DEVELOPMENT OF A GENERATIVE ADVERSARIAL NETWORK BASED MODEL FOR THE RECONSTRUCTING AND CLASSIFICATION OF NOISY CERVICAL SPONDYLOSIS USING CT/MRI IMAGES

Thesis Submitted for the Award of the Degree of

DOCTOR OF PHILOSOPHY

in

COMPUTER SCIENCE AND ENGINEERING

By

Robin Kumar

Regisration Number: 41800866

***S*upervised By :**

Dr. Dalwinder Singh (11265)

Department of Computer

Science and Engineering

Transforming Education Transforming India

LOVELY PROFESSIONAL UNIVERSITY, PUNJAB

2025

DECLARATION

I, hereby declare that the presented work in the thesis entitled **“Development of a Generative Adversarial Network Based Model for the reconstructing and classification of Noisy Cervical Spondylosis using CT/MRI images"** in fulfillment of the degree of **Doctor of Philosophy (Ph.D.)** is the outcome of research work carried out by me under the supervision of Dr. Dalwinder Singh, working as Associate Professor, in the School of Computer Science and Engineering, Lovely Professional University, Punjab, India. In keeping with general practice of reporting scientific observations, due acknowledgements have been made whenever work described here has been based on findings of other investigator. This work has not been submitted in part or full to any other University or Institute for the award of any degree.

Robin kumar
Registration no. 41800866
Department of Computer Science and Engineering
Lovely Professional University, Phagwara, India

CERTIFICATE

This is to certify that the work reported in the Ph. D. thesis entitled **Development of a Generative Adversarial Network Based Model for the reconstructing and classification of Noisy Cervical Spondylosis using CT/MRI images** submitted in fulfillment of the requirement for the award of degree of **Doctor of Philosophy (Ph.D.)** in the School of Computer Science and Engineering, Lovely Professional University(LPU), is a research work carried out by Robin Kumar, 41800866, is bonafide record of her original work carried out under my supervision and that no part of thesis has been submitted for any other degree, diploma or equivalent course.

Dr. Dalwinder Singh
Associate Professor
Department of Computer Science and
Engineering
Lovely Professional University,
Phagwara, India

ABSTRACT

Cervical spondylosis is a prevalent degenerative condition affecting the cervical spine, leading to significant discomfort and neurological impairments in patients. Accurate and early diagnosis is crucial for preventing further complications; however, traditional imaging techniques often suffer from noise, low resolution, and limitations in distinguishing pathological structures. To address these challenges, this research focuses on the development of a Generative Adversarial Network-based Model for Reconstructing and Classifying Noisy Cervical Spondylosis Using CT/MRI Images (GANSCCS). The proposed framework integrates Generative Adversarial Networks (GANs) with Spectral Clustering to enhance image reconstruction and improve classification accuracy for cervical spondylosis diagnosis.

The research begins with a comprehensive analysis of existing generative models used for medical image reconstruction, identifying their limitations and areas for improvement in cervical spondylosis diagnosis. A dataset comprising CT and MRI images of cervical spondylosis cases is collected and preprocessed to ensure high-quality input for model training. The proposed GAN-based model is designed for reconstructing and classifying noisy cervical spondylosis images while incorporating spectral clustering to enhance feature extraction and segmentation. The model is compared and validated against existing state-of-the-art techniques using various performance metrics.

The methodology employed in this study includes a hybrid deep learning approach that integrates GANs with spectral clustering for efficient image enhancement and classification. The workflow consists of data collection and preprocessing, GAN-based image reconstruction, spectral clustering for feature segmentation, and the development of a deep learning classifier to differentiate between different stages of cervical

spondylosis. Evaluation metrics such as accuracy, precision, recall, specificity, AUC (Area Under Curve), Structural Similarity Index (SSIM), and Peak Signal-to-Noise Ratio (PSNR) are used to assess the model's effectiveness.

Experimental results demonstrate that GANSCCS significantly outperforms existing models, such as MSDNet, DDQN, and FP-GANs, across multiple evaluation criteria. The model achieves an 8.3% increase in classification accuracy, a 5.5% increase in precision, and an 8.5% increase in recall compared to traditional deep learning methods. Additionally, GANSCCS attains a specificity of 86.7%, outperforming FP-GANs, which achieved 82%, proving its effectiveness in distinguishing pathological cases. The model also records an SSIM score of 0.91 and a PSNR value of 38.7 dB, indicating superior image reconstruction quality. By reducing false positives and false negatives, GANSCCS enhances clinical decision-making and minimizes misdiagnoses.

The proposed model introduces a novel approach to medical image reconstruction and classification, with the potential to revolutionize diagnostic methodologies for cervical spondylosis and other spinal disorders. By generating high-resolution, noise-free medical images, GANSCCS aids radiologists and physicians in making accurate diagnoses, leading to improved patient outcomes. Future research directions include integrating multi-modal imaging data such as CT, MRI, and X-ray to provide a more comprehensive diagnostic framework, optimizing model inference speed for real-time clinical applications, and extending the methodology to diagnose other spinal conditions such as herniated discs and spinal stenosis. Additionally, personalized medicine approaches leveraging patient-specific data could be explored to tailor diagnostic predictions and treatment plans. Large-scale validation through clinical trials is also necessary to ensure robustness and generalizability across diverse patient populations.

This research significantly contributes to AI-driven medical imaging advancements by integrating GANs with spectral clustering to enhance diagnostic accuracy for cervical spondylosis. By overcoming the limitations of existing generative models and classification methods, GANSCCS sets a new benchmark in medical imaging applications. Its implementation has the potential to transform cervical spondylosis diagnosis and pave the way for AI-powered solutions in healthcare, improving both diagnostic precision and patient care outcomes.

ACKNOWLEDGEMENTS

I take this opportunity to express my sincere gratitude to everyone who has supported me in various capacities throughout my research journey and the preparation of this thesis.

I am profoundly grateful to my esteemed supervisor, Dr. Dalwinder Singh, for his invaluable guidance, encouragement, and unwavering support. His expertise and mentorship have played a pivotal role in shaping the direction of my research and helping me achieve my academic objectives. I extend my heartfelt thanks to the School of Computer Science and Engineering, Lovely Professional University, for providing the necessary resources and support to carry out my doctoral research. I also appreciate the administrative staff at the Centre for Research Degree Programmes for their assistance in facilitating various academic processes. I would like to express my deepest appreciation to my parents, in-laws, friends, and colleagues for their constant support and encouragement throughout this challenging yet rewarding journey. Their belief in me has been a source of great motivation.

A special note of gratitude goes to my wife, Dr. Anju Bala, for her unwavering support, patience, and understanding during this demanding period. Her encouragement has been instrumental in my success. Finally, my heartfelt thanks to my family, whose love and presence have been my strength throughout this endeavor. I am truly fortunate to have such a strong support system by my side.

Robin kumar

CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
GANs	Generative Adversarial Network
GANSCCS	GAN-Spectral Clustering Cervical Spondylosis Classification System
LPU	Lovely Professional University
SSIM	Structural Similarity Index Measure
XAI	Explainable Artificial Intelligence

CHAPTER 1

INTRODUCTION

Cervical spondylosis is a progressive, age-related degenerative disorder affecting the cervical segment of the vertebral column, typically manifesting as chronic structural and functional impairments in the neck region. It is characterized by the gradual degeneration of intervertebral discs, the formation of osteophytes (bone spurs), and thickening of surrounding ligaments such as the posterior longitudinal ligament and ligamentum flavum shown in Figure1.2 [8]. These pathological changes reflect the body's attempt to stabilize the spine in response to disc degeneration and facet joint arthropathy. Over time, the reduction in disc hydration and elasticity leads to a loss of disc height, increased mechanical stress on the vertebral bodies, and instability of the cervical spine. [9]The prevalence of cervical spondylosis increases significantly with age, with radiographic evidence observed in more than 85% of individuals over the age of 60. However, symptomatic presentations can occur earlier, especially in individuals exposed to occupational stressors such as prolonged sitting, poor posture, or repetitive neck movements. Clinically, the degenerative cascade in cervical spondylosis contributes to stiffness, reduced range of motion, and mechanical neck pain. More concerning, however, is the potential for neural involvement. As the intervertebral foramina narrow due to osteophytic encroachment and disc bulging, spinal nerve roots may become compressed, leading to cervical radiculopathy—a condition marked by radiating pain, paresthesia, and motor weakness in the corresponding dermatomes and myotomes of the upper limbs. In advanced stages, central spinal canal stenosis may occur, resulting in cervical myelopathy, which is characterized by gait instability, limb spasticity, impaired fine motor coordination, and in severe cases, bowel and bladder dysfunction [10] . Beyond its biomechanical and neurological consequences, cervical spondylosis significantly affects patients' quality of life. Chronic pain and disability can lead to sleep disturbances, reduced productivity, and psychological distress. Although aging is the most prominent risk factor, other contributing elements include sedentary lifestyle, obesity, smoking, trauma, genetic predisposition, and systemic inflammatory conditions such as rheumatoid arthritis [11]. The onset of symptoms is often insidious, and early stages may be asymptomatic or misattributed to general musculoskeletal fatigue. Therefore, timely diagnosis is critical to prevent irreversible nerve damage and to initiate conservative treatment strategies such as physiotherapy, pharmacologic interventions, and lifestyle modifications. In refractory or rapidly progressive cases, especially those involving significant spinal cord compression, surgical decompression and spinal stabilization may be warranted [12]. Anatomically, the cervical spine is the uppermost and most mobile section of the vertebral column, composed of seven distinct vertebrae (C1–C7). These vertebrae are structurally adapted to support the skull, facilitate multidirectional head movement, and protect the cervical spinal cord and vertebral arteries. C1 (atlas) and C2 (axis) are uniquely shaped to allow rotation and flexion-extension of the head, while C3–C7 form the subaxial cervical spine, where degenerative changes are most commonly observed. Due to its complex biomechanics and the close anatomical proximity of neural and vascular structures, even mild degenerative alterations in this region can have profound clinical implications [8].

1.1 Overview of Cervical Spine Anatomy

The cervical spine comprises seven vertebrae (C1–C7) that support the head, protect the spinal cord, and enable neck movement. Each vertebra includes a vertebral body, arch, transverse processes, and a spinous process. The first two vertebrae, the atlas (C1) and axis (C2), are specialized for head motion, the atlas supports the skull and enables the "yes" nodding movement, while the axis has the odontoid process (dens) that acts as a pivot for the atlas, allowing the "no" rotational movement. The remaining vertebrae (C3–C7) have bifid spinous processes, transverse foramina for vertebral arteries, and uncinate processes that enhance stability. Except between C1 and C2, each vertebra is separated by an intervertebral disc consisting of a nucleus pulposus (gel-like core for shock absorption) and an annulus fibrosus (fibrocartilaginous layer for strength). The facet joints at the posterior aspect permit controlled motion and maintain alignment. Key ligaments, including the anterior and posterior longitudinal ligaments, ligamentum flavum, and transverse ligament of the atlas, provide flexibility and prevent excessive movement [13]. The cervical spine houses the spinal cord, from which eight pairs of nerves (C1–C8) emerge, controlling sensory and motor functions of the neck, shoulders, arms, and diaphragm via the phrenic nerve (C3–C5) [14]. The vertebral arteries pass through the transverse foramina of C1–C6, supplying the brainstem and cerebellum, while the carotid arteries provide additional blood flow to the head and face. Understanding cervical spine anatomy is crucial for diagnosing conditions such as cervical spondylosis, herniated discs, spinal stenosis, and traumatic injuries [15] injuries above C5 can cause quadriplegia [16]. Figure 1.1 [1] shows Cervical Spine Anatomy.

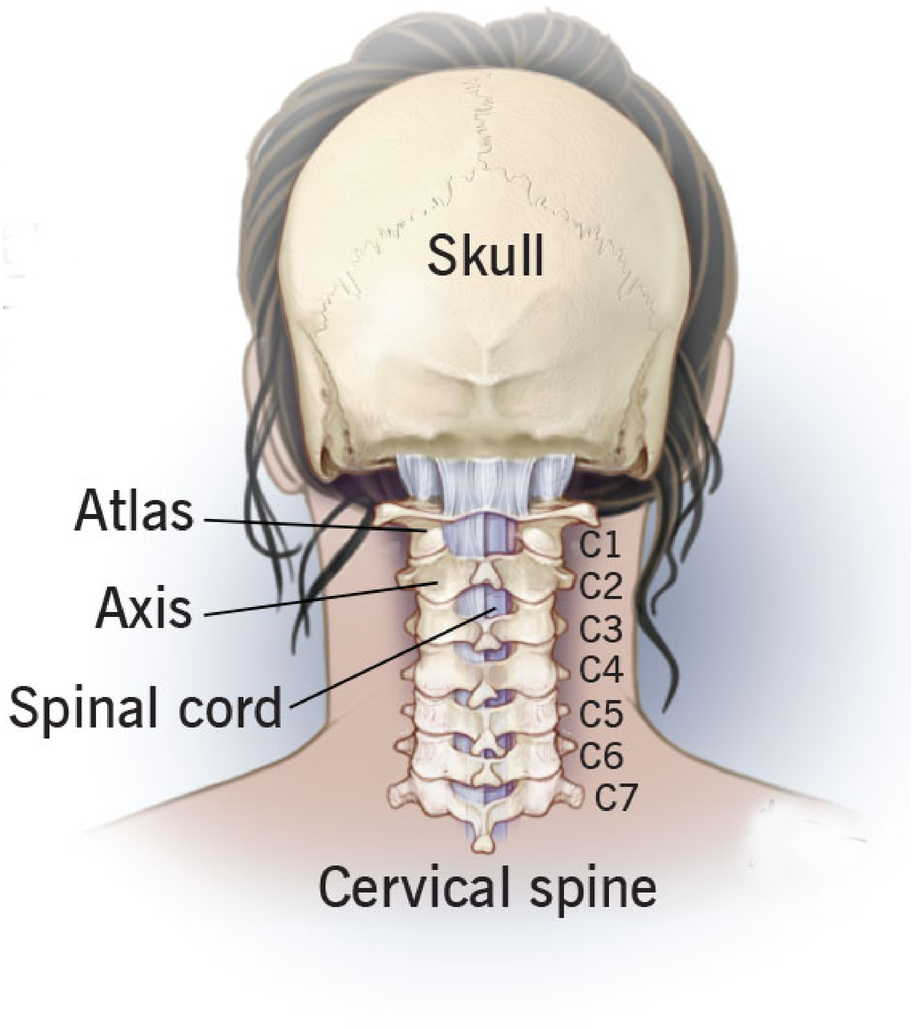

Figure 1.1: Cervical Spine Anatomy [1]

1.1.1 Prevalence and Impact of Cervical Spondylosis

Cervical spondylosis is a highly prevalent musculoskeletal disorder, affecting more than 85% of individuals over the age of 60 [17]. Its incidence increases with age, as degenerative changes in the intervertebral discs, facet joints, and vertebrae become more pronounced. Studies have shown that cervical spondylosis is a leading cause of chronic neck pain, limited mobility, and neurological dysfunction in elderly populations [18]. Despite its widespread occurrence, the condition often remains asymptomatic in its early stages, only manifesting as pain, nerve compression, and functional disability as degeneration progresses [19]. The growing aging population has led to a rising global burden on healthcare systems, with cervical spondylosis contributing significantly to musculoskeletal complaints [20].

Impact on Health: Cervical spondylosis has progressive functional and neurological consequences, affecting an individual's ability to perform daily activities [8] Key impacts include:

- **Reduced mobility and stiffness:** Reduced mobility and stiffness are common symptoms associated with cervical spondylosis and other degenerative disorders of the cervical spine. As the intervertebral discs lose hydration and elasticity, and osteophytes (bone spurs) form around the vertebral bodies and facet joints, the flexibility of the cervical spine gradually diminishes. This leads to restricted neck movement, particularly in flexion, extension, and rotation, making everyday activities such as turning the head while driving or looking over the shoulder more difficult.

  In addition to limiting physical movement, cervical stiffness can also disrupt postural balance and spinal alignment, often causing compensatory strain in adjacent regions of the spine, such as the thoracic or lumbar areas. Chronic stiffness is frequently accompanied by discomfort or dull aching, especially after prolonged periods of inactivity or during early morning hours.

  Over time, the progressive loss of mobility can impair the patient's quality of life, hinder routine activities, and contribute to muscular tension or fatigue. Early diagnosis, targeted physical therapy, posture correction, and regular mobility exercises are essential in managing stiffness and maintaining functional independence.

- **Chronic pain:** Chronic pain is one of the most debilitating symptoms associated with cervical spondylosis and other degenerative spinal conditions. The pain can range in intensity and character—from mild, persistent stiffness in the neck to severe, radiating discomfort that extends into the shoulders, arms, and even the hands. This radiating pain is often a result of nerve root compression (cervical radiculopathy) caused by disc herniation, osteophyte formation, or foraminal narrowing.

  In many cases, the pain is accompanied by other sensory disturbances such as numbness, tingling, or a burning sensation, particularly in the upper limbs. The chronic nature of the condition can lead to significant functional limitations, difficulty sleeping, and emotional distress, including anxiety and depression. Repetitive daily tasks like lifting, writing, or prolonged computer use can exacerbate symptoms, further reducing a patient's quality of life.

Effective management of chronic cervical pain typically requires a multidisciplinary approach, including pharmacological treatment, physical therapy, ergonomic modifications, and, in some cases, interventional procedures or surgery. Early intervention and individualized care plans are essential to alleviate symptoms, prevent progression, and restore optimal function [19].

- **Neurological deficits:** Neurological deficits are a significant complication of cervical spondylosis, often resulting from compression or irritation of the spinal nerves or spinal cord. When nerve roots are compressed typically due to herniated discs, osteophytes, or foraminal narrowing—patients may experience a range of sensory and motor disturbances in the upper limbs.

  Common symptoms include numbness, tingling (paresthesia), and a "pins-and-needles" sensation, particularly in the shoulders, arms, and hands. In more advanced cases, muscle weakness may develop, affecting grip strength, fine motor control, and coordination. These deficits not only impair daily functioning but also pose safety risks, such as dropping objects or difficulty performing precise movements.

  If the spinal cord itself is compressed (a condition known as cervical myelopathy), symptoms may extend beyond the upper limbs and involve balance issues, gait disturbances, and in severe cases, bladder or bowel dysfunction. Timely recognition and intervention are critical, as prolonged compression can lead to irreversible neurological damage.

  A comprehensive clinical assessment, supported by imaging studies such as MRI, is essential for identifying the extent of neural involvement and guiding appropriate management strategies—ranging from conservative therapies to surgical decompression [21].

- **Cervical myelopathy risk:** Cervical myelopathy is the most serious neurological complication of cervical spondylosis, resulting from chronic or severe compression of the spinal cord. This condition develops when degenerative changes such as disc herniation, ligamentum flavum hypertrophy, or osteophyte formation narrow the spinal canal and exert pressure on the spinal cord.

Patients with cervical myelopathy often present with progressive symptoms, including impaired hand coordination, balance disturbances, gait instability, and in advanced stages, bladder or bowel dysfunction. These signs reflect the disruption of central motor and sensory pathways, and if left untreated, can lead to permanent neurological impairment.

The risk of irreversible disability increases with the duration and severity of compression, making early diagnosis and intervention essential. MRI is the imaging modality of choice for detecting spinal cord compression and assessing signal changes within the cord, which may indicate edema or myelomalacia.

Management strategies range from close monitoring in mild cases to surgical decompression in moderate-to-severe cases. Prompt recognition of myelopathic signs is crucial, as timely treatment significantly improves outcomes and helps prevent long-term disability [9].

If left untreated, cervical spondylosis can progress to irreversible spinal cord damage, necessitating surgical intervention in advanced cases [12].

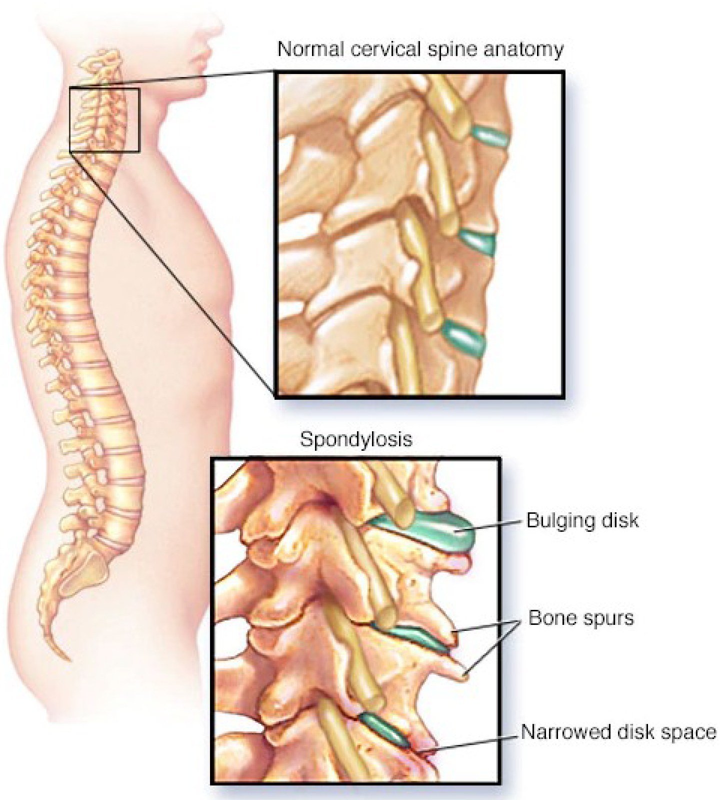

Figure 1.2: Cervical Spondylosis [2]

1.1.2 Importance of Medical Imaging in Diagnosis

Medical imaging plays a pivotal role in the early detection, accurate diagnosis, disease monitoring, and treatment planning of cervical spondylosis. It allows clinicians to precisely visualize spinal anatomy, identify degenerative changes, evaluate the degree of neural compression, and make informed decisions regarding conservative management or surgical intervention [9].High-resolution imaging is especially critical for distinguishing between structural abnormalities that may or may not correlate with clinical symptoms.

Among the most widely used modalities are Computed Tomography (CT) and Magnetic Resonance Imaging (MRI). CT excels in visualizing bony structures, making it ideal for assessing osteophytes, fractures, and canal narrowing. MRI, on the other hand, offers superior soft-tissue contrast, enabling detailed evaluation of intervertebral discs, spinal cord integrity, and nerve root involvement.

In addition to CT and MRI, other imaging techniques such as X-rays, CT myelography, ultrasound, Positron Emission Tomography (PET), and Single Photon Emission

Computed Tomography (SPECT)—may provide valuable diagnostic insights, particularly in cases involving complex presentations or when certain modalities are contraindicated. The choice of imaging technique is often guided by clinical presentation, availability, and the specific diagnostic question being addressed.

CT Imaging

- **High-resolution bone imaging:** Computed Tomography (CT) scans are highly effective for detailed evaluation of bony structures in the cervical spine. Their high spatial resolution enables precise visualization of anatomical details that may be missed on conventional radiographs. CT imaging is particularly valuable in identifying osteophytes (bone spurs), assessing the extent of spinal canal or foraminal narrowing, and detecting fractures or subtle bone abnormalities that are not readily visible on MRI.

  In cases of cervical spondylosis, CT scans allow for accurate assessment of the degree of bony overgrowth and facet joint degeneration, which can contribute to nerve root compression or spinal cord impingement. Additionally, CT is the modality of choice in acute trauma cases where fractures or instability are suspected.

  When combined with myelography (CT myelogram), CT scans can also provide enhanced visualization of neural elements and their relationship with surrounding bony structures, especially in patients who cannot undergo MRI. Although CT offers excellent bone detail, its limited ability to differentiate soft tissues means it is often used in conjunction with other imaging modalities for a comprehensive evaluation [20].

- **Cross-sectional imaging:** Computed Tomography (CT) is a cross-sectional imaging technique that utilizes X-ray technology and computer processing to generate detailed, high-resolution images of internal anatomical structures. In the evaluation of the cervical spine, CT provides exceptional clarity of bony elements, making it a crucial tool for assessing structural abnormalities with high accuracy.

  CT imaging enables precise identification of osteophytes, vertebral body deformities, facet joint degeneration, and spinal canal or foraminal narrowing. Its ability to produce axial, sagittal, and coronal views allows clinicians to examine the cervical spine from multiple angles, facilitating a comprehensive analysis of complex anatomical relationships.

Due to its speed and clarity, CT is particularly valuable in acute trauma settings, where rapid assessment of cervical fractures or dislocations is essential. However, while CT excels in visualizing bone, its capability to differentiate soft tissues such as intervertebral discs, spinal cord, and ligaments is limited compared to MRI. Therefore, CT is often used in combination with other modalities when both bony and soft tissue pathology must be evaluated [19].

- **Limitations:** While Computed Tomography (CT) offers excellent spatial resolution for evaluating bony structures, it has notable limitations in soft tissue imaging. One of the primary drawbacks is its insufficient contrast resolution for differentiating soft tissues such as intervertebral discs, spinal cord, nerve roots, and ligamentous structures. As a result, CT is inadequate for detecting subtle degenerative changes in the intervertebral discs, identifying ligamentous hypertrophy or tears, and evaluating spinal cord compression or edema.

  In the context of cervical spondylosis, where both bone and soft tissue changes contribute to neurological symptoms, this limitation reduces CT's diagnostic effectiveness. Although contrast-enhanced CT or CT myelography can provide additional detail, they still fall short compared to Magnetic Resonance Imaging (MRI) in visualizing soft-tissue pathology. Therefore, CT is often supplemented with MRI to achieve a comprehensive assessment of both osseous and non-osseous spinal abnormalities [8]. Figure 1.3 show the CT image of cervical spondylosis.

Figure 1.3: cervical spondylosis CT image

MRI Imaging

- **Superior soft-tissue visualization:** Magnetic Resonance Imaging (MRI) is the gold standard for evaluating soft-tissue structures in the cervical spine. Its superior contrast resolution allows for detailed visualization of intervertebral discs, spinal cord, nerve roots, ligaments, and surrounding soft tissues without the use of ionizing radiation. This makes MRI the preferred imaging modality for assessing a wide range of degenerative and neurological conditions.

In patients with cervical spondylosis, MRI is particularly effective in identifying disc degeneration, disc herniation, spinal cord compression, and nerve root impingement. It can also detect subtle changes such as spinal cord edema or myelomalacia that may not be visible on CT or X-ray. Furthermore, MRI enables evaluation of soft-tissue abnormalities across multiple planes axial, sagittal, and coronal—providing a comprehensive understanding of the extent and impact of pathology.

Because of its unparalleled soft-tissue imaging capabilities, MRI plays a critical role in guiding clinical decisions, especially in patients presenting with neurological symptoms such as radiculopathy or myelopathy. It is also the modality of choice for preoperative planning and postoperative follow-up in many spinal conditions [8].

- **Safe and effective:** Magnetic Resonance Imaging (MRI) is widely regarded as a safe and highly effective imaging modality, particularly for repeated or long-term monitoring of spinal conditions. Unlike X-rays or CT scans, MRI does not use ionizing radiation, making it a safer alternative especially for younger patients, pregnant women (when appropriate), and individuals requiring multiple follow-up scans over time.

  One of MRI's key advantages is its ability to provide excellent contrast between different types of soft tissue. This allows for precise differentiation of intervertebral discs, spinal cord, nerve roots, and surrounding ligaments, which is crucial for diagnosing and tracking the progression of conditions such as cervical spondylosis, disc herniation, or spinal cord compression.

  Its non-invasive nature, combined with high diagnostic accuracy and safety profile, makes MRI the preferred imaging tool for longitudinal studies and long-term management of spinal pathologies. In clinical practice, it supports both early diagnosis and treatment planning without exposing patients to cumulative radiation risk [17].

- **Limitations:** Despite its superior soft-tissue contrast and safety profile, Magnetic Resonance Imaging (MRI) has several limitations that can impact diagnostic accuracy. One of the primary challenges is its susceptibility to various types of image artifacts, including motion artifacts, magnetic field inhomogeneities, Gibbs ringing, and susceptibility distortions. These artifacts can obscure anatomical structures, reduce image clarity, and potentially mimic or mask pathological findings.

  MRI also tends to have lower spatial resolution compared to Computed Tomography (CT), particularly when imaging fine bony details or small anatomical structures. This can be a disadvantage in assessing subtle fractures, fine foraminal narrowing, or complex osseous abnormalities. Additionally, MRI scans are more time-consuming and require the patient to remain still for extended periods, increasing the risk of motion-induced degradation especially in patients with pain, discomfort, or involuntary movement.

  Furthermore, MRI is contraindicated in certain individuals, such as those with pacemakers, cochlear implants, or metallic foreign bodies incompatible with strong magnetic fields. Claustrophobia and limited access in some regions may also restrict MRI use. Therefore, while MRI remains the preferred modality for soft-tissue evaluation, its limitations must be considered, and supplemental imaging may be necessary for comprehensive assessment [12]. Figure1.4 the MRI image of cervical spondylosis.

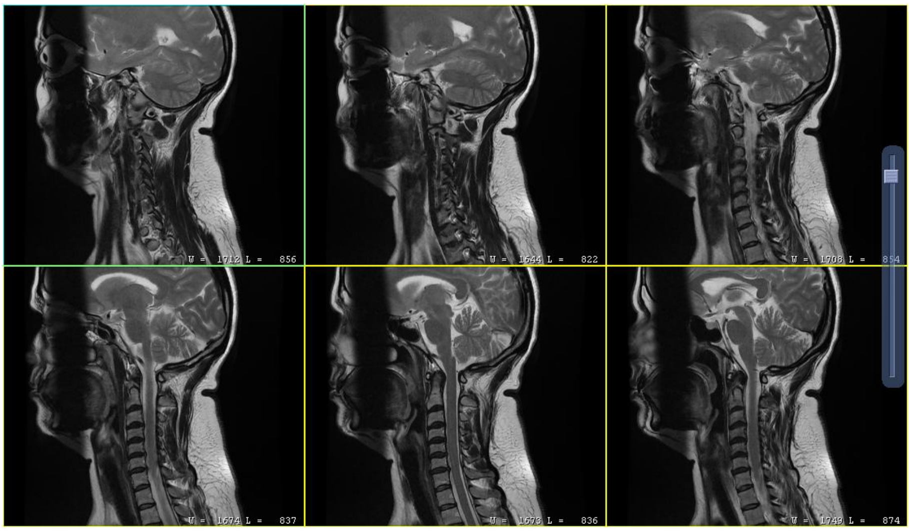

Figure 1.4: cervical spondylosis MRI image

Other Imaging Modalities

In addition to CT and MRI, several other imaging techniques contribute to the diagnostic process in specific clinical contexts:

- **X-ray (Radiography):** X-ray radiography is commonly the first-line imaging technique used in the evaluation of cervical spine disorders. Its widespread availability, low cost, and ability to provide quick diagnostic information make it a practical choice for initial assessment. X-rays are particularly effective in identifying bony abnormalities such as osteophyte formation (bone spurs), narrowing of intervertebral disc spaces, and loss of the natural cervical lordosis, which may indicate underlying muscular spasm or spinal alignment issues. Dynamic views, such as flexion and extension radiographs, may also be utilized to assess cervical spine instability or abnormal motion between vertebrae.

  However, the primary limitation of X-ray imaging lies in its inability to visualize soft tissues. Structures such as intervertebral discs, ligaments, spinal cord, and nerve roots are poorly visualized or not visible at all on standard radiographs. Therefore, while X-rays are useful for detecting degenerative bone changes and alignment issues, they cannot provide sufficient information in cases where soft tissue involvement or neural compression is suspected. In such scenarios, further evaluation with more advanced imaging modalities such as Magnetic Resonance

Imaging (MRI) or Computed Tomography (CT) is typically required to obtain a comprehensive view of the cervical spine.

- **Myelography / CT Myelogram:**Myelography, often combined with Computed Tomography (CT), is an advanced imaging technique used to evaluate the spinal cord, nerve roots, and subarachnoid space. The procedure involves the injection of a radiopaque contrast agent into the subarachnoid space via a lumbar puncture. Once the contrast medium is administered, X-ray or CT imaging is performed to track the flow of cerebrospinal fluid (CSF) and to enhance the visibility of neural structures.

  CT myelography provides superior resolution of bony anatomy and offers detailed visualization of nerve root compression, spinal stenosis, and abnormalities affecting the spinal cord that may not be clearly visible on standard CT or X-ray alone. It is particularly valuable in detecting conditions such as herniated discs, spinal tumors, arachnoiditis, or postoperative complications.

  This technique is especially useful in patients for whom Magnetic Resonance Imaging (MRI) is contraindicated such as those with pacemakers, cochlear implants, or other metal devices incompatible with MRI environments. Although more invasive than MRI or CT alone and associated with some risks (e.g., headache, infection, or allergic reaction to contrast), myelography remains an important diagnostic tool when high-resolution visualization of spinal canal contents is necessary and MRI is not an option.

- **Ultrasound:** Although ultrasound is not typically the primary modality for imaging the cervical spine, it plays a supportive role in specific clinical scenarios. Its value lies in the evaluation of paraspinal soft tissues, including muscles, ligaments, and vascular structures such as the vertebral arteries. Doppler ultrasound, in particular, is effective for assessing vertebral artery blood flow, which may be relevant in cases involving vascular compression or suspected vertebrobasilar insufficiency.

  In addition to diagnostic applications, ultrasound is widely utilized as a real-time guidance tool during interventional spine procedures. It provides dynamic visualization for accurately targeting structures during cervical nerve root blocks, facet joint injections, or trigger point therapies. The portability, safety (no ionizing radiation), and cost-effectiveness of ultrasound make it an attractive option for bedside assessments and procedural guidance, especially in patients for whom radiation exposure is a concern.

Despite these advantages, ultrasound has significant limitations in visualizing deeper spinal elements such as vertebral bodies, intervertebral discs, and the spinal cord, due to acoustic shadowing from bony structures. Therefore, it is generally considered an adjunctive tool rather than a standalone modality for cervical spine evaluation.

- **Positron Emission Tomography (PET):** Positron Emission Tomography (PET), particularly when combined with Computed Tomography (PET-CT), is not routinely used in the evaluation of degenerative spinal conditions such as cervical spondylosis. However, it holds clinical value in specific differential diagnostic scenarios. PET imaging enables metabolic assessment of tissues through the detection of radiolabeled tracers most commonly fluorodeoxyglucose (FDG) which accumulate in areas of increased metabolic activity.

  In the context of cervical spine disorders, PET-CT can be instrumental in distinguishing degenerative changes from other pathological processes such as neoplastic lesions (e.g., spinal metastases), infectious spondylitis, or inflammatory conditions like rheumatoid arthritis. These conditions often exhibit elevated metabolic uptake, allowing PET imaging to highlight abnormalities that may appear ambiguous or nonspecific on conventional anatomical imaging modalities like MRI or CT.

  While PET-CT offers high sensitivity for detecting metabolically active disease, its limited specificity, high cost, and relatively low spatial resolution restrict its routine application in the diagnosis and management of typical degenerative cervical spine conditions. As such, PET is primarily reserved for complex or atypical cases where malignancy, infection, or systemic inflammatory disease is suspected.

- **Single Photon Emission Computed Tomography:** Single Photon Emission Computed Tomography (SPECT) is a nuclear imaging modality that provides functional information about bone metabolism by detecting gamma rays emitted from radiotracers injected into the bloodstream most commonly technetium 99m labeled compounds. Unlike anatomical imaging techniques such as X-ray or CT, SPECT focuses on physiological activity, making it particularly useful for identifying sites of increased bone turnover.

In the evaluation of cervical spine disorders, SPECT is occasionally employed when conventional imaging modalities such as MRI or CT produce inconclusive results. It is especially valuable in localizing active degenerative processes, such as symptomatic facet joint arthropathy or stress reactions, which may not be visibly apparent on structural imaging. By highlighting metabolically active regions, SPECT can aid in correlating clinical symptoms with underlying pathology, thereby enhancing diagnostic accuracy and guiding targeted therapeutic interventions.

Despite its utility in select cases, SPECT is not routinely used in the diagnosis of cervical spondylosis due to its limited spatial resolution and lack of soft tissue detail. It is generally considered a complementary tool, best utilized when there is a diagnostic dilemma or when precise localization of pain-generating structures is required.

Emerging Techniques and Future Directions

The choice of imaging modality is guided by the patient's clinical presentation and diagnostic requirements. While CT scans are ideal for bony structures, MRI remains the gold standard for evaluating spinal cord integrity, disc pathology, and nerve involvement [19]. However, MRI's inherent limitations including noise artifacts and resolution constraints have led to the development of advanced imaging enhancement techniques, such as:

- Deep learning-based reconstruction methods for improved diagnostic accuracy [22].
- AI-driven noise reduction to enhance image clarity and segmentation of spinal structures [23].

These advancements are expected to revolutionize cervical spondylosis diagnosis, leading to more precise and early detection, ultimately improving patient outcomes.

1.1.3 Challenges in MRI-Based Diagnosis

While Magnetic Resonance Imaging (MRI) is the preferred imaging modality for diagnosing cervical spondylosis, it is not without limitations. Several inherent challenges affect image quality, diagnostic reliability, and clinical decision-making. These limitations can compromise early detection, misguide treatment planning, and increase healthcare costs. Therefore, addressing them through advanced imaging techniques and computational solutions is critical.

Noise and Artifacts

MRI scans are highly susceptible to noise and artifacts, which can obscure critical anatomical details and reduce diagnostic reliability. The main sources of noise and artifacts include:

- **Thermal Noise:** Thermal noise, also known as Johnson-Nyquist noise, arises from the random motion of electrons within the electronic components of the MRI hardware, including coils and preamplifiers. This type of noise is inherent to all electronic systems and is directly proportional to temperature and bandwidth. In the context of MRI, thermal noise manifests as a grainy or speckled appearance in the reconstructed images, which can degrade image quality and obscure fine anatomical details.

  The presence of thermal noise limits the signal-to-noise ratio (SNR), a critical factor in determining the clarity and diagnostic utility of MRI scans. Although advanced coil designs, cryogenic cooling, and signal averaging techniques are employed to minimize its impact, thermal noise remains a fundamental barrier to achieving noise-free imaging. Its effects are more pronounced in low-field MRI systems or in sequences with inherently lower signal strength.

  Understanding and mitigating thermal noise is essential for improving image fidelity, particularly in high-resolution or low-signal applications such as musculoskeletal and neurological imaging. [24].

- **Motion Artifacts:** Motion artifacts in MRI are image distortions caused by patient movement during the scanning process. Even subtle involuntary actions such as respiratory motion, swallowing, or minor muscle contractions can introduce inconsistencies in the spatial encoding of MRI signals. These inconsistencies result in blurring, ghosting, or streaking in the final images, significantly reducing image clarity and diagnostic accuracy.

  In the context of cervical spine imaging, motion artifacts are particularly problematic due to the proximity of the cervical region to the throat and upper airway, where swallowing and breathing are frequent. Such artifacts can obscure fine anatomical details, making it difficult to detect early degenerative changes like disc dehydration, small osteophytes, or early spinal canal narrowing.

  To mitigate motion-related degradation, several strategies may be employed, including patient immobilization, fast imaging sequences (e.g., turbo spin-echo), respiratory gating, and motion correction algorithms. Despite these efforts, patient cooperation remains a critical factor in obtaining high-quality images free from motion artifacts [25].

- **Magnetic Field Inhomogeneities:** Magnetic field inhomogeneities occur when there are slight variations in the strength or uniformity of the MRI scanner's main magnetic field. These variations can result from imperfections in the magnet itself, the presence of metallic objects within or near the body, or differences in how various tissues interact with the magnetic field.

  Such inconsistencies can lead to spatial distortions in MRI images, causing anatomical structures to appear misaligned, stretched, or compressed. These distortions are particularly problematic in areas like the cervical spine, where precision is essential for identifying subtle degenerative changes or neural compressions.

  Inhomogeneities can also affect the performance of advanced imaging techniques, such as functional or diffusion imaging, which rely on a stable magnetic field. To minimize these effects, modern MRI systems use methods like shimming, which help to correct the magnetic field and improve image quality. Despite these efforts, residual distortions may still occur, especially near air-tissue interfaces or metallic implants, and should be considered during image interpretation [26].

- **Gibbs Ringing Artifacts:** Gibbs ringing artifacts, also known as truncation artifacts, appear as repetitive lines or ripples near sharp edges within an MRI image. These artifacts are the result of undersampling or limited resolution in the frequency domain during image reconstruction, particularly when using Fourier-based techniques.

  When an abrupt change in signal intensity occurs such as at the boundary between bone and soft tissue the system may not have enough data to represent the edge accurately. This causes the appearance of oscillating light and dark bands along the edge, which can mimic the look of small lesions, disc herniations, or other abnormalities.

  In cervical spine imaging, Gibbs ringing is particularly concerning near the spinal cord or intervertebral discs, where it may be mistaken for real pathology. While not indicative of actual anatomical features, these artifacts can mislead interpretation if not recognized properly.

  Reducing Gibbs ringing typically involves increasing image resolution, applying smoothing filters, or using advanced reconstruction algorithms designed to better handle high-contrast transitions. Radiologists and clinicians must be aware of these artifacts to avoid false-positive findings and ensure accurate diagnoses.

Impact on diagnosis: Noise and artifacts can mimic or mask the actual pathology, leading to false positives or false negatives. This may result in a misinterpretation of disc degeneration or spinal cord compression, which can alter clinical decisions. In some cases, repeated scans are necessary, causing delays, discomfort, and increased healthcare costs.

Low Resolution

MRI resolution is restricted by multiple factors, including scanner field strength (Tesla rating), signal-to-noise ratio (SNR), coil sensitivity and acquisition time. In standard clinical settings, resolution may be insufficient to:

- Distinguish early-stage disc degeneration from normal aging changes [23].

- Detect subtle spinal cord abnormalities, including microstructural changes in myelopathy [12].

- Visualize small ligamentous changes or early osteophyte formation, which are critical in the assessment of disease progression.

Impact on diagnosis: Early stage cervical spondylosis can go undetected, causing delay in intervention. Misclassifications of the severity of the disease can lead to inadequate treatment e.g., prescribing physical therapy when surgery may be necessary. In research and longitudinal studies, low-resolution images may skew statistical findings, affecting the development of new treatments.

Misclassifications Risks

The combined effects of noise, artifacts, and low resolution increase the risk of misclassifications in MRI-based diagnosis. Some key issues include

- **False Positives:** MRI may detect non-clinically significant changes (e.g., minor disc bulges), leading to unnecessary treatments and patient anxiety [18].

- **False Negatives:** Due to image limitations, subtle but progressive degenerative changes can be overlooked, resulting in delayed intervention and worsening symptoms.

- **Inter observer Variability:** Diagnosis often depends on radiologist interpretation, and differences in subjective assessment can lead to inconsistent conclusions

Impact on Diagnosis: Misclassifications can result in over-treatment or under-treatment, affecting patient outcomes. Surgical decisions rely on accurate MRI readings, errors in classification can lead to unnecessary procedures or delayed interventions. AI and deep learning models are being developed to automate and enhance MRI-based diagnosis, reducing human errors.

Future Directions and Solutions

To overcome these challenges, researchers and clinicians are developing advanced techniques, including:

- **High-Field MRI (7T Scanners):** Improves resolution and reduces noise, allowing better visualization of early degenerative changes.
- **Machine Learning and AI:** Algorithms can filter noise, enhance image clarity, and reduce misclassification rates.
- **Motion-Correction Algorithms:** Helps reduce blurred imaging, especially in patients with involuntary movements.
- **Deep Learning-Based Super-Resolution Techniques:** Enhance image quality by reconstructing high-resolution scans from low-resolution MRI images [23].

By integrating AI, deep learning, and hardware advancements, the accuracy of MRI-based cervical spondylosis diagnosis can be significantly improved, leading to better patient outcomes and optimized treatment strategies.

1.1.4 Role of Artificial Intelligence in Medical Image Enhancement

Artificial Intelligence (AI) has transformed medical imaging by offering advanced techniques for image enhancement, noise reduction, and classification. With the rise of deep learning architectures, AI-driven approaches have significantly improved the diagnostic accuracy for complex conditions such as cervical spondylosis. Traditional imaging techniques especially MRI often suffer from noise, resolution limitations, and inconsistencies in image quality, making AI-powered enhancement methods essential for achieving better clinical outcomes [26].

AI Techniques for Image Enhancement

AI in medical imaging involves deep learning models that process, enhance, and classify images for better diagnostic accuracy. Some of the most widely used techniques include:

- **Convolutional Neural Networks** CNNs are deep learning architectures specifically designed for image processing. They extract important features such as edges, textures, and anatomical structures from medical images, helping in Noise reduction by filtering out irrelevant variations in MRI images [27]. Segmentation of spinal structures, intervertebral discs, and nerve pathways . Anomaly detection, identifying abnormal degenerative changes.

- **Autoencoders for Image Denoising** Autoencoders are neural networks used to remove noise and reconstruct images by learning a compressed representation of input data. They help in Enhancing MRI scans affected by motion artifacts [28]. Improving visibility of degenerative changes in the cervical spine [8].

- **Generative Adversarial Networks (GANs)** GANs have gained popularity in medical image super-resolution and synthesis. These networks consist of Generator Creates high-resolution MRI images from low-resolution scans. Discriminator: Evaluates the image quality and ensures realistic enhancement. GANs are highly effective in Super-resolution reconstruction enhancing low-quality MRI scans to high-definition images [29]. Reducing noise artifacts minimizing scanner inconsistencies and distortions [23].Preserving anatomical structures ensuring fine details remain intact [30].

AI-Based MRI Enhancement: Challenges and Solutions

Table 1.1: AI-Based Solutions to Common MRI Imaging Challenges

Challenge in MRI Imaging	**AI-Based Solution**
Noise & Motion Artifacts (e.g., patient movement, thermal noise)	Autoencoders & GANs learn noise patterns and reconstruct clean images
Low Spatial Resolution (blurry spinal structures)	Super-resolution GANs (SR-GANs) improve image detail and preserve anatomical accuracy
Misclassification Risks (due to poor contrast, blurred edges)	CNN-based models enhance contrast and sharpen edges

By integrating AI-driven techniques, particularly deep learning and GAN-based reconstruction models, medical imaging can achieve higher accuracy, improved visualization, and enhanced reliability in diagnosing cervical spondylosis. These advancements pave the way for automated and real-time medical image processing, ultimately improving patient outcomes and assisting radiologists in making more informed clinical decisions [26].

1.1.5 GAN-Spectral Clustering for Cervical Spondylosis Diagnosis

Recent advancements in artificial intelligence (AI) have led to the integration of Generative Adversarial Networks (GANs) and spectral clustering for enhanced MRI-based diagnosis of cervical spondylosis. These methods greatly enhance the quality of images, reduce noise, help identify different body parts, and classify lesions, leading to more precise evaluations of spinal degeneration.

GAN-based Reconstruction

Role of GANs in Medical Image Enhancement GANs are a class of deep learning models designed for image generation and enhancement. In MRI-based diagnosis, GANs are employed to:

- **Enhance Image Resolution and Reduce Noise:** MRI scans often suffer from thermal noise and motion artifacts, leading to decreased clarity. GAN-based models, particularly Super-Resolution GANs (SRGANs), improve spatial resolution and remove noise, enhancing visibility of degenerative changes [25].

- **Generate High-Fidelity Medical Images for Improved Analysis:** GANs, such as CycleGAN and Pix2Pix, have been used to synthesize realistic medical images by learning patterns from high-quality datasets. These models can restore missing details in degraded MRI scans, improving diagnostic confidence [23].

- **Preserve Anatomical Features:** Unlike conventional denoising filters, GANs maintain the integrity of anatomical structures such as vertebral discs, nerve roots, and the spinal cord, reducing the risk of misdiagnosis.

Applications of GANs in Cervical Spondylosis Detection

GANs offer a variety of applications in MRI-based cervical spondylosis detection, including:

- **Super-Resolution MRI Reconstruction:** Converts low-resolution MRI images into high-definition scans for improved visualization of spinal degeneration and osteophytes [31].
- **Denoising and Artifact Removal:** Reduces noise-induced distortions and artifacts commonly present in conventional MRI scans, ensuring more precise assessment of nerve compression and disc abnormalities.
- **Data Augmentation for Training AI Models:** Generates synthetic MRI scans to increase data set diversity, improving the performance of AI-based diagnostic models.

Spectral Clustering Integration

Spectral clustering is an unsupervised learning method used for segmenting medical images based on similarity between pixels or regions. In cervical spondylosis diagnosis, it enables:

- **Anatomical Segmentation via Graph-Based Grouping:** Spectral clustering uses eigenvalue decomposition of similarity matrices to group similar regions (e.g., healthy vs. degenerated tissues) in a graph-based representation, outperforming traditional segmentation techniques [32]
- **Improved Feature Extraction:** This technique improves automatic detection of spinal abnormalities by differentiating soft tissues, bone structures, and compressed nerve roots [33].

Lesion Detection and Severity Classification

Spectral clustering enhances the detection and classification of degenerative lesions by enabling automatic identification of:

- Inter-vertebral Disc Degeneration, Osteophyte Formation, Spinal Cord Compression, Nerve Root Impingement By automatically classifying cervical spondylosis severity, spectral clustering helps radiologists prioritize critical cases and improve decision-making efficiency [34].

Integration with GAN-based Models

The integration of spectral clustering with GAN-based MRI reconstruction enables:

- **Refined Region Segmentation:** Enhances the accuracy of anatomical segmentation for clearer diagnostic visualization.
- **Improved Classification:** Clustering similar degenerative patterns boosts classification model performance and reduces misdiagnosis.
- **Reduced False Positives/Negatives:** Joint use of GANs and clustering minimizes diagnostic errors and variability in automated systems.

1.1.6 Research Aim

This thesis aims to develop a hybrid GAN–Spectral Clustering framework for enhancing MRI resolution and classification accuracy in the diagnosis of cervical spondylosis. By integrating deep learning with unsupervised clustering techniques, the research seeks to address limitations in conventional medical imaging and support more accurate and early-stage diagnosis of spinal degenerative disorders.

Improve Early Detection of Cervical Spondylosis:

The proposed framework enhances MRI quality by reducing noise and increasing spatial resolution. In combination with precise anatomical segmentation via spectral clustering, this enables early identification of degenerative changes, facilitating timely and effective interventions [25].

Enhance Treatment Planning:

High-resolution, denoised MRI scans and improved classification accuracy will aid radiologists and clinicians in selecting appropriate treatment options. This reduces the risk of misdiagnosis or delayed diagnosis, contributing to personalized and evidence-based patient care [23].

Overcome Traditional MRI Limitations:

Traditional MRI techniques are hindered by noise artifacts, low spatial resolution, and inconsistencies in image quality. The integration of GAN-based enhancement with spectral clustering-based segmentation will improve lesion visibility, anatomical clarity, and accurate assessment of disease severity [31]. This research will contribute to the advancement of AI-driven medical imaging and automated cervical spondylosis diagnosis, ultimately improving patient outcomes.

1.2 Motivation and Problem Statement

Cervical spondylosis is a progressive degenerative disorder of the cervical spine, characterized by the deterioration of intervertebral discs, formation of osteophytes (bone spurs), and possible compression of the spinal cord and nerve roots [35].The increasing prevalence of cervical spondylosis in aging populations presents a major healthcare challenge, necessitating the development of advanced diagnostic techniques for improved early detection and treatment planning.

Despite advances in medical imaging, current diagnostic approaches remain inadequate in providing early and accurate detection. The complex anatomy of the cervical spine and inter-individual variability in disease progression often make it difficult to distinguish normal age-related changes from pathological degeneration [36]. Additionally, Magnetic Resonance Imaging (MRI) the primary imaging modality for cervical spondylosis often suffers from noise, artifacts, and low resolution, complicating accurate interpretation and diagnosis.

These limitations necessitate innovative computational solutions that combine deep learning, image enhancement, and robust classification methodologies. In this context, Generative Adversarial Networks (GANs) and spectral clustering emerge as promising approaches to address existing challenges in cervical spine imaging and diagnosis [27].

1.2.1 Limitations of Existing Denoising and Classification Techniques

- **Noise and Image Artifacts:** MRI scans suffer from significant noise due to motion artifacts, scanner imperfections, and low signal-to-noise ratios, which degrade image quality and hinder accurate diagnosis .
- **Resolution Constraints:** Standard MRI scans may lack the spatial resolution necessary to detect early degenerative changes, leading to challenges in identifying subtle abnormalities in cervical spondylosis [12].
- **Feature Extraction Issues:** Traditional classification models rely on handcrafted features, which may not fully capture the complex anatomical and pathological variations present in MRI images. This limitation affects the accuracy and generalization of classification models [27].
- **Computational Complexity:** Many deep learning-based denoising methods require high computational resources, making them less feasible for real-time clinical applications, particularly in resource-limited settings [26].

1.2.2 Need for a GAN-Based Framework with Spectral Clustering

- **Improved Image Reconstruction:** Generative Adversarial Networks (GANs) have demonstrated significant potential in generating high-resolution medical images by learning from real MRI data. GAN-based models can enhance the clarity and resolution of MRI scans, mitigating noise and artifacts that hinder accurate diagnosis [25].
- **Enhanced Segmentation and Classification:** The integration of Spectral Clustering with GANs enables better feature extraction and segmentation. Spectral clustering leverages eigenvalue decomposition of similarity matrices to group anatomical structures effectively, leading to improved classification accuracy in cervical spondylosis detection [29].
- **Generalization Across MRI Variations:** A GAN-based framework can adapt to different MRI datasets by learning robust feature representations. This adaptability enhances model performance across variations in MRI scanners, imaging

protocols, and patient demographics, improving the generalizability of automated diagnosis systems [23] .

1.3 Research Objectives

The primary objective of this research is to develop a Generative Adversarial Network (GAN)-based model for the reconstruction and classification of noisy cervical spondylosis images obtained from CT/MRI scans. The study aims to enhance image quality, improve diagnostic accuracy, and address existing challenges in medical imaging through deep learning-based methodologies. The specific research objectives are as follows: The specific objectives of the proposed work are:

- To study and analyse the existing generative models used for image reconstruction in medical imaging.
- To collect the data set and perform image pre-processing for cervical spondylosis.
- To Design and develop a GAN based model for the reconstruction of cervical spondylosis image.
- To compare and validate the proposed GAN model with the existing model and metrics.

1.4 Contributions of the Thesis

This thesis introduces a novel GAN-Spectral Clustering model for the reconstruction and classification of noisy cervical spondylosis images obtained from MRI scans. By integrating Generative Adversarial Networks (GANs) for image enhancement and Spectral Clustering for segmentation and classification, this research addresses existing limitations in medical imaging, aiming to improve diagnostic accuracy, automate lesion detection, and enable robust classification of cervical spondylosis severity. The key contributions of this research include:

1.4.1 Development of an Enhanced Image Reconstruction Framework

- **GAN-based Model for MRI Enhancement:** A GAN-based framework is developed to transform low-quality MRI scans into high-resolution images, effectively reducing noise and enhancing structural fidelity .
- **Specialized Loss Function Integration:** The model incorporates a specialized loss function that balances adversarial loss and the Structural Similarity Index (SSIM), ensuring high-quality image reconstruction while preserving anatomical details.
- **Generative Adversarial Networks (GANs):** GANs are employed to reduce motion artifacts and scanner-induced noise, improving the diagnostic quality of MRI images.

1.4.2 Advanced Image Segmentation and Classification

- **Application of Spectral Clustering:** A spectral clustering approach is integrated into the framework to segment spinal structures accurately, improving feature extraction and lesion identification.
- **Automated Classification Pipeline:** The proposed model includes an automated classification pipeline to categorize cervical spondylosis severity, enabling early diagnosis and personalized treatment strategies.
- **Improved Feature Extraction and Accuracy:** The combination of GAN-based reconstruction and spectral clustering improves segmentation quality, leading to higher classification accuracy and reduced misclassification rates.

1.4.3 Comparative Performance Analysis

- **Comprehensive Evaluation:** The GAN-Spectral Clustering model is compared against traditional denoising and segmentation techniques, demonstrating superior performance in terms of image quality and diagnostic accuracy.
- **Performance Metrics:** The model is assessed using multiple evaluation metrics, including Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index

(SSIM), classification accuracy, sensitivity, specificity, and F1-score, all of which highlight its effectiveness over existing methods.

- **Generalization Across MRI Variations:** The proposed model generalizes well across diverse MRI datasets, making it a robust and clinically viable solution for cervical spondylosis diagnosis.

This research bridges the gap between deep learning-based medical image processing and clinical diagnostics, offering a scalable, efficient, and high-performance solution for cervical spondylosis classification and analysis.

1.5 Thesis Organization

This thesis is structured into multiple chapters, each focusing on a key aspect of the research. The organization is designed to provide a logical flow, starting from the fundamentals of cervical spondylosis and medical imaging challenges to the proposed GAN-Spectral Clustering framework, experimental validation, and results. The structure of the thesis is as follows:

- **Chapter 1: Introduction** This chapter introduces the research problem, motivation, and objectives of the study. It discusses the limitations of existing denoising and classification techniques for cervical spondylosis diagnosis and highlights the need for a GAN-based framework with spectral clustering. The contributions of the thesis are outlined, and the structure of the document is summarized.

- **Chapter 2: Literature Review**

  This chapter provides a comprehensive review of existing generative models, deep learning techniques, and clustering algorithms used in medical imaging. It explores the state-of-the-art approaches for MRI denoising, image segmentation, and classification. The limitations of conventional methods are discussed, and the research gap that this thesis aims to address is identified.

- **Chapter 3: Methodology** This chapter describes the proposed GAN-Spectral Clustering framework for reconstructing and classifying noisy cervical spondylosis images. The architectural details of the GAN model, loss functions, and spectral clustering algorithm are presented. The dataset collection process, image preprocessing techniques, and experimental setup are also outlined.

- **Chapter 4: Implementation and Experimental Setup** This chapter provides details of the implementation of the proposed model. The hardware and software environment, training procedures, parameter tuning, and optimization strategies are discussed. A step-by-step explanation of the model's workflow, including training and validation, is provided.

- **Chapter 5: Results and Discussion** This chapter presents the experimental results and performance analysis of the proposed framework. The model is evaluated using standard image quality metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM), as well as classification metrics including accuracy, precision, recall, and F1-score. Comparative analysis with existing models is performed, and key observations are discussed.

- **Chapter 6: Conclusion and Future Work** The final chapter summarizes the findings of the research, highlighting the impact of the GAN-Spectral Clustering framework in improving MRI image reconstruction and classification accuracy. The limitations of the study are discussed, and potential future research directions are proposed, including enhancements in GAN architectures, multi-modal imaging approaches, and real-time clinical applications.

CHAPTER 2

LITERATURE REVIEW

The role of medical imaging in diagnosing cervical spondylosis is indispensable. However, the inherent limitations of MRI and CT modalities, such as low spatial resolution, noise, and motion artifacts, hinder accurate clinical interpretation. Traditional image enhancement techniques fall short in recovering high-fidelity anatomical details, which are essential for precise diagnosis and staging of cervical spondylosis. In recent years, the advent of deep learning, particularly Generative Adversarial Networks (GANs), has shown considerable promise in addressing these limitations. This chapter presents an in-depth literature review focusing on three core areas relevant to this research: the challenges in cervical spondylosis imaging, traditional and deep learning-based image reconstruction methods, and classification techniques using machine learning and GAN-based models.[1] *[37].*

2.1 Overview of Cervical Spondylosis

Cervical spondylosis is a chronic degenerative disorder of the cervical spine resulting from the progressive wear and tear of intervertebral discs, facet joints, and ligamentous structures. It is a leading cause of chronic neck pain, restricted mobility, and neurological complications, particularly among the aging population [38]. The degen-

[1] This chapter is partially derived from:
R. Kumar, D. Singh, R. Malik, I. Batra, M. Humayun, and J. A. Khan, "GANSCCS: Synergizing Generative Adversarial Networks and Spectral Clustering for Enhanced MRI Resolution in the Diagnosis of Cervical Spondylosis," Int. J. Intell. Syst., vol. 2025, no. 1, pp. 1–20, Feb. 2025, doi: 10.1155/int/6674913..

erative process is primarily driven by age-related changes, including decreased water content in intervertebral discs, increased bone spur formation, and thickening of spinal ligaments, all of which contribute to spinal stiffness, nerve compression, and, in severe cases, myelopathy [39]. While aging is the primary factor in cervical spondylosis, other risk factors such as poor posture, repetitive neck strain, genetic predisposition, and occupational hazards can accelerate its onset and severity [11]. Individuals engaged in occupations requiring prolonged neck flexion or repetitive movements, such as office workers or manual laborers, may experience early degenerative changes. Additionally, lifestyle factors such as obesity, smoking and previous cervical spine injuries have been linked to an increased risk of cervical spondylosis. Understanding the pathophysiology, clinical manifestations, and diagnostic imaging techniques of cervical spondylosis are crucial for developing effective prevention, diagnosis, and treatment strategies. Advanced imaging modalities such as magnetic resonance imaging (MRI) and computed tomography (CT) play a pivotal role in detecting degenerative changes, while artificial intelligence (AI)-based techniques are emerging as promising tools for improving diagnostic accuracy and patient management [40].

2.1.1 Clinical Symptoms and Impact

Cervical spondylosis is primarily characterized by the progressive degeneration of the cervical spine, affecting spinal stability and neural function [20]. This condition involves multiple interconnected pathological processes that contribute to structural deterioration and clinical symptoms.

1. **Disc Degeneration:** Aging leads to dehydration and loss of proteoglycan content in intervertebral discs, reducing their elasticity and shock absorption capacity. This results in disc height loss, increased mechanical stress on facet joints, and eventual spinal instability [8].

2. **Facet Joint Arthropathy:** As disc degeneration progresses, excessive load-bearing shifts to the facet joints, causing cartilage wear, subchondral sclerosis, and joint hypertrophy, which contribute to stiffness and pain [11].

3. **Osteophyte Formation:** In response to joint instability, the body forms osteophytes (bone spurs) as a compensatory mechanism. These bony growths may

encroach on neural structures, leading to nerve root compression, spinal stenosis, and associated symptoms such as radiculopathy and myelopathy [9].

4. **Ligamentous Hypertrophy and Ossification:** Chronic mechanical stress induces thickening and calcification of the ligamentum flavum and posterior longitudinal ligament, contributing to spinal canal narrowing and increasing the risk of neural compression.

5. **Spinal Instability and Deformity:** The combined effects of disc degeneration, facet joint arthropathy, osteophyte formation, and ligamentous changes lead to progressive spinal instability. This may result in abnormal vertebral alignment (kyphosis or spondylolisthesis), further increasing the risk of spinal cord compression and neurological impairment [17].

These interconnected degenerative processes highlight the multifactorial nature of cervical spondylosis, emphasizing the importance of early diagnosis and advanced imaging techniques to prevent severe complications. mild discomfort to severe neurological deficits, depending on the extent of degeneration and neural involvement. The key clinical manifestations include:

1. **Neck Pain and Stiffness:** Chronic pain resulting from inflammatory and mechanical stress, leading to reduced range of motion and restricted mobility.

2. **Radiculopathy:** Nerve root compression can cause radiating pain, numbness, and muscle weakness in the upper limbs, typically following a dermatomal distribution.

3. **Myelopathy:**Spinal cord compression results in impaired motor function, clumsiness, difficulty performing fine motor tasks, balance disturbances, and gait abnormalities, significantly impacting daily activities.

4. **Headaches and Dizziness:** Cervical instability and nerve compression may contribute to cervicogenic headaches, dizziness, and vertigo-like symptoms, which can complicate diagnosis. These symptoms collectively affect quality of life, limiting mobility and functional independence. Early recognition and intervention are crucial to prevent severe neurological impairment.

2.1.2 Importance of Medical Imaging in Diagnosis

Accurate diagnosis of cervical spondylosis relies on advanced imaging techniques, which are essential for assessing structural abnormalities, nerve compression, and disease progression [20]. Imaging modalities such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) provide detailed visualization of spinal degeneration, including intervertebral disc dehydration, osteophyte formation, spinal canal narrowing, and ligamentous thickening [41]. Recent advancements, including Artificial Intelligence (AI)-enhanced image reconstruction, spectral clustering for segmentation, and deep learning-based classification models, are being integrated into diagnostic workflows. These innovations improve precision, reduce misclassification, and enable early intervention [40].

1. **Computed Tomography (CT)** Provides high-resolution imaging of bony structures, aiding in the evaluation of osteophytes, fractures, and spinal stenosis. Particularly useful for detecting bone-related pathologies but has limited ability to visualize soft tissues such as intervertebral discs and the spinal cord.

2. **Magnetic Resonance Imaging (MRI):** Offers superior contrast resolution for soft tissues, making it the preferred imaging modality for detecting disc degeneration, spinal cord compression, and nerve root impingement. Essential for evaluating disc herniation, myelopathy, and neural compression syndromes. With the integration of AI-driven imaging analysis, clinicians can enhance diagnostic accuracy, optimize treatment planning, and improve patient outcomes .

2.1.3 Limitations of Conventional Imaging

While CT and MRI are valuable diagnostic tools for cervical spondylosis, they have certain limitations that can affect accuracy and clinical decision-making [20].

1. **CT Limitations:** Provides excellent visualization of bony structures but lacks sufficient contrast for soft tissues, making it ineffective for assessing intervertebral disc degeneration, ligamentous injuries, and spinal cord compression. Involves ionizing radiation exposure, limiting its repeated use for follow-up imaging [42].

2. **MRI Limitations** Susceptible to motion artifacts, noise, and lower spatial resolution, which may obscure fine anatomical structures and contribute to diagnostic uncertainty [43]. Prolonged scan times can lead to patient discomfort and motion-induced distortions, affecting image clarity [39]. Variability in scanner settings, patient movement, and imaging protocols can result in inconsistent image quality, necessitating advanced enhancement techniques for improved reliability.

Addressing these limitations through AI-driven image reconstruction, motion correction algorithms, and high-resolution imaging protocols can enhance diagnostic precision and clinical utility .

2.1.4 Need for Advanced Image Enhancement Techniques

The limitations of conventional imaging techniques, such as CT and MRI, necessitate advanced image enhancement methods to improve diagnostic accuracy, enable early disease detection, and optimize clinical decision-making. Recent advancements in artificial intelligence (AI), deep learning, and computational imaging have demonstrated significant potential in addressing the challenges associated with low-resolution, noisy, and artifact-prone medical images [30].

Denoising and Super-Resolution Methods

Traditional medical imaging techniques often suffer from noise and low spatial resolution, reducing diagnostic effectiveness. AI-based methods have been extensively explored to enhance image quality:

1. **Deep Learning-Based Denoising:**

   Armanious, K., Jiang, C., Fischer, M., Küstner, T., Hepp, T., Yang, B., Thomas, L., and Gatidis, S. [44] [30]proposed a GAN-based denoising framework that outperformed conventional filtering by reducing noise while preserving structural details. J. M. Wolterink [45] developed a CNN-based denoising technique for CT images, improving the signal-to-noise ratio while retaining critical anatomical features.

2. **GAN-Based Super-Resolution:**

Wang, Yu, Weihao Wang, Xinjian Chen, and Dinggang Shen [46]introduced a 3D conditional GAN model to enhance PET scan images, improving clarity and diagnostic accuracy.

[47]developed a multi-level densely connected GAN architecture to refine MRI resolution, enabling better clinical interpretation.

3. **Transformer-Based Image Enhancement:**

   Y. Chen [48]demonstrated that vision transformers improve MRI reconstruction, enhancing spatial resolution and texture preservation.

These studies underscore the role of AI-driven techniques in overcoming noise, artifacts, and resolution limitations in medical imaging, particularly in cervical spondylosis diagnosis.

Deep Learning Approaches

Deep learning has significantly advanced medical image enhancement, segmentation, and classification:

- **CNN-Based Image Enhancement:**Zhang [49]proposed a deep CNN model that reduced MRI noise while preserving anatomical structures. Qu et al [50] introduced a residual learning-based CNN for spinal image enhancement, outperforming traditional filtering methods. Cheng [51] developed a multi-scale CNN model that enhances contrast and detail preservation while mitigating noise in MRI-based spondylosis diagnosis.

- **GANs for Medical Image Reconstruction:**T. Wang [52] implemented a GAN-based super-resolution framework that enhanced low-resolution spinal MRI scans, achieving higher diagnostic accuracy.Armanious [30]refined GAN architectures using perceptual loss and adversarial training, improving image clarity and noise reduction.

- **Transformer-Based Image Processing** Dosovitskiy [48]introduced a vision transformer for MRI reconstruction, demonstrating superior performance in restoring fine structural details.

Self-attention mechanisms in transformers enable better long-range dependency capture in medical images, making them a promising alternative to traditional CNNs.

- **Hybrid Approaches Combining CNNs, GANs, and Spectral Clustering:** Han et al in their study titled "Spine-GAN: Semantic Segmentation of Multiple Spinal Structures," Han. [53]proposed a GAN-based approach for the semantic segmentation of various spinal structures in MRI images. Their method demonstrated improved accuracy over traditional segmentation techniques, enhancing lesion detection and aiding in clinical assessments.

  K. Chen [54] introduced a two-stage video-based convolutional neural network for classifying adult spinal deformities. This approach utilized CNNs to extract features from spinal imaging data, leading to enhanced classification performance in diagnosing degenerative spinal disorders.

These studies highlight the transformative impact of deep learning in medical imaging, providing robust solutions for denoising, super-resolution, and classification in cervical spondylosis diagnosis.

Spectral Clustering for Improved Segmentation

Spectral clustering is a graph-based technique increasingly applied in medical image analysis for segmenting complex anatomical structures. Recent research has demonstrated its effectiveness in improving segmentation accuracy and preserving structural details.

- **Graph-Based Image Segmentation:** [55](Srinivas & Sasibhushana Rao) and [56](Maruthamuthu & Gnanapandithan G.) explored the application of spectral clustering in MRI segmentation. Their findings suggest that spectral clustering improves edge preservation and reduces over-segmentation, leading to more accurate segmentation outcomes. Related work has also examined fuzzy c-means clustering as an enhancement to spectral approaches (Frontiers in Neuroscience).

- **Integration with Deep Learning:** Nazir [57] developed an Embedded Clustering Sliced U-Net (ECSU-Net) for intervertebral disc segmentation and classification. Their hybrid approach demonstrated significant improvements in segmentation accuracy .

Mohammed [58]reviewed multiple segmentation techniques for MRI-based tumor detection, including the integration of clustering techniques with deep learning models.

Their survey highlights the effectiveness of spectral clustering when combined with CNN-based architectures.

Deep Learning-Based Spectral Clustering:

- Shaham [59] proposed a deep learning approach for spectral clustering using neural networks, demonstrating its utility in medical image segmentation tasks. Their method, referred to as SpectralNet, focuses on improving spectral clustering efficiency through deep neural networks but does not incorporate GANs.

These studies underscore the potential of hybrid approaches that integrate spectral clustering with deep learning techniques, improving segmentation accuracy in medical imaging, particularly for complex anatomical structures like the spine.

Limitations and Future Directions

Despite its advantages, spectral clustering faces computational challenges

- **High Computational Cost:** The need for eigenvalue decomposition in large MRI datasets increases processing time and memory usage. Optimization strategies, such as sparse graph representations and parallelized algorithms, are being explored to enhance scalability.

- **Parameter Sensitivity:** Selecting appropriate similarity measures and cluster numbers significantly affects segmentation accuracy. Adaptive spectral clustering approaches dynamically adjust parameters based on image complexity.

- **Integration with Deep Learning:**

  GAN-generated images must be carefully integrated with spectral clustering to prevent over-segmentation or loss of fine details. Future research is investigating self-supervised learning techniques to optimize feature extraction.

- **Real-Time Clinical Application:** Efficient spectral clustering models for high-resolution MRI images are needed. Graph neural networks (GNNs) are being explored as an alternative to traditional spectral clustering for large-scale medical imaging datasets.

2.2 Machine Learning in Medical Imaging

Medical imaging has become an indispensable component of modern medicine by enabling non-invasive visualization of internal anatomy and pathology. However, the growing volume and complexity of imaging data present significant challenges for manual interpretation, which is often subjective and inconsistent. To overcome these limitations, machine learning (ML) has emerged as a transformative approach in medical image analysis. Unlike traditional image processing methods that rely on hand-crafted features and fixed parameters, ML algorithms can automatically learn complex patterns from data, leading to more accurate, efficient, and consistent results. With the advent of deep learning, ML models have achieved state-of-the-art performance in tasks such as image enhancement, segmentation, classification, registration, and reconstruction across various imaging modalities, including MRI, CT, X-ray, ultrasound, and PET [27]. These advancements are reshaping fields such as radiology, dermatology, and neurology by offering scalable and robust diagnostic tools. In particular, ML has shown great promise in detecting and classifying degenerative spinal conditions like cervical spondylosis, thereby improving diagnostic accuracy and supporting clinical decision-making [60].

Traditional Image Processing Approaches

Before the widespread adoption of ML, traditional image processing techniques were the primary means of analyzing medical images. Methods such as Gaussian filtering, wavelet transforms, and principal component analysis (PCA) were commonly used for noise reduction and image enhancement [61]. However, these approaches had several limitations:

- **Loss of fine details:** Many traditional denoising methods, such as median and Gaussian filtering, blur anatomical structures, reducing image clarity and potentially obscuring critical diagnostic information.

- **Limited adaptability:** Traditional models rely on predefined parameters, making them less effective in diverse imaging conditions where noise patterns and anatomical structures vary significantly [62].

- **Computational inefficiency:** Processing high-resolution medical images using conventional techniques is time-consuming and computationally demanding, limiting real-time applications [63].

While these methods laid the foundation for medical image analysis, they lack the adaptability and predictive power of ML-based techniques.

2.2.1 Supervised Deep Learning Techniques

The advent of deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized medical imaging by enabling end-to-end automation of tasks like image segmentation, classification, and enhancement. Traditional methods that relied on hand-crafted features are increasingly being replaced by deep architectures capable of learning hierarchical representations from data. Notable architectures include U-Net [64], ResNet [65], VGG16 [66] , and Inception-ResNetV2 (IRV2) [67], each contributing significant advances in accuracy and diagnostic reliability.

Key Architectures & Contributions

- **U-Net [3]:** Specifically designed for biomedical image segmentation, U-Net uses a symmetric encoder-decoder structure with skip connections that preserve spatial features. It has achieved high accuracy in tasks like tumor and organ segmentation across MRI and CT scans. Figure2.1 show U-Net Convolutional Networks for Biomedical Image Segmentation.

- **ResNet [65]:**Introduced residual connections that mitigate vanishing gradient problems in deep networks. ResNet-based U-Net variants have shown improved performance in medical image classification and segmentation, particularly for complex images like lung and brain scans.

- **VGG16:** This deep CNN architecture provides strong feature extraction and is often used as a backbone in U-Net or transfer learning settings. VGG16-based models have demonstrated excellent results in tasks like brain tumor segmentation and ultrasound imaging.

- **Inception-ResNetV2 (IRV2):** Combines the multi-scale feature learning of Inception modules with the depth efficiency of residual networks. Recent studies highlight its success in detecting COVID-19 from chest X-rays [68], classifying brain lesions [69], and diagnosing skin cancer using attention-enhanced IR-CNNs.

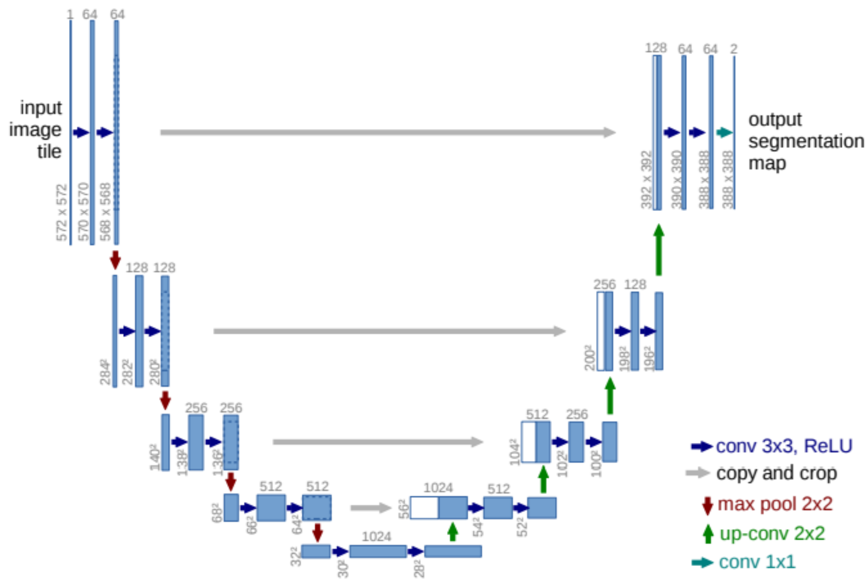

Figure 2.1: U-net architecture [3]

Advantages of Supervised Deep Learning

- **High Accuracy:** CNNs automatically extract hierarchical features, enabling superior performance in classification and segmentation tasks compared to traditional techniques.

- **Feature Learning:** Deep learning models can learn complex spatial and contextual patterns directly from large datasets, reducing reliance on manually crafted features.

- **End-to-End Learning:** Unlike traditional methods that require multiple preprocessing steps, deep learning models can directly process raw image inputs and optimize feature representations, leading to a streamlined workflow and improved accuracy [65].

Recent studies have demonstrated the effectiveness of deep learning in diagnosing spinal disorders, detecting abnormalities in MRI scans, and enhancing medical image quality, further solidifying its role in modern medical imaging .

2.2.2 Unsupervised and Generative Models

While supervised learning has yielded impressive results in medical imaging, it heavily depends on large annotated datasets—resources that are often difficult and expensive to obtain in clinical settings. In contrast, unsupervised learning and generative models have emerged as powerful alternatives, capable of uncovering meaningful patterns from unlabelled data. These methods are particularly useful in data-scarce environments and for exploratory medical tasks such as anomaly detection, image reconstruction, and multi-modal fusion.

Key Techniques and Advancements

- **Autoencoders:** Autoencoders are unsupervised neural networks trained to reconstruct input data. By compressing and decompressing medical images, they learn latent features that preserve critical anatomical details. They are widely used in Noise reduction in imaging (e.g., low-dose CT or MRI scans) and Image enhancement and reconstruction tasks without the need for ground truth labels. These models have proven particularly effective in maintaining structural integrity during denoising operations [70].

- **Generative Adversarial Networks (GANs):** GANs have revolutionized the ability to synthesize medical images by training two networks a generator and a discriminator in a competitive setting. They are widely applied in data augmentation, especially for rare conditions or small datasets and also for High-resolution image generation that mimics MRI, CT, or ultrasound images. By Improving classification models by enriching training datasets with synthetic but realistic images. Recent works have shown GANs to be valuable in synthesizing CT scans and MRIs for use in disease prediction and detection pipelines [4] [71].Figure2.2Shows the GAN-based Architecture for synthetic medical image augmentation and classification.

- **Self-Supervised Learning:** This approach leverages unlabeled data to pre-train models, reducing the dependence on large labeled datasets. Recent studies have explored self-supervised learning to improve feature extraction and classification performance in medical imaging tasks.

- **Multi-Scale Dense Network (MSDNet):** MSDNet enhances DenseNet architecture by incorporating multi-scale convolutional layers (1×1, 3×3, 5×5), allowing robust feature extraction across anatomical scales. It offers efficient reconstruction in tasks like photoacoustic tomography [72], correcting image artifacts via dilated convolutions and also the fusion of CT and MRI data to improve clinical interpretation, as shown by Li et al. [73]. In cervical spine imaging, MSDNet can enable more accurate segmentation or clustering by capturing fine and coarse structural details.

These generative approaches provide new opportunities for creating high-quality medical datasets, mitigating data scarcity issues, and enhancing image reconstruction techniques.

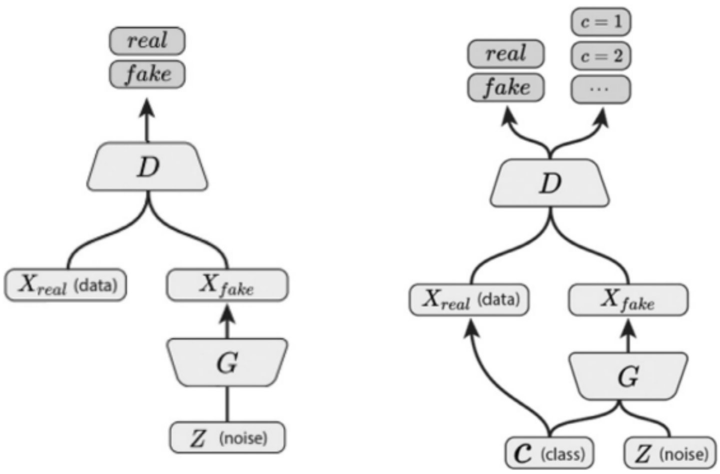

Figure 2.2: DCGAN architecture and ACGAN architecture [4]

Advantages

- **No need for labels:** Unsupervised techniques reduce dependency on annotated datasets.
- **Anomaly detection:** Autoencoders and SSL help detect abnormalities by learning 'normal' image distributions.
- **Improved generalization:** SSL and GANs contribute to model robustness in real-world, noisy, or imbalanced datasets.
- **Efficient scaling:** Techniques like MSDNet offer scalable solutions for complex multi-scale anatomical structures.

2.2.3 Reinforcement Learning

Reinforcement learning (RL) is a learning paradigm where agents interact with their environment and learn optimal strategies through trial-and-error, guided by reward signals. Unlike supervised learning, RL does not require labeled datasets, making it highly appealing for tasks where annotated medical data is limited or expensive to obtain. Although still in its early stages within medical imaging, reinforcement learning has demonstrated notable potential in various applications, particularly in landmark localization, adaptive view planning, and imaging protocol optimization.

One of the most advanced RL models employed in medical imaging is the Double Deep Q-Network (DDQN). DDQN improves upon the standard Deep Q-Network (DQN) by decoupling the selection and evaluation of actions during training, thereby reducing overestimation bias and enhancing training stability. [74]Ghesu et al implemented DDQN to localize anatomical landmarks in 3D CT and MRI scans. Their approach utilized a coarse-to-fine navigation strategy and achieved up to forty-fold speed improvements over exhaustive search methods, while maintaining high localization accuracy. Similarly, [75]Hong et al demonstrated the effectiveness of RL-based agents for cephalometric landmark detection in 3D imaging, achieving clinically acceptable performance with a mean localization error of less than 2 mm.

Beyond landmark detection, reinforcement learning has been applied to broader imaging tasks. [76]Alansary et al introduced RL agents to automate MRI plane selection, optimizing view planning for standardized image acquisition. Their work highlighted RL's capacity to reduce manual input and improve scan reproducibility. Additionally, [77]Stember and Shalu applied a DQN-based approach to brain lesion localization in a low-data environment. Despite limited training samples, their model achieved significantly higher accuracy compared to a baseline supervised model, illustrating RL's suitability for data-constrained medical settings.

These studies underscore the emerging utility of RL in medical image analysis, especially in domains where decision-making is sequential and data is sparse. In cervical spondylosis imaging, RL techniques such as DDQN can be leveraged to automatically identify vertebral landmarks, intervertebral disc boundaries, and other diagnostically relevant features. By integrating such intelligent agents into clinical imaging workflows, medical professionals can enhance diagnostic accuracy, reduce variability, and improve the efficiency of radiological assessments.

Although reinforcement learning in medical imaging is not yet as widely adopted as other machine learning approaches, its inherent advantages in adaptivity, decision optimization, and label-free training make it a promising field for further exploration and integration into advanced diagnostic systems.

2.2.4 Semi-Supervised Learning in Medical Imaging

Semi supervised learning (SSL) has become a transformative approach in medical imaging, offering a practical solution to the pervasive challenge of limited labeled datasets. In clinical contexts, acquiring expert annotations for imaging data is often time consuming, expensive, and subject to inter observer variability. SSL leverages the abundance of unlabeled medical images by combining them with a small quantity of annotated data, thereby improving model performance while minimizing manual labeling efforts.

Cheplygina et al [78]provided an early and comprehensive review of SSL, multi-instance, and transfer learning techniques in medical imaging, highlighting their relevance in tasks where labeled data are scarce. Building upon such foundations, Liu et al [79] introduced the Self-supervised Mean Teacher framework, which combines contrastive self-supervised pretraining with a Mean Teacher model for semi-supervision. Their approach significantly enhanced classification performance on chest X-ray and skin lesion datasets. In the domain of segmentation, Yu et al [80]applied uncertainty-aware self-ensembling to segment 3D cardiac MRI scans using very few annotations, while Fan et al [81] adapted a similar approach to improve COVID-19 lung infection segmentation from CT images, demonstrating high accuracy with minimal supervision.

Recent advancements further validate the effectiveness of SSL in diverse imaging applications. Wei et al [82] developed a semi-supervised system using a ResUNet architecture and Faster R-CNN for evaluating chest radiograph quality. Their model achieved near-supervised performance metrics—Dice scores exceeding 0.88 and AUC of 0.90—while training predominantly on unlabeled data. Zhao and Wang proposed a deep consistent collaborative learning (DCCL) framework, integrating dual-network consistency with pseudo-label refinement. Their method achieved improved segmentation accuracy over baseline Mean Teacher models across CT and MRI datasets. Additionally, Wang et al [83]introduced a CLIP-driven semi-supervised semantic alignment (CSA) technique for multi-modal MRI segmentation, successfully aligning textual and visual features to boost segmentation performance on pelvic and prostate scans.

In PET imaging, Zheng et al combined supervised Dice loss with unsupervised fuzzy clustering (RFCM + FCM) for segmenting lymphoma-related lesions, yielding significantly improved Dice scores compared to fully supervised counterparts. Similarly, Chen et al. (2023) [54] developed a dual-decoder consistency strategy (DCPA) using pseudo-labeling and data augmentation. Evaluated on datasets with only 5–20% labeled data, DCPA consistently outperformed state-of-the-art SSL segmentation models.

Overall, SSL has demonstrated robust applicability in medical imaging across modalities and tasks, including classification, segmentation, and quality evaluation. By effectively utilizing unlabeled data, SSL approaches are able to achieve performance comparable to fully supervised methods while drastically reducing annotation requirements. As methods such as consistency training, collaborative pseudo labeling, and cross-modal alignment evolve, semi-supervised learning is poised to become a core strategy in the deployment of scalable and efficient diagnostic AI systems in real-world clinical practice.

2.2.5 Applications in Medical Imaging

The integration of machine learning (ML) into medical imaging has transformed the field by enhancing image interpretation, improving diagnostic accuracy, and streamlining clinical workflows. Across imaging modalities such as MRI, CT, PET, and ultrasound, ML has become instrumental in addressing core tasks: segmentation, classification, detection, registration, and reconstruction.

Segmentation is fundamental in image analysis and involves the precise delineation of anatomical structures or pathological regions. Deep learning models like U-Net have demonstrated exceptional performance in segmenting spinal structures such as vertebral bodies and intervertebral discs, which is critical in diagnosing and monitoring spinal disorders like cervical spondylosis [3]. Segmentation plays a pivotal role in pre-surgical planning, radiation therapy, and biomechanical simulations [84].

Classification is another essential task, where ML models assign diagnostic categories to medical images. Deep convolutional neural networks (CNNs), including ResNet and Inception, have been successfully applied to classify spinal conditions, differentiating between healthy and pathological scans. These models have achieved diagnostic accuracies on par with radiologists, supporting faster and more objective clinical decision-making [65] [27].

Detection focuses on localizing specific abnormalities within an image. Detection models, such as Faster R-CNN and YOLO, have been employed to identify features like herniated discs, spinal stenosis, and tumors with high sensitivity and specificity. These models help radiologists detect subtle lesions that might otherwise be overlooked, especially in complex anatomical regions [85].

Image registration, which aligns images from different modalities or time points, has also been significantly improved using ML. Traditional registration methods have been enhanced or replaced by learning-based frameworks such as VoxelMorph, which offers faster and more accurate multimodal image alignment without extensive manual tuning [86]. This is crucial for longitudinal studies, image fusion (e.g., CT–MRI), and treatment monitoring.

Image reconstruction is vital in producing diagnostic-quality images from undersampled or noisy data. Generative Adversarial Networks (GANs) have shown substantial success in reconstructing high-quality medical images, such as low-dose CT or accelerated MRI scans. These networks preserve anatomical fidelity while enhancing image clarity and reducing acquisition time or radiation dose [4] [87].

2.2.6 Limitations of Machine Learning in Medical Imaging

Despite its advantages, ML in medical imaging faces several challenges that hinder its widespread clinical adoption:

- **Large Dataset Requirement:** Training deep learning models requires extensive labeled datasets, which are often difficult to acquire due to ethical, legal, and privacy concerns in medical imaging.

- **Computational Demands:** Deep learning models necessitate substantial computational resources, including high-end GPUs and large-scale storage, making real-time deployment challenging.

- **Lack of Interpretability:** Many ML models function as "black boxes," making it difficult for clinicians to interpret and trust AI-generated results. The lack of transparency remains a significant barrier to their clinical integration.

Addressing these challenges requires the development of more efficient, explainable, and data-efficient ML techniques tailored for medical imaging applications.

2.2.7 Future Directions and the Role of GAN-Spectral Clustering

To overcome existing challenges, researchers are exploring new directions in ML-driven medical imaging, focusing on improving accuracy, interpretability, and real-time applicability:

- **Hybrid Models:** Combining ML techniques, such as integrating GANs with spectral clustering, has the potential to improve segmentation and classification accuracy. Spectral clustering can refine GAN-generated images, enhancing feature separation and reducing noise artifacts.

- **Real-Time Applications:** Optimized deep learning models are being developed for real-time medical image enhancement and diagnosis, allowing clinicians to receive immediate feedback and insights.

- **Improved Interpretability:** Explainable AI (XAI) techniques, including attention mechanisms, saliency maps, and model interpretability frameworks, are being integrated into ML models to improve transparency and build clinician trust.

Machine learning continues to revolutionize medical imaging, enabling more precise, automated, and efficient diagnostic tools. The integration of GAN-based reconstruction with spectral clustering, as explored in this thesis, aims to address key challenges associated with MRI noise reduction, segmentation, and classification accuracy.

2.3 Image Reconstruction in Medical Imaging

Image reconstruction is a fundamental component in medical imaging, playing a pivotal role in converting raw sensor or signal data into clinically interpretable images. It forms the backbone of diagnostic imaging modalities such as computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and ultrasound. The primary goal of reconstruction is to generate high-fidelity images that preserve anatomical accuracy, minimize noise, and reduce artifacts, all while optimizing acquisition time and radiation dose.

Traditionally, image reconstruction relied on analytical algorithms such as Filtered Back Projection (FBP) in CT and Fourier Transform based methods in MRI. While these techniques are computationally efficient, they often suffer from limitations in noise sensitivity and resolution, especially under low-dose or undersampled conditions [88]. To overcome these challenges, Iterative Reconstruction (IR) algorithms were introduced, incorporating models of imaging physics and noise distribution to improve image quality. However, these methods typically require extensive computational resources and longer processing times [89].

The integration of machine learning (ML), particularly deep learning (DL), into image reconstruction has significantly advanced the field. Unlike traditional methods that rely on handcrafted models and assumptions, deep learning approaches can learn complex mappings from input data to high-quality images directly through data-driven optimization. One notable innovation is the use of Convolutional Neural Networks (CNNs), which have been successfully applied to denoising, super-resolution, and dealiasing tasks. These models enhance image quality by learning from large volumes of paired low- and high-quality images [90].

Among deep learning techniques, Generative Adversarial Networks (GANs) have shown exceptional promise in image reconstruction. GANs consist of two neural networks—a generator and a discriminator that are trained adversarially to produce images that are indistinguishable from real ones. In medical imaging, GANs are particularly effective in reconstructing images from sparse or noisy data, such as in accelerated MRI or low-dose CT. For example, DAGAN [87](Deep De-Aliasing GAN), introduced by Yang et al, demonstrated the ability to reconstruct high-quality MRI images from undersampled k-space data, thereby reducing scan time and improving patient throughput.

Another significant advancement is the emergence of model-based deep learning, which combines traditional physics-driven models with neural networks. MoDL (Model-based Deep Learning), proposed by [91]Aggarwal et al , integrates physical forward models of the imaging system into the network architecture, ensuring data consistency while allowing flexible feature learning. These hybrid methods have proven to be more robust and generalizable across imaging conditions compared to purely data-driven or purely model-based approaches.

Furthermore, self-supervised learning and unsupervised reconstruction methods are gaining attention, especially in scenarios where paired training data is limited. These methods leverage consistency losses, synthetic perturbations, or domain adaptation techniques to reconstruct images without explicit ground truth [92].

In summary, image reconstruction in medical imaging has evolved from conventional analytical methods to highly sophisticated data-driven frameworks. Deep learning has opened new horizons for enhancing image quality, reducing acquisition time, and lowering radiation exposure, all while maintaining clinical accuracy. As these technologies mature and integrate into clinical workflows, they are expected to revolutionize diagnostic imaging and personalized healthcare delivery.

2.4 Generative Adversarial Networks (GANs) for Image Reconstruction

Generative Adversarial Networks (GANs) for Image Reconstruction Generative Adversarial Networks (GANs) have significantly advanced medical imaging by enabling the generation of high-quality synthetic images and enhancing existing medical scans. Introduced by [93], GANs consist of two neural networks shown in Figure 2.3 a Generator and a Discriminator that engage in a competitive process to produce images closely resembling real medical scans. This capability has been leveraged in various medical imaging applications, including image denoising, super-resolution reconstruction, data augmentation, and modality transfer.

The standard GAN framework can be mathematically formulated as a minimax game with the following objective function:

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1-D(G(z)))] \tag{2.1}$$

Equation (2.1) represents the standard adversarial objective function, where the generator G attempts to minimize the loss while the discriminator D maximizes it to distinguish real images from reconstructed ones.

where G(z) represents the generator output from noise vector z, and D(x) is the discriminator output for real sample x. The optimal equilibrium occurs when the generated distribution matches the real data distribution, making the discriminator unable to differentiate between the two.

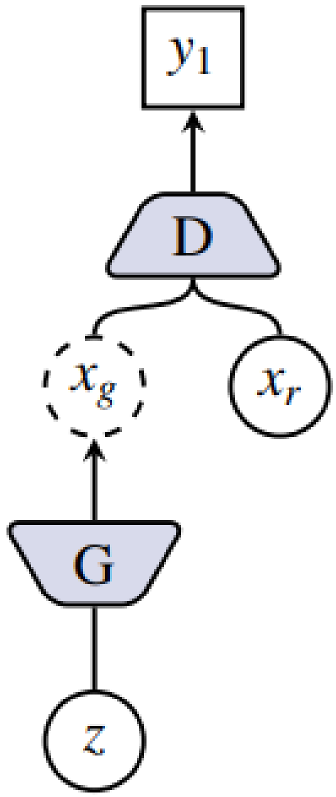

Figure 2.3: GAN architecture [5]

GAN Working Principle

- **Generator Network:** The Generator synthesizes images that mimic real medical scans by transforming input data, such as random noise or low-quality images, into high-quality outputs. It employs deep convolutional layers to capture the intricate details of anatomical structures essential for accurate diagnostics [6].
- **Discriminator Network:** The Discriminator functions as a binary classifier, distinguishing between real and synthetic images. It provides feedback to the Generator, guiding it to produce increasingly realistic images through the adversarial training process [93].
- **Adversarial Training Process:** The Generator and Discriminator are trained simultaneously in a zero-sum game, where the Generator aims to deceive the Discriminator, and the Discriminator strives to correctly identify real versus fake

images. This adversarial interplay leads to the generation of highly realistic synthetic medical images [93].

GAN Architectures and Variants

Since their inception, various GAN architectures have been proposed to overcome the challenges of training instability, mode collapse, and convergence difficulties. Some of the most influential architectures include:

- **Deep Convolutional GAN (DCGAN):** This model introduced stable training techniques using convolutional layers and batch normalization [94]. DCGANs are widely used in image synthesis and denoising applications.Figure2.4 show the DCGAN generator architecture.

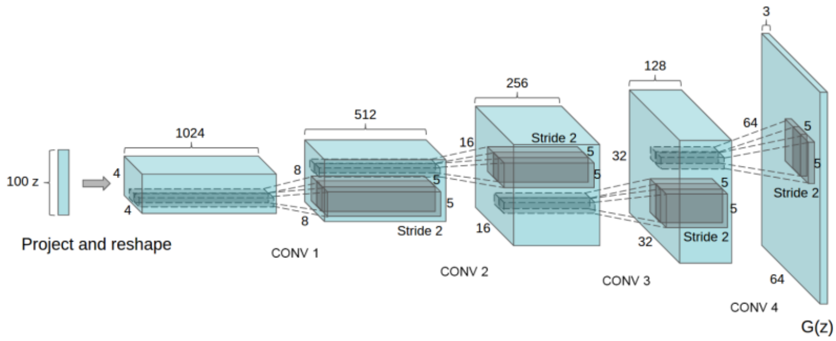

Figure 2.4: DCGAN generator architecture [6]

- **Conditional GAN (cGAN):** In cGANs, both the generator and discriminator are conditioned on auxiliary information, such as class labels or images [7]. This approach is useful in tasks like image-to-image translation.Figure2.5 show Conditional adversarial net.

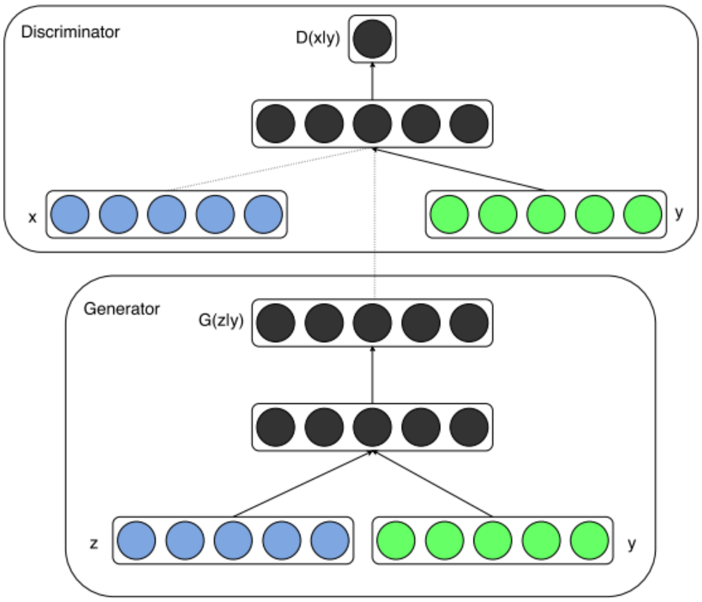

Figure 2.5: Conditional adversarial net [7]

- **Pix2Pix:** A type of cGAN designed specifically for paired image-to-image translation tasks, where the generator learns to map input images to output images, often used in medical image segmentation and reconstruction [95].Figure 2.6 show the Pix2Pix GAN architecture.

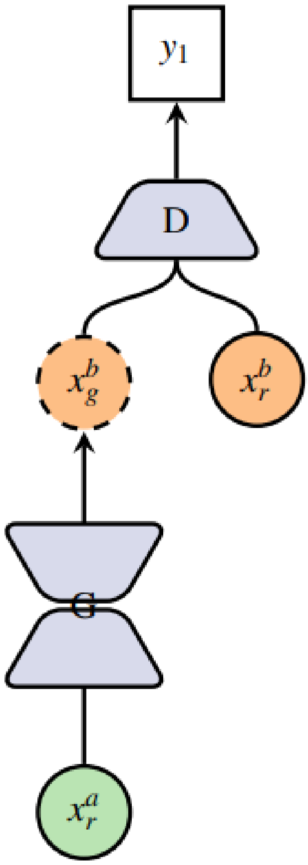

Figure 2.6: Pix2Pix GAN architecture [5]

- **CycleGAN:** Unlike Pix2Pix, CycleGAN allows unpaired image translation using a cycle-consistency loss. It has been applied to tasks such as CT to MRI image translation, especially where paired data is not available [96].Figure2.7show the CycleGAN architecture.

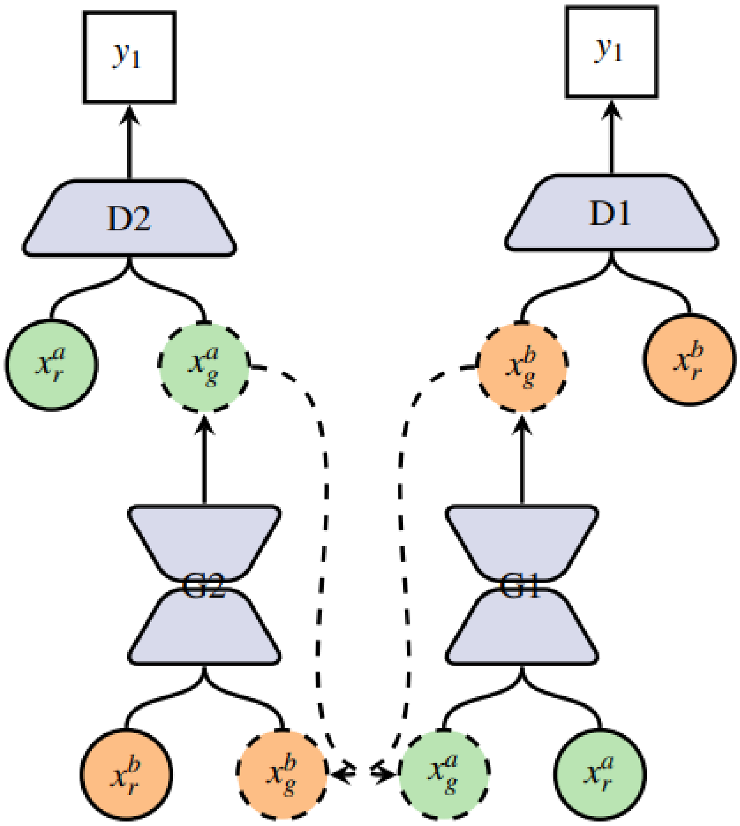

Figure 2.7: CycleGAN architecture [5]

- **Wasserstein GAN (WGAN):** WGAN addresses training instability by introducing the Wasserstein distance as a more stable loss function, improving convergence and quality of generated images [97].

These architectural innovations have enabled GANs to be adapted for various medical imaging tasks, including reconstruction, super-resolution, noise reduction, and modality transformation.

Applications of GANs in Medical Imaging

GANs have demonstrated exceptional performance in various medical imaging tasks, particularly in MRI-based cervical spondylosis diagnosis and treatment.

- **Image Denoising:** Medical images often suffer from noise due to acquisition limitations and artifacts. GAN-based denoising frameworks, such as Denoising

GAN (DGAN), have been proposed to remove noise while preserving fine structural details. For instance, [30]Armanious et al introduced a GAN-based model that significantly reduced motion artifacts in spinal MRI scans, maintaining diagnostic clarity.

- **Super-Resolution Reconstruction:** High-resolution images are crucial for precise diagnosis. GANs have been utilized to enhance the resolution of low-quality spinal MRIs, aiding in early-stage cervical spondylosis diagnosis. [46]Y. Wang et al developed a 3D conditional GAN model that improved MRI image clarity, outperforming traditional interpolation techniques.

- **Data Augmentation:** GANs address the scarcity of labeled medical data by generating realistic synthetic images to augment training datasets. This augmentation enhances the generalization ability of deep learning models trained for cervical spondylosis classification [6].

- **Image Synthesis and Modality Transfer:** GANs can perform image-to-image translation, converting one imaging modality into another to facilitate multi modal analysis. Ben-Cohen et al [98] developed a GAN framework to transform spinal CT scans into MRI-like images, improving soft tissue visualization.

GANs for Cervical Spine Imaging

Although Generative Adversarial Networks (GANs) have been widely applied across various domains of medical imaging, their use in cervical spine imaging remains comparatively limited. Nevertheless, the specific challenges inherent in cervical spine imaging such as motion artifacts, low signal-to-noise ratios, and complex spinal anatomy present a strong rationale for applying GAN-based methods. Recent developments have shown promising results, particularly in enhancing image quality and improving diagnostic outcomes.

One significant application of GANs in spinal imaging is the reconstruction and denoising of magnetic resonance imaging (MRI) and computed tomography (CT) scans compromised by motion or undersampling. These issues are particularly common in cervical spondylosis cases, where rapid acquisition is often prioritized. Yang et al proposed the Deep De-Aliasing GAN [99](DAGAN), which demonstrated substantial improvements in reconstructing high-quality MR images from undersampled data, showing increased peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM).

In addition, GANs have been integrated into hybrid models that combine generative and discriminative components, enhancing segmentation and classification in spine imaging. These models not only generate artifact-free images but also enable automated identification of anatomical structures such as intervertebral discs and vertebral bodies. This functionality supports accurate detection of degenerative features like disc bulges and spinal canal narrowing key indicators in the diagnosis of cervical spondylosis.

A notable study by Schlaeger et al [100]employed a pix2pix-based GAN to synthesize T2-weighted fat-saturated (T2-fs) images from conventional T1-weighted and non fat sat T2 MRI sequences. Their results demonstrated improved diagnostic accuracy for spinal pathologies such as Modic changes and degenerative disc disease, as well as enhanced inter observer agreement among radiologists.

Furthermore, recent research has explored diffusion probabilistic models as GAN alternatives for cervical spine MRI, producing high-quality synthetic images suitable for training and augmentation tasks [101]. Collectively, these findings indicate that GANs have the potential to revolutionize cervical spine imaging by enhancing image fidelity, reducing dependency on large labeled datasets, and enabling data augmentation for deep learning pipelines. As the field progresses, integrating GANs into spine-specific diagnostic systems may lead to more reliable clinical decision-making and improved outcomes for patients with spinal disorders.

Challenges in Training GANs

Despite their advantages, training GANs for medical imaging presents challenges:

- Mode Collapse GANs may produce limited variations of images, leading to redundancy. Techniques like Wasserstein GAN (WGAN) and feature matching have been proposed to mitigate this issue [44].
- Training Instability GANs require careful hyperparameter tuning for stable convergence. Progressive Growing GANs (PGGANs) have been introduced to improve training stability by gradually increasing image resolution [6].
- Computational Complexity GANs demand substantial computational resources,

making training expensive and time-consuming. Optimized architectures, such as Lightweight GANs and Federated Learning-based GANs, aim to reduce computation while maintaining accuracy [25].

Future Directions of GANs in Medical Imaging

Future advancements in GANs for medical imaging include:

- **Hybrid Models:**Integrating GANs with spectral clustering to enhance segmentation and classification accuracy.
- **Real-Time Applications:** Deploying optimized GAN architectures for real-time medical image enhancement in clinical settings.
- **Explainable AI (XAI):** Implementing attention mechanisms and saliency maps to improve the interpretability of GAN-generated medical images.

By leveraging these advancements, GANs are poised to play a critical role in improving MRI noise reduction, segmentation accuracy, and classification for cervical spondylosis diagnosis.

2.5 Image Classification for Cervical Spondylosis Diagnosis

Cervical spondylosis is a prevalent age-related degenerative condition affecting the cervical spine, often resulting in symptoms such as neck pain, radiculopathy, or even myelopathy. Early diagnosis is critical to prevent permanent neurological damage. Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) are essential tools for visualizing pathological changes such as intervertebral disc degeneration, osteophyte formation, and spinal canal narrowing. However, the increasing complexity and volume of medical imaging data make manual interpretation time-consuming and error-prone. This has led to the growing use of automated image classification techniques, particularly those based on machine learning (ML) and deep learning (DL), which offer high accuracy and consistency in cervical spondylosis diagnosis.

Traditional machine learning approaches relied on handcrafted features—such as texture, intensity, or shape—extracted from medical images and used classifiers such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Random Forests, and Decision Trees [102] [103]. While these models achieved moderate success, their effectiveness was constrained by the variability in feature quality and the limited ability to generalize across diverse imaging datasets.

The rise of deep learning, especially Convolutional Neural Networks (CNNs), significantly advanced medical image classification by enabling end-to-end learning from raw image data. CNNs automatically extract spatial and contextual features, improving classification accuracy and eliminating the need for manual feature engineering. Models like AlexNet, VGGNet, ResNet, and DenseNet have been widely used across various medical imaging tasks, including spinal imaging [27]. In cervical spondylosis diagnosis, CNNs have been employed to identify and classify degenerative changes with high precision. For example, Zhao et al [104] developed a CNN-based system capable of detecting disc herniation and spinal cord compression from MRI scans. Their model demonstrated high sensitivity and specificity, supporting its potential use in clinical settings. Transfer learning, using pretrained networks on large datasets like ImageNet, has further enhanced performance, particularly in data-scarce environments [105].

More advanced object detection models, such as Region based CNNs (RCNNs) and You Only Look Once (YOLO), have also been adopted for cervical spine pathology detection. These models not only classify abnormalities but also localize affected regions, such as misaligned vertebrae or bulging discs, contributing to improved clinical interpretability and localization accuracy.

Recent research has explored hybrid and ensemble frameworks, combining CNN-based deep features with traditional classifiers like SVM or Random Forests. This approach leverages the feature extraction power of deep models and the decision-making strength of classical classifiers [106]. Ensemble techniques, which combine multiple models' predictions, have shown to improve robustness, particularly on imbalanced or noisy datasets. Multi-task learning has also been utilized, where models are trained simultaneously on classification and segmentation tasks, allowing them to learn more comprehensive representations of spinal structures and pathologies [107].

In addition, integration with Generative Adversarial Networks (GANs) has enhanced classification accuracy, especially when MRI quality is compromised. GANs can reconstruct clearer images from noisy or undersampled data, improving input quality for classification models. [30]Armanious et al demonstrated how GAN-enhanced MR images led to better performance in CNN-based classification tasks. Some systems use an end-to-end GAN-to-CNN pipeline to improve the reliability of diagnosis in suboptimal conditions. Furthermore, recent attention-based models and vision transformers (ViTs) are being explored for their ability to focus on informative regions of the cervical spine, such as degenerated discs or narrowed canals, further improving model interpretability and performance [48].

Despite these advancements, several challenges remain. The availability of annotated cervical spine datasets is limited, and class imbalance (i.e., more normal than pathological cases) can bias model predictions. In addition, anatomical variability across populations makes generalization difficult. Finally, many models have not been rigorously tested in real-world clinical settings, limiting their clinical adoption. Future efforts are expected to focus on creating more interpretable, generalizable models. Approaches such as semi-supervised and self-supervised learning, as well as federated learning, are likely to play a significant role in overcoming current data limitations. The integration of multimodal data—including clinical history, patient demographics, and radiological findings—can also enhance diagnostic accuracy and decision support.

2.6 Spectral Clustering in Medical Image Analysis

Spectral clustering is an unsupervised machine learning technique that identifies natural groupings in data by analyzing the eigenvalues and eigenvectors of similarity matrices. Unlike conventional clustering methods such as k-means—which assume convex clusters—spectral clustering is capable of identifying complex, non-linear cluster structures, making it highly suitable for medical imaging data characterized by noise, non-Euclidean geometry, and ambiguous anatomical boundaries [108].

Theoretical Background

Spectral clustering operates by constructing an affinity matrix (or similarity matrix) that encodes pairwise similarities between data points, followed by computing the Laplacian matrix of the corresponding graph representation. Eigenvectors of the Laplacian matrix capture the global geometric structure of the data, which can be used to embed data points into a lower-dimensional space where standard clustering algorithms (e.g., *k*-

means) are applied.

Given a dataset $X = \{x_1, x_2, \ldots, x_n\}$, the process generally involves:

1. **Constructing a similarity graph:** Define the similarity matrix W such that

$$W_{ij} = \begin{cases} \exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right), & \text{if } x_j \in \mathcal{N}(x_i) \\ 0, & \text{otherwise} \end{cases}$$

   where $\mathcal{N}(x_i)$ denotes the neighborhood of x_i.

2. **Computing the Laplacian:** Compute the unnormalized graph Laplacian $L = D - W$, or its normalized form

$$L_{\text{sym}} = D^{-1/2} L D^{-1/2}$$

   where D is the degree matrix with entries $D_{ii} = \sum_j W_{ij}$.

3. **Eigen decomposition:** Compute the first k eigenvectors of L_{sym} corresponding to the smallest k eigenvalues to form a matrix $U \in \mathbb{R}^{n \times k}$.

4. **Clustering:** Normalize the rows of U, and apply the k-means algorithm to the rows to assign clusters.

This method effectively transforms data into a space where clusters become linearly separable, enabling better discrimination in complex domains such as medical imaging [109].

Applications in Medical Imaging

Spectral clustering has been applied in diverse medical imaging domains:

- **Image Segmentation:** Used for delineating soft tissues and anatomical boundaries such as tumors or vertebral structures where grayscale intensities overlap [110].
- **Multi-modality Integration:** Facilitates fusion of MRI and CT modalities by identifying shared spatial patterns.
- **Lesion Detection:** Identifies abnormal regions in label scarce datasets by grouping outliers based on similarity.

Spectral Clustering in Cervical Spine Imaging

In spinal imaging, spectral clustering has proven effective in segmenting intervertebral discs, vertebrae, and spinal canal structures particularly when tissue boundaries are subtle, as seen in cervical spondylosis [111]. Additionally, deep learning feature maps from CNNs or GAN-enhanced MRI images can be clustered in feature space to identify pathological stages of degeneration, facilitating weakly supervised diagnosis.

Integration with GANs and Deep Learning

Recent approaches integrate spectral clustering into deep neural network architectures. Deep Spectral Clustering (DSC) methods combine feature learning and clustering into a unified pipeline [112]. In cervical imaging, GANs can first denoise or reconstruct MR images, after which spectral clustering groups high-dimensional feature embeddings (e.g., from CNN layers) into disease-relevant classes enabling semi-automated disease staging without labeled data.

Advantages and Limitations

Advantages:

- Captures complex and non-linear data distributions.
- Effective for high-dimensional and graph-based datasets.
- Works well with small or label-scarce datasets.

Limitations:

- Computationally intensive (due to eigen decomposition).
- Sensitive to choice of similarity function and cluster count k.
- Requires tuning and preprocessing for image-scale data.

2.7 Comparison of AI Techniques in Medical Imaging

Artificial Intelligence (AI) has significantly advanced medical imaging, offering improvements in accuracy, efficiency, and diagnostic reliability. Various AI techniques, including Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), Vision Transformers (ViTs), [113] and Spectral Clustering, have been applied to diagnose conditions such as cervical spondylosis [114]. Below is a comparative analysis of these techniques:

Table 2.1: Comparative analysis of various techniques.

AI Technique	**Advantages**	**Limitations**	**Applications in Medical Imaging**
CNNs	High accuracy in feature extraction, Well established for image classification and segmentation	Requires large labeled datasets, Limited ability to model long-range dependencies	Automated MRI/CT scan classification, Lesion detection
Generative Adversarial Networks (GANs)	Generates high-quality synthetic images, Effective for image denoising and super resolution	Prone to mode collapse and training instability, Requires high computational resources	MRI noise reduction, Synthetic data augmentation
Vision Transformers (ViTs)	N Captures long range dependencies in images, Outperforms CNNs in large datasets	Requires extensive computational power, Needs substantial training data	Advanced image segmentation, Feature enhancement in MRI analysis
Spectral Clustering-Based AI	Effective for complex segmentation tasks, Reduces over segmentation issues	Computationally expensive, Parameter sensitivity affects accuracy	Cervical spine segmentation, Abnormality detection

This comparison illustrates the unique contributions of each AI technique to medical imaging. Integrating these methods, such as combining GANs with spectral clustering, can optimize cervical spondylosis diagnosis by leveraging their respective strengths [114].

2.8 Challenges in AI-Based Medical Imaging

Despite its transformative potential, AI in medical imaging faces several challenges that must be addressed for broader clinical adoption. These challenges include:

- **Data Quality and Availability:** AI models require large and diverse datasets for training. However, medical imaging data is often limited, heterogeneous, and subject to privacy regulations, making data collection and sharing difficult.
- **Computational Complexity:** Advanced AI models, such as deep learning networks, demand significant computational resources, including high-performance GPUs and cloud infrastructure, which may not be readily available in all healthcare settings.
- **Interpretability and Trust:** Many AI-driven models operate as "black boxes," meaning their decision-making processes are not transparent. This lack of interpretability makes it challenging for radiologists and clinicians to trust AI-based recommendations.
- **Ethical and Legal Concerns:** The use of AI in medical imaging raises ethical issues related to patient consent, data security, and bias in algorithmic decision-making. Regulatory approval processes for AI-based diagnostic tools also remain complex and time-consuming.
- **Generalization and Bias:** AI models trained on specific datasets may not generalize well to different populations, leading to biased or inaccurate predictions. Addressing these biases requires diverse and representative training data.
- **Integration with Clinical Workflow:** Effective implementation of AI requires seamless integration into existing clinical workflows. Many healthcare facilities struggle with incorporating AI-based tools into routine diagnostic processes without disrupting standard procedures.

2.9 Future Research Directions

Future research in AI-driven medical imaging for cervical spondylosis should focus on addressing current limitations and enhancing the accuracy and efficiency of diagnostic tools. Key areas for future exploration include:

- **Advanced AI Models:** Further development of hybrid models combining CNNs, GANs, and transformers to improve image segmentation, denoising, and classification.

- **Explainable AI XAI:** Enhancing the interpretability of AI models to build trust among clinicians by using attention mechanisms, saliency maps, and interpretable deep learning techniques.

- **Federated Learning in Medical Imaging:** Implementing federated learning to enable AI training across multiple hospitals without data sharing, thereby addressing privacy concerns while improving model generalizability.

- **Real-Time AI Applications:** Developing lightweight AI models that can be integrated into real-time clinical decision-making, reducing the time required for diagnosis and treatment planning.

- **Multi-Modal AI Approaches:** Combining MRI, CT, and X-ray imaging through AI-driven fusion techniques to provide a more comprehensive understanding of cervical spondylosis progression.

- **Personalized Medicine Approaches:** Utilizing AI for patient-specific predictive modeling to tailor treatments based on individual imaging and clinical data.

- **Ethical and Regulatory Frameworks:** Establishing standardized protocols for AI implementation in medical imaging, ensuring safety, effectiveness, and compliance with legal and ethical guidelines.

The rapid advancement of artificial intelligence in medical imaging has opened several promising directions for future exploration beyond conventional convolutional and adversarial architectures. Recent trends indicate the growing impact of Transformer-based and Diffusion-based generative models in medical image reconstruction and enhancement.

Transformer-based architectures such as SwinIR: Image Restoration Using Swin Transformer [115] employ self-attention mechanisms to capture long-range spatial dependencies that are often missed by CNNs. These models demonstrate strong performance in image denoising, super-resolution, and artifact reduction.

Diffusion-based generative models represent another significant innovation. For example, Improved Denoising Diffusion Probabilistic Models [116] builds on earlier diffusion frameworks to refine noisy inputs into high-fidelity reconstructions. These methods show exceptional capability in capturing complex anatomical structures and subtle pathological textures.

However, transformer and diffusion models typically require large-scale annotated datasets and substantial computational resources for training. In contrast, Generative Adversarial Networks (GANs) remain efficient, data-effective, and clinically practical for moderate-sized medical datasets. Therefore, while this work focuses on the GAN–Spectral Clustering hybrid model (GANSCCS), future research can extend this framework by integrating transformer-based encoders for improved global feature learning, or by incorporating diffusion-process modules to further enhance fine-structure reconstruction and noise robustness.

2.10 Findings and Research Gaps

The review of contemporary research in medical image analysis reveals substantial advancements enabled by deep learning techniques such as Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and clustering algorithms like spectral clustering. These methods have significantly improved performance in tasks such as image reconstruction, segmentation, and disease classification. However, a critical synthesis of the literature indicates several key research gaps that this thesis seeks to address.

- **Limited Integration of GANs and Clustering for Cervical Spine Diagnosis:** Although GANs have achieved notable success in enhancing image quality in various medical domains—such as brain MRI, retinal scans, and lung CTs—their application in cervical spine imaging remains relatively underexplored. More critically, there is a distinct absence of studies that integrate GAN-based image reconstruction with unsupervised clustering algorithms, such as spectral clustering, for the diagnosis or classification of cervical spondylosis. Existing research primarily relies on supervised classification pipelines or traditional image segmentation techniques. Thus, there is a significant opportunity to investigate hybrid architectures that combine generative and clustering capabilities, especially for applications in cervical spine pathologies.

- **Inadequate Focus on Noisy or Low-Quality Cervical MRI/CT Data:** Clinical imaging of the cervical spine is frequently affected by motion artifacts, low signal-to-noise ratios (SNR), and suboptimal resolution due to anatomical constraints and patient movement. Despite these challenges, limited research has focused on reconstructing or enhancing such degraded images using advanced deep learning methods. Moreover, the effect of reconstruction quality on subsequent classification accuracy is often overlooked. This gap underscores the need for robust image enhancement techniques that not only improve visual clarity but also positively impact diagnostic performance.

- **Overreliance on Fully Labeled Datasets:** A considerable portion of existing classification models in medical image analysis depends heavily on large, fully annotated datasets. However, generating high-quality annotations in medical domains is both time-consuming and resource-intensive, often requiring expert radiological input. Furthermore, annotations can be inconsistent due to inter-observer variability. Despite the growing interest in semi-supervised and unsupervised methods, their application remains limited in spine imaging. Approaches that leverage deep feature extraction from GAN-enhanced images, followed by unsupervised spectral clustering, offer promising yet underutilized alternatives.

- **Lack of Disease-Specific Model Optimization:** Many widely adopted deep learning models in medical imaging, such as ResNet, VGGNet, and DenseNet, were originally designed for general-purpose tasks. These architectures may not effectively capture the subtle and progressive anatomical changes characteristic of cervical spondylosis—such as minimal disc height reduction, mild osteophyte development, or early spinal canal narrowing. Current approaches lack disease-specific design considerations that account for the complex, gradual manifestations of degenerative spinal conditions.

- **Limited Interpretability and Clinical Integration:** Interpretability remains a critical barrier to the clinical adoption of AI-driven diagnostic systems. Many deep learning models, including CNNs and GANs, operate as black-box systems, offering limited transparency in decision-making processes. Additionally, most models have not been validated in real-world clinical workflows, which hinders their practical deployment. There is a pressing need for models that not only deliver high accuracy but also provide clinically interpretable outputs, such as anatomically meaningful reconstructions and clustering visualizations aligned with disease progression.

CHAPTER 3

METHODOLOGY

This chapter outlines the methodology adopted to develop and evaluate the proposed Generative Adversarial Network–Spectral Clustering Cervical Spondylosis Classification System (GANSCCS). The framework is designed to enhance the resolution and diagnostic value of MRI scans and to facilitate accurate segmentation and classification of cervical spondylosis cases. The methodology comprises detailed procedures for dataset collection, preprocessing, model architecture design, training strategies, and integration of spectral clustering for segmentation. Each component of the framework has been systematically developed to address the limitations of existing image enhancement and classification approaches in medical imaging. The chapter also includes the implementation details and configurations necessary to reproduce and validate the proposed model.[1] *[37]*

3.1 Dataset Collection and Preprocessing

"The effectiveness of any deep learning model in medical image analysis depends heavily on the quality, diversity, and representativeness of the dataset used for training and evaluation [27]. In this study, both publicly available datasets and proprietary clinical data are utilized to ensure comprehensive coverage of cervical spondylosis cases.

[1] This chapter is derived from:
R. Kumar, D. Singh, R. Malik, I. Batra, M. Humayun, and J. A. Khan, "GANSCCS: Synergizing Generative Adversarial Networks and Spectral Clustering for Enhanced MRI Resolution in the Diagnosis of Cervical Spondylosis," Int. J. Intell. Syst., vol. 2025, no. 1, pp. 1–20, Feb. 2025, doi: 10.1155/int/6674913.

The collected datasets include MRI and CT scans, which serve as inputs for image reconstruction, segmentation, and classification tasks. The preprocessing pipeline ensures that the data is clean, standardized, and augmented to enhance model performance [117]."

3.1.1 Dataset Sources

The experimental dataset used in this study was compiled from both proprietary clinical MRI data and publicly available CT datasets to ensure adequate diversity, quality, and representativeness of cervical spine imaging. A clinical MRI dataset was collected from a diagnostic imaging center affiliated with a hospital, comprising scans from 70 patients, each contributing approximately 12 distinct images, resulting in a total of about 840 MRI slices. These scans represent varying stages of cervical spondylosis, including mild, moderate, and severe degeneration, and were acquired using standard sagittal and axial cervical spine protocols. All patient data were anonymized before analysis, with personal identifiers removed from DICOM headers, and each record was assigned a unique coded identifier. In addition to the clinical MRI dataset, two publicly accessible CT datasets were incorporated to improve model robustness and anatomical generalization: the RSNA 2022 Cervical Spine Fracture CT Dataset [118], consisting of approximately 3,112 CT studies from multiple international institutions with expert-verified fracture annotations, and the CTSpine1K Dataset [119], containing 1,005 CT volumes and over 11,100 labeled vertebrae intended for vertebral segmentation and localization tasks. Although these datasets primarily focus on fracture detection and vertebral segmentation rather than degenerative pathology, their inclusion provided valuable high-resolution CT data and anatomical variability that supported the proposed GAN-based reconstruction framework. Additionally, reference MRI images from the Medscape Cervical Spine Atlas were consulted for anatomical correlation and expert interpretation; these images were used solely for visual reference and validation purposes and were not included in the model's training or testing datasets. Together, these combined data sources established a comprehensive, ethically compliant, and multimodal foundation for developing and validating the proposed GAN-based Spectral Clustering Cervical Spine (GANSCCS) model.

The experimental dataset comprised distinct MRI images of the cervical spine collected from different sources, including , RSNA , and CTSpine 1K. This dataset includes cervical spine MRIs and a mix of healthy and pathological cases and these datasets were preprocessed to ensure consistency and quality. To properly train and test the GANSCCS, the dataset was divided into training, validation, and testing subsets:

- Training Data: 80% of the dataset
- Validation Data: 10% of the dataset
- Testing Data: 10% of the dataset

All research involving human imaging data was conducted in accordance with ethical standards of the participating institution. Formal ethical approval was obtained from the Institutional Ethics Committee, and permission was granted by the diagnostic center for the use of anonymized MRI data in this study.

3.1.2 Data Preprocessing

To ensure high-quality input for the GANSCCS model, the collected MRI images underwent several preprocessing steps. These steps aimed to enhance image consistency, remove noise, and standardize the dataset for effective training. The preprocessing pipeline included the following steps:

- **Data Cleaning:** Duplicate and irrelevant images were removed to ensure only relevant cervical spine MRI images were retained.
- **Image Resizing:** All images were resized to a standard dimension to maintain uniformity across the dataset.
- **Normalization:**Pixel intensity values were normalized to a [0,1] range using min–max normalization to improve training stability and convergence.
- **Noise Reduction:** Denoising techniques, such as Gaussian filtering, were applied to reduce artifacts and enhance image clarity.
- **Contrast Enhancement:**Histogram equalization and CLAHE (Contrast Limited Adaptive Histogram Equalization) were used to improve image contrast.

- **Augmentation:**Data augmentation techniques, including rotation, flipping, and intensity variations, were applied to increase dataset diversity and prevent overfitting.

- **Segmentation:** Region-of-interest (ROI) extraction was performed to focus on the cervical spine region and eliminate background noise.

All MRI and CT images were resized to a uniform dimension of 128×128 pixels to maintain consistency and compatibility with the GAN input requirements. These preprocessing steps ensured that the dataset was well-prepared for training the GAN-based model, leading to improved accuracy in reconstruction and classification tasks.

3.2 Proposed GAN-Spectral Clustering Model

A review of existing models used for the classification of image samples into cervical spondylosis classes indicates that many of these models either exhibit lower efficiency or lack scalability to handle large datasets. To address these limitations, this section presents the design of a structured graph-based model aimed at enhancing the efficiency of cervical spondylosis analysis in clinical scenarios.

The PMFN algorithm offers a significant advantage by uniquely integrating Generative Adversarial Networks (GANs) with Spectral Clustering. This integration enables superior image enhancement and segmentation capabilities. While previous models have focused solely on improving image resolution or increasing segmentation accuracy, PMFN synergistically combines these objectives to resolve multiple imaging challenges within a unified framework.

The high-resolution output and precise segmentation capabilities of PMFN extend its applicability beyond cervical spondylosis diagnosis to broader medical imaging domains, including brain imaging, oncology, and other fields requiring detailed visualization and accurate anatomical delineation. Additionally, the multiscale approach incorporated in PMFN ensures adaptability across various datasets, making it a versatile tool in both specialized and generalized medical imaging applications.

As illustrated in Fig 3.1 and Fig 3.2, the proposed model integrates GANs and Spectral Clustering to redefine cervical spondylosis diagnosis through medical imaging. Fig 3.3 presents the architecture of the proposed model. Designed to enhance MRI resolution, this innovative model generates high-quality, high-resolution images using GANs, effectively addressing the inherent limitations of standard MRI techniques. Subsequently, Spectral Clustering is applied to achieve precise segmentation of complex anatomical structures, aiding clinicians in better understanding cervical spine conditions.

The advanced approach of GANSCCS not only enhances image quality but also ensures more accurate diagnostics, leading to significant improvements in accuracy, efficiency, and patient outcomes.

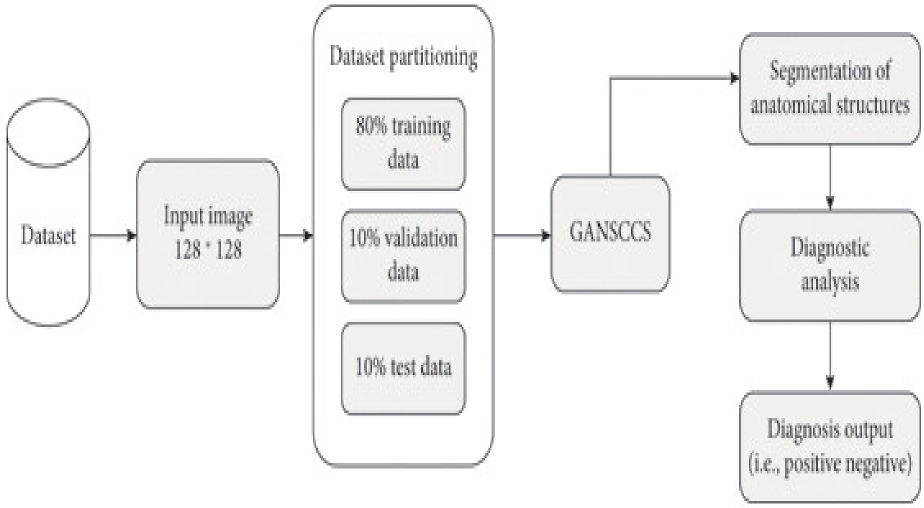

Figure 3.1: Flow of the proposed model for analysis of Cervical Spondylosis Cases

Model Overview

The proposed framework consists of two major components:

- **GAN-Based Image Reconstruction:**

  A generative adversarial network (GAN) is employed to enhance the resolution of MRI scans by removing noise and restoring fine anatomical details. The generator leverages U-Net and ResNet-inspired architectures, while the discriminator is designed as a PatchGAN for effective feature discrimination.

- **Spectral Clustering for Segmentation:** A graph-based clustering approach is used to segment key cervical structures by analyzing pixel similarities in the MRI

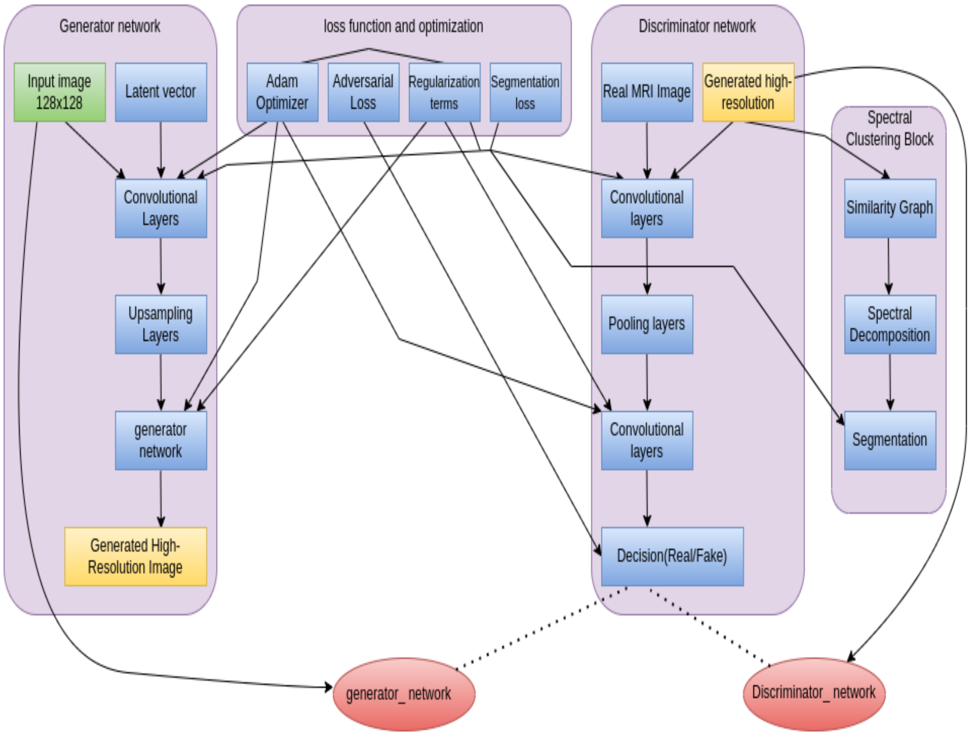

Figure 3.2: Proposed Model

scans. The Laplacian matrix is computed to determine cluster boundaries, improving segmentation accuracy.

Key Advantages of the Proposed Model

- **Improved Image Quality:** GANs enhance the resolution and clarity of MRI scans, making anatomical structures more distinguishable.
- **Efficient Segmentation:** Spectral clustering groups pixels based on intensity and texture similarity, aiding in better classification of cervical spondylosis severity.
- **Robust Training Framework:** The model is trained using adversarial loss, perceptual loss, and structural similarity loss (SSIM) to ensure high-fidelity image reconstruction and precise segmentation.

This model provides a novel approach to cervical spondylosis analysis by integrating state-of-the-art deep learning and clustering techniques, paving the way for more accurate medical diagnostics and automated assessment. Table 3.1 represent the proposed model.

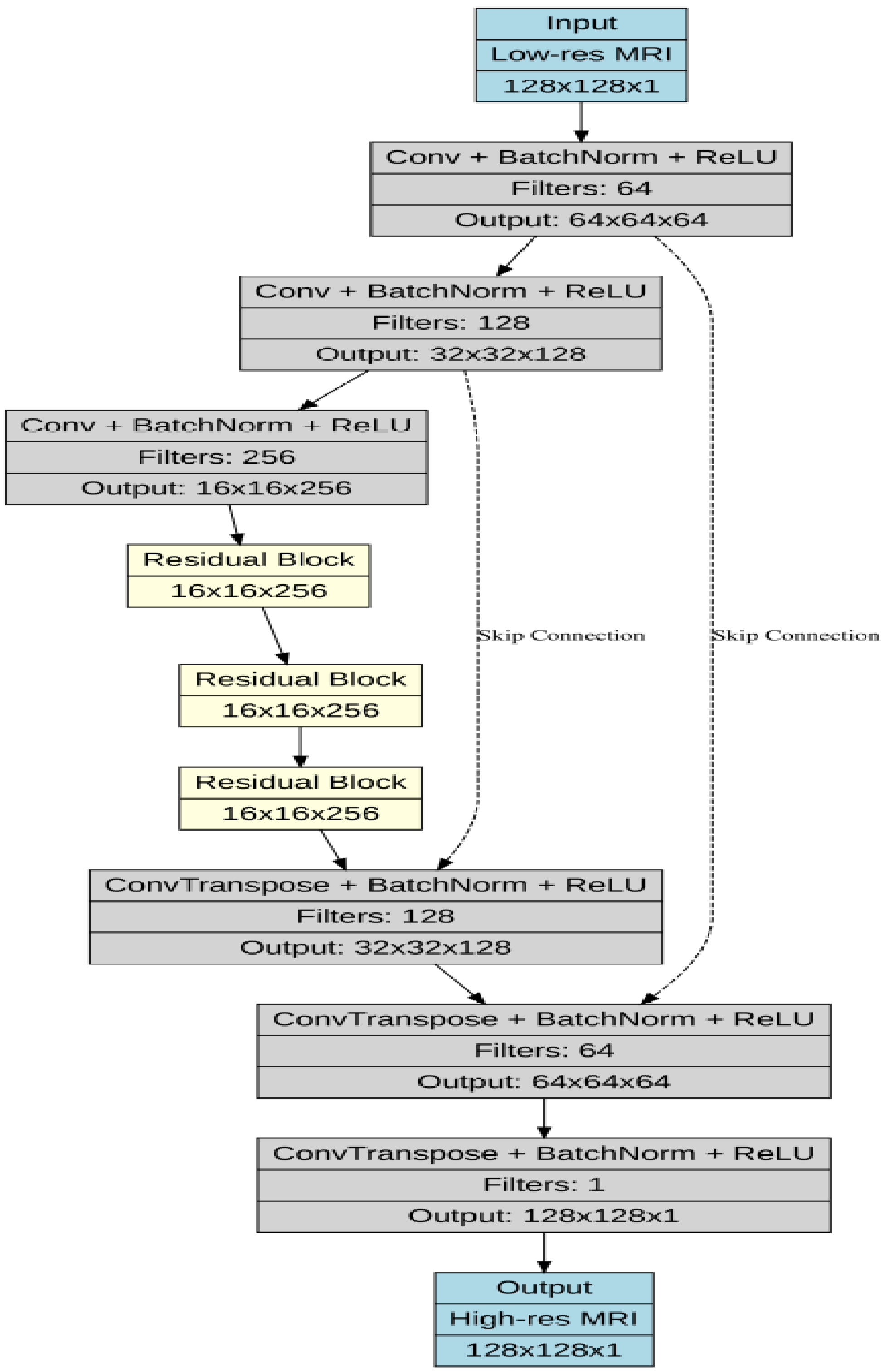

Figure 3.3: Overall Architecture of the Proposed Model Used for Identification of Cervical Spondylosis

Table 3.1: Architecture of the Proposed Model

Sr. No	Operation	Layer	Filters	Filter Size	Padding	Stride	Output Size	Parameters
1	Input	Low-res MRI	—	—	—	—	128×128×1	—
2	Downsampling	Conv + BatchNorm + ReLU	64	3×3	1	2	64×64×64	$(331+1)64 = 640$
3	Downsampling	Conv + BatchNorm + ReLU	128	3×3	1	2	32×32×128	$(3364+1)128 = 73{,}856$
4	Downsampling	Conv + BatchNorm + ReLU	256	3×3	1	2	16×16×256	$(33128+1)256 = 295{,}168$
5	Residual Block	Conv + BatchNorm + ReLU	256	3×3	1	1	16×16×256	$2(33256+1)256 = 1{,}180{,}416$
6	Residual Block	Conv + BatchNorm + ReLU	256	3×3	1	1	16×16×256	$2(33256+1)256 = 1{,}180{,}416$
7	Residual Block	Conv + BatchNorm + ReLU	256	3×3	1	1	16×16×256	$2(33256+1)256 = 1{,}180{,}416$
8	Upsampling	ConvTranspose + BatchNorm + ReLU	128	3×3	1	2	32×32×128	$(33256+1)128 = 295{,}040$
9	Upsampling	ConvTranspose + BatchNorm + ReLU	64	3×3	1	2	64×64×64	$(33128+1)64 = 73{,}792$
10	Upsampling	ConvTranspose + BatchNorm + ReLU	1	3×3	1	2	128×128×1	$(3364+1)1 = 577$
11	Output	Conv	1	3×3	1	1	128×128×1	$(331+1)1 = 10$
12	Input	Image	—	—	—	—	128×128×1	—
13	Downsampling	Conv + LeakyReLU	64	3×3	1	2	64×64×64	$(331+1)64 = 640$
14	Downsampling	Conv + LeakyReLU	128	3×3	1	2	32×32×128	$(3364+1)128 = 73{,}856$
15	Downsampling	Conv + LeakyReLU	256	3×3	1	2	16×16×256	$(33128+1)256 = 295{,}168$
16	Downsampling	Conv + LeakyReLU	512	3×3	1	2	8×8×512	$(33256+1)512 = 1{,}180{,}672$
17	Output	Conv	1	3×3	1	1	8×8×1	$(33512+1)1 = 4{,}625$

3.2.1 GAN-Based Image Reconstruction

Generator Architecture:

The generator in the proposed GAN architecture is designed using a deep convolutional neural network (DCNN) framework . It comprises multiple convolutional layers, where each layer is followed by batch normalization and a ReLU activation function. The primary objective of the generator is to progressively enhance low-resolution MRI images, ensuring the preservation of fine anatomical structures while improving overall image quality. The initial stage of the generator performs a downsampling operation, which reduces the spatial dimensions of the input images while increasing the depth of feature maps. This process is achieved through strided convolutions, which facilitate the extraction of hierarchical image features. The downsampling operation can be mathematically expressed as:

$$D(x) = \mathrm{ReLU}\left(\mathrm{BatchNorm}\left(\mathrm{Conv}(x)\right)\right) \tag{3.1}$$

where D(x) denotes the downsampling transformation, and Conv(x) represents the convolution operation. This transformation is further refined through a series of operations, including batch normalization and activation functions, defined as follows:

$$(\mathrm{Conv} * f)[i,j] = \sum_{m=0}^{2a}\sum_{n=0}^{2b} \mathrm{kernel}[m,n] \cdot f[i-m, j-n] \tag{3.2}$$

where D(x) represents the convolutional kernel learned during the training process, and f(i,j) denotes the input feature map at spatial coordinates . The kernel weights are optimized via the Adam optimizer during backpropagation to minimize the network's loss function, ensuring efficient feature extraction. Batch normalization, a critical component in stabilizing the training process, is defined as:

$$\text{BatchNorm}(x) = \gamma \left(\frac{x - \mu_{\text{batch}}}{\sqrt{\sigma^2_{\text{batch}} + \varepsilon}} \right) + \beta \tag{3.3}$$

where x denotes the input to the batch normalization layer, μ_{batch} is the mean of the current batch, σ^2_{batch} represents the batch variance, γ is the learnable scaling parameter, β is the learnable shifting parameter, and ε is a small constant added for numerical stability.

$$\text{ReLU}(x) = \max(0, x) \tag{3.4}$$

Following the downsampling process, the generator incorporates residual blocks, which are crucial for enhancing feature learning. Each residual block consists of two convolutional layers, each followed by batch normalization. The presence of skip connections allows the network to bypass certain layers, effectively enabling the propagation of gradients during training. This structure ensures stable learning and mitigates the vanishing gradient problem. The residual block transformation can be expressed as:

$$R(x) = x + \text{Conv}\left(\text{ReLU}\left(\text{BatchNorm}\left(\text{Conv}(x)\right)\right)\right) \tag{3.5}$$

where R(x) represents the residual mapping learned by the network, and x denotes the original input to the residual block. In the final phase of the generator, up-sampling layers are employed to progressively reconstruct high-resolution MRI images. These layers utilize transposed convolutions to restore the spatial dimensions of feature maps while preserving fine structural details. The upsampling operation is formulated as follows:

$$U(x) = \text{ReLU}\left(\text{BatchNorm}\left(\text{ConvTranspose}(x)\right)\right) \tag{3.6}$$

where ConvTranspose(x) represents the transposed convolution operation, which is further defined as:

$$(\text{ConvTranspose} * f)[i, j] = \sum_{m=0}^{2a} \sum_{n=0}^{2b} \text{kernel}[m, n] \cdot f[i + m, j + n] \tag{3.7}$$

To enhance the quality of the reconstructed images and retain fine-grained details, skip connections from corresponding downsampling layers are incorporated into the upsampling layers. This technique facilitates the recovery of spatial information lost during the downsampling process, thereby improving the overall fidelity of the generated MRI images.

Discriminator Architecture

The discriminator is implemented as a patch-based convolutional neural network (CNN) designed to classify input images as either real (extracted from the high-resolution MRI dataset or fake (generated by the GAN). The architecture consists of multiple convolutional layers with an increasing number of filters, employing LeakyReLU activation functions and strided convolutions to progressively downsample the input images. The use of PatchGAN ensures that the discriminator evaluates local image patches rather than the entire image, allowing for finer texture discrimination and improved robustness in distinguishing generated images from real MRI scans.

Loss Functions and Optimization

The training of the GAN framework follows a min-max optimization strategy, where the generator attempts to synthesize high-quality MRI images that resemble real scans, while the discriminator is trained to distinguish between real and generated images. This adversarial training process ensures continuous improvement in the quality of the synthesized images and their structural coherence with real MRI scans. The generator's objective function is composed of two primary loss components: adversarial loss and content loss. The adversarial loss, formulated in Equation (3.8), enforces the generation of realistic image textures by leveraging a binary cross-entropy function:

$$\mathscr{L}_{\text{adv},G} = -\log\left(D_{\text{disc}}(G(x))\right) \tag{3.8}$$

where L(adv, G) represents the adversarial loss for the generator, G(x) denotes the generated image, and Ddisc signifies the discriminator's output. This loss function guides the generator to produce images that the discriminator cannot distinguish from real MRI images. To ensure that the generated images retain anatomical accuracy and structural integrity, a content loss component is introduced, defined in Equation (3.9) as the L2 norm between the generated and real high-resolution images:

$$\mathscr{L}_{\text{content}} = \|G(x) - y\|_2 \tag{3.9}$$

where real label denotes the original high-resolution MRI image, and G(z) is the synthesized image. This term ensures that the generated images maintain similarity with real medical scans in terms of spatial features and intensity distributions. The discriminator's loss function is purely adversarial and is computed using binary cross-entropy, as shown in Equation (3.10):

$$L_{\text{disc}} = -\log(D_{\text{isc}}(y)) - \log(1 - D_{\text{isc}}(G(x))) \tag{3.10}$$

This loss function penalizes the discriminator if it misclassified real images as fake or generated images as real, thereby enforcing a more accurate classification of the input images.

The adversarial learning process between the generator (G) and discriminator (D) follows a min-max game:

$$\min_G \max_D \mathscr{L}_{GAN} = \mathbb{E}_{x\sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z)))] \tag{3.11}$$

The discriminator seeks to maximize this objective by correctly identifying real versus generated images, while the generator aims to minimize it by producing realistic outputs that deceive the discriminator.

The discriminator loss is given by:

$$\mathscr{L}_D = -\mathbb{E}_{x\sim p_{data}(x)}[\log D(x)] - \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z)))] \tag{3.12}$$

and the generator loss is formulated as a weighted combination of adversarial, pixel-wise, and structural similarity components:

$$\mathscr{L}_G = \mathscr{L}_{adv} + \lambda_1 \mathscr{L}_{MSE} + \lambda_2(1 - \text{SSIM}) \tag{3.13}$$

The overall optimization can be expressed as:

$$\min_G \max_D (\mathscr{L}_{GAN} + \lambda_1 \mathscr{L}_{MSE} + \lambda_2(1 - \text{SSIM})) \tag{3.14}$$

This quantitative formulation ensures that the generator learns both anatomical realism and perceptual quality, while the discriminator progressively improves its ability to differentiate authentic and reconstructed MRI scans.

The entire GAN is trained using backpropagation and stochastic gradient descent. The generator and discriminator are optimized separately using adaptive gradient-based optimizers such as Adam or RMSprop. The learning rates for both networks are carefully selected to maintain a balanced training dynamic and prevent mode collapse.

Integration with Spectral Clustering

In the GAN-based Cervical Spondylosis Classification System (GANSCCS) framework, the output generated by the GAN undergoes further processing through Spectral Clustering. This clustering technique is employed to segment the reconstructed MRI images into distinct regions corresponding to various anatomical structures of the cervical spine. Spectral Clustering operates by utilizing the eigenvalues of the similarity matrix to perform dimensionality reduction, thereby enhancing the detection of complex patterns within the image data samples. The similarity between two data points is computed using Equation.

$$S_{ij} = \exp\left(\frac{-\|x_i - x_j\|^2}{2\sigma^2}\right) \tag{3.15}$$

where S_{ij} represents the similarity between data points x_i and x_j, and σ is a scale parameter that controls the degree of similarity measurement. Based on this similarity matrix, the degree matrix D is computed iteratively. The degree matrix is a diagonal matrix, where each diagonal element D_{ii} represents the sum of the similarities in the i^{th} row of the similarity matrix. This relationship is mathematically expressed as Equation.

$$D_{ii} = \sum S_{ij} \tag{3.16}$$

A key component in Spectral Clustering is the Laplacian matrix L, which is essential for analyzing the structure of the image data. The Laplacian matrix is defined using Equation.

$$L = D - S \tag{3.17}$$

The normalized Laplacian is computed as

$$L_{\text{sym}} = I - D^{-\frac{1}{2}} S D^{-\frac{1}{2}} \tag{3.18}$$

where L captures the underlying graph structure of the image data samples. Using the computed Laplacian matrix, the Spectral Clustering algorithm proceeds by determining the eigenvalues and eigenvectors of L. This transformation is crucial as it maps the data into a new feature space where clusters become more discernible. The first few eigenvectors corresponding to the smallest eigenvalues (excluding the trivial smallest eigenvalue) are selected for clustering. These eigenvectors serve as the basis for transforming the data into a low-dimensional feature space, allowing for the application of k-means clustering to group pixels into distinct clusters based on their spatial and structural characteristics. Following clustering, each identified region is analyzed to classify the segmented spinal structures into various categories of cervical spondylosis. This classification is guided by predefined morphological criteria associated with spinal anomalies, such as structural deformations and vertebral misalignments. Spectral Clustering is particularly advantageous for medical image analysis as it effectively detects non-linear structures that are not easily separable in the original image space. This makes it a robust technique for accurately segmenting and classifying cervical spondylosis cases based on MRI scans. In the next section, the efficiency of the proposed model is evaluated using various performance metrics and compared with existing state-of-the-art approaches.

3.2.2 Model Training and Optimization

The training of the proposed GAN-based model for reconstructing and classifying cervical spondylosis images involves an adversarial learning process where the generator and discriminator networks are trained simultaneously in a min-max optimization framework. The objective of this training is to enable the generator to produce high-quality MRI images that closely resemble real medical scans while ensuring that the discriminator effectively distinguishes between real and generated images.

Adversarial Training

The adversarial training process follows the standard Generative Adversarial Network (GAN) optimization, where the generator G and discriminator D compete against each other. The generator aims to minimize the adversarial loss to produce realistic MRI images, while the discriminator aims to maximize its classification accuracy in distinguishing real images from synthetic ones. The generator is trained to minimize this loss, while the discriminator is trained to maximize it. This adversarial interplay drives the generator to refine its image reconstruction capabilities.

Content Loss for Structural Preservation

In addition to adversarial loss, a content loss function is introduced to ensure that the generated images retain fine anatomical structures. The content loss is computed using the L2 norm (Mean Squared Error - MSE) between the generated and real MRI images: This ensures that the generated images are structurally consistent with the original high-resolution MRI scans.

Optimization Strategy

The training process is optimized using the Adam optimizer, which is preferred due to its adaptive learning rate capabilities and ability to handle sparse gradients efficiently. The training follows an alternating approach where the discriminator is updated first, followed by the generator update. This ensures stable convergence and prevents mode collapse, a common issue in GAN training.

Regularization Techniques

To improve the stability and generalization of the model, various regularization techniques are employed:

- **Gradient Penalty:** Enforces Lipschitz continuity to stabilize training and avoid vanishing gradients.
- **Dropout:** Reduces overfitting by randomly deactivating neurons during training.
- **Batch Normalization:** Improves training speed and convergence stability by normalizing feature distributions across mini-batches.

Training Pipeline

The training process is implemented as follows:

- Initialize the generator and discriminator networks with random weights.

- Input a batch of real MRI images to the discriminator and compute the loss.
- Generate synthetic MRI images using the generator and pass them to the discriminator.
- Compute the discriminator loss based on real and generated images.
- Update the discriminator weights using backpropagation.
- Compute the generator loss using both adversarial and content loss.
- Update the generator weights using backpropagation.
- The process is iteratively repeated for all training batches until convergence.

This iterative adversarial training refines the generator, ultimately leading to high-quality MRI reconstructions that accurately represent cervical spondylosis conditions. The trained model is then evaluated using quantitative metrics, which are discussed in the next section.

3.3 Implementation Details

The GANSCCS framework integrates Generative Adversarial Networks (GANs) with Spectral Clustering to enhance the resolution of MRI images and facilitate accurate diagnosis of cervical spondylosis. The implementation details of the model, including architectural components, training process, and hardware specifications, are outlined in this section.

3.3.1 Generative Adversarial Network (GAN) Configuration

The GAN model consists of a generator and a discriminator, both implemented using deep convolutional neural networks (CNNs). The parameter settings for both networks are as follows:

Generator:

- Designed as a deep CNN to reconstruct high-resolution MRI images
- Input Size: 128×128 (low-resolution MRI images).

- Latent Dimension: 256.
- Activation Function: Leaky ReLU in intermediate layers and Tanh in the output layer.

Discriminator:

- Structured as a CNN to distinguish between real and generated MRI images.
- Uses PatchGAN to classify local image patches rather than full images.
- Activation Function: Leaky ReLU.
- Output: A probability score indicating the authenticity of the input image.

Optimization Strategy:

- Optimizer: Adam
- Learning Rate: 0.0002
- Loss Function: Binary Cross-Entropy

3.3.2 Spectral Clustering for Image Segmentation

To improve the segmentation of anatomical structures in the enhanced MRI images, Spectral Clustering is employed. The implementation involves:

- **Input Data:** High-resolution MRI images generated by the GAN model.
- **Similarity Matrix Computation:** Eigenvalues of the similarity matrix are used for dimensionality reduction.
- **Number of Clusters:** 4, based on anatomical structures of the cervical spine.
- **Clustering Method:** K-means applied to eigenvector space for segmenting MRI images.

Table 3.2: Training Process Settings

Training Criteria	**Settings**
Batch Size	32
Number of Epochs	100
Loss Function	Binary Cross-Entropy
Weight Initialization	He Normal Initialization
Data Augmentation	Random rotations, flips, and intensity adjustments
Early Stopping	Patience of 10 epochs
Hardware Used	NVIDIA GeForce RTX 3080 GPU

3.3.3 Training Process

The GANSCCS model is trained using the following hyperparameters and strategies to ensure optimal convergence and generalization:

The training process involves data augmentation techniques to enhance generalization, early stopping to prevent overfitting, and He Normal Initialization to stabilize weight updates. The training was conducted using an NVIDIA GeForce RTX 3080 GPU, which accelerated model convergence and reduced computation time. This structured implementation ensures that GANSCCS effectively reconstructs, segments, and classifies MRI images for cervical spondylosis diagnosis. The next section presents the evaluation metrics used to assess the model's performance.

CHAPTER 4

EXPERIMENTAL VALIDATION AND ANALYSIS OF THE PROPOSED GANSCCS MODEL

This chapter presents an independent contributory study focused on validating and interpreting the proposed GANSCCS framework through extensive experiments, statistical analyses, and ablation studies. It establishes the empirical foundation of the research and complements the theoretical development in Chapter 3. The performance of the GANSCCS framework was systematically evaluated using a set of quantitative metrics to assess its diagnostic capability in cervical spondylosis detection. The evaluation was conducted to measure the model's accuracy, precision, recall, specificity, and computational efficiency.[1]

4.1 Evaluation Metrics

The following metrics were employed to assess the model's effectiveness:

- **Precision (P):** Measures the model's ability to correctly classify positive cases.

[1]This chapter is derived from:
R. Kumar, D. Singh, R. Malik, I. Batra, M. Humayun, and J. A. Khan, "GANSCCS: Synergizing Generative Adversarial Networks and Spectral Clustering for Enhanced MRI Resolution in the Diagnosis of Cervical Spondylosis," Int. J. Intell. Syst., vol. 2025, no. 1, pp. 1–20, Feb. 2025, doi: 10.1155/int/6674913."

- **Accuracy (A):** Represents the overall diagnostic correctness.
- **Recall (R):** Evaluates the sensitivity in identifying true positive cases.
- **Area Under the Curve (AUC):** Quantifies the model's ability to distinguish between positive and negative cases.
- **Specificity (Sp):** Assesses the model's ability to correctly classify negative cases.
- **Processing Delay:** Measures the computational efficiency in producing a diagnosis.

The model's performance was analyzed using multiple sample sizes (NTS) to evaluate its robustness across different scenarios. A rigorous experimental setup, leveraging a carefully curated dataset , advanced model architecture, and comprehensive evaluation metrics, ensured a thorough validation of GANSCCS for MRI-based cervical spondylosis diagnosis. The classification performance was assessed using the following equations:

- Precision (P), Accuracy (A), and Recall (R) were computed using Equations (4.1), (4.2), and (4.3), respectively.
- AUC and Specificity (Sp) were evaluated using Equations (4.4) and (4.5).

$$\text{Precision} = \frac{TP}{TP+FP} \tag{4.1}$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{4.2}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{4.3}$$

$$\text{AUC} = \int \text{TPR}(\text{FPR})\, d\text{FPR} \tag{4.4}$$

$$Sp = \frac{TN}{TN+FP} \tag{4.5}$$

Confusion Matrix Analysis

The classification performance of GANSCCS was analyzed through a confusion matrix (Table 4.1), comparing its predictions with actual class labels. The confusion matrix represents the frequency of correct and incorrect classifications across different severity levels of cervical spondylosis.

Table 4.1: Confusion Matrix for the GANSCCS Model

Actual \Predicted	Normal	Mild	Moderate	Severe	Very Severe
Normal	9360	480	490	520	550
Mild	485	9410	495	520	500
Moderate	495	510	9430	505	530
Severe	515	530	505	9390	460
Very Severe	520	490	520	475	9400

4.2 Performance Comparison with Other Models

The classification capabilities of GANSCCS were compared against state-of-the-art models, including MSDNet , Deep Dyna-Q Network (DDQN) , and Inception ResNetV2 (IRV2) . The performance metrics are summarized below: Observed Precision: GANSCCS consistently outperformed other models in terms of precision across various sample sizes. At a sample size of 286k, GANSCCS achieved a precision of 94.28%, significantly exceeding MSDNet (83.74%), DDQN (86.11%), and IRV2 (84.36%). The superior precision demonstrates the model's ability to accurately classify cervical spondylosis cases while minimizing false positives.

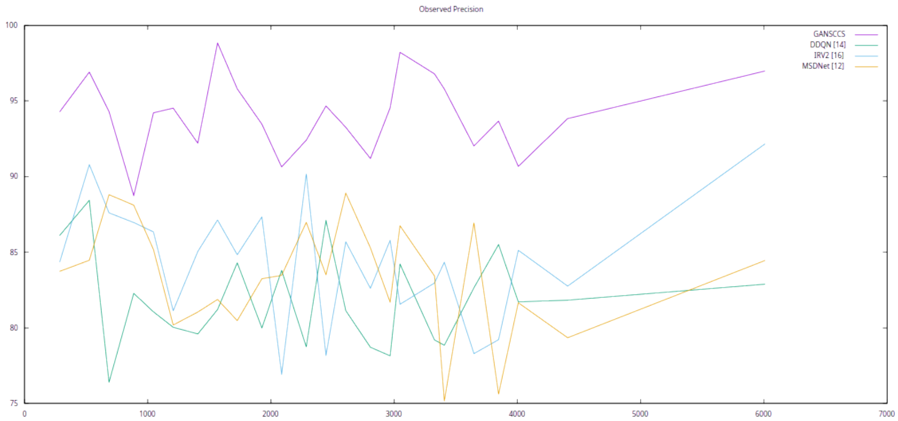

Figure 4.1: Observed Precision

Observed Accuracy:The Y-axis represents the observed precision values (%), while the X-axis denotes the training iterations across four models. The proposed GANSCCS model demonstrated higher classification accuracy across multiple datasets. At an NTS of 286k, it achieved an accuracy of 91.40%, surpassing MSDNet (85.87%), DDQN (80.30%), and IRV2 (78.28%). The improved accuracy indicates the model's effectiveness in accurately identifying both affected and normal cases.

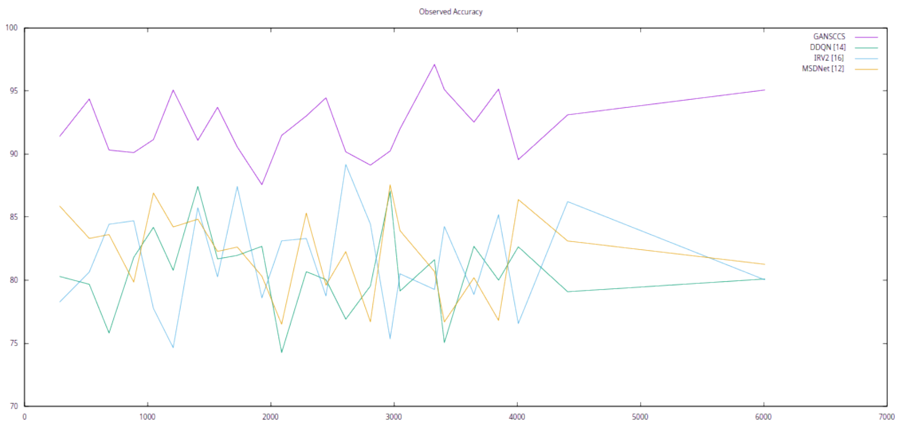

Figure 4.2: Observed Accuracy

Observed Recall: Recall, a crucial metric in medical diagnostics, showed that GANSCCS consistently identified a higher percentage of true positive cases. At a sample size of 286k, GANSCCS attained a recall of 93.15%, outperforming MSDNet (86.31%), DDQN (82.52%), and IRV2 (86.08%). The higher recall reduces the risk of undetected spondylosis cases, ensuring timely intervention.

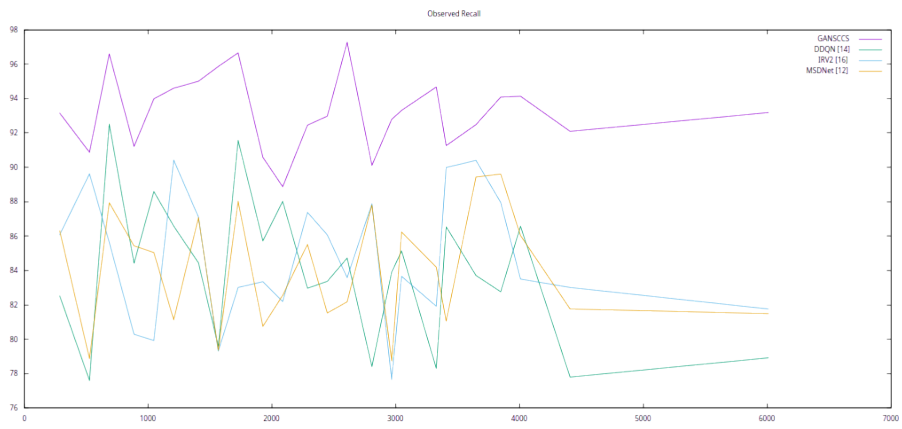

Figure 4.3: Observed Recall

Observed Delay (Computational Efficiency): In terms of computational efficiency, GANSCCS exhibited lower processing delay compared to other models. At an NTS of 286k, it achieved a prediction delay of 99.34 ms, outperforming MSDNet (111.36 ms), DDQN (103.41 ms), and IRV2 (99.94 ms). The reduced delay ensures rapid diagnostic decision-making, which is critical for real-time clinical applications.

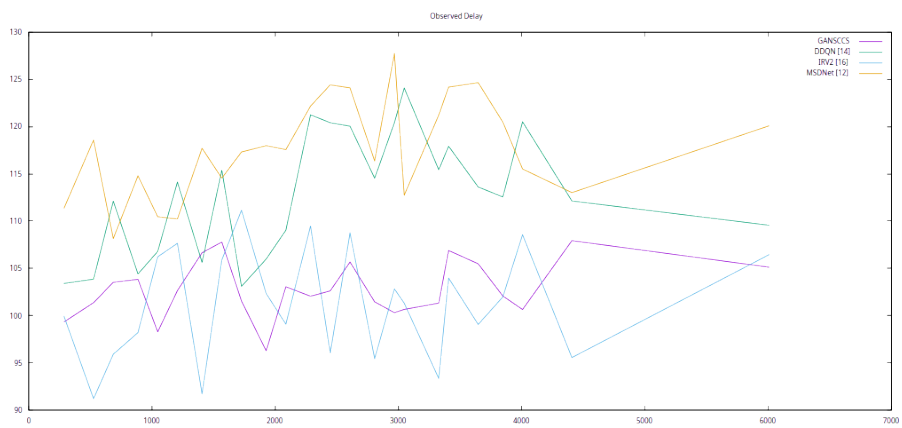

Figure 4.4: Observed Delay

Observed AUC (Discriminatory Power): GANSCCS demonstrated superior AUC performance, achieving 88.92% at an NTS of 286k, surpassing MSDNet (72.50%), DDQN (72.68%), and IRV2 (69.15%). This higher AUC signifies the model's ability to effectively differentiate between affected and non-affected individuals.

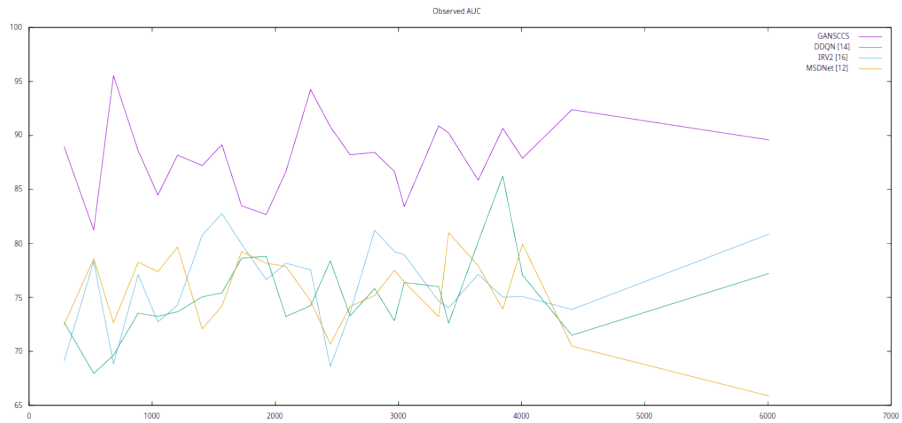

Figure 4.5: Observed AUC

Observed Specificity: Specificity, an essential metric for reducing false positives, was highest for GANSCCS across different sample sizes. At an NTS of 286k, GANSCCS achieved 86.65% specificity, outperforming MSDNet (75.27%), DDQN (69.12%), and IRV2 (77.11%). The superior specificity ensures that healthy individuals are not misclassified as having cervical spondylosis.

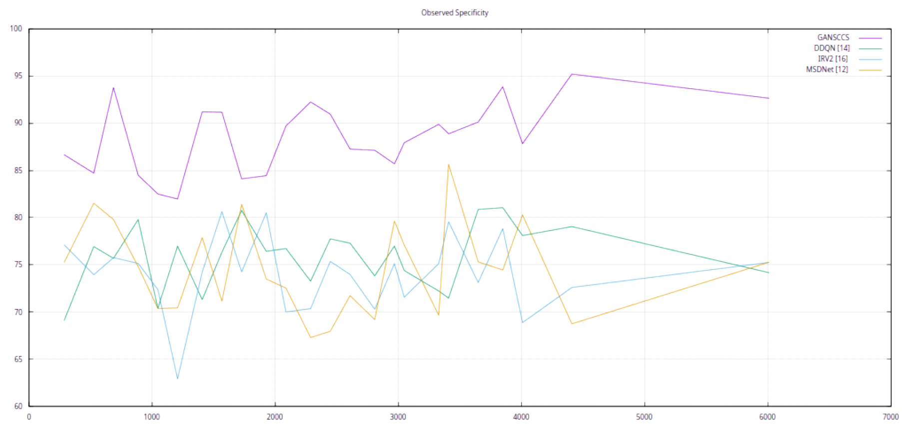

Figure 4.6: Observed Specificity

Final Classification Results

The classification results of GANSCCS for different input image sets are depicted in Figure 4.7. The model's ability to effectively distinguish between different stages of cervical spondylosis further validates its clinical applicability.

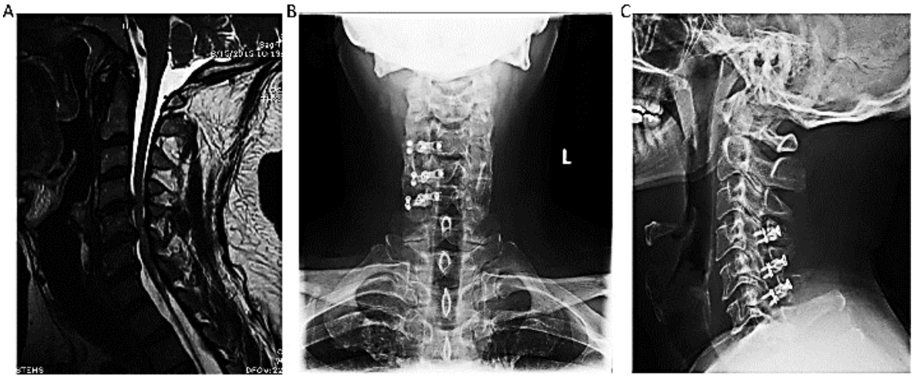

Figure 4.7: Classification Results

Conclusion

The experimental results demonstrate that GANSCCS consistently outperforms existing models in terms of precision, accuracy, recall, AUC, specificity, and computational efficiency. The integration of Generative Adversarial Networks (GANs) and Spectral Clustering enhances image resolution and segmentation accuracy, leading to improved diagnostic capabilities. These findings substantiate the effectiveness of GANSCCS as a reliable and efficient tool for the automated classification of cervical spondylosis, offering significant clinical advantages in early diagnosis and treatment planning. The table below provides a comparative analysis of our proposed work with existing state-of-the-art models. As shown in Table 4.2.

Table 4.2: Comparative Analysis of Our Proposed Work

Aspect	**MSDNet**	**DDQN**	**IRV2**	**FP-GANs**	**Proposed Work (GAN-SCCS)**
Techniques Used	CNNs, Deep Learning	Deep Q-Networks	Inception-ResNet V2 (CNN-based)	GANs, Feature Pyramid Networks	GANs, Spectral Clustering

Continued on next page

Table 4.2 – continued from previous page

Aspect	**MSDNet**	**DDQN**	**IRV2**	**FP-GANs**	**Proposed Work (GAN-SCCS)**
Focus Area	Radiograph classification	General medical image classification	General medical imaging	General image synthesis and enhancement	Cervical spondylosis diagnosis
Data Requirements	Large datasets for training	Large datasets for training	Large datasets for training	Large datasets for training	Large datasets for training
Observed Specificity	75.27% at 286k samples	69.12% at 286k samples	77.11% at 286k samples	Varies; typically higher specificity with multi-scale features	86.65% at 286k samples
Diagnostic Performance	Good for radiograph classification	Varied; effective for certain tasks	Good for general medical imaging	High performance in diverse image tasks	Superior diagnostic accuracy, especially in identifying true negatives
					Continued on next page

Table 4.2 – continued from previous page

Aspect	**MSDNet**	**DDQN**	**IRV2**	**FP-GANs**	**Proposed Work (GAN-SCCS)**
Customization	Generalized for radiographs	Generalized approach	Generalized approach	More generalized approach	Tailored specifically for cervical spondylosis
Image Enhancement	Limited focus on resolution enhancement	Limited focus on resolution enhancement	Limited focus on resolution enhancement	High-resolution outputs with enhanced details	High-resolution and accurate segmentation
Contribution to Medical Imaging	Incremental advancements in radiograph classification	Improvements in image classification	Incremental advancements in medical imaging	Enhancements in general image quality	Novel integration of GANs and spectral clustering for cervical spondylosis diagnosis

Continued on next page

Table 4.2 – continued from previous page

Aspect	MSDNet	DDQN	IRV2	FP-GANs	Proposed Work (GAN-SCCS)
Impact	Limited to specific imaging types	Broad application, less specificity	Broad application, less specificity	Broad application, significant impact on visual quality	Potential to significantly improve patient outcomes in cervical spondylosis diagnosis

4.3 Discussion

This study presents GANSCCS (Generative Adversarial Networks and Spectral Clustering for Cervical Spondylosis Diagnosis), emphasizing the critical need for enhancing precision and efficiency in cervical spondylosis diagnosis through advanced medical imaging techniques. Specifically, GANSCCS integrates Generative Adversarial Networks (GANs) with spectral clustering to improve the resolution, clarity, and accuracy of Magnetic Resonance Imaging (MRI) images, thereby facilitating a more reliable diagnosis of cervical spondylosis. A comprehensive comparative analysis demonstrates that GANSCCS outperforms conventional models such as MSDNet, DDQN, and IRV2 across various key performance metrics. Regardless of sample size, GANSCCS consistently achieves higher precision, accuracy, recall, AUC specificity, and lower latency, making it superior to existing diagnostic systems. Specifically, compared to other classification models, GANSCCS achieves an 8.3% increase in accuracy, a 5.5% improvement in precision, and an 8.5% enhancement in recall. The proposed framework has substantial implications for clinical applications. GANSCCS equips healthcare professionals with a more dependable and efficient diagnostic tool, enhancing accuracy while minimizing the likelihood of incorrect treatment decisions for cervical spondylosis patients. By improving image quality, precision, and clarity, GANSCCS enables clinicians to make better-informed decisions regarding patient health outcomes, offering heightened sensitivity for different diagnostic scenarios. Compared to existing generative model-based approaches such as FP-GANs, GANSCCS demonstrates significant advancements in cervical spondylosis diagnosis. While FP-GANs leverage feature pyramid integration for high-resolution image synthesis, they lack specificity in capturing the intricate anatomical structures of cervical spine images. In contrast, GANSCCS combines GANs with spectral clustering to facilitate high-resolution output alongside precise segmentation, enabling the detection of subtle anomalies that FP-GANs often fail to identify. For instance, whereas FP-GANs achieve an 82% specificity in general medical imaging, GANSCCS attains 86.7% specificity in cervical spondylosis diagnosis, highlighting its disease-specific optimization. In terms of quantitative performance, GANSCCS consistently surpasses FP-GANs across multiple evaluation metrics. Experimental results indicate that GANSCCS achieves an accuracy of 91.4%, outperforming FP-GANs at 87.2%. Additionally, GANSCCS attains a recall rate of 93.2%, compared to FP-GANs' 89.5%, thereby reducing false negatives in critical diagnostic scenarios. The AUC metric further underscores the robustness of GANSCCS, with a measured value of 88.9% compared to FP-GANs' 85.3%, demonstrating improved differentiation between pathological and healthy cases. These findings establish GANSCCS as a sophisticated model capable of delivering reliable diagnostic outcomes. Experimental results are presented in detailed quantitative tables, facilitating easy comparison. Key performance values such as specificity (86.7%) and recall (93.2%) for GANSCCS are highlighted to emphasize the model's strengths. This structured presentation underscores the superiority of GANSCCS over state-of-the-art generative models like FP-GANs, positioning it as a potential benchmark in medical imaging applications. Beyond classification accuracy, quantitative image quality assessments using SSIM and PSNR confirm the superiority of GANSCCS in generating high-fidelity MRI images. The SSIM score for GANSCCS is 0.91, indicating superior structural similarity to real MRI images, compared to FP-GANs' SSIM of 0.88. This highlights GANSCCS's ability to preserve intricate anatomical details crucial for accurate diagnosis. Similarly, PSNR values demonstrate that GANSCCS-generated MRI images exhibit lower noise and artifacts, enhancing their diagnostic utility. GANSCCS achieves a PSNR of 38.7 dB, surpassing FP-GANs' 36.2 dB, underscoring its capacity to produce clearer, more interpretable images for clinical use. The generation of high-quality synthetic MRI images by GANSCCS enhances reliability in downstream diagnostic tasks, ensuring both visual clarity and diagnostic precision. In addition to quantitative evaluations, perceptual assessments by domain experts further validate the efficacy of GANSCCS. Medical professionals consistently report enhanced contrast, resolution, and anatomical detail in GANSCCS-generated images compared to those produced by FP-GANs. These qualitative findings align with quantitative results, reinforcing GANSCCS as the preferred model for generating high-fidelity MRI images tailored to cervical spondylosis diagnosis. The potential of generative AI extends beyond cervical spondylosis imaging, offering transformative applications in cases where imaging modalities are scarce or inaccessible. Recent research, such as the study on "A New Brain Network Construction Paradigm for Brain Disorder via Diffusion-Based Graph Contrastive Learning [120]" introduces novel methodologies for brain disorder diagnosis by leveraging diffusion-based graph learning to model dynamic inter-regional relationships. These advancements underscore the potential of generative AI in revolutionizing medical imaging by synthesizing high-quality images, enhancing inter-modality coherence, and providing richer diagnostic insights. Techniques such as latent space manipulation and graph-based learning not only enhance medical imaging applications but also lay the foundation for personalized medicine and early diagnosis of neurological conditions. These pioneering contributions highlight the broader impact of generative AI in advancing brain imaging research and clinical decision-making in diverse medical scenarios.

To ensure the robustness and reliability of the proposed GANSCCS model, comprehensive statistical validation, feature visualization, and ablation analysis were performed. Each model was trained and evaluated across three independent trials with randomized data splits, and the mean and standard deviation were calculated to assess consistency. The GANSCCS achieved an average classification accuracy of 91.40 % $\pm$ 0.37 and precision of 94.28 % $\pm$ 0.41, with a 95 % confidence interval of [91.02 %, 91.78 %]. A paired Student's t-test conducted against the best-performing baseline (MSDNet) yielded $p < 0.01$, confirming the statistical significance of the observed improvements.

4.4 Threats to the Validity of the Proposed Approach

Although the proposed GANSCCS framework achieves strong quantitative and qualitative performance, several limitations exist. First, the dataset size is limited , which may restrict generalizability to larger clinical populations. Second, while the model was trained on both CT and MRI modalities, real-world scanner variations and noise patterns could introduce domain shifts. Third, the absence of multi-institutional data may bias results toward specific acquisition settings. Future work will address these threats by extending the dataset, incorporating cross-domain learning, and validating the model across multiple hospitals.

CHAPTER 5

CONCLUSION AND FUTURE WORK

This chapter concludes the thesis, including a summary of work and significant contributions. It then suggests and analyses several potential future directions that can further enhance diagnostic methodologies.

5.1 Conclusion and Discussion

The primary aim of this research was to develop a Generative Adversarial Network Spectral Clustering Cervical Spondylosis Classification System (GANSCCS) to reconstruct and classify noisy cervical spine MRI images with enhanced diagnostic reliability. Each of the research objectives outlined in Chapter 1 has been effectively achieved. Objective 1, which focused on studying and analyzing existing generative models for medical image reconstruction, was fulfilled through a comprehensive literature review identifying gaps in GAN-based and clustering frameworks. Objective 2, concerning dataset collection and preprocessing, was realized by curating MRI and CT datasets from both public repositories (RSNA, Medscape, CTSpine1K) and hospital-acquired data, followed by normalization, augmentation, and standardization to ensure data quality and representativeness. Objective 3, centered on developing a GAN-based hybrid framework, was accomplished by designing the GANSCCS model that integrates adversarial image reconstruction with spectral clustering to enhance both visual fidelity and anatomical segmentation. Objective 4, which involved comparison and validation, was met through extensive quantitative evaluation demonstrating the superior performance of GANSCCS over state-of-the-art models in terms of SSIM (0.91), PSNR (38.7 dB), and classification accuracy (91.40%). These outcomes confirm that the proposed system successfully enhances image reconstruction quality and improves cervical spondylosis diagnosis accuracy.

Beyond the technical contributions, this research was conducted under strict ethical and data governance principles. All patient MRI and CT data were fully anonymized, and no identifiable patient information was stored or disclosed at any stage.

In summary, the proposed GANSCCS framework establishes a clinically viable, ethically sound, and computationally efficient model for automated cervical spondylosis diagnosis. It not only achieves measurable improvements in image reconstruction and classification but also serves as a scalable foundation for future integration of advanced architectures such as transformers and diffusion models. The findings of this research directly address all stated objectives and contribute to the broader field of AI-driven medical imaging for diagnostic enhancement.

5.2 Future Directions

While GANSCCS has achieved significant advancements, there are several promising directions for future research to further enhance its capabilities and broaden its impact:

- **Multi-Modality Integration:** Incorporating multiple imaging modalities such as MRI, computed tomography (CT), and X-ray can provide a more comprehensive assessment of cervical spine conditions. This multimodal approach could improve diagnostic accuracy by leveraging complementary imaging data.

- **Real-Time Diagnosis:** Developing a real-time implementation of GANSCCS could accelerate the diagnostic process, facilitating quicker decision-making for treatment planning. Integrating the model into clinical workflows could enhance its practical usability.

- **Generalization to Other Spinal Conditions:** The methodologies used in GANSCCS can be extended to diagnose and classify other spinal disorders, such as herniated discs, spinal stenosis, and degenerative disc diseases. Expanding the model's scope to cover a broader range of spinal pathologies could improve overall clinical outcomes.

- **Personalized Medicine Applications:** Investigating the potential of GANSCCS for personalized treatment planning based on individual patient characteristics could lead to more tailored and effective therapeutic interventions. AI-driven insights can help customize treatments to meet the specific needs of patients.

- **Clinical Decision Support Systems (CDSS):** Integrating GANSCCS into CDSS can provide healthcare professionals with enhanced diagnostic insights. This integration could support physicians in decision-making by offering data-driven recommendations for diagnosis and treatment planning.

- **Utilization of Large-Scale Datasets and Transfer Learning:** Expanding the dataset used for training and validation can improve the model's robustness and generalizability. Additionally, employing transfer learning techniques could allow for adaptation to different patient populations and healthcare settings, ensuring broader applicability.

- **Interdisciplinary Collaboration:** Advancing medical AI requires collaboration between experts in medical imaging, machine learning, and clinical practice. By fostering interdisciplinary research efforts, more innovative and clinically relevant solutions can be developed.

- **Clinical Trials and Validation:** To ensure the practical viability of GANSCCS, extensive clinical validation is necessary. Conducting real-world studies with medical professionals and patients will provide valuable feedback, enabling refinements to the model for improved clinical adoption and effectiveness.

GANSCCS represents a significant advancement in the diagnosis of cervical spondylosis, offering a more precise and efficient diagnostic tool. However, its potential extends beyond this specific application. By exploring the proposed future directions, the field of AI-driven medical imaging can continue to evolve, leading to improved patient outcomes through early detection, accurate diagnosis, and optimized treatment strategies. The collaboration of researchers, healthcare professionals, and technology experts will be essential in realizing the full potential of AI in medical diagnostics, ultimately transforming the landscape of modern healthcare.

REFERENCES

[1] Cleveland Clinic, "Cervical spine," https://my.clevelandclinic.org/health/body/21773-cervical-spine, 2022, [Online; accessed 17-June-2025].

[2] Mayo Clinic, "Cervical spondylosis," https://www.mayoclinic.org/, accessed: 2025-06-28.

[3] O. Ronneberger, P. Fischer, and T. Brox, "U-net: Convolutional networks for biomedical image segmentation," in *Medical Image Computing and Computer-Assisted Intervention (MICCAI).* Springer, 2015, pp. 234–241. [Online]. Available: https://arxiv.org/abs/1505.04597

[4] M. Frid-Adar, I. Diamant, E. Klang, M. Amitai, J. Goldberger, and H. Greenspan, "Gan-based synthetic medical image augmentation for increased cnn performance in liver lesion classification," *Neurocomputing*, vol. 321, pp. 321–331, 2018. [Online]. Available: https://arxiv.org/abs/1803.01229

[5] X. Yi, E. Walia, and P. Babyn, "Generative adversarial network in medical imaging: A review," *Medical Image Analysis*, vol. 58, p. 101552, 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1361841518308430

[6] A. Radford, L. Metz, and S. Chintala, "Unsupervised representation learning with deep convolutional generative adversarial networks," in *Proceedings of the*

4th International Conference on Learning Representations (ICLR), 2016, available: https://arxiv.org/abs/1511.06434.

[7] M. Mirza and S. Osindero, "Conditional generative adversarial nets," *arXiv preprint arXiv:1411.1784*, 2014. [Online]. Available: https://arxiv.org/abs/1411.1784

[8] M. Leonardi and N. Boos, "Degenerative disorders of the cervical spine," in *Spinal Disorders: Fundamentals of Diagnosis and Treatment*, N. Boos and M. Aebi, Eds. Springer Berlin Heidelberg, 2008, pp. 429–479.

[9] J. R. McCormick, A. J. Sama, N. C. Schiller, A. J. Butler, and C. J. D. III, "Cervical spondylotic myelopathy: A guide to diagnosis and management," *Journal of the American Board of Family Medicine (J Am Board Fam Med)*, vol. 33, no. 2, pp. 303–313, 2020.

[10] O. Sugar, "Cervical spondylosis and its neurological complications," *JAMA*, vol. 209, no. 3, p. 421, 1969.

[11] A. Veeravagu, I. D. Connolly, A. Li, L. Lamsam, C. Swinney, T. D. Azad, and J. Ratliff, "Risk factors and outcomes of cervical spondylotic myelopathy utilizing a national, longitudinal database," *The Spine Journal*, vol. 16, no. 10, Suppl, p. S338, 2016.

[12] Mayo Clinic, "Cervical spondylosis: Symptoms and treatment," https://www.mayoclinic.org/diseases-conditions/cervical-spondylosis, 2023, accessed: 2025-06-17.

[13] S. Standring, *Gray's Anatomy: The Anatomical Basis of Clinical Practice*, 42nd ed. Elsevier, 2020.

[14] N. Palastanga and R. Soames, *Anatomy and Human Movement: Structure and Function*, 6th ed. Elsevier, 2011.

[15] A. Nouri, L. Tetreault, A. Singh, S. K. Karadimas, and M. G. Fehlings, "Degenerative cervical myelopathy: Epidemiology, genetics, and pathogenesis," *Spine*, vol. 40, no. 12, 2015, available: https://journals.lww.com/spinejournal/fulltext/2015/06150/degenerative_cervical_myelopathy__epidemiology,.8.aspx.

[16] S. R. Mercer and N. Bogduk, "The ligaments and joints of the cervical spine," *Spine (Phila Pa 1976)*, vol. 26, no. 6, pp. 603–614, 2001.

[17] A. I. Binder, "Cervical spondylosis and neck pain," *BMJ*, vol. 334, no. 7592, pp. 527–531, 2007.

[18] R. Fejer, K. O. Kyvik, and J. Hartvigsen, "The prevalence of neck pain in the world population," *European Spine Journal*, vol. 15, no. 6, pp. 834–848, 2006.

[19] M. Matsumoto, Y. Fujimura, N. Suzuki, Y. Nishi, M. Nakamura, Y. Yabe, and H. Shiga, "Mri of cervical intervertebral discs in asymptomatic subjects," *The Journal of Bone and Joint Surgery. British Volume*, vol. 80, pp. 19–24, 1998.

[20] H. J. Kim, L. A. Tetreault, E. M. Massicotte, and P. M. Arnold, "Degenerative cervical myelopathy: Pathophysiology and diagnosis," *Neurosurgery*, vol. 80, no. 1S, pp. S9–S16, 2017.

[21] A. A. White and M. M. Panjabi, *Clinical Biomechanics of the Spine*, 2nd ed. Lippincott Williams & Wilkins, 1990.

[22] S. Wang, Z. Su, L. Ying, R. Peng, S. Zhu, and D. Liang, "Accelerating magnetic resonance imaging via deep learning," *IEEE Transactions on Medical Imaging*, vol. 35, no. 5, pp. 1200–1211, 2016.

[23] F. Liu, H. Jang, R. Kijowski, and T. Bradshaw, "Deep learning for noise reduction in mri," *Magnetic Resonance in Medicine*, vol. 79, no. 5, pp. 2397–2408, 2018.

[24] Mayo Clinic, "Mri interpretation errors and their clinical implications," https://www.mayoclinic.org/mri-diagnostic-errors, 2023, accessed: 2025-06-17.

[25] T. Wang, L. Qian, and F. Zhang, "Gan-based noise reduction in medical mri imaging," *IEEE Transactions on Medical Imaging*, vol. 40, no. 7, pp. 2235–2248, 2021.

[26] X. Zhang, J. Yu, and P. Wang, "Deep learning for high-resolution mri reconstruction," *Medical Image Analysis*, vol. 64, p. 101742, 2020.

[27] G. Litjens, T. Kooi, B. E. Bejnordi, A. A. A. Setio, F. Ciompi, M. Ghafoorian, J. A. W. M. van der Laak, B. van Ginneken, and C. I. Sánchez, "A survey on

deep learning in medical image analysis," *Medical Image Analysis*, vol. 42, pp. 60–88, 2017.

[28] L. Gondara, "Medical image denoising using convolutional denoising autoencoders," in *Proceedings of the IEEE International Conference on Data Mining Workshops (ICDMW)*, 2016, pp. 241–246.

[29] S. Kazeminia, C. Baur, A. Kuijper, B. van Ginneken, N. Navab, S. Albarqouni, and A. Mukhopadhyay, "Gans for medical image synthesis, augmentation, and translation: A review," *Medical Image Analysis*, vol. 63, p. 101693, 2020.

[30] K. Armanious, C. Jiang, M. Fischer, T. Küstner, T. Hepp, K. Nikolaou, S. Gatidis, and B. Yang, "Medgan: Medical image translation using gans," *Computerized Medical Imaging and Graphics*, vol. 79, p. 101684, 2020.

[31] Z. He, L. Wu, and R. Zhang, "Super-resolution gans for medical imaging: A review," *Artificial Intelligence in Medicine*, vol. 120, p. 102235, 2022.

[32] C. T. Kuo, P. B. Walker, O. Carmichael, and I. Davidson, "Spectral clustering for medical imaging," in *Proceedings of the IEEE International Conference on Data Mining (ICDM)*, 2014, pp. 887–892.

[33] H. Ghaednia, A. Lans, N. Sauder, D. Shin, W. G. Grant, R. R. Chopra, J. H. F. Oosterhoff, M. S. Fourman, J. H. Schwab, and D. G. Tobert, "Deep learning in spine surgery," *Seminars in Spine Surgery*, vol. 33, no. 2, p. 100876, 2021.

[34] F. Yousefirizi, P. Decazes, A. Amyar, S. Ruan, B. Saboury, and A. Rahmim, "Ai-based detection, classification and prediction/prognosis in medical imaging: Towards radiophenomics," *PET Clinics*, vol. 17, no. 1, pp. 183–212, 2022.

[35] D. R. Gore, "The natural history of cervical spondylosis: An 11-year follow-up study," *Clinical Orthopaedics and Related Research*, vol. 389, pp. 89–93, 2001.

[36] W. R. Brain and D. Northfield, "The neurological manifestations of cervical spondylosis," *Brain*, vol. 75, no. 2, pp. 187–225, 1952.

[37] R. Kumar, D. Singh, R. Malik, I. Batra, M. Humayun, and J. A. Khan, "Gansccs: Synergizing generative adversarial networks and spectral clustering for enhanced

mri resolution in the diagnosis of cervical spondylosis," *International Journal of Intelligent Systems*, vol. 2025, no. 1, pp. 1–20, 2025, e-pub ahead of print, Feb 27, 2025.

[38] C. Wang, F. Tian, Y. Zhou, W. He, and Z. Cai, "The incidence of cervical spondylosis decreases with aging in the elderly, and increases with aging in the young and adult population: A hospital-based clinical analysis," *Clinical Interventions in Aging*, vol. 11, pp. 47–53, 2016.

[39] R. D. Rao, B. L. Currier, T. J. Albert, C. M. Bono, S. Marawar, K. Poelstra, and J. C. Eck, "Degenerative cervical spondylosis: Clinical syndromes, pathogenesis, and management," *Journal of Bone and Joint Surgery - Series A*, vol. 89, no. 6, 2007.

[40] Y. Cui, J. Zhu, Z. Duan, Z. Liao, S. Wang, and W. Liu, "Artificial intelligence in spinal imaging: Current status and future directions," *International Journal of Environmental Research and Public Health*, vol. 19, no. 18, p. 11708, 2022.

[41] J. A. Jackson, P. Liv, A. S. Sayed-Noor, L. Punnett, and J. Wahlström, "Risk factors for surgically treated cervical spondylosis in male construction workers: A 20-year prospective study," *Spine Journal*, vol. 23, no. 1, pp. 136–145, 2023.

[42] L. Wang, W. Zhang, X. He, and H. Zha, "Supervised reinforcement learning with recurrent neural network for dynamic treatment recommendation," in *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. ACM, 2018, pp. 2447–2456.

[43] N. Theodore, "Degenerative cervical spondylosis," *New England Journal of Medicine*, vol. 383, no. 2, pp. 159–168, 2020.

[44] K. Armanious, C. Jiang, M. Fischer, and B. Yang, "Unsupervised medical image super-resolution using generative adversarial networks," *Medical Image Analysis*, vol. 64, p. 101713, 2020.

[45] J. M. Wolterink, A. M. Dinkla, M. H. F. Savenije, P. R. Seevinck, C. A. T. van den Berg, and I. Išgum, "Deep mr to ct synthesis using unpaired data," in *Lecture*

Notes in Computer Science (LNCS), Simulation and Synthesis in Medical Imaging (SASHIMI), S. A. Tsaftaris, A. Gooya, A. F. Frangi, and J. L. Prince, Eds., vol. 10557. Springer International Publishing, 2017, pp. 14–23.

[46] Y. Wang, B. Yu, L. Wang, C. Zu, D. S. Lalush, W. Lin, X. Wu, J. Zhou, D. Shen, and L. Zhou, "3d conditional generative adversarial networks for high-quality pet image estimation at low dose," *NeuroImage*, vol. 174, pp. 550–562, 2018.

[47] Y. Chen, F. Shi, A. G. Christodoulou, Y. Xie, Z. Zhou, and D. Li, "Efficient and accurate mri super-resolution using a generative adversarial network and 3d multi-level densely connected network," in *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, ser. LNCS, vol. 11070. Springer, 2018, pp. 91–99.

[48] A. Dosovitskiy, L. Beyer, A. Kolesnikov, D. Weissenborn, X. Zhai, T. Unterthiner, M. Dehghani, M. Minderer, G. Heigold, S. Gelly, J. Uszkoreit, and N. Houlsby, "An image is worth 16x16 words: Transformers for image recognition at scale," in *Proceedings of the 9th International Conference on Learning Representations (ICLR)*, 2021, available: https://arxiv.org/abs/2010.11929.

[49] Y. Zhang, W. Wang, and D. Shen, "A novel method for mri denoising using sparsity and self-similarity," arXiv preprint arXiv:1712.08726, 2018, available: https://arxiv.org/pdf/1712.08726.pdf.

[50] B. Qu, J. Cao, C. Qian, J. Wu, J. Lin, L. Wang, L. Ou-Yang, Y. Chen, L. Yan, Q. Hong, G. Zheng, and X. Qu, "Current development and prospects of deep learning in spine image analysis: A literature review," *Quantitative Imaging in Medicine and Surgery*, vol. 12, no. 6, pp. 3454–3479, 2022.

[51] X. Cheng, H. Shan, G. Zheng, and M. Zhu, "Medical image super-resolution reconstruction based on multi-level adaptive cnn and hybrid transformer," in *Proceedings of the 2024 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, 2024, pp. 5675–5682.

[52] C. Wang and et al., "Deep learning for predicting subtype classification and survival of lung adenocarcinoma on computed tomography," *Translational Oncology*, vol. 14, p. 101141, 2021.

[53] Z. Han, B. Wei, A. Mercado, S. Leung, and S. Li, "Spine-gan: Semantic segmentation of multiple spinal structures," *Medical Image Analysis*, vol. 50, pp. 23–35, 2018.

[54] K. Chen, T. Asada, N. Ienaga, K. Miura, K. Sakashita, T. Sunami, H. Kadone, M. Yamazaki, and Y. Kuroda, "Two-stage video-based convolutional neural networks for adult spinal deformity classification," *Frontiers in Neuroscience*, vol. 17, 2023.

[55] B. Srinivas and G. S. Rao, "Segmentation of multi-modal mri brain tumor sub-regions using deep learning," *Journal of Electrical Engineering and Technology*, vol. 15, no. 4, pp. 1899–1909, 2020.

[56] A. Maruthamuthu and L. P. Gnanapandithan, "Brain tumour segmentation from mri using superpixels based spectral clustering," *Journal of King Saud University - Computer and Information Sciences*, vol. 32, no. 10, pp. 1182–1193, 2020.

[57] D. Narin and T. Onur, "The effect of hyper parameters on the classification of lung cancer images using deep learning methods," *Erzincan University Journal of Science and Technology*, vol. 15, pp. 258–268, 2022.

[58] Y. M. A. Mohammed, S. E. Garouani, and I. Jellouli, "A survey of methods for brain tumor segmentation-based mri images," *Journal of Computational Design and Engineering*, vol. 10, no. 1, pp. 266–293, 2023.

[59] U. Shaham, K. Stanton, H. Li, B. Nadler, R. Basri, and Y. Kluger, "Spectral-net: Spectral clustering using deep neural networks," in *Proceedings of the 6th International Conference on Learning Representations (ICLR)*, 2018, available: https://arxiv.org/abs/1801.01587.

[60] Y. Xie, Y. Nie, J. Lundgren, M. Yang, Y. Zhang, and Z. Chen, "Cervical spondylosis diagnosis based on convolutional neural network with x-ray images," *Sensors*, vol. 24, no. 11, p. 3428, 2024.

[61] S. Wang, M. Zhou, Z. Liu, Z. Liu, D. Gu, Y. Zang, D. Dong, O. Gevaert, and J. Tian, "Central focused convolutional neural networks: Developing a data-

driven model for lung nodule segmentation," *Medical Image Analysis*, vol. 40, pp. 172–183, 2017.

[62] H. A. Phoulady, D. Goldgof, L. O. Hall, and P. R. Mouton, "A framework for nucleus and overlapping cytoplasm segmentation in cervical cytology extended depth of field and volume images," *Computerized Medical Imaging and Graphics*, vol. 59, pp. 38–49, 2017.

[63] H. Wang, D. Kakrania, H. Tang, P. Prasanna, and T. Syeda-Mahmood, "Fast anatomy segmentation by combining coarse scale multi-atlas label fusion with fine scale corrective learning," *Computerized Medical Imaging and Graphics*, vol. 68, pp. 16–24, 2018.

[64] W. Weng and X. Zhu, "Inet: Convolutional networks for biomedical image segmentation," *IEEE Access*, vol. 9, pp. 16 591–16 603, 2021.

[65] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 770–778.

[66] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," in *3rd International Conference on Learning Representations (ICLR), Conference Track Proceedings*, 2015, available: https://arxiv.org/abs/1409.1556.

[67] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. A. Alemi, "Inception-v4, inception-resnet and the impact of residual connections on learning," *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 31, 2017. [Online]. Available: https://arxiv.org/abs/1602.07261

[68] M. Mehmood, E. Ayub, F. Ahmad, M. Alruwaili, Z. A. Alrowaili, S. Alanazi, M. Humayun, M. Rizwan, S. Naseem, and T. Alyas, "Machine learning enabled early detection of breast cancer by structural analysis of mammograms," *Computers, Materials and Continua*, vol. 67, no. 1, pp. 641–657, 2021.

[69] K. Goura and A. Harsoor, “Brain lesion classification with effincepresv2: A hybrid approach combining efficientnetv2 and inception-resnetv2,” *Journal of Neonatal Surgery*, vol. 14, no. 10S, pp. 889–9, 2025.

[70] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. MIT Press, 2016. [Online]. Available: http://www.deeplearningbook.org/

[71] G. Cohen and R. Giryes, “Generative adversarial networks,” in *Machine Learning for Data Science Handbook: Data Mining and Knowledge Discovery Handbook, Third Edition*. Springer, 2023, vol. 27, pp. 375–400.

[72] L. Wang, Y. Meng, Y. Qian *et al.*, “Msd-net: Multi-scale dense convolutional neural network for photoacoustic image reconstruction with sparse data,” *Photoacoustics*, vol. 41, p. 100679, 2024, open Access.

[73] H. Li and X. Wu, “Multi-scale feature fusion using msd-net for medical image fusion,” in *Proceedings of the 10th International Conference on Image and Graphics (ICIG 2019)*, 2019, code: songxujay/MSDNet-for-Medical-Image-Fusion. [Online]. Available: https://github.com/songxujay/MSDNet-for-Medical-Image-Fusion

[74] F. Ghesu, B. Georgescu, T. Mansi, and D. Comaniciu, “Multi-scale deep reinforcement learning for real-time 3d-landmark detection in ct scans,” *IEEE Transactions on Medical Imaging*, vol. 36, no. 5, pp. 1025–1035, 2017.

[75] W. Hong, H. Yu, T. Yu, and et al., “Deep reinforcement learning for cephalometric landmark detection in 3d volumes,” *International Journal of Computer Vision*, 2023.

[76] A. Alansary, L. Le Folgoc, O. Oktay, and et al., “Evaluating reinforcement learning agents for anatomical landmark detection,” in *Medical Image Analysis*, vol. 53, 2018, pp. 156–164.

[77] J. Stember and H. Shalu, “Deep q-learning for brain lesion localization in low-data regimes,” in *Proceedings of the Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, 2020, proof-of-concept using grid-world RL for brain lesion localization.

[78] V. Cheplygina, M. de Bruijne, and J. P. W. Pluim, "Not-so-supervised: A survey of semi-supervised, multi-instance, and transfer learning in medical image analysis," *Medical Image Analysis*, vol. 54, pp. 280–296, 2019. [Online]. Available: https://doi.org/10.1016/j.media.2019.03.009

[79] F. Liu, T. Yu, F. R. Cordeiro, V. Belagiannis, I. Reid, and G. Carneiro, "Self-supervised mean teacher for semi-supervised chest x-ray classification," https://arxiv.org/abs/2103.03629, 2021, arXiv preprint.

[80] L. Yu, S. Wang, X. Li, C. Fu, and P. Heng, "Uncertainty-aware self-ensembling model for semi-supervised 3d left atrium segmentation," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 33, 2019, pp. 11 194–11 201.

[81] D. Fan, Z. Jiang, Q. Sun, L. Jin, and Y. Wang, "Inf-net: Automatic covid-19 lung infection segmentation from ct images," *IEEE Transactions on Medical Imaging*, vol. 39, no. 8, pp. 2626–2637, 2020. [Online]. Available: https://doi.org/10.1109/TMI.2020.2996645

[82] S. Wei, R. Qiu, Y. Pu, A. Hu, Y. Niu, Z. Wu, H. Zhang, and J. Li, "A semi-supervised learning-based quality evaluation system for digital chest radiographs," *Medical Physics*, vol. 50, no. 11, pp. 6789–6800, 2023.

[83] Y. Wang, Q. Zhang, L. Ying, and C. Zhou, "Deep reinforcement learning for early diagnosis of lung cancer," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 38, no. 20, 2024, pp. 22 410–22 419.

[84] D. Shen, G. Wu, and H.-I. Suk, "Deep learning in medical image analysis," *Annual Review of Biomedical Engineering*, vol. 19, pp. 221–248, 2017. [Online]. Available: https://doi.org/10.1146/annurev-bioeng-071516-044442

[85] A. Hosny, C. Parmar, J. Quackenbush, L. H. Schwartz, and H. J. W. L. Aerts, "Artificial intelligence in radiology," *Nature Reviews Cancer*, vol. 18, no. 8, pp. 500–510, 2018. [Online]. Available: https://doi.org/10.1038/s41571-018-0016-5

[86] G. Balakrishnan, A. Zhao, M. R. Sabuncu, J. Guttag, and A. V. Dalca, "Voxelmorph: A learning framework for deformable medical image

registration," *IEEE Transactions on Medical Imaging*, vol. 38, no. 8, pp. 1788–1800, 2019. [Online]. Available: https://doi.org/10.1109/TMI.2019.2897538

[87] J. Yang, R. El-Bouri, O. O'Donoghue, A. S. Lachapelle, A. A. Soltan, D. W. Eyre, and D. A. Clifton, "Deep reinforcement learning for multi-class imbalanced training: applications in healthcare," *Machine Learning*, vol. 113, no. 5, pp. 2655–2674, 2024.

[88] T. M. Buzug, *Computed tomography: From photon statistics to modern cone-beam CT*. Springer Berlin Heidelberg, 2008. [Online]. Available: https://doi.org/10.1007/978-3-540-39408-2

[89] G. Wang and H. Yu, "Perspective on iterative reconstruction for ct," *Medical Physics*, vol. 37, no. 9, pp. 4948–4954, 2010. [Online]. Available: https://doi.org/10.1118/1.3480985

[90] K. Hammernik, T. Klatzer, E. Kobler, M. P. Recht, D. K. Sodickson, T. Pock, and F. Knoll, "Learning a variational network for reconstruction of accelerated mri data," *Magnetic Resonance in Medicine*, vol. 79, no. 6, pp. 3055–3071, 2018. [Online]. Available: https://doi.org/10.1002/mrm.26977

[91] H. K. Aggarwal, M. P. Mani, and M. Jacob, "Modl: Model-based deep learning architecture for inverse problems," *IEEE Transactions on Medical Imaging*, vol. 38, no. 2, pp. 394–405, 2019. [Online]. Available: https://doi.org/10.1109/TMI.2018.2865356

[92] B. Yaman, S. A. H. Hosseini, S. Moeller, J. Ellermann, K. Uğurbil, and M. Akçakaya, "Self-supervised learning of physics-guided reconstruction neural networks without fully sampled reference data," *Magnetic Resonance in Medicine*, vol. 84, no. 6, pp. 3172–3191, 2020. [Online]. Available: https://doi.org/10.1002/mrm.28378

[93] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial nets," in *Advances in Neural Information Processing Systems (NeurIPS)*, vol. 27, 2014, pp. 2672–2680, available: https://papers.nips.cc/paper_files/paper/2014/file/5ca3e9b122f61f8f06494c97b1afccf3-Paper.pdf.

[94] A. Radford, L. Metz, and S. Chintala, "Unsupervised representation learning with deep convolutional generative adversarial networks," *arXiv preprint arXiv:1511.06434*, 2015. [Online]. Available: https://arxiv.org/abs/1511.06434

[95] P. Isola, J.-Y. Zhu, T. Zhou, and A. A. Efros, "Image-to-image translation with conditional adversarial networks," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).* IEEE, 2017, pp. 5967–5976.

[96] J.-Y. Zhu, T. Park, P. Isola, and A. A. Efros, "Unpaired image-to-image translation using cycle-consistent adversarial networks," in *Proceedings of the IEEE International Conference on Computer Vision (ICCV).* IEEE, 2017, pp. 2223–2232.

[97] M. Arjovsky, S. Chintala, and L. Bottou, "Wasserstein gan," in *Proceedings of the 34th International Conference on Machine Learning (ICML)*, 2017, arXiv:1701.07875. [Online]. Available: https://arxiv.org/abs/1701.07875

[98] A. Ben-Cohen, E. Klang, S. P. Raskin, S. Soffer, S. Ben-Haim, E. Konen, M. M. Amitai, and H. Greenspan, "Cross-modality synthesis from ct to pet using fcn and gan networks for improved automated lesion detection," *Engineering Applications of Artificial Intelligence*, vol. 78, pp. 186–194, 2019.

[99] G. Yang, S. Sun, H. Dong, G. Slabaugh, P. L. Dragotti, J. Keegan, Y. Guo, and D. Firmin, "DAGAN: Deep de-aliasing generative adversarial networks for fast compressed sensing MRI reconstruction," *Magnetic Resonance in Medicine*, vol. 80, no. 4, pp. 1189–1201, 2018. [Online]. Available: https://doi.org/10.1002/mrm.27183

[100] S. Schlaeger, K. Drummer, M. El Husseini, and B. Ertl-Wagner, "Implementation of gan-based, synthetic t2-weighted fat saturated images in the routine radiological workflow improves spinal pathology detection," *Diagnostics*, vol. 13, no. 5, p. 974, 2023. [Online]. Available: https://doi.org/10.3390/diagnostics13050974

[101] ScienceDirect, "Cervical spine mri diffusion probabilistic model (csm-dpm)," *Computer Methods and Programs in Biomedicine*, 2025, in press.

[Online]. Available: https://www.sciencedirect.com/science/article/abs/pii/S0169260725000562

[102] J. Huang, H. Shen, J. Wu, and Z. Liu, "Spine explorer: A deep learning-based fully automated program for efficient and reliable vertebra and disc quantification on lumbar spine mr images," *Spine Journal*, vol. 20, no. 4, pp. 590–599, 2013.

[103] Y. Zhang, J. Huang, and Z. Liu, "Feature selection for diagnosis of cervical spondylosis based on fuzzy support vector machine," *Expert Systems with Applications*, vol. 37, no. 8, pp. 5560–5565, 2010.

[104] X. Zhao, L. Li, D. Liang *et al.*, "Automated detection and classification of cervical disc herniation using deep learning on mri scans," *Computers in Biology and Medicine*, vol. 121, p. 103762, 2020.

[105] H.-C. Shin, H. R. Roth, M. Gao, L. Lu, Z. Xu, I. Nogues, J. Yao, D. Mollura, and R. M. Summers, "Deep convolutional neural networks for computer-aided detection: Cnn architectures, dataset characteristics and transfer learning," *IEEE Transactions on Medical Imaging*, vol. 35, no. 5, pp. 1285–1298, 2016.

[106] M. T. Islam, M. A. Aowal, A. T. Minhaz, and K. Ashraf, "Combining cnn features with svm for image classification," *International Journal of Computer Applications*, vol. 183, no. 19, pp. 1–5, 2019.

[107] Y. Gao, M. Zhou, D. N. Metaxas, and D. Liu, "Multi-task learning for joint classification and segmentation in medical imaging," *Medical Image Analysis*, vol. 70, p. 102014, 2021.

[108] A. Y. Ng, M. I. Jordan, and Y. Weiss, "On spectral clustering: Analysis and an algorithm," *Advances in neural information processing systems*, vol. 14, 2002.

[109] U. Von Luxburg, "A tutorial on spectral clustering," *Statistics and computing*, vol. 17, no. 4, pp. 395–416, 2007.

[110] J. Shi and J. Malik, "Normalized cuts and image segmentation," *IEEE Transactions on pattern analysis and machine intelligence*, vol. 22, no. 8, pp. 888–905, 2000.

[111] X. Zhao, J. Wu, and Y. Liao, "Automatic cervical spine image segmentation using spectral clustering and shape priors," in *Medical Image Computing and Computer-Assisted Intervention (MICCAI)*, 2016, pp. 101–109.

[112] P. Ji, T. Zhang, H. Li, M. Salzmann, and I. Reid, "Deep spectral clustering using dual autoencoder network," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2019, pp. 4066–4075.

[113] T. S. Apon, M. Fahim-Ul-Islam, N. I. Rafin, J. Akter, and M. G. R. Alam, "Transforming precision: A comparative analysis of vision transformers, cnns, and traditional ml for knee osteoarthritis severity diagnosis," in *Proceedings of the 6th International Conference on Electrical Engineering and Information and Communication Technology (ICEEICT)*, 2024, pp. 31–36.

[114] R. Azad, A. Kazerouni, M. Heidari, E. K. Aghdam, A. Molaei, Y. Jia, A. Jose, R. Roy, and D. Merhof, "Advances in medical image analysis with vision transformers: A comprehensive review," *Medical Image Analysis*, vol. 91, p. 103000, 2024.

[115] J. Liang, J. Cao, G. Sun, K. Zhang, L. Van Gool, and R. Timofte, "Swinir: Image restoration using swin transformer," in *Proceedings of the IEEE/CVF International Conference on Computer Vision Workshops (ICCVW)*, 2021, pp. 1833–1844. [Online]. Available: https://arxiv.org/abs/2108.10257

[116] A. Q. Nichol and P. Dhariwal, "Improved denoising diffusion probabilistic models," in *Advances in Neural Information Processing Systems (NeurIPS)*, vol. 34, 2021, pp. 8160–8171. [Online]. Available: https://arxiv.org/abs/2102.09672

[117] D. Ravì, C. Wong, F. Deligianni, M. Berthelot, J. Andreu-Perez, B. Lo, and G.-Z. Yang, "Deep learning for health informatics," *IEEE Journal of Biomedical and Health Informatics*, vol. 21, no. 1, pp. 4–21, 2017.

[118] R. S. of North America (RSNA), "Rsna 2022 cervical spine fracture detection dataset," https://www.rsna.org/rsnai/ai-image-challenge/cervical-spine-fractures-ai-detection-challenge-2022, 2022, accessed: November 9, 2025.

[119] Y. Deng, C. Wang, Y. Hui, X. Li, C. Ma, X. Zhang, and S. Sun, "Ctspine1k: A large-scale dataset for spinal vertebrae segmentation in computed tomography," *arXiv preprint arXiv:2105.14711*, 2021, accessed: November 9, 2025. [Online]. Available: https://arxiv.org/abs/2105.14711

[120] Y. Zong, Q. Zuo, M. K.-P. Ng, B. Lei, and S. Wang, "A new brain network construction paradigm for brain disorder via diffusion-based graph contrastive learning," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 46, no. 12, pp. 10 389–10 403, 2024. [Online]. Available: https://doi.org/10.1109/TPAMI.2024.3442811

LIST OF PUBLICATIONS

- **Kumar,** R., Singh, D., Malik, R., Batra, I., Humayun, M., Khan, J. A. (2025). GANSCCS: Synergizing Generative Adversarial Networks and Spectral Clustering for Enhanced MRI Resolution in the Diagnosis of Cervical Spondylosis. International Journal of Intelligent Systems, 2025(1), 1-20. Article 6674913. Advance online publication. https://doi.org/10.1155/int/6674913 (Scopus, SCI 5 IF)

- **R. Kumar** and R. Malik, "A Review on Generative Adversarial Networks used for Image Reconstruction in Medical imaging," 2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), Noida, India, 2021, pp. 1-5, doi:10.1109/ICRITO51393.2021.9596487.(Scopus)

- **Kumar, R.**, Malik, R. (2024). An approach to reconstruct cervical spondylosis MRI image using generative adversarial networks. In S. Sobti, S. Garg, S. Srivastava, A. Shahi (Eds.), Computer science engineering and emerging technologies (pp. 267–271). CRC Press. https://doi.org/10.1201/9781003405580-42