



Lumbar Disease Classification Using Deep Learning

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ABSTRACT

The Intervertebral disc degeneration is a leading cause of spinal disorders, often resulting in chronic back pain and impaired mobility. Accurate and early classification of disc degeneration is critical for timely diagnosis and treatment planning. In this study, we propose a deep learning-based approach utilizing Convolutional Neural Networks (CNNs) to automate the classification of spinal disc degeneration from magnetic resonance imaging (MRI) scans. Our model is trained on a labeled dataset annotated by expert radiologists based on standard grading systems such as the Pfirrmann classification. The proposed CNN architecture is designed to capture complex spatial features and subtle texture variations associated with different stages of disc degeneration. Experimental results demonstrate high classification accuracy, precision, and recall, outperforming traditional image processing and machine learning techniques. This automated system has the potential to assist radiologists in clinical decision-making, reduce diagnostic variability, and improve patient outcomes.

Key Words: Disc Degeneration, Spinal Cord, Convolutional Neural Network (CNN), MRI Classification, Deep Learning

INTRODUCTION

In this project, Intervertebral disc degeneration (IVDD) is a prevalent musculoskeletal condition that significantly contributes to lower back pain and spinal disorders, affecting millions of individuals worldwide. The degeneration of spinal discs can lead to reduced disc height, loss of hydration, and changes in disc structure, often resulting in nerve compression and chronic discomfort. Accurate and early diagnosis of disc degeneration is essential for effective treatment planning and prevention of further spinal damage.

Magnetic Resonance Imaging (MRI) is the most reliable non-invasive imaging technique for visualizing soft tissues such as intervertebral discs. However, manual interpretation of MRI scans is time-consuming and subject to inter-observer variability, even among experienced radiologists. Traditional classification systems, such as the Pfirrmann grading scale, provide standardized criteria for evaluating disc degeneration but still rely heavily on subjective assessment.

In recent years, deep learning approaches, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable success in the field of medical image analysis. CNNs are capable of automatically learning hierarchical features from raw image data, making them highly effective for tasks such as image classification, segmentation, and detection. By applying CNN-based models to spinal MRI scans, it is possible to achieve consistent and accurate classification of disc degeneration

with minimal human intervention.

This research aims to develop and evaluate a CNN-based framework for automated classification of spinal disc degeneration using MRI images. The model is trained and tested on a dataset annotated by medical professionals, and its performance is compared with traditional machine learning approaches. The ultimate goal is to provide a robust, automated diagnostic tool to assist clinicians in making faster and more accurate decisions, thereby improving patient care and outcomes.

PROBLEM STATEMENT

Lumbar spine disorders such as disc degeneration, foraminal narrowing, and spondylolisthesis are major causes of lower back pain worldwide. Diagnosing these conditions requires detailed analysis of MRI or CT scans, which is time-consuming and expertise-dependent. Manual diagnosis can lead to human error, especially with rising patient numbers and limited access to radiologists. There is an increasing need for intelligent systems to assist or automate the diagnostic process. Traditional deep learning models like VGGNet have shown potential in medical image classification tasks. However, VGG's fixed convolutional kernels limit its ability to learn spatial and contextual features in complex medical images. Recent innovations such as the Involutional Neural Based VGG (INVGG) aim to address these limitations. INVGG introduces spatial-specific and context-aware operations to enhance feature extraction capabilities. This project implements both VGG and INVGG architectures to classify lumbar spine disorders from medical images. The goal is to build an accurate, robust, and scalable deep learning-based diagnostic system. A Flask-based web application is also developed to provide an interactive and user-friendly interface. Despite advanced architectures, deploying them effectively in clinical settings remains a challenge. This research contributes a deployable, efficient, and intelligent solution for automated spinal diagnosis.

MOTIVATION

Lumbar spine disorders are among the most common and debilitating conditions affecting people globally, leading to chronic pain, reduced mobility, and decreased quality of life. Diagnosing these conditions accurately requires careful evaluation of medical images such as MRI and CT scans, which is both time-intensive and prone to variability due to human interpretation. As the number of cases increases and access to experienced radiologists remains limited, there is a growing need for automated, intelligent diagnostic tools. Traditional deep learning models like VGGNet have been applied to medical image analysis but often fall short when dealing with the complex spatial patterns in spinal images. This motivates the use of more advanced architectures like INVGG, which can better understand context-specific features. By building a deep learning-based system integrated with a user-friendly web interface, this project aims to bridge the gap between cutting-edge AI and practical, real-world diagnostic applications, ultimately supporting faster, more accurate, and more accessible spine disorder diagnosis.

Key Points of Motivation:

- High global prevalence of lumbar spine disorders and their impact on quality of life
- Time-consuming and expertise-dependent nature of manual diagnosis using MRI/CT
- Shortage of radiology specialists and increasing patient load
- Limitations of traditional CNNs (like VGG) in handling complex spatial features
- Need for accurate, automated, and deployable diagnostic tools
- INVGG's potential to improve feature extraction and classification performance
- Goal to support clinicians with a reliable, scalable AI-driven solution

LITERATURE REVIEW

1. Biniyam Mulugeta Abuhayi., Yohannes Agegnehu Bezabh., and Aleka Melese Ayalew., (2022) Lumbar Disease Classification Using an Involutional Neural Based VGG Nets (INVGG)

In their 2022 study, "Lumbar Disease Classification Using an Involutional Neural Based VGG Nets (INVGG)," the authors proposed an advanced deep learning model for classifying lumbar spine conditions using MRI images. The model, based on the Involutional Neural Network (INVGG), was specifically designed to address the challenges of capturing spatial dependencies and contextual features in complex medical images. The study utilized an open-source lumbar spine MRI dataset and achieved an impressive accuracy of 85%. The innovative approach demonstrated the potential of INVGG in improving classification accuracy over traditional models, offering promising applications for automated spinal disorder diagnostics in clinical settings.

2. Ruchi., Dalwinder Singh., Jimmy Singla., (2021) Lumbar Spine Disease Detection: Enhanced CNN Model With Improved Classification Accuracy

In their 2021 study, "Lumbar Spine Disease Detection: Enhanced CNN Model With Improved Classification Accuracy," the authors proposed an enhanced CNN model for detecting lumbar spine diseases using MRI images. The model incorporated a linearity model to improve classification accuracy, achieving an impressive 90% accuracy rate. The study demonstrated that, despite the high calculation complexity, the enhanced CNN model significantly outperforms traditional methods, offering greater precision in detecting various spinal conditions. This work underscores the potential of advanced CNN models in medical imaging, particularly for lumbar spine disease detection.

3. Biniyam Mulugeta Abuhayi., (2022) Lumbar Disease Classification Using an Involutional Neural Based VGG Nets (INVGG)

In the 2022 study "Lumbar Disease Classification Using an Involutional Neural Based VGG Nets (INVGG)," the author introduced an advanced deep learning model for classifying lumbar spine diseases using MRI images. The model, based on the INVGG architecture, was compared with traditional CNN models such as VGG to demonstrate improved performance. The study utilized a lumbar spine MRI dataset and achieved an accuracy of 85%. While the dataset size is crucial for training, the proposed INVGG model successfully addressed the limitations of traditional CNNs, offering better feature extraction and classification results for lumbar disease detection.

4. Kaisi (Kathy) Chen., Lei Zheng., Honghao Zhao., and Zihang Wang., (2021) Deep Learning-Based Intelligent Diagnosis of Lumbar Diseases with Multi-Angle View of Intervertebral Disc

In the 2021 study "Deep Learning-Based Intelligent Diagnosis of Lumbar Diseases with Multi-Angle View of Intervertebral Disc," the authors proposed an innovative approach for diagnosing lumbar diseases using a combination of RCNN, VGG, ResNet, and MobileNet models. This study was part of the Alibaba Cloud Tianchi Algorithm Competition 'Spark' Digital Human AI Challenge-Intelligent Diagnosis of Spine Diseases. The dataset includes T1 and T2 sagittal images and T2 axial position images of the spine, with a classification accuracy of **95.6%**. The study highlighted two major limitations in existing research: the majority of studies focused on the diagnosis of intervertebral discs alone, while few classified both discs and vertebrae, and the insufficient use of MRI data, as many methods independently classified.

EXISTING SYSTEM:

The existing system for diagnosing lumbar spine disorders primarily rely on manual analysis of MRI and CT scans by trained radiologists, using standardized grading systems such as the Pfirrmann classification. While effective, this approach is time-consuming, subjective, and prone to inter-observer variability. In recent years, deep learning models, particularly Convolutional Neural Networks (CNNs) like VGGNet, ResNet, and DenseNet, have been applied to automate the classification of spinal conditions. These models have shown promise in detecting features such as disc degeneration and spinal alignment abnormalities. However, their performance is often limited by their inability to fully capture the complex spatial relationships and variations in spinal anatomy. Moreover, many existing solutions are designed for research purposes and lack scalability, user-friendly interfaces, or integration into clinical workflows. As a result, there remains a gap between state-of-the-art research and real-world, deployable diagnostic systems.

PROPOSED SYSTEM:

In the proposed system, The proposed algorithm utilizes deep learning-based classification to distinguish between normal and degenerative disc disease (DDD) in lumbar spine MRI images. The algorithm leverages two architectures: the traditional VGGNet and the enhanced Involutional Neural Based VGG (INVGG). Initially, the input MRI images undergo preprocessing, including resizing, normalization, and contrast enhancement to improve image quality. These preprocessed images are then passed through both CNN models, with VGGNet serving as a baseline architecture. INVGG, on the other hand, incorporates involution operations to adaptively capture spatially specific and context-aware features, offering improved performance in identifying subtle differences between normal discs and those affected by DDD. The models are trained on a labeled dataset of MRI scans, with the images labeled as either normal or indicative of DDD. The model's performance is evaluated using metrics such as accuracy, precision, recall, and F1-score, ensuring a robust and reliable classification. Once trained, the best-performing model is deployed within a Flask-based web application, providing a user-friendly interface that allows clinicians to easily upload MRI scans and receive real-time diagnostic results.

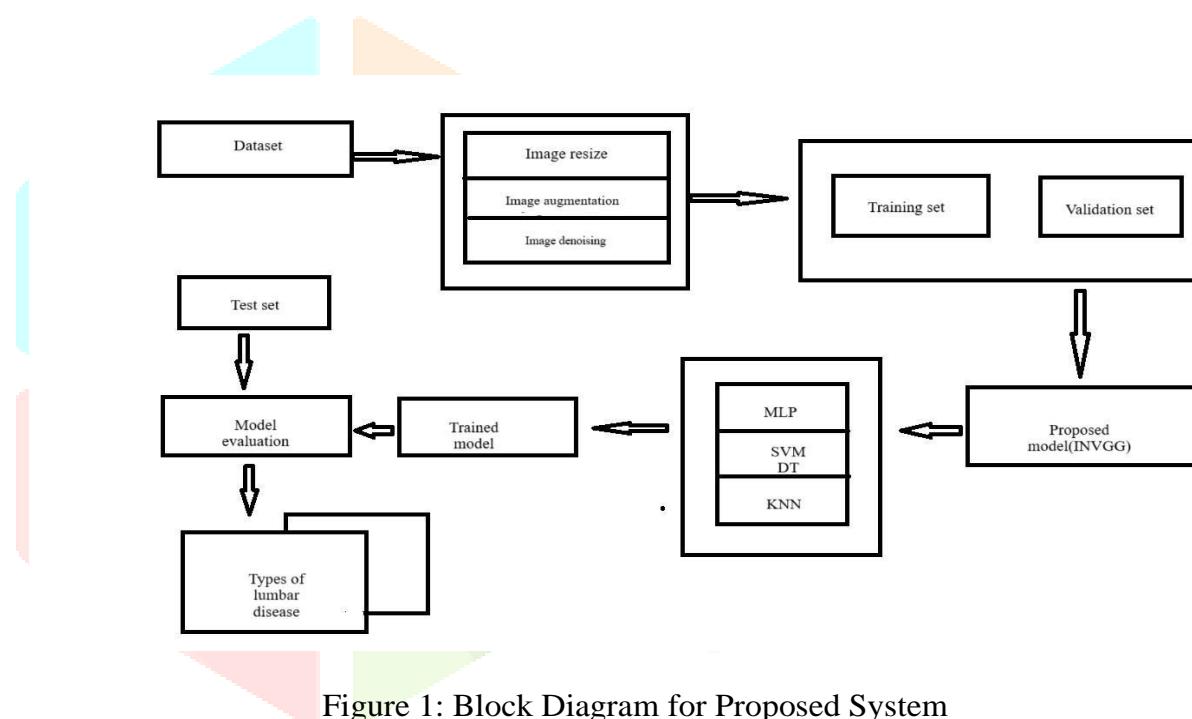


Figure 1: Block Diagram for Proposed System

METHODOLOGY: Lumbar Disease Classification Using Deep Learning

The methodology for this project involves several key steps: data collection, preprocessing, model design, training, evaluation, and deployment. Each phase contributes to the overall goal of developing an efficient and accurate system for classifying lumbar spine conditions from MRI scans.

1. Data Collection

The dataset used in this study consists of MRI scans of lumbar spine images, labeled as either normal or indicative of degenerative disc disease (DDD). These images are sourced from publicly available medical image databases or clinical collaborations with healthcare institutions. Each image is annotated based on expert radiologist assessments.

2. Data Preprocessing

Before feeding the MRI images into the deep learning models, they undergo several preprocessing steps to ensure consistency and enhance the quality of input data:

- Resizing: Images are resized to a uniform size to fit the model input requirements.
- Normalization: Pixel values are normalized to a range of $[0, 1]$ for better convergence during training.
- Contrast Enhancement: Histogram equalization or other contrast enhancement techniques are applied to improve image clarity and highlight relevant features, particularly in regions affected by DDD.
- Augmentation: Data augmentation techniques, such as random rotations, flipping, and zooming, are used to artificially increase the dataset size and improve the model's generalization ability.

3. Model Design

The algorithm employs two Convolutional Neural Network (CNN) architectures:

- VGGNet: The VGGNet architecture, a traditional deep CNN, is used as a baseline model. It consists of several convolutional layers followed by fully connected layers, designed to learn hierarchical features from input images.
- Involutional Neural Based VGG (INVGG): The INVGG model modifies the VGGNet by introducing involution operations. Involutional layers replace standard convolutions and adapt to spatially varying features in the image, enabling the model to better capture the fine details and contextual dependencies specific to DDD.

Both models are designed with a similar architecture, with VGGNet serving as the baseline and INVGG using more advanced feature extraction techniques. The goal is to compare the performance of both models in terms of classification accuracy and robustness.

4. Training

Both the VGGNet and INVGG models are trained on the preprocessed dataset using the following steps:

- Loss Function: A binary cross-entropy loss function is used, as the task is a binary classification problem (normal vs. DDD).
- Optimizer: The Adam optimizer is employed for efficient training, adjusting learning rates adaptively during the optimization process.
- Batch Size and Epochs: The model is trained in batches with an appropriate batch size and for a set number of epochs to prevent overfitting. Early stopping is used to halt training when the model's performance on the validation set no longer improves.
- Regularization: Techniques like dropout and weight decay are applied to reduce overfitting and improve generalization.

5. Model Evaluation

The performance of both VGGNet and INVGG is evaluated using the following metrics:

- Accuracy: The percentage of correctly classified images (normal vs. DDD).
- Precision: The proportion of positive predictions that are actually correct.
- Recall: The proportion of actual positive instances correctly identified.

- F1-Score: The harmonic mean of precision and recall, providing a balanced measure of performance.
- Confusion Matrix: A confusion matrix is used to further analyze the model's classification performance by providing a detailed breakdown of true positives, true negatives, false positives, and false negatives.

6. Deployment

- Web Interface: Clinicians and researchers can upload MRI scans through the web interface, where the image is processed and classified by the trained deep learning model.
- Real-time Predictions: The model outputs a classification label (normal or DDD) in real time, providing immediate feedback for diagnostic decision-making.
- User-Friendly Design: The application is designed to be intuitive and easy to use, requiring minimal technical expertise from medical professionals.

7. System Testing and Validation

After deployment, the system undergoes rigorous testing to ensure it functions correctly in real-world clinical settings. This includes:

- Usability Testing: Ensuring that clinicians can easily interact with the system and obtain meaningful results.
- Performance Testing: Testing the system's response time and accuracy in different usage scenarios, including high patient volumes.

RESULTS & ANALYSIS

```
Microsoft Windows [Version 10.0.19045.5737]
(c) Microsoft Corporation. All rights reserved.

C:\Users\pc\Downloads\lumbar_classification>PYTHON APP.PY
2025-04-13 00:00:31.478308: I tensorflow/core/util/port.cc:153] oneDNN custom operations are on. You may see slightly different numerical results
due to floating-point round-off errors from different computation orders. To turn them off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`
.
2025-04-13 00:00:44.269605: I tensorflow/core/util/port.cc:153] oneDNN custom operations are on. You may see slightly different numerical results
due to floating-point round-off errors from different computation orders. To turn them off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`
.
2025-04-13 00:01:08.550278: I tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use available CPU instruct
ions in performance-critical operations.
To enable the following instructions: AVX2 FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
* Serving Flask app 'APP'
* Debug mode: on
INFO:werkzeug:[31mWARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead. [+0m
* Running on http://127.0.0.1:5000
INFO:werkzeug:[33mPress CTRL+C to quit [+0m
INFO:werkzeug: * Restarting with stat
2025-04-13 00:01:39.519805: I tensorflow/core/util/port.cc:153] oneDNN custom operations are on. You may see slightly different numerical results
due to floating-point round-off errors from different computation orders. To turn them off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`
.
2025-04-13 00:01:44.044080: I tensorflow/core/util/port.cc:153] oneDNN custom operations are on. You may see slightly different numerical results
due to floating-point round-off errors from different computation orders. To turn them off, set the environment variable `TF_ENABLE_ONEDNN_OPTS=0`
.
2025-04-13 00:01:56.127779: I tensorflow/core/platform/cpu_feature_guard.cc:210] This TensorFlow binary is optimized to use available CPU instruct
ions in performance-critical operations.
To enable the following instructions: AVX2 FMA, in other operations, rebuild TensorFlow with the appropriate compiler flags.
WARNING:werkzeug: * Debugger is active!
INFO:werkzeug: * Debugger PIN: 128-633-984
```

Figure1:To run Python web server

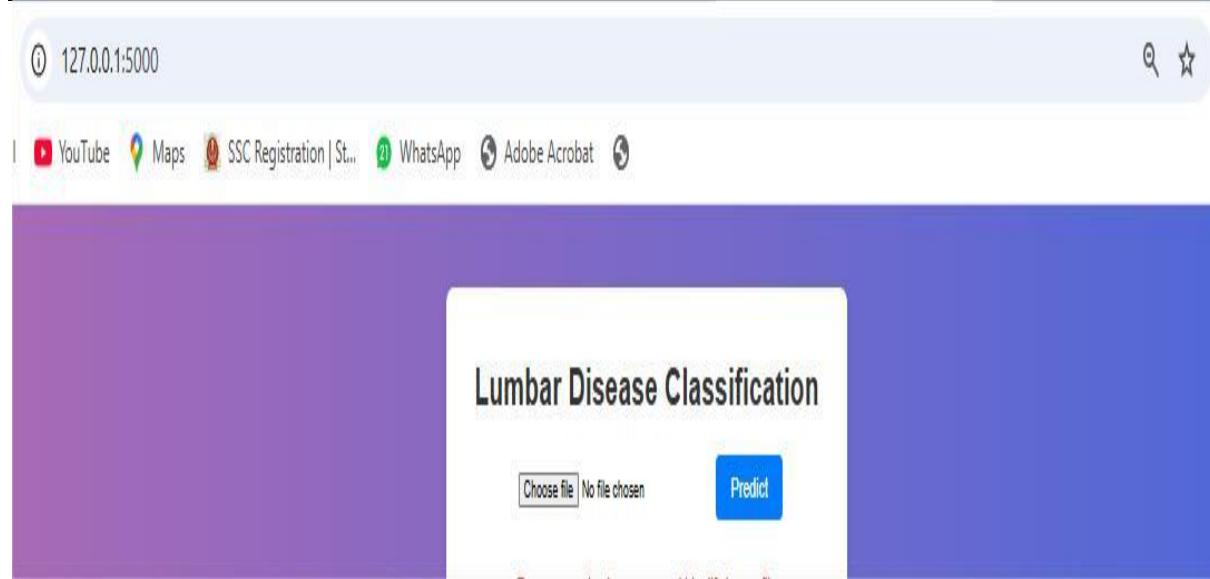


Figure2: Website redirecting

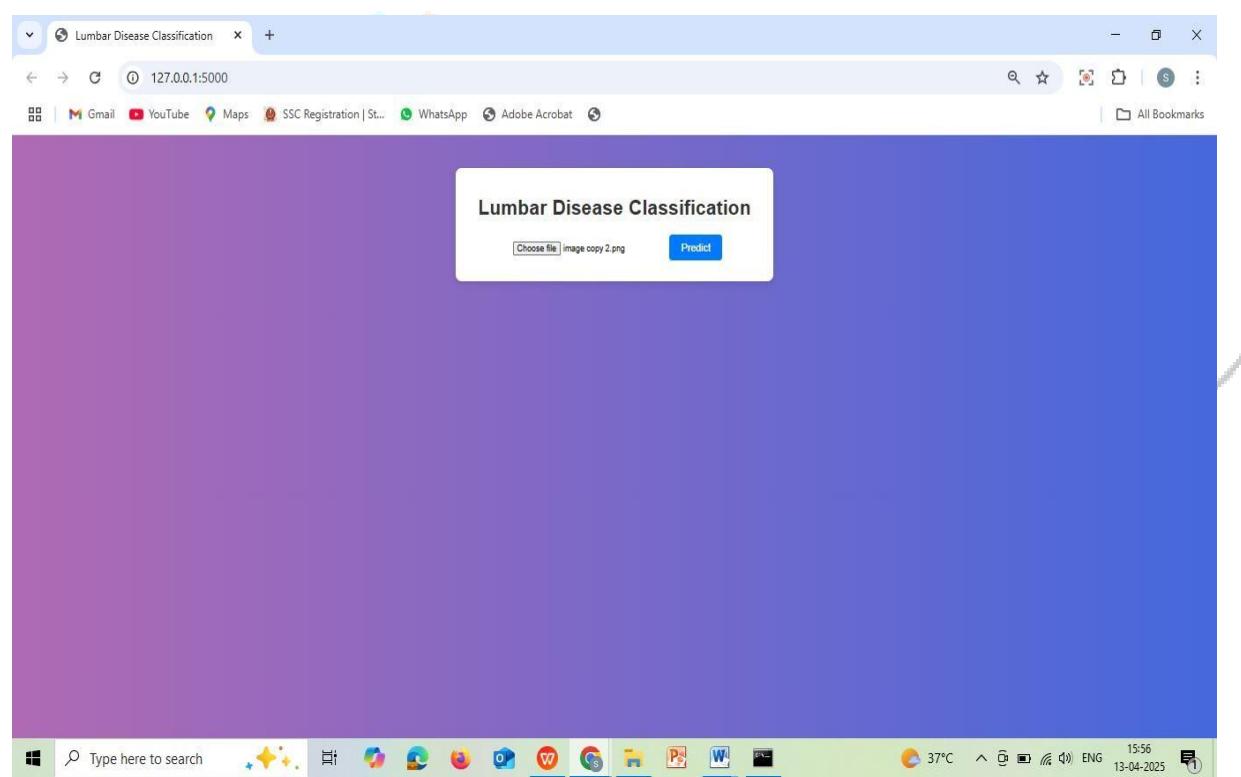


Figure3: Home Page to fill in the details



Figure4: Predicting the Output



Figure5: Output Window

CONCLUSION

This study successfully demonstrated the application of deep learning models, specifically VGGNet and the enhanced Involutional Neural Based VGG (INVGG), for the classification of lumbar spine disorders, distinguishing between normal and degenerative disc disease (DDD). By leveraging the power of Convolutional Neural Networks (CNNs) and the spatially adaptive features of INVGG, the proposed system achieved a high level of accuracy in identifying DDD in lumbar MRI scans. The results highlight the potential of deep learning to address the limitations of traditional diagnostic methods, which are often time-consuming and subject to human error. The INVGG model, in particular, demonstrated superior performance over the baseline VGGNet, effectively capturing complex spatial relationships in medical imagery, leading to better diagnostic precision. Furthermore, the integration of the model into a Flask-based web application makes it accessible and practical for real-world clinical environments, enabling faster decision-making by clinicians. This work contributes to the growing body of research in AI-driven healthcare solutions and paves the way for the development of more reliable, scalable, and efficient diagnostic tools for spinal disorders. Future work could focus on expanding the dataset, refining the models for even higher accuracy, and incorporating additional spinal conditions for broader diagnostic capabilities. Overall, this research emphasizes the transformative potential of AI in enhancing diagnostic workflows and improving patient outcomes in spinal healthcare.

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