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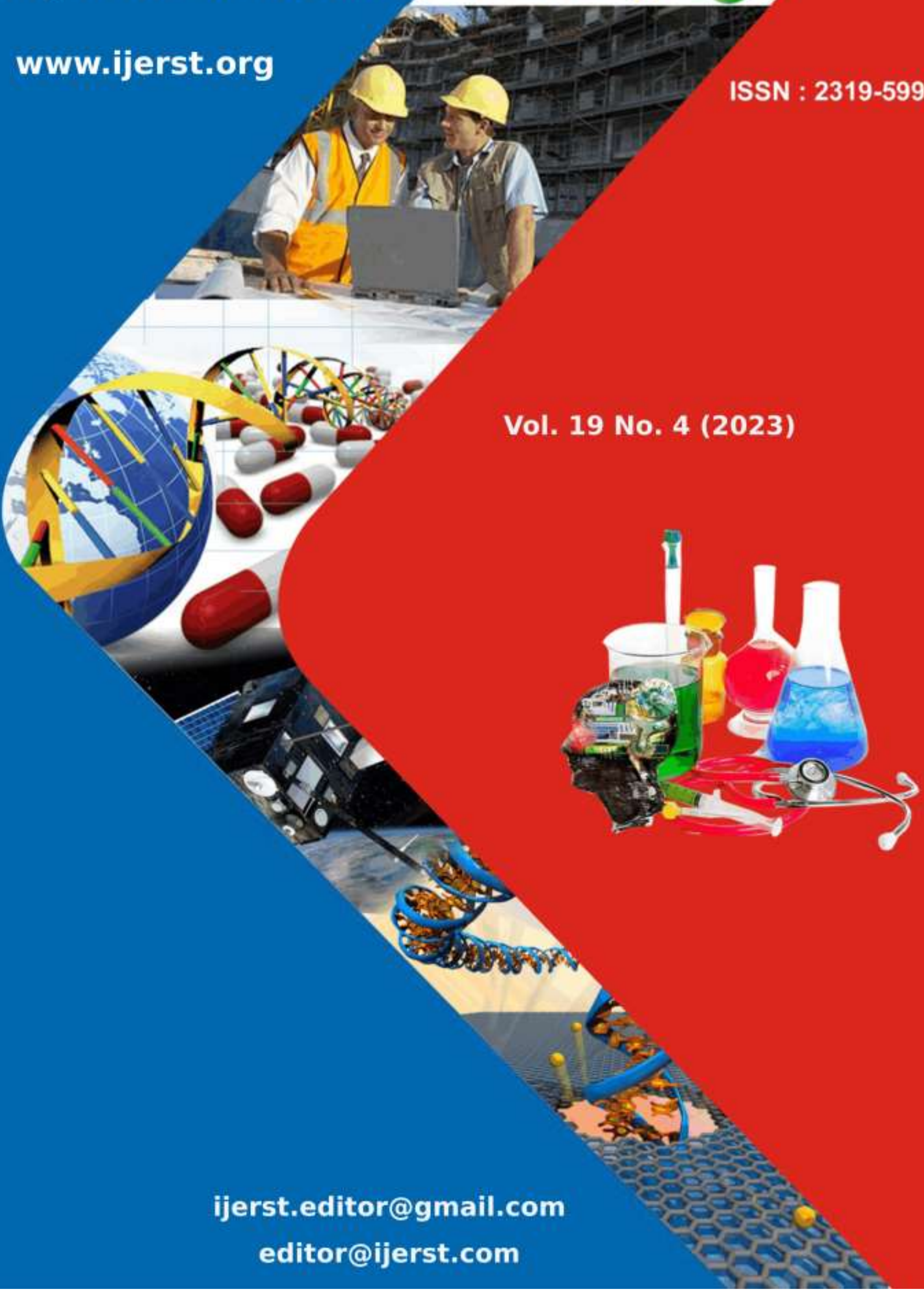

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Research Paper

Automated Lumbar Spine Degeneration Classification: Deep Learning and Web-Based Approach

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***Abstract*— Lumbar Spine Degenerative Classification** project **focuses on automating the diagnosis of lumbar spine degeneration using advanced image analysis techniques. Traditional methods rely on manual interpretation of MRI scans, which can be time-consuming and inconsistent. To improve accuracy and efficiency, this system processes medical images using specialized computational models. The images undergo pre-processing to enhance quality and ensure uniformity. A structured approach extracts important features from MRI scans for precise classification. Fine-tuning techniques optimize performance for reliable results. The system is designed for real-world use through a web-based interface, allowing easy access for medical professionals. It reduces errors and speeds up the diagnostic process. Future improvements include expanding its capabilities to detect other spinal disorders. This work enhances healthcare accessibility and supports better patient care.**

Keywords—Image Processing, Deep Learning, Convolutional Neural Networks (CNNs), Transfer Learning, Web-Based Interface.

I. INTRODUCTION

Lumbar spine degeneration is a widespread medical condition affecting millions worldwide, often resulting in chronic pain, reduced mobility, and a lower quality of life. The primary cause is age-related wear and tear on intervertebral discs, though other factors such as genetics, lifestyle, and injuries also contribute. Traditional diagnostic methods, including X-rays and MRI scans, rely on manual interpretation by radiologists and orthopedic specialists. However, this approach can be time-consuming and subject to human error, highlighting the need for more efficient diagnostic techniques..

Advancements in medical imaging and deep learning have opened new possibilities for automating lumbar spine degeneration classification. AI-based models can analyze medical images with improved accuracy, assisting healthcare professionals in making faster and more reliable diagnoses. These automated systems enhance objectivity in assessments and contribute to better patient outcomes by enabling early detection and targeted treatment strategies.

The lumbar spine consists of five vertebrae (L1–L5), which support the upper body and facilitate movement. L1, the topmost lumbar vertebra, plays a crucial role in weight-bearing and spinal cord protection. L2 offers flexibility but is vulnerable to fractures. L3, positioned at the center, assists in bending and twisting, though it is prone to herniation. L4, located below L3, is a common site for disc herniation and nerve compression. L5, the lowest lumbar vertebra, bears the most weight, connects to the sacrum, and is particularly susceptible to degeneration due to its load-bearing function.

The severity of lumbar spine degeneration is classified into different grades based on structural changes in the spine. Grade 1, representing mild degeneration, is characterized by minimal disc space narrowing, mild facet osteoarthritis, and no significant stenosis or spondylolisthesis. Grade 2, indicating moderate degeneration, involves more noticeable disc space narrowing (25-50%), moderate facet osteoarthritis, and mild stenosis or spondylolisthesis.

Severe degeneration falls under Grade 3, where disc space narrowing becomes significant (50-75%), and moderate to severe spinal stenosis or spondylolisthesis is observed. Grade 4 represents extreme degeneration, with near-total or total disc collapse, severe facet osteoarthritis, and severe stenosis. The most advanced stage, Grade 5, is ankylosis, where complete fusion of the affected segment eliminates motion and flexibility, leading to severe mobility restrictions.

This classification system helps standardize the assessment of lumbar spine degeneration, allowing clinicians and researchers to communicate effectively about disease severity. However, variations in classification criteria exist, as different specialists may adopt slightly different systems. By integrating deep learning techniques, automated classification can provide more consistent and precise evaluations, reducing variability and aiding in early intervention and improved patient care.

II. RELATED WORK

Recent advancements in medical image analysis have leveraged deep learning techniques for disease detection and diagnosis, particularly in spinal disorders like lumbar spine degeneration. Convolutional neural networks (CNNs) have demonstrated high accuracy in classifying MRI and CT scans, with transfer learning methods such as

VGG16 and ResNet enhancing performance. Studies show that AI-driven diagnostic tools can match or exceed radiologists in certain cases, improving efficiency and consistency. Web-based platforms integrating automated image analysis enable real-time decision support, reducing workload and enhancing accessibility. Research also explores telemedicine applications, extending diagnostic capabilities to remote areas with limited specialist availability. Ongoing efforts focus on refining deep learning models, improving interpretability, and integrating multi- modal imaging for better clinical applicability.

Briana Lui (2021) [1] introduce Opioid use disorder (OUD) has previously been shown to negatively impact postoperative outcomes. As the number of spine surgeries continues to rise annually, more patients with preexisting OUD will be seen in operating rooms. Our retrospective cohort study aims to expand on the independent association between preoperative OUD and outcomes following lumbar-spine surgery

Nagy Mekhail MD, PhD (2010) [2] introduces retro-spective longitudinal observational cohort study, The primary outcome measure was the incidence of open lumbar decompression surgery at the same level(s) as the mild intervention during 5-year follow-up. Secondary outcome measures were the change in pain levels using the Numeric Rating Scale and opioid medications utilization using Morphine Milligram Equivalent dose per day from baseline to 3, 6, and 12 months post-mild procedure. Postprocedural complications (minor or major) were also collected.

Yasmina Al Khalil (2022) [3] introdues Magnetic resonance imaging (MRI) is the modality of choice for detecting and visualizing almost all spinal disorders, as it provides non-invasive sof tissue visualization with excellent contrast, more detailed compared to other modalities1–5 Thus, it is widely utilized in orthopedic and neurosurgical diagnostics, ranging from dedicated imaging in scoliosis, intervertebral disc disease, and osteoporosis to injuries including vertebral fractures as well as to computer-assisted surgical intervention planning and guidance Visual image reading represents the standard approach in the clinical setting for evaluation of routine spine MRI. Reporting derived from visual image assessment by the radiologist may be enhanced by using the approach of structured reporting and by implementing semi-quantitative grading schemes

Seung Min Ryu (2023) [4] introduces a deep learning-based approach for diagnosing vertebral compression fractures (VCFs) and detecting vertebral levels in lumbar spine lateral radiographs (LSLRs). Using a dataset of 1102 VCF patients and 1171 controls, a modified U-Net architecture was implemented, where a shared encoder trained decoders for both fracture detection and vertebral level identification. The multi-task model outperformed single-task models in sensitivity and accuracy. Internal validation achieved high accuracy (0.929 per patient) and strong sensitivity (0.944), while external validation showed good performance (0.713 accuracy per patient). The model demonstrated a 96% and 94% success rate for vertebral level detection in internal and external datasets, respectively, suggesting its potential to support radiologists in clinical diagnosis.

Sk. Hasane Ahammad (2020) [5] introduces a deep learning framework for spinal cord injury (SCI) detection using a CNN-based segmentation and boosting classifier. Traditional manual diagnosis by radiologists is time- consuming and challenging due to high-dimensional feature spaces. The proposed model automates the classification of normal and abnormal SCI images, improving accuracy and efficiency. A real-time wearable sensor is used to capture spinal disorder data in various shapes and orientations. The CNN-deep segmentation model enhances the detection process, offering better classification results. Compared to existing CNN-based classifiers, this approach provides higher computational efficiency. Experimental results show a true positive rate of 0.9859 and an accuracy of 98.94%. The error rate is reduced to just 1.9%, demonstrating superior prediction performance. The model enables faster and more precise SCI diagnosis. This advancement can significantly aid radiologists in medical imaging applications.

MUHAMMAD YASEEN (2024) [6] introduces a two-stage deep learning-based approach for cervical spine fracture detection. The first stage employs a Convolutional Neural Network (CNN) model to classify CT scan images as fractured or non-fractured, using Grad-CAM for enhanced visualization. In the second stage, the study utilizes YOLOv5 and YOLOv8 models to detect fractures in specific vertebrae, training on a dataset of 9170 images. The models are evaluated using performance metrics such as precision, recall, mAP50, and mAP50-90. The comparison of YOLO versions highlights improvements in accuracy and efficiency. This approach demonstrates the potential of deep learning in automating cervical spine fracture detection, aiding radiologists in timely and accurate diagnosis.

Rakesh Kumar (2024) [7] introduces a systematic review on scoliosis detection, focusing on vertebra identification and Cobb Angle (CA) estimation The methodology includes deep learning (DL)-based approaches such as Convolutional Neural Networks (CNNs), U-Net for segmentation, and YOLO for vertebra detection. The process involves image preprocessing, vertebra segmentation, feature extraction, and CA estimation using regression models or geometric calculations

Sebastiaan R.S. Arends (2022) [8] introduces a multi-scale CNN for automatic vertebral body segmentation and labeling in radiotherapy planning. Two methods were tested: a combined approach (one CNN for both tasks) and a sequential approach (separate CNNs for segmentation and labeling). The model was trained on 580 vertebrae and validated on 202 vertebrae using Dice Similarity Coefficient (DSC) and Hausdorff Distance (HD) for accuracy assessment. The sequential approach proved more robust in external validation. Radiation oncologists rated 77% of automatic delineations as clinically acceptable, showing the model's potential to improve efficiency and consistency in spinal radiotherapy planning.

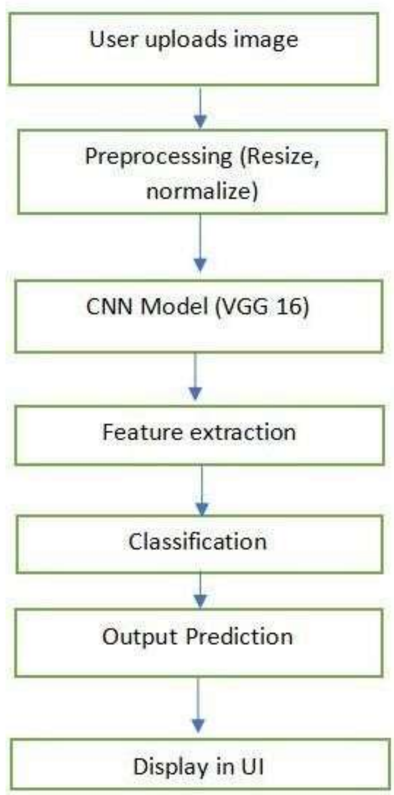
.James Thomas Patrick Decourcy Hallinan (2021) [9] introduces two-step deep learning process for spinal MRI analysis. Faster R-CNN with ResNet101 is trained to detect regions of interest (ROIs) such as the central canal, lateral recesses, and neural foramina. Once detected, a CNN classifier categorizes conditions into normal, mild, moderate, or severe using six convolutional layers with ReLU activation, batch normalization, and max-pooling, followed by two fully connected layers with softmax activation. A weighted categorical loss function improves classification accuracy. To prevent learning irrelevant background features, an ROI detection model ensures the CNN focuses only on relevant areas. Predictions are visualized as bounding boxes, and Integrated Gradients generate heatmaps to highlight key features influencing classification. This method improves diagnostic precision and enhances spinal abnormality classification in real-world applications.

Nils Christian Lehnen (2021) [10] introduces Convolutional Neural Network (CNN) to analyze MRI scans and detect degenerative changes in the lumbar spine, such as disc herniation, bulging, spinal canal stenosis, nerve root compression, and spondylolisthesis. The CNN was trained on 146 patient MRI datasets and validated against a radiologist's assessment. The methodology involves image preprocessing, CNN-based feature extraction, automated segmentation, and classification of spinal conditions. Performance was evaluated using confusion matrices and McNemar's test, showing high accuracy in detecting spinal canal stenosis (98%), nerve root compression (91%), and disc herniations (87%). The results highlight the feasibility of deep learning for automated lumbar spine diagnosis, reducing radiologists' workload and improving diagnostic efficiency.

Zeina El Kojok (2024) [11] introduces generative models to enhance AI-based detection of incidental Vertebral Compression Fractures (VCFs) in chest CT scans. First, a synthetic dataset is generated using the CTSpine1K dataset to simulate realistic grayscale images. Then, different models—DCGAN, VAE, and VAE-GAN—are evaluated, with VAE-GAN achieving the best performance based on Frechet Inception Distance (FID). To improve real-world applicability, the GAN model undergoes transfer learning using real CT scan data from AUBMC to generate additional samples. A CNN classifier is then trained on the augmented dataset (real + synthetic images), significantly improving classification accuracy from 73% to 89%. This approach demonstrates that synthetic data enhances model performance, aiding in the early detection of overlooked spinal fractures.

Guillermo Sánchez Rosenberg (2022) [12] introduces deep learning-based fracture detection on sagittal radiographs of the thoracolumbar (TL) spine using ResNet18 and VGG16 convolutional neural networks (CNNs). A dataset of 630 vertebra images from 151 patients was used, with 302 showing fractures and 328 without fractures. After data augmentation, both models were trained, validated, and tested to classify vertebral fractures. ResNet18 outperformed VGG16, achieving 91% sensitivity, 89% specificity, and 88% accuracy. A heatmap analysis was conducted to visualize the model's decision-making process, revealing that in 81% of cases, the warm zones in the heatmap aligned with actual fractures. The study found that vertebras T12 to L2 were most frequently affected, with A4, A3, and A1 being the most common fracture types per the AO Spine Classification. The findings suggest that ResNet18 can accurately identify traumatic vertebral fractures, potentially improving diagnosis in regions with limited CT/MRI access.

III. METHODOLOGY



A. System Overview

The proposed model aims to automate the process of detecting and classifying lumbar spine degeneration using a deep learning-based approach. The system is designed to receive an MRI image of the lumbar spine through a simple web interface and return the predicted grade of degeneration, ranging from Grade 1 to Grade 5. The overall architecture consists of an image preprocessing module, a pretrained convolutional neural network (CNN) based on VGG16 for feature extraction, and a classifier trained to detect the severity of spinal degeneration. By leveraging the capabilities of transfer learning, the system achieves efficient and accurate classification even with a limited dataset. The frontend provides a minimal user interface that allows for easy input and output display, while the backend operates locally, processing the uploaded image and generating the result without requiring deployment to a server.

B. Development Environment and Tools

The system was developed using Python as the primary programming language due to its extensive support for machine learning and deep learning libraries. TensorFlow were utilized for designing and training the neural network model, while NumPy and Pandas played a crucial role in data manipulation and preprocessing. For handling image data, libraries such as Tensor Flow were used to perform resizing, normalization, and format conversion. The model development and experimentation were conducted within Jupyter Notebook, providing an interactive and efficient environment for iterative testing. To provide user interaction, a simple frontend was built using HTML, CSS, and JavaScript, which enabled image input and output display in the local system. The model has not yet been deployed on a production server but functions effectively through localhost for testing purposes.

C. Image Preprocessing and Feature Extraction

Before feeding the MRI images into the model, several preprocessing steps were performed to ensure uniformity and compatibility with the CNN architecture. Each image was resized to 224x224 pixels to match the input requirements of the VGG16 network. Additionally, pixel values were normalized to the range of 0 to 1 to ensure consistent intensity scaling, which improves model convergence. Images were also converted to RGB format to comply with the three-channel input expected by the pretrained model. Following preprocessing, feature extraction was carried out using the convolutional layers of the VGG16 architecture. Instead of training a CNN from scratch, the pretrained VGG16 model, originally trained on ImageNet, was used to extract meaningful features from the input images. This transfer learning approach significantly reduced the need for a large training dataset while maintaining high performance.

D. Classification and Model Optimization

The classification module builds upon the feature representations extracted from VGG16 by adding custom fully connected layers tailored for the specific task of lumbar spine degeneration classification. The final layers of the model include dense layers followed by a softmax activation function to output the probability distribution across five possible grades. The model was trained using a categorical cross-entropy loss function and optimized using the Adam optimizer, which is well-suited for deep learning tasks. A portion of the dataset was reserved for validation to monitor the model's generalization capability during training. Techniques such as dropout regularization and learning rate tuning were employed to minimize overfitting and improve robustness. The performance of the model was evaluated using metrics such as accuracy, precision, recall, and F1-score, along with the analysis of the confusion matrix to visualize classification errors.

E. Local Execution via UI

To provide a user-friendly experience, a lightweight web interface was developed using HTML, CSS, and JavaScript. This interface enables users to upload MRI images directly from their device and receive the classification result without navigating away from the page. Once an image is submitted, it is passed to the locally running Python backend, where the trained model processes it and returns the predicted grade. The output is then displayed in a readable format on the same webpage. Since the current implementation runs on localhost, all operations, including model execution and data handling, are performed locally on the user's machine. This setup facilitates easy testing and demonstration of the model's functionality without the complexity of deploying to a remote server.

F. Model Execution and Testing

The trained model was saved in .h5 format and loaded during runtime for prediction. A standalone Python script handles the image input, preprocessing, and model inference steps. For testing purposes, a diverse set of MRI images was used to ensure the model's accuracy across different cases of spine degeneration. Performance was assessed by computing key metrics and validating results against known ground truth labels. The system demonstrated strong classification performance on test data, indicating that it generalizes well even on previously unseen images. Through comprehensive testing, it was confirmed that the model provides consistent and reliable outputs under different input conditions.

G. Future Enhancements

Although the current system operates efficiently on a local environment, future development will focus on deploying the model through a web server using frameworks such as Flask or Django. This will allow the system to be accessible remotely and scalable for real-time use in medical settings. Integration with medical imaging formats like DICOM is also planned, enabling direct support for clinical MRI scans. Additionally, interpretability tools such as Grad-CAM will be implemented to provide visual explanations of the model's decisions, enhancing its transparency for medical professionals. Furthermore, the model may be expanded to detect other spinal conditions and diseases, broadening its applicability in spinal diagnostics.

In this project, we created a system that can check MRI images and tell how much the spine is damaged. We used Python and machine learning tools to train a model that learns from MRI scans. To make it easy to use, we built a simple webpage where users can upload an image and get the result. Right now, everything works on our own computer (localhost), and there is no server or online website yet. In the future, we plan to make it better by putting it online and showing results in a more helpful way. This system can help doctors save time and make fewer mistakes while checking spine problems.

IV. RESULTS

The system was trained and tested using MRI images of the lumbar spine, classified into different grades based on the level of degeneration. We used a transfer learning approach with the VGG16 model, which gave better accuracy compared to training from scratch. The images were preprocessed and resized to a fixed size before being used for training. After training, the model was able to correctly classify most of the test images into their respective grades with high accuracy.

We tested the model on several MRI images through a local web interface, where users could upload an image and instantly get the predicted degeneration grade. The predictions were fast and matched the expected output in most cases. This shows that the model is reliable and can be used for real-time diagnosis support..

A. Sample User Interface

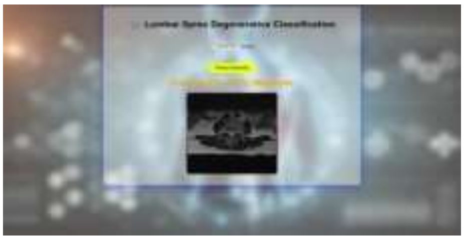
The user interface was designed using HTML, CSS, and JavaScript. It allows the user to select an image and get a prediction on the same page after clicking the upload button.

Figure 1: User Interface for MRI Image Upload

B. Input Image 1 and Output Prediction

The first sample MRI image (Figure 2) was uploaded through the interface. After processing the image, the system predicted the degeneration grade correctly based on the trained model.

Figure 2: Sample Input-Output MRI Image – Case 1



V. CONCLUSIONS

This research focuses on automating lumbar spine degeneration classification to improve diagnosis accuracy and efficiency. By processing MRI scans through structured preprocessing and classification techniques, the system provides a reliable method for assessing spine conditions. The web-based interface allows medical professionals to easily access and analyze results, reducing dependency on manual interpretation. This approach minimizes human error and speeds up the diagnostic process. Future improvements will include refining classification accuracy, integrating additional spinal disorder detection, and expanding telemedicine support. Overall, this system enhances medical diagnosis, ensuring better patient care and accessibility.

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