Clinical Implementation Documentation

Automated Feature Extraction

Advanced computer vision techniques will be implemented to extract key anatomical parameters—pelvic incidence, pelvic tilt, lumbar lordosis angle, sacral slope, pelvic radius, and the degree of spondylolisthesis—directly from X-ray or CT imaging. These features will be derived using automated anatomical landmark detection, ensuring consistent and precise measurements for input into the machine learning (ML) model for classification.

The workflow will include a pre-processing phase to standardise image quality, ensuring uniform brightness and contrast to optimise landmark detection accuracy. A radiologist interface will be provided to enable specialists to review and validate the extracted features. Any approved adjustments will feed back into the model's training data to improve performance over time. By automating these measurements, this approach will reduce errors, improve consistency, and accelerate clinical workflows.

Integration into Clinical Systems

A secure middleware layer will be deployed to connect the ML model with Picture Archiving and Communication Systems (PACS) and Electronic Health Record (EHR) systems. The middleware will leverage standards such as FHIR and DICOM to ensure seamless data exchange.

Additionally, role-based access controls and audit logs will be implemented to maintain compliance with healthcare privacy regulations, ensuring that patient data remains accessible only to authorised personnel.

Data Flow:

1. Images will be uploaded to PACS as usual.
2. The middleware will automatically forward the images to the ML model for feature extraction and classification.
3. The results—including classification scores, confidence indicators, and annotated images—will be returned directly to the EHR or radiologist dashboard, seamlessly integrating into existing workflows.
4. Clinicians will receive notifications when new classifications are ready for review. In cases with low confidence or ambiguous findings, the system will prompt additional clinical review or request further imaging.

Clinical Decision Support System (CDSS)

Ambiguous cases can be flagged for further review or additional imaging, ensuring patient safety and facilitating informed decision-making.

The outputs from the ML model will be integrated into a Clinical Decision Support System (CDSS) to assist surgeons and radiologists with real-time predictions. These predictions—labelled as Normal, Herniated Disc, or Spondylolisthesis—will include confidence scores and be accompanied by highlighted visual overlays pinpointing abnormalities. The system will also indicate the parameters that influenced each decision, enhancing interpretability.
For instance, a surgeon reviewing a patient's imaging will be able to see highlighted regions of abnormal curvature alongside quantitative measurements. This will aid in surgical planning or in

deciding whether additional imaging is required. Ambiguous cases will be flagged for further review or follow-up imaging to ensure patient safety and support informed decision-making.

Training, Adoption, and Ongoing Support

To ensure a smooth integration of the new workflow, practical workshops and hands-on training sessions will be provided for clinicians. These sessions will be led by technical specialists and experienced radiologists who have participated in early pilot tests, offering real-world insights and case examples.

Clear communication and ongoing support will be prioritised through the provision of a help desk and periodic updates. Emphasis will be placed on how the system enhances, rather than replaces, clinical expertise. This approach is designed to foster trust, encourage adoption, and ensure the system's long-term success.