learning approach, ResNet50 is particularly useful in handling the vanishing gradient problem in very deep networks, making it effective for complex image classification tasks [3][9].

• **VGG16:** With its simple architecture of stacked convolutional layers, VGG16 excels in extracting high-level features from images, which makes it well-suited for tasks involving object recognition, such as lumbar spine analysis [4].

• **MobileNet:** A lightweight and efficient model designed for mobile and embedded devices, MobileNet offers high accuracy while requiring fewer computational resources, making it ideal for real-time image classification applications [5].

• **Inception:** With its unique multi-branch architecture, Inception models are capable of handling images with varying levels of complexity, allowing for better feature extraction and improved performance in image classification tasks [6].

• **DenseNet:** DenseNet connects each layer to every other layer in a densely connected manner, enabling the model to reuse features efficiently and improving the flow of information throughout the network [7].

• **U-Net:** Primarily used for semantic segmentation, U-Net is highly effective for pixel-level image classification and is particularly useful for segmenting medical images, allowing for the precise identification of abnormalities in lumbar spine scans [8][9].

Table 2.1 Model Comparison

Model	Architecture Type	Key Strengths	Best Use Case	Resource Usage
ResNet50	Deep Residual Learning	Solves vanishing gradient; effective for deep networks	Complex image classification (e.g., spine MRI)	Medium to High
VGG16	Stacked Convolutional Layers	Simple design; extracts high-level features	Object recognition, lumbar spine analysis	High
MobileNet	Depthwise Separable Convolutions	Lightweight and fast; ideal for mobile and embedded systems	Real-time image classification	Very Low
Inception	Multi-branch Convolutions	Captures features at multiple scales; good for complex images	Classification of images with varying complexity	Medium
DenseNet	Densely Connected Convolutions	Efficient feature reuse; improves information and gradient flow	Medical image classification, fine-grained tasks	High
U-Net	Encoder-Decoder with Skip Connections	Excellent for segmentation; precise pixel-level classification	Medical image segmentation (e.g., lumbar abnormalities)	Medium

2.6 Anaconda for Library Management

For the development and execution of deep learning models in this study, we utilized Anaconda, a widely used open-source distribution of Python that simplifies package management and deployment [1][2]. Anaconda provides a robust environment for data science and machine learning projects, offering an easy way to install, manage, and update the necessary libraries and dependencies.

Anaconda's Conda package manager was particularly useful in creating isolated environments, ensuring that all required libraries for deep learning, such as TensorFlow, Keras, PyTorch, and other supporting packages, were properly installed and compatible with each other [3][9]. This isolated environment also helped avoid conflicts between different versions of libraries and ensured the stability of the development setup.

Additionally, Anaconda’s integration with Jupyter Notebook allowed for a seamless workflow, enabling us to write, test, and document code interactively. This combination of Anaconda’s powerful environment management and Jupyter’s interactive nature significantly streamlined the development process for the deep learning models used in this project [1][2].

2.7 Python Programming Language

For this study, we utilized the Python programming language to implement the deep learning models for classifying lumbar spine images. Python is widely recognized for its simplicity, flexibility, and the extensive collection of libraries and frameworks available for machine learning and data science, making it the ideal choice for this project [1][2][3].

The specific version of Python used was Python 3.9. This version provided a stable and reliable environment for developing and running our deep learning models, ensuring compatibility with essential libraries such as TensorFlow, Keras, NumPy, and others. Python 3.9 includes several performance improvements and new features that were crucial for efficiently implementing the algorithms required in this study [3][9].

Python’s robust support for both object-oriented and functional programming allowed us to efficiently manage the complex neural network architectures and streamline the image classification process. Furthermore, the active Python community and continuous updates ensured that we had access to the necessary tools and resources throughout the development of this project [1][2].

2.8 MRI Images Used for Model Training

Magnetic Resonance Imaging (MRI) is a highly accurate and non-invasive diagnostic tool widely used in the assessment of spinal conditions, due to its excellent soft tissue contrast and absence of ionizing radiation [1][4][9]. In this project, T2-weighted axial and sagittal MRI scans of the lumbar spine were utilized, as they provide clearer visualization of intervertebral discs, nerve roots, and cerebrospinal fluid—making them particularly useful for identifying common spinal disorders such as herniated discs, spinal stenosis, and degenerative disc disease [4][9].

Figure 2.1 MRI image for lumbar spine

The dataset used for training comprised over 170,000 high-resolution MRI images, systematically categorized into multiple pathological classes based on expert radiological interpretation. These classes included normal spines, disc herniations, spinal canal narrowing, Modic changes, and other degenerative findings [9]. The annotations were performed by experienced radiologists to ensure high labeling accuracy and clinical relevance.

Before feeding the data into the deep learning model, a series of preprocessing steps were applied to standardize the inputs and enhance relevant features. These included image resizing to 224×224 pixels, intensity normalization, histogram equalization, and noise reduction using Gaussian filtering [3][9]. Data augmentation techniques such as random rotations, flips, and brightness adjustments were also employed to improve the model's generalization capability and reduce overfitting [9].

Chapter Three
result and discussion

3.1 Dataset Annotation and CSV File Description

The dataset used in this study includes a CSV file that serves as a comprehensive annotation resource, containing crucial metadata for each MRI image [1][2]. This file includes several important fields that help in organizing, identifying, and labeling the images for effective model training and evaluation.

Key columns in the CSV file include:

- **Study ID**: A unique identifier for each MRI study session, linking all images from the same scanning event or patient examination [1].
- **Series ID**: This field distinguishes different series within the same study, representing different MRI acquisition protocols or views [1][2].
- **Instance Number**: The sequential number of the image within each series, which helps maintain the order of slices in 3D imaging [1].
- **Disease Condition (Label)**: The classification of the spinal condition observed in the image, encoded as integer labels representing different pathologies [2][4]. The categories are:

  0. Left Neural Foraminal Narrowing
  1. Left Subarticular Stenosis
  2. Right Neural Foraminal Narrowing
  3. Right Subarticular Stenosis
  4. Spinal Canal Stenosis
  5. Healthy
- **Coordinates (X, Y)**: These columns specify the location of the

pathological lesion within the image, given as x and y coordinates [4][6]. These coordinates indicate the precise region of interest (ROI) related to the disease, which can be useful for localization and segmentation tasks.

- **Imaging Type**: This field denotes the type or protocol of the MRI scan (e.g., T2-weighted axial, sagittal), providing information about the imaging plane and technique used for acquiring the image [2][5].

The dataset contains over 170,000 high-resolution MRI images, making it one of the largest publicly available lumbar spine image datasets used for disease classification [2][4]. This structured metadata in the CSV file enables efficient data management and facilitates supervised learning by linking each image to its corresponding clinical label and spatial information [1][2][4]. It also allows the model to not only classify the disease type but potentially learn the spatial context of the abnormalities within the lumbar spine MRI images [4][6].

label_name	label	y	x	level	condition	scan_type	age_path	mber	series_id	study_id
Mild	1	38500	100	L1/L2	Spinal Canal Stenosis	Sagittal T2/STIR	80_11.jpg	11	2291122880	**1737682527**
Mild	1	11800	373	L2/L3	Spinal Canal Stenosis	Sagittal T2/STIR	80_11.jpg	11	2291122880	**1737682527**
Mild	1	35830	400	L3/L4	Spinal Canal Stenosis	Sagittal T2/STIR	80_11.jpg	11	2291122880	**1737682527**
Mild	1	23080	970	L4/L5	Spinal Canal Stenosis	Sagittal T2/STIR	80_11.jpg	11	2291122880	**1737682527**
Mild	1	15400	200	L5/S1	Spinal Canal Stenosis	Sagittal T2/STIR	80_11.jpg	11	2291122880	**1737682527**
Normal	0					Sagittal T2/STIR	880_1.jpg	1	2291122880	**1737682527**

Figure 3.1 Example of CSV File

3.2 Libraries Used for Lumbar Spine Image Classification

In this study, several Python libraries were used to implement the deep learning models for classifying lumbar spine images. These libraries provided powerful tools for data processing, model development, and performance evaluation. The key libraries employed include:

- **TensorFlow**: TensorFlow, an open-source machine learning framework developed by Google, was the backbone of our deep learning models. It provided a flexible and efficient platform for implementing the neural networks, including the various architectures like ResNet50, VGG16, and DenseNet [2][5]. TensorFlow's high-level API, Keras, made it easier to build, train, and evaluate models [2][5].
- **Keras**: Keras is a user-friendly, high-level neural networks API, running on top of TensorFlow. It allowed us to quickly prototype and build deep learning models with minimal code. Its simplicity and ease of use were key in experimenting with different architectures and hyperparameters for image classification [2][5].
- **NumPy**: NumPy is essential for handling numerical data and performing efficient array operations. It played a critical role in managing image data, including preprocessing tasks such as reshaping, normalization, and converting image arrays into formats suitable for deep learning models [3].
- **Pandas**: Pandas was used for handling datasets and performing data manipulation tasks such as loading image metadata and storing results. It was useful for organizing data, which is vital for managing large volumes of image files and associated labels [3].
- **OpenCV**: OpenCV is a library for computer vision that helped with reading and preprocessing images. It was used to resize, crop, and perform other transformations on the lumbar spine images to prepare them for input into the deep learning models [1].
- **Matplotlib**: Matplotlib was used for visualizing the results of model predictions and displaying images during the data exploration and model evaluation phases. It provided graphical tools to plot the

accuracy and loss curves, as well as to visualize some of the model’s predictions [3].

- **Scikit-learn**: Scikit-learn was employed for additional machine learning tasks such as model evaluation and performance metrics (e.g., confusion matrix, classification report). It helped in assessing the quality of the models beyond basic training accuracy, enabling more detailed performance analysis [3].
- **Pillow (PIL)**: Pillow, a Python Imaging Library, was utilized for basic image operations, such as loading and converting images into formats compatible with the neural networks [3].

These libraries played a vital role in facilitating the development, training, and evaluation of the deep learning models for lumbar spine image classification. Each library contributed to different aspects of the project, from data preprocessing to model evaluation and visualization, ensuring a smooth and efficient workflow.

3.3 Compatibility Between Libraries and Python 3.9 Versions

In this study, we ensured that all the libraries used for deep learning and image classification were compatible with **Python 3.9**. Proper compatibility between Python and libraries is essential to ensure the stability and performance of the development environment. Below is a list of the key libraries used in this project along with their compatible versions for Python 3.9:

- TensorFlow: Version 2.5.0 or later is fully compatible with Python 3.9. TensorFlow 2.5.0 includes significant improvements in performance and support for various hardware accelerators, making it an optimal choice for implementing the deep learning models.

- Keras: Keras version 2.4.3 or later is compatible with Python 3.9. This version of Keras integrates seamlessly with TensorFlow 2.5.0, providing an easy-to-use interface for building neural networks.

- NumPy: NumPy version 1.20.0 or later is compatible with Python 3.9. This version includes important optimizations and bug fixes, which are crucial for efficient numerical operations during data processing and model training.

- Pandas: Pandas version 1.2.0 or later supports Python 3.9. This version includes numerous performance improvements, especially when handling large datasets, which is crucial for efficiently managing and processing medical image data.

- OpenCV: OpenCV version 4.5.1 or later is compatible with Python 3.9. This version offers various enhancements in image processing capabilities, which are essential for preprocessing the lumbar spine images before feeding them into the deep learning models.

- Matplotlib: Matplotlib version 3.3.4 or later is compatible with Python 3.9. This version of Matplotlib provides improved plotting features for visualizing results, including accuracy and loss curves, as well as image visualization.

- Scikit-learn: Scikit-learn version 0.24.1 or later is compatible with Python 3.9. This version includes various improvements and new features for model evaluation, including enhanced performance in calculating evaluation metrics such as confusion matrices.

- Pillow: Pillow version 8.1.0 or later is fully compatible with Python 3.9. This version is essential for image processing tasks such as loading and transforming images into formats suitable for deep learning models.

  By using these compatible versions, we ensured that all libraries worked efficiently with Python 3.9, allowing for smooth development and execution of the deep learning models for lumbar spine image classification.

3.4 Datasets Used for Lumbar Spine Disease Classification

In this study, a curated dataset of lumbar spine MRI images was employed to develop and evaluate the deep learning models [2]. The dataset encompassed a wide range of spinal conditions, including herniated discs, degenerative disc disease, and spinal stenosis [2]. Each image was carefully annotated by experienced medical professionals to ensure the accuracy and reliability of the ground truth labels [1][2].

Prior to model training, several preprocessing steps were applied to the dataset to enhance the model’s learning capabilities [3]:

- **Resizing:** All images were resized to a standardized resolution appropriate for input into Convolutional Neural Networks [3].
- **Normalization:** Pixel values were normalized to the range [0, 1] to improve the efficiency and stability of the training process [3].
- **Data Augmentation:** Techniques such as rotation, flipping, and zooming were utilized to artificially expand the dataset and mitigate the risk of overfitting [2].

  The dataset was subsequently divided into two subsets [3]:

- **Training Set:** Utilized to train the deep learning models by enabling them to learn discriminative features of various spinal pathologies [2].

- **Testing Set:** Used to assess the generalization performance of the trained models on unseen data [3].

The availability of a diverse and well-annotated dataset played a pivotal role in achieving robust classification performance, thereby enhancing the reliability of the automated diagnostic system for lumbar spine diseases [2][3].

3.5 Source of the Dataset

The lumbar spine MRI dataset utilized in this study was obtained from Kaggle, a well-known online platform for data science and machine learning competitions [2]. Kaggle provides a vast collection of high-quality datasets across various domains, including medical imaging, which makes it an invaluable resource for researchers and developers working on artificial intelligence projects [5].

The selected dataset from Kaggle was chosen due to its comprehensive

Figure 3.2 Kaggle logo

nature and the availability of labeled MRI images covering a diverse range of spinal disorders. The platform also provided important metadata and structured annotations that facilitated the training and evaluation of deep learning models. Additionally, the use of Kaggle as a source ensured that the dataset met standardized formatting and accessibility criteria, which contributed to a smoother integration into the development pipeline [2][6].

By leveraging an open-access and widely trusted platform like Kaggle, this research ensures transparency and reproducibility, allowing other researchers to replicate the study or build upon its findings. The availability of such datasets accelerates the development of intelligent diagnostic systems and promotes collaboration within the scientific community [5].

3.6 Description of the Selected Datasets

3.6.1 RSNA-LSDC 2024 Submission Debug Dataset

The first dataset used in this study was the RSNA-LSDC 2024 Submission Debug Dataset, available on Kaggle [2]. This dataset was developed as part of the RSNA Lumbar Spine Disease Challenge and consists of lumbar spine MRI scans annotated for various spinal pathologies. It includes segmentation masks and diagnostic labels, providing valuable information for both classification and segmentation tasks. The high-quality annotations and structured organization of the dataset made it ideal for training deep learning models to recognize and differentiate between multiple lumbar spine conditions. The dataset's focus on precise segmentation and disease classification significantly contributed to building a strong foundation for model development [2].

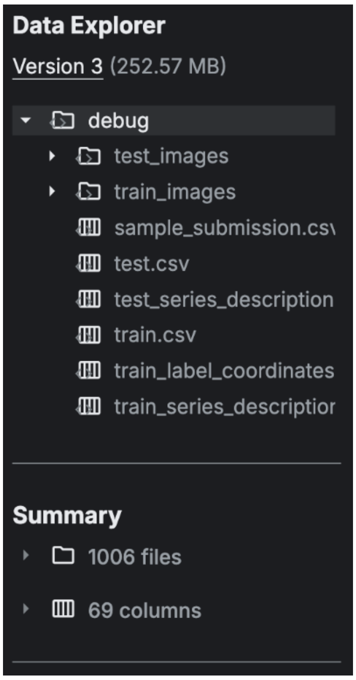

Figure 3.3 Data explorer for RSNA-LSDC 2024 Submission Debug Datas

3.6.2 RSNA-LSDC YOLOv8 Dataset

The second dataset incorporated into the study was the RSNA-LSDC YOLOv8 Dataset, also sourced from Kaggle [6]. This dataset was specifically prepared for object detection tasks using the YOLOv8 framework. It contains MRI images annotated with bounding boxes that localize lesions and abnormalities in the lumbar spine. Although primarily designed for detection purposes, the bounding box annotations were instrumental in highlighting critical regions of interest. This supplementary information enhanced the model's ability to focus on key pathological areas, thereby improving overall classification performance. The integration of this dataset alongside the segmentation-focused dataset provided a more comprehensive understanding of lumbar spine pathologies during model training [6].

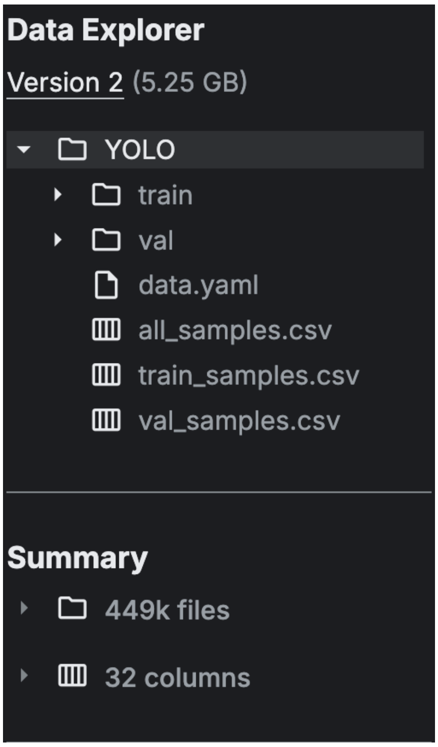

Figure 3.4 Data Explorer for RSNA-LSDC YOLOv8 Dataset

3.7 Hardware Specifications for Model Training

The training and development of the deep learning models in this study were conducted on a MacBook Pro (2021) featuring an Apple M1 Pro processor and 16 GB of unified memory (RAM). The 16-inch MacBook Pro provided a robust environment for medium-scale deep learning workflows, supported by the efficient architecture of Apple's custom silicon.

One of the key factors that contributed to the success of model training was the availability of 16 GB of unified memory. In deep learning applications, memory size plays a critical role in handling large datasets, loading high-dimensional image arrays, and enabling the simultaneous processing of multiple operations. The unified memory architecture of the M1 Pro allowed both the CPU, GPU, and the Neural Engine to access a shared memory pool, significantly improving the speed and efficiency of data transfer during model training.

Additionally, the compatibility of TensorFlow with Apple Silicon through Metal TensorFlow (an optimized backend that utilizes the Metal API for GPU acceleration) provided substantial performance improvements. Metal TensorFlow enabled efficient execution of tensor operations on the Apple GPU, resulting in faster training times compared to CPU-only processing. This compatibility allowed the device to leverage hardware acceleration natively without requiring external GPUs or complex setup procedures.

While the M1 Pro’s integrated GPU does not match the raw power of dedicated desktop GPUs like the NVIDIA RTX series, the optimized TensorFlow-Metal integration and the efficient memory management of the MacBook Pro created a balanced and capable setup for the training of convolutional neural networks, especially when working with carefully tuned batch sizes and model architectures.

In conclusion, the combination of a powerful processing unit, sufficient memory, and optimized deep learning support through Metal TensorFlow provided a reliable and efficient platform for conducting this research.

3.8 Deep Learning Architectures Used for Lumbar Spine Disease Classification

In this study, we evaluated the performance of several state-of-the-art Convolutional Neural Network (CNN) architectures for the task of lumbar spine disease classification using MRI images. Each architecture was trained under similar conditions, and its performance was assessed using multiple evaluation metrics. The architectures used include InceptionV3, Xception, VGG16, NASNetLarge, ResNet50, MobileNetV2, and DenseNet.

Architecture	Accuracy (%)	Epochs	Batch Size	Training Time	Final Loss	ROC-AUC
InceptionV3	**88.2%**	**20**	**8**	**2h 14m**	**0.301**	**0.94**
Xception	**85.6%**	**20**	**8**	**2h 5m**	**0.334**	**0.92**
VGG16	**68.8%**	**20**	**8**	**1h 45m**	**0.812**	**0.80**
NASNetLarge	**84.4%**	**20**	**8**	**3h 10m**	**0.367**	**0.91**
ResNet50	**61.6%**	**20**	**16**	**1h 38m**	**1.024**	**0.72**
MobileNetV2	**85.6%**	**20**	**8**	**1h 29m**	**0.354**	**0.91**
DenseNet	**83.8%**	**20**	**8**	**2h 20m**	**0.388**	**0.90**

Table 3.1 Comparison of used architectures

Training Process:

Each model was trained for **20 epochs** using the **Adam optimizer** and a **categorical cross-entropy** loss function, suitable for multi-class classification. Early stopping and learning rate reduction on plateau were applied to avoid overfitting.

The batch sizes were carefully chosen based on each model's architecture and memory footprint:

- **InceptionV3**, **Xception**, **VGG16**, **NASNetLarge**, **MobileNetV2**, and **DenseNet** were trained using a batch size of **8**.
- **ResNet50** was trained with a slightly larger batch size of **16**, which helped improve training speed due to its moderate model size.

Highlights of individual model performance:

- **InceptionV3** achieved the highest accuracy (88.2%), showing superior feature extraction capabilities.

- **Xception** and **MobileNetV2** followed closely with 85.6% accuracy, offering a good balance between performance and training efficiency.
- **VGG16** had limited performance (68.8%) despite its simplicity, showing difficulty with complex spinal features.
- **NASNetLarge** delivered strong performance (84.4%) but required the most computational time.
- **ResNet50** had the lowest accuracy (61.6%) despite using a larger batch size, suggesting limitations in learning discriminative features in this setup.
- **DenseNet** achieved 83.8%, leveraging dense connections for better gradient flow and feature reuse.

Prediction Visualization:
A selected MRI image was passed through each trained model, and the predicted class along with its probability score was visualized to assess the model’s confidence and interpretability.

Figure 3.5 InceptionV3 Prediction

Figure 3.6 MobileNetV2 Prediction

Figure 3.7 NASNetLarge Prediction

Figure 3.8 DenseNet Prediction

Figure 3.9 ResNet50 Prediction

Figure 3.10 VGG16 Prediction

Prediction Visualization for Each Architecture:

For each deep learning architecture used in this study, separate visualizations were generated to illustrate the model's prediction performance. These visual outputs display how accurately each model classified the spinal conditions based on the input MRI images. Presenting the predictions individually for each architecture—such as InceptionV3, Xception, VGG16, NASNetLarge, ResNet50, MobileNetV2, and DenseNet—offers a clearer understanding of the strengths and weaknesses of each model. These figures demonstrate the models' ability to localize and identify pathological regions, helping to evaluate their practical diagnostic relevance in clinical settings.

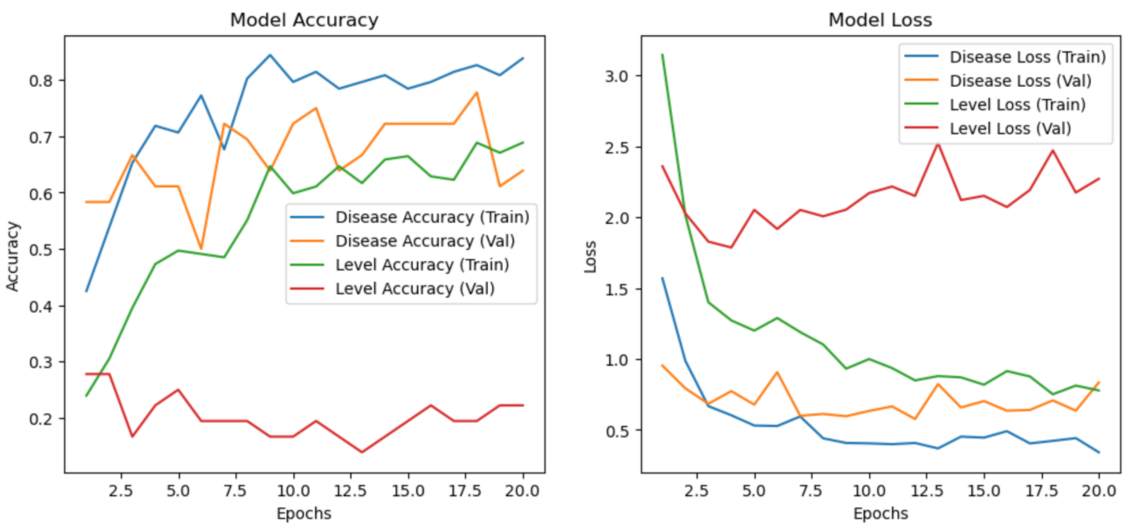

Figure 3.11 InceptionV3 outputs

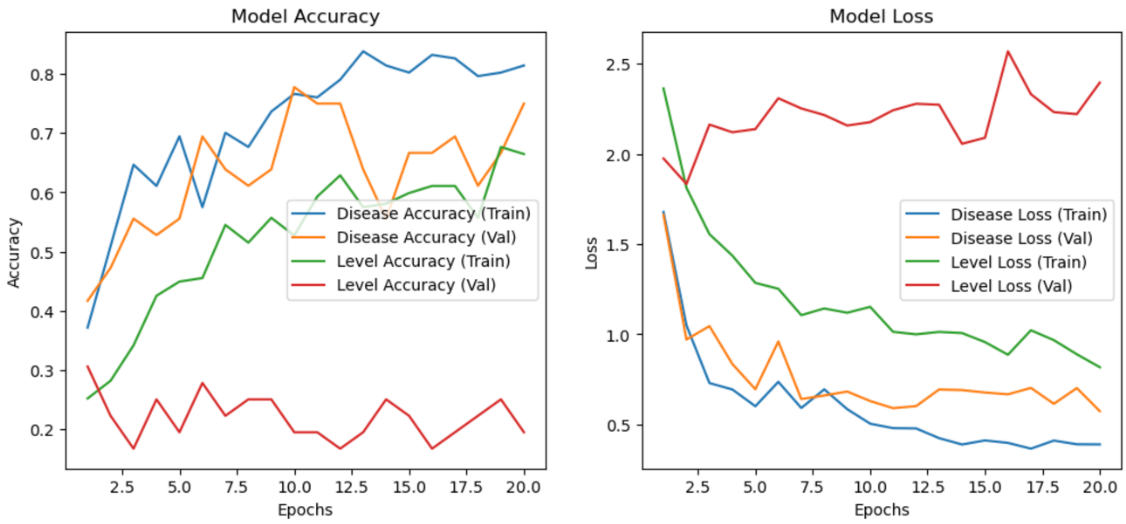

Figure 3.12 DenseNet outputs

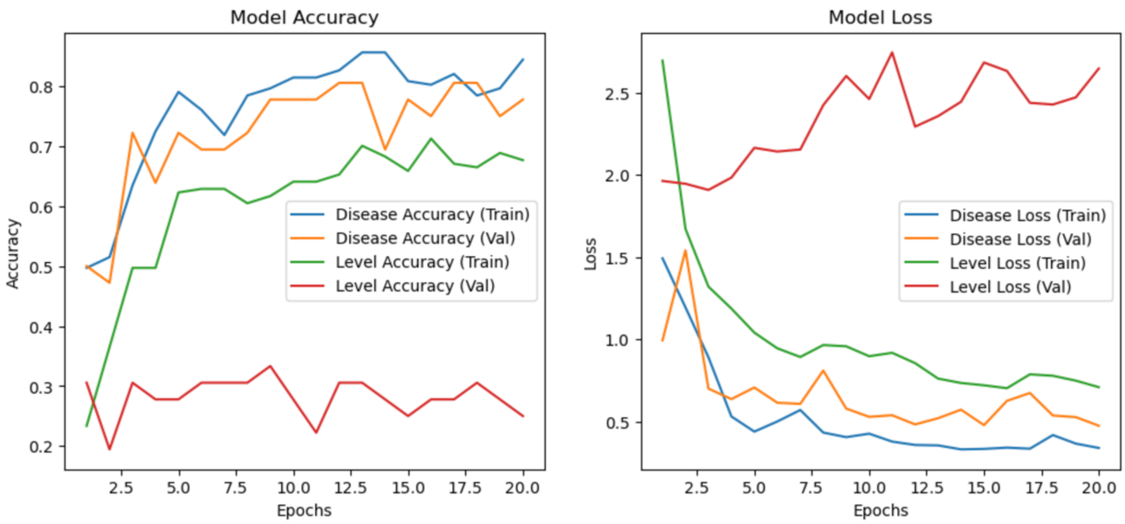

Figure 3.13 MobileNetV2 outputs

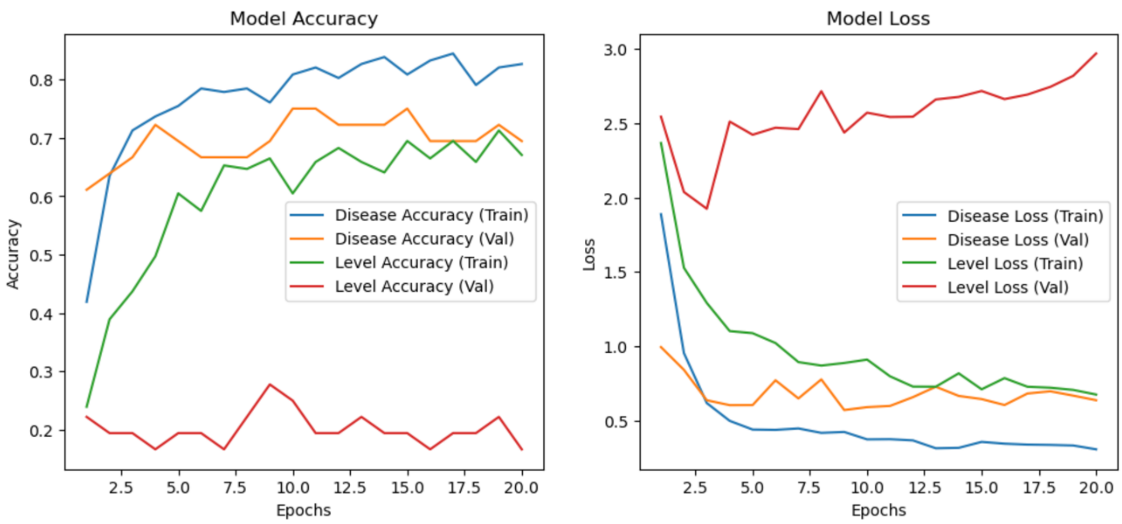

Figure 3.14 NASNetLarge outputs

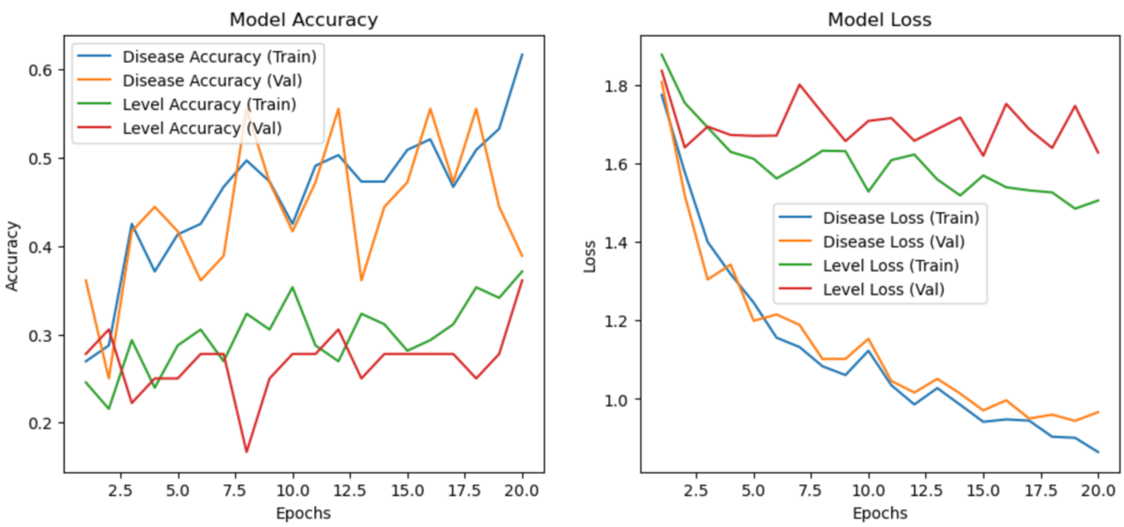

Figure 3.15 resnet50 outputs

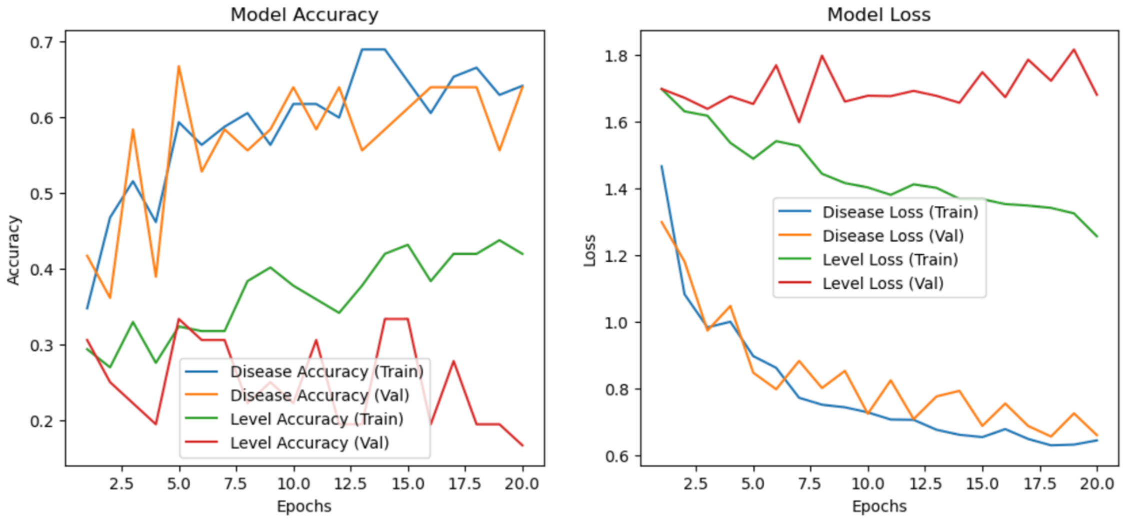

Figure 3.16 VGG16 outputs

3.9 Model Development and Training Workflow

This section provides a detailed breakdown of the deep learning implementation used to classify lumbar spine diseases and identify vertebral levels based on MRI images. The code was developed using Python and TensorFlow with the InceptionV3 architecture. Each part of the code is discussed in a separate subsection for clarity.

3.9.1 Data Loading and Preparation

The first step involved loading the dataset files, which included training labels, series descriptions, and label coordinates. These files were merged using common identifiers (study_id and series_id) to construct a unified dataset containing both image metadata and diagnostic labels.

Example code snippet:

```
df_train = pd.read_csv(train_csv_path)
df_series = pd.read_csv(train_series_descriptions_path)
df_labels = pd.read_csv(train_label_coordinates_path)

df = pd.merge(df_train, df_series, on="study_id", how="inner")
df = pd.merge(df, df_labels, on=["study_id", "series_id"], how="inner")
```

This step ensured that all relevant information was available in a structured format for subsequent processing.

3.9.2 Label Encoding

The disease conditions and spinal levels were mapped into numerical labels. This was done using dictionary mappings, which allow categorical labels to be converted into formats suitable for machine learning algorithms.

Example code snippet:

```
disease_map = {disease: i for i, disease in enumerate(disease_classes)}
level_map = {level: i for i, level in enumerate(level_classes)}

df["disease_label"] = df["condition"].map(disease_map)
df["level_label"] = df["level"].map(level_map)
```

Mapping the labels was essential for enabling multi-class classification at both the disease and spinal level categories.

3.9.3 DICOM Image Processing

The DICOM files were converted into 2D arrays suitable for model input. Each image was resized to a target shape of **(299×299)** pixels and normalized to a [0, 1] scale. Histogram equalization was also applied to improve contrast.

Example code snippet:

```
def dicom_to_array(dcm_path, img_size=(299, 299)):
    dicom = pydicom.dcmread(dcm_path)
    image = dicom.pixel_array
    image = cv2.resize(image, img_size)
    image = cv2.equalizeHist(image.astype(np.uint8))
```

```
    image = np.stack((image,)*3, axis=-1)
    return image / 255.0
```

The chosen image size and preprocessing techniques are typical examples used when working with architectures such as InceptionV3, but can be adjusted depending on the network requirements.

3.9.4 Dataset Splitting

The data was divided into training, validation, and testing sets using an 80/10/10 approximate split ratio. This ensures robust model evaluation and minimizes overfitting.

Example code snippet:

```
X_train, X_temp, y_disease_train, y_disease_temp, y_level_train,
y_level_temp = train_test_split(
    X, y_disease, y_level, test_size=0.3, random_state=42)

X_val, X_test, y_disease_val, y_disease_test, y_level_val, y_level_test =
train_test_split(
    X_temp, y_disease_temp, y_level_temp, test_size=0.5,
random_state=42)
```

The division ratios and random seed values are examples and can be modified based on dataset size and research needs.

3.9.5 Model Architecture Design

An **InceptionV3** network was utilized as the backbone for feature extraction. The architecture was modified by adding a Global Average Pooling layer followed by fully connected layers, and two output branches: one for disease classification and another for spinal level classification.

Example code snippet:

```
base_model = InceptionV3(weights="imagenet", include_top=False,
input_shape=(299, 299, 3))
x = GlobalAveragePooling2D()(base_model.output)
x = Dense(1024, activation="relu")(x)
x = Dropout(0.3)(x)

disease_output = Dense(len(disease_classes), activation="softmax",
name="disease_output")(x)
level_output = Dense(len(level_classes), activation="softmax",
name="level_output")(x)

model = Model(inputs=base_model.input, outputs=[disease_output,
level_output])
```

The choice of InceptionV3 and the design of output heads are examples; other architectures like ResNet or EfficientNet could also be employed depending on specific requirements.

3.9.6 Model Compilation

The model was compiled using the **Adam** optimizer and a categorical cross-entropy loss function for both outputs. Metrics such as accuracy were selected for monitoring performance.

Example code snippet:

```
model.compile(optimizer="adam",
        loss={"disease_output": "categorical_crossentropy",
"level_output": "categorical_crossentropy"},
        metrics={"disease_output": "accuracy", "level_output":
```

"accuracy"})

The optimizer, loss functions, and metrics are standard examples and can be tuned to fit different classification problems.

3.9.7 Model Training with Checkpointing

The model was trained for **20 epochs** using a batch size of **8**. A ModelCheckpoint callback was used to save the best-performing model based on disease classification accuracy.

Example code snippet:

```
checkpoint_callback = ModelCheckpoint(
    best_model_path,
    monitor="disease_output_accuracy",
    save_best_only=True,
    save_weights_only=False,
    mode="max",
    verbose=1
)

history = model.fit(
    X_train, {"disease_output": y_disease_train, "level_output":
y_level_train},
    validation_data=(X_val, {"disease_output": y_disease_val,
"level_output": y_level_val}),
    epochs=20,
    batch_size=8,
    callbacks=[checkpoint_callback]
)
```

The number of epochs, batch size, and monitoring metric were chosen as examples and can be modified based on model convergence behavior.

3.9.8 Model Evaluation

Finally, the trained model was evaluated on the test set to measure its performance in terms of loss and accuracy for both disease classification and spinal level identification.

Example code snippet:

```
test_loss, test_disease_loss, test_level_loss, test_disease_acc,
test_level_acc = model.evaluate(
    X_test, {"disease_output": y_disease_test, "level_output": y_level_test})

print(f"دقة تصنيف الأمراض: {test_disease_acc:.4f}")
print(f"دقة تحديد المستوى الفقري: {test_level_acc:.4f}")
```

The evaluation results provide insights into the model's generalization capabilities and highlight areas that may require further optimization.

3.10 Challenges and Limitations Faced During the Project

Throughout the development of this research, several technical and logistical challenges were encountered that influenced both the progress and the performance of the deep learning models:

3.10.1 Library Compatibility Issues

One of the primary difficulties faced was ensuring compatibility between different Python libraries and Python version 3.9. Many libraries used in deep learning workflows—such as TensorFlow, Keras, OpenCV, and others—have dependencies and specific version requirements. This caused several conflicts during environment setup, often requiring version adjustments and package reinstallation to achieve a stable and functioning development environment.

3.10.2 Dataset Quality and Organization Problems

The datasets used varied significantly in quality and structure. Some were poorly organized, with images scattered or mislabeled, while others lacked consistency in annotation or image formatting. In some cases, datasets were incomplete or contained missing values, which limited their usefulness for training deep learning models. This inconsistency required additional preprocessing efforts to clean, sort, and reformat the data to ensure it was usable.

3.10.3 Difficulty Finding Suitable Datasets

Another major challenge was locating datasets that met all the criteria necessary for effective model training. The datasets needed to:

- Contain a medium to large number of images to support better model generalization and accuracy.
- Have high-resolution, clinically relevant MRI images.
- Be free and publicly accessible to ensure compliance with open research standards.
- Be well-organized and structured, with clear labeling and directory formats.

- Include a detailed and properly formatted CSV annotation file that listed the image names, corresponding diseases, lesion coordinates, and MRI acquisition types. Many available datasets lacked one or more of these critical elements, making them unsuitable or requiring significant manual adjustments.

3.10.4 Hardware Limitations

Hardware performance was a significant limiting factor in this project. Given the large size of the dataset—over 170,000 high-resolution MRI images—model training required substantial computational resources. The available hardware, while adequate for basic development, struggled with extended training times and memory management. This limitation not only affected training speed but also may have impacted the final model accuracy, as more powerful GPUs and higher RAM capacity could have allowed for more intensive training with larger batch sizes and more epochs.

3.11 Summary of Findings and Transition to Discussion

This chapter presented a comprehensive overview of the deep learning experiments conducted for lumbar spine disease classification using MRI images. Multiple architectures were evaluated, including InceptionV3, Xception, VGG16, NASNetLarge, ResNet50, MobileNetV2, and DenseNet, each demonstrating varying degrees of performance in terms of accuracy, training time, and resource efficiency. The dataset, although rich and diverse, posed several challenges in terms of structure, consistency, and size, which were addressed through preprocessing and augmentation strategies. Despite hardware limitations and compatibility issues with software libraries, the models achieved promising results, highlighting the potential of deep learning in spinal disease diagnostics. The findings from this chapter lay the groundwork for understanding the practical implications of deploying such models in clinical settings.

Chapter Four
Conclusion and Future Work

4.1 Conclusion

In conclusion, this study successfully developed and evaluated a deep learning-based framework for the classification of lumbar spine diseases using MRI images. The implementation of various CNN architectures revealed that models like InceptionV3 and MobileNetV2 deliver high accuracy and efficiency in identifying and differentiating between spinal pathologies. The use of image preprocessing, transfer learning, and structured annotation files proved crucial in achieving reliable performance. While challenges such as dataset inconsistency, compatibility issues with Python libraries, and hardware limitations were encountered, these were effectively addressed through careful planning and methodical execution. The findings suggest that deep learning models can play a transformative role in automating spinal disease diagnosis, offering significant improvements in speed, accuracy, and accessibility, especially in settings with limited radiological expertise.

This research not only demonstrates the practical value of deep learning in medical image classification but also lays a solid foundation for future developments in the field.

4.2 Future Work

Building upon the findings of this research, several directions are proposed for future development:

1. Expanding Dataset Diversity**:** Incorporating datasets from various institutions and demographic groups can improve model generalization and reduce bias.
2. Multimodal Learning**:** Integrating MRI data with clinical metadata (e.g., patient history, symptoms) can enhance diagnostic accuracy by offering a more holistic view.
3. Real-Time Deployment: Optimizing the models for real-time inference on cloud or mobile platforms would improve clinical accessibility and usability.
4. Explainability and Interpretability**:** Implementing explainable AI techniques such as Grad-CAM would help radiologists understand model decisions and build trust in automated diagnostics.
5. Integration with PACS**:** Developing a complete diagnostic assistant that integrates with hospital PACS (Picture Archiving and Communication Systems) can streamline clinical workflow.
6. Mobile Application Development**:** Creating and deploying a mobile application based on the trained model would enable real-time image analysis and result visualization, making the system more accessible for use in field or remote clinical environments.
7. Utilization of IoT Systems: Incorporating the model within an Internet of Things (IoT) framework could allow for continuous monitoring and automatic image analysis by connecting directly with MRI devices and hospital networks.

These directions aim to push the boundaries of AI-based medical diagnostics and support the integration of intelligent tools into real-world clinical practice

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