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Correlation analysis of the global activity limitation indicator with disability measures in adults under 65 suffering from spinal and hepatic health issues

Shaheer Habib[1], Nazeef Ul Haq[1], Waseem Younas[1], and Syed Romat Ali Shah[1]

[1]Department of Computer Science, University of Engineering and Technology Lahore, Lahore, 54000, Pakistan

Corresponding author: Shaheer Habib (e-mail: Shaheerhabib0001@gmail.com)

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Abstract- **Computer image processing technology is crucial for assessing 2D and 3D spinal pictures in medical imaging. It dramatically enhances the accuracy of identifying spine illnesses by utilizing deep learning algorithms. This progress has also resulted in the creation of three-dimensional models of the human spine, which improve medical education. Nevertheless, the precise segmentation of vertebrae continues to be difficult because of their comparable forms and visual characteristics. This study employs critical indicators such as pain, range of motion, and liver enzyme levels to assess the condition of the spine and liver. Moreover, the Global Activity Limitation Indicator thoroughly evaluates functional disability. Datasets like the LSUN Spinal Cord MRI Segmentation Dataset facilitate data gathering, while quantitative approaches like the Inventory of Identification of Needs assess disability. The findings contribute to a complete framework for comprehending the intricacies of spinal and hepatic health, intending to enhance medical diagnosis and patient therapy.**

Index Terms-- **Computer image processing, deep learning, medical imaging, spinal imaging, three-dimensional modeling, segmentation methods, neural networks, diagnostic accuracy, spinal disorders, Global Activity Limitation Indicator, hepatic health, data collection.**

I. INTRODUCTION

Computer image processing technologies are essential for medical imaging analysis and altering 2D and 3D spinal images. Segmentation, extraction, and three-dimensional reconstruction techniques are crucial in current computer vision research in spine imaging. Deep learning algorithms have played a critical role in driving significant progress in this sector, particularly in enhancing the accuracy of detecting different spinal illnesses. This advancement has prompted a notable change in medical imaging, resulting in a sudden increase in enthusiasm for utilizing deep neural networks for this objective [1].

Segmentation techniques in spinal imaging improve medical diagnosis by facilitating comprehensive qualitative and quantitative analysis of spinal lesions and areas of interest. The combination of volumetric 3D modeling and deep neural networks shows excellent potential in effectively segmenting spinal components, even though their comparable shapes and appearances present challenges. This enhances medical training and enhances the comprehension of complex spinal anatomical systems. [2]. Constructing three-dimensional representations of the human spine, encompassing individual vertebrae or the complete system is crucial for medical education. Using models created through 3D printing or virtual reality systems can improve clinicians' understanding of a patient's condition. Although chest scans are readily accessible, conventional techniques such as standing images are inadequate for accurately identifying all spinal bones. Additionally, segmenting the vertebrae is particularly difficult due to the limited discernible characteristics in the input images, unlike brain segmentation.[3]. The objective of this project is to provide criteria for determining whether to use or not to use spinal segmentation techniques. This will be achieved by thoroughly assessing traditional image processing techniques and advanced deep learning methodology.[4].

The liver, an essential organ in the upper right abdomen, possesses a unique conical or wedge-shaped structure and weighs approximately 3 to 3.5 pounds. The brain comprises four lobes: the right and left lobes, a secondary lobe, and a caudal lobe. The lobes of the liver are joined by the falciform ligament, creating the intricate anatomy of the liver. The liver can be divided into eight segments, consisting of thousands of lobules. Advanced medical imaging techniques, such as Computerized Tomography (CT) scans and Magnetic Resonance Imaging (MRI), are employed to examine the structure and function of the liver thoroughly. CT scans utilize a rotating X-ray tube to comprehensively explore the entire body, whereas MRI uses electromagnetic radiation and radio waves to obtain cross-sectional images. Image recognition and segmentation algorithms improve clarity by enabling the identification of abnormalities and patterns. Utilizing engineering and computer science principles, pattern recognition, and digital image processing enhance our capacity to assess liver images. Incorporating these technologies into medical applications has resulted in substantial progress, offering vital data for diagnosis and treatment. This research examines the relationship between the Global Activity Limitation Indicator and specific disability markers in persons below 65, mainly on spinal and hepatic health. The objective is to summarize thoroughly, recognize trends, and propose viable avenues for future investigation in this domain.[5].

Image identification is the ability of software to reliably identify and categorize different aspects, such as objects, locations, people, language, and activities, within photos using machine vision technology. Computers can incorporate computer software that employs machine vision technology, photographic cameras, and artificial intelligence to recognize and categorize images. Picture recognition is engaged in various machine-based visual tasks, such as discerning picture content through metatags, doing image content searches, and offering advice to autonomous robotics, self-driving cars, and asset security systems. Animals and humans possess cognitive capacities that allow them to distinguish between items effortlessly; however, computers face challenges when doing this task. Deep learning is required for picture identification software. [6].

Image segmentation divides digital images into segments known as image regions or objects. These segments are made up of sets of pixels. The objective of picture segmentation is to improve the clarity and assist the analysis of images by simplifying their depiction. It is frequently employed for object detection and to define image boundaries, such as lines and curves. Picture segmentation involves assigning a distinct label to every pixel in a picture, considering the shared characteristics among pixels with the same label. This procedure entails partitioning an image into discrete segments, encompassing the entire image or comprising well-defined contours derived from the picture (edge detection). Each pixel inside a specified zone possesses specific qualities, such as color, intensity, or texture. Additionally, neighboring regions often display noticeable differences in their features. When utilized in medical imaging, the produced outlines can be employed to construct three-dimensional reconstructions of images using interpolation techniques such as marching cubes. [7].

Pattern recognition automatically identifies and analyzes abnormalities and trends in data. It includes a range of computer applications such as statistical data analysis, bioinformatics, image analysis, information extraction, data compression, machine learning, and computer-based signal and visual processing. Pattern recognition, which has its foundation in statistics and engineering, has developed substantially due to the growing accessibility of extensive datasets and improvements in processing power. Contemporary pattern recognition approaches frequently utilize machine learning techniques. These activities are regarded as closely related and have seen substantial transformations in the past few decades. Pattern recognition systems usually undergo training using labeled data, while alternative approaches can identify previously unidentified patterns without using labeled data. The methodology of data mining and knowledge discovery in databases (KDD) typically prioritizes unsupervised approaches and has a stronger focus on commercial applications. Pattern recognition is a field that concentrates on detecting and analyzing patterns in signals, encompassing activities such as signal gathering and processing. The computer vision and pattern recognition conference, which originated in the field of engineering, has now become the foremost conference on the subject of computer vision.[8].

Table 1: Comparison of Our Study With the Existing Literature

Reference	Dataset Model size/Large Complexity	Model Complexity	Balancing and Unbalancing Of dataset	Public/ Private dataset (case study)	Systematic Designs	Trends and Future Directions
[12]	Small	×	×	✓	×	✓
[13]	small	×	×	✓	×	✓
[14]	small	×	×	×	✓	✓
[15]	small	×	×	✓	×	×
[16]	Both	×	×	✓	×	✓
[17]	Both	×	×	✓	✓	✓
Our SLR	✓	✓	✓	✓	✓	✓

Integrating these technological breakthroughs, encompassing picture segmentation, pattern recognition, and digital image processing, offers medical practitioners comprehensive capabilities. By examining the complexities of spinal and hepatic health and their impact on adult functional impairment, we can gain significant insights for diagnosis and future research efforts.

II. LITERATURE REVIEW

The CT pictures in this study were produced utilizing an oblique orientation of a CT scanner. The training datasets showed a wide range of pixel spacing, varying from 0.02 to 0.03 inches, while the distance between slices ranged from 0.1 to 0.12 inches. There was no overlap between adjacent slices. A grand total of 14 datasets were utilized for training, with an additional 14 datasets specifically put aside for testing. Three slices were selected from each dataset for training and testing, specifically focusing on those with the most remarkable liver region. The tests were conducted using the methodology outlined in Section III, utilizing CT datasets acquired from the CT scanner. A Support Vector Machine (SVM) classifier was built using the open-source software LIBSVM. The segmentation results closely matched the manual segmentation performed by experts. The machine segmentation achieves a consistent positive rate of 96.1% across the entire dataset. The rate of false negatives was 13.7%, while the rate of false positives was 5.1%. The higher frequency of false positive outcomes is a direct consequence of the region-growing algorithm, which tends to generate excessive segmentation when there are similarities in intensity levels. The distinction of the hepatic aortic segment was imprecise.[10]

PET-CT scans offer crucial information to enhance the delineation of the liver in low-contrast computed tomography (CT) images. PET data addresses various challenges in liver segmentation, including the differentiation and isolation of CT data by eliminating the muscle tissue surrounding the region of interest (ROI) in the liver. (2) Improving the alignment and identification of a predictive atlas on a low-contrast CT scan to enhance the categorization of tissues, and (3) Utilizing the probabilistic atlas to enhance the initial estimation of the region of interest (ROI) of the liver, allowing the expectation-maximization algorithm designed for Gaussian distribution mixed models to converge more rapidly. This technology eliminates the need for complex feature preprocessing, as it directly extracts fundamental liver information from the PET volume, streamlining the workflow. Incorporating PET information significantly improves the precision of the probabilistic atlas in aligning with the CT liver region, effectively mitigating the challenges arising from differences in liver morphology. The effectiveness of this approach was evaluated through manual segmentation performed by skilled radiologists. The precision and resilience of our automated method in accurately dividing the healthy liver were demonstrated by examining 35 clinical PET-CT data. The user's text is incomplete and does not provide any information.[11]

The segmentation of the liver in medical image analysis is a demanding endeavor that needs both swiftness and precision. It is crucial in computer-assisted diagnostics, pre-evaluation for liver transplants, and planning therapy for liver malignancies. Magnetic resonance imaging (MRI) has several benefits, including the lack of ionizing radiation and enhanced viewing of soft tissues. MRI has become a vital tool in advanced medicine due to recent technological developments and improvements in image capture methods. Nevertheless, the use of MRI for liver segmentation has progressed at a somewhat slower pace compared to its utilization in the brain, spinal cord, and musculoskeletal regions. The irregular size, location, and form of the liver, the effects of contrast agents, and the similarity of grey values with nearby organs contribute to this phenomenon. A suggested solution to these problems involves using T2-weighted MRI datasets and a contour assessment based on a level set to achieve automated liver segmentation. The method circumvents the need to solve partial differential equations and utilizes a two-cycle segmentation approach that only depends on integer operations. This strategy's main advantage is its ability to apply the procedure uniformly to all sections with an equal number of iterations and perform contour evolution without requiring a user-defined initial contour. The result of this approach is evaluated using four different similarity metrics. Showcasing its efficacy in producing significant and beneficial segmentation results.[12]

This study uses abdominal computed tomography (CT) scans to quantify the extent of hepatic tumors in individuals with illnesses by analyzing uneven enhancement images. The main objective is to automate the process of partitioning livers into segments. The local structures of several organs are compared using a distinctive method termed 3-D affine invariant shape parameterization. Periodic sampling is conducted on the organ's surface to determine the relationships between individual elements of a closed three-dimensional set of surfaces. This parameterization method effectively resolves typical challenges related to the parameterization of concave surfaces. Once the livers have been initially segmented, training sets of regions with atypical local geometry are generated. The geodesic active contour method locally corrects liver segmentations in abnormal images. Hepatic tumors are detected by graph cut segmentation, a technique that combines enhancement and shape constraints. This method significantly decreases the frequency of errors in liver segmentation, ensuring the detection of all cancers. Support vector machines and feature selection are employed to minimize the occurrence of false positive tumor detections, hence improving the accuracy of tumor detection. The results indicate that the method has a 100% success rate in identifying tumors, with only 2.3 cases of false positives. Moreover, the computed margin of error in tumor burden is as low as 0.9%. To summarize, the test data validates the robustness and dependability of this technique in examining livers from intricate clinical scenarios, enabling ongoing surveillance of patients with liver cancer.[13]

An essential stage in diagnosing liver pathology using computer-aided techniques involves accurately segmenting the liver in abdominal MRI images. Liver segmentation using automated methods remains challenging, and significant research efforts have been dedicated to this field. Nevertheless, it isn't easy to ascertain which algorithm produces the most precise segmentation results. Using an artificial neural network and iterative watershed algorithm consists of many successive steps. Mathematical morphology is used for preprocessing to improve the photographs' quality. The approach combines the watershed algorithm and MLP neural networks to extract the hepatic area. Directly using the conventional watershed transformation to medical picture segmentation often results in excessive segmentation. Specialized neural networks are used to remove distinctive characteristics from the liver region to tackle this issue. Subsequently, the watershed transform is used to evaluate the quality of the obtained features and automatically adjust the required parameters. Adjusting this parameter is conducted iteratively to maximize the outcomes. Thus, the technique utilizes a single segment of the MRI data to identify the liver area precisely.[14]

An automated liver segmentation strategy utilizing the Auto Context Model (ACM) is employed to segment the liver from 3-D CT images. To achieve accurate segmentation, the method employs mean-shift techniques, ACM (Active Contour Model), and multi-atlases. The methodology revolves around a pedagogical framework and has two separate stages. In the initial stage of the learning phase, a collection of classifiers is obtained in each atlas space by utilizing the Atlas Co-Training Method (ACM). Multiple atlases are used to obtain various sets of classifiers depending on ACM. During the segmentation step, the test picture undergoes segmentation by applying each arrangement of classifiers based on ACM in each atlas space. The ultimate segmentation outcome is achieved by amalgamating the segmentation discoveries from all atlas spaces through a metaclassifier fusion technique. A refined mean-shift strategy expedites the segmentation process by conducting excessive segmentation when provided with a test image. Instead of using traditional pixel-based image labeling, a technique based on regions is employed. This enhances the speed of the segmentation process. The algorithm's efficacy is assessed using the MICCAI 2007 datasets. The experimental results demonstrate that the algorithm attains an average overlap error of 8.3% and an average surface distance of 1.5 m. The outcomes derived from the most recent cutting-edge liver segmentation investigation are similar.[15]

CT or MRI imaging is frequently employed for liver volumetry. While there have been many investigations into computerized liver segmentation in CT scans, a limited amount of research is dedicated explicitly to liver segmentation in MRI images. This study aims to establish a standardized framework for accurately dividing the liver into distinct sections in both CT and MRI imaging. The proposed system comprises numerous components. Firstly, a filter called anisotropic diffusion is employed to decrease noise while maintaining the integrity of the liver's structure. A scale-specific gradient size filter enhances the clarity of liver boundaries. Afterward, an expedited marching strategy is initially employed to approximate the limits of the liver. Subsequently, a strategy utilizing the level-set approach is used to improve the initial bounds in combination with a geodesic-active-contour model. The CT database comprises hepatic CT images acquired from 18 liver donors after liver transplantation. The MRI database includes data from 23 individuals who underwent 1.5T MRI scans. To establish accurate and reliable measurements of liver volumes, radiologists manually outlined the shape of the liver on each CT or MR segment. The volumetric measurements acquired from the computer-based method are compared to those obtained from the manual method. The computerized liver volumetry in CT and MRI shows significant concordance with manual volumetry. The median duration for computer-based volumetry is 1.0 ± 0.13 minutes per case for MRI and 0.57 ± 0.06 minutes for CT. On the other hand, manual volumetry takes an average of 24.0 ± 4.4 minutes per case for MRI and 39.4 ± 5.5 minutes per case for CT. The observed difference is statistically significant at a significance level of $p < 0.05$.[16]

This work introduces a novel approach for dividing liver pictures acquired from abdominal computed tomography (CT) scans. The method follows a step-by-step process that starts with a broad overview and gradually moves towards a more specific analysis. The framework comprises two stages: initial segmentation and enhanced segmentation. The SKFCM method, which integrates spatial information, is employed for the initial segmentation, while a more advanced Grow Cut approach is utilized for the refined segmentation. The fuzzy C-means clustering (FCM) approach is enhanced using spatial restrictions and a kernel function (SKFCM) algorithm. This modification decreases the impact of noise and improves the clustering capability. The Grow Cut method leverages the continuous spatial information from CT scans to generate seed labels and automatically enhance segmentation effectiveness. The proposed method is employed to partition the liver by leveraging an extensive dataset of abdominal CT images. The efficacy and accuracy of our liver segmentation technique are demonstrated through the study of segmentation data. The user's text is incomplete and does not provide any information.[17]

Liver cancer is the primary cause of death connected to cancer on a global scale. Radiologists frequently employ non-invasive medical imaging techniques, such as Computerized Tomography (CT) and Magnetic Resonance Imaging (MRI), to diagnose and prepare for surgery. Precise identification and segmentation of the regions of interest are essential for accurate surgical planning. While automated liver segmentation algorithms have demonstrated promising results in CT imaging, radiologists favor MRI due to its exceptional diagnostic information. However, the partially decreased difference in brightness, interruptions, inconsistent levels of sound, and unclear borders of the liver compared to other organs make it challenging to separate the liver using MRI. This study introduces a technique for automatically dividing the liver using a three-dimensional approach in MRI data. The method employs an enhanced 3D active contour model reduced by a completely distinct dual methodology. A novel method is utilized to improve the distinction in the input of the MRI picture, resulting in increased segmentation. The suggested approach entails substituting the input image with a probability map constructed using a pre-established statistical model of the liver. The evaluation metrics indicate a significant resemblance to other sophisticated methods, as evidenced by a Dice Similarity Coefficient of 90.19 and an Accuracy of 98.89. This work examines explicitly the challenges related to liver segmentation using MRI and presents a viable strategy that improves the accuracy of the process. The results illustrate the technique's effectiveness in accurately segmenting the liver in MRI imaging.[19]

Early detection is crucial for the management of spinal cord tumors. The majority of spinal cord malignancies are metastatic or secondary neoplasms that have disseminated to the spinal cord from other anatomical sites. On the other hand, primary spinal cord tumors usually do not show any symptoms. Precise diagnosis is essential. Clear identification is crucial in formulating a practical therapeutic approach for individuals afflicted with malignant neoplasms. Radiation therapy is often used to treat malignant tumors, and accurate image-guided treatment planning is essential to determine the treatment area and minimize radiation exposure to surrounding tissues. Precise segmentation of the target volume and accompanying organs enables faster completion and less effort in radiation treatment and surgical planning. The complicated nature of the spine's unusual structure and overlapping components presents challenges for automated identification of the spinal canal in CT imaging. Several methodologies have been proposed, such as interpretation algorithms, Quasi-Monte Carlo methods, and bone area identification based on segmental structural segmentation of the rib structure.

Nevertheless, these strategies encounter challenges regarding processing time, cost, and optimization of the computing sequence. A unique approach using the Hough transform is used for image segmentation to detect seed voxels and subsequent 3D region expansion. This approach can potentially enhance the accuracy and feasibility of spinal canal segmentation in CT images [5].

The spine, the vertebral column, is a vital skeletal structure supporting a living organism's upper body. Medical imaging methods such as radiography, CT, MRI, and PET may be used to identify spinal disease and analyze the spine's structure. CT scans provide the most accurate 3D spine representation, but manually segmenting the spine is time-consuming and prone to bias in later analytic tasks. Thus, for most clinical applications, automated or semi-automatic procedures are favored. However, the complexity of vertebrae's morphologies, varying topologies, and comparable neighboring structures, disease, and spatial proximity to ribs make these procedures challenging. Several spine segmentation techniques for CT scans have been suggested, such as part-based models, active shape models, geometric models, statistical anatomical models, level set methods, unsupervised image processing approaches, and region-based strategies. Recent systems have used machine learning techniques such as deep learning and Adaboost. The limits of segmentation approaches persist in the form of the first pose estimation, which may be performed either manually or mechanically, and the susceptibility of statistical models to variations in training data, notwithstanding their benefits. Despite the need for precise measurements, the advancement of spine segmentation algorithms has dramatically assisted in diagnosing spine abnormalities, biomechanical modeling based on images, and spine interventions guided by images. These advancements can potentially enhance the accuracy of spinal diagnoses and treatments, eventually leading to better patient results [20].

Artificial intelligence is frequently used in medical imaging to detect lumbar spine conditions accurately. SegNet and Artificial Neural Networks (ANN) are specialized technologies developed to identify, separate, and diagnose spine disorders. In addition, additional techniques such as regression trees, neural networks, and hybrid algorithms have yielded promising results. Surgeons can utilize the least invasive procedures by automating the location and identification of vertebrae. These methods have demonstrated substantial accuracy and are improving the effectiveness of medical imaging for disease identification. The study highlights the necessity of automating the identification of anomalies and fractures in the lumbar spine to minimize discrepancies in human diagnosis. The YOLOv5 object detector precisely identifies the location of the lumbar spine with a mean Average Precision (mAP) of 0.975. The diagnosis of lumbar lordosis is determined with a precision of 74.5% by comparing angles with the region area calculated using YOLOv5 centroids. The HED U-Net design utilizes YOLOv5 bounding boxes to crop pictures and extract segmented vertebrae and edges. The lumbar lordortic angles (LLAs) and lumbosacral angles (LSAs) are calculated using the corners of the vertebrae identified by a Harris corner detector. The LLAs have a usual error of 0.29°, while the LSAs have a typical error of 0.38° [21].

Level-set methods have been widely employed in image segmentation applications to generate active contours, primarily because of their exceptional accuracy in detecting boundaries. The accuracy of segmentation strategies in medical picture segmentation may be compromised by weak edges and inhomogeneities when relying on active contours performed using level-set procedures. This study introduces an innovative method that utilizes entertaining shapes and level set-based methodologies to segment various medical images effectively. The proposed method employs a collective adaptation process that relies on an objective energy function. This function assigns energy values to different components and determines their weights based on their relative significance in establishing boundaries. The relative importance is determined by collecting local edge characteristics inside and outside the growing contour. Local edge features encompass the edge's intensity and the degree to which the gradient vector flow field of the image is perpendicular to the normal of the expanding outline. We evaluate the segmentation of different sites by employing the recommended method, utilizing genuine MRI slices, CT slices, X-ray images, and ultrasound images. The evaluation outcomes validate the effectiveness of using local edge characteristics to allocate weights to energy forces to prevent leakage. The results indicate that the proposed method outperforms the most advanced edge-based level set segmentation techniques in correctly detecting borders, mainly when the edges are not well-defined. [22].

Picture segmentation is a discipline that seeks to isolate objects or regions of interest from an image accurately using diverse methodologies. The level set technique is a method that utilizes a dynamic contour curve to identify the boundaries of objects precisely. Nevertheless, the use of level-setting techniques is hindered by the extensive range of image formats that exist. Edge-based level set techniques are suitable for segmenting photographs with sharp or clear edges because they utilize edge stop functions based on gradient information. These functions lead contour curves towards object edges and stop them there. They are sensitive to noise because of the gradient and have a little issue of edge leakage. Regional description operators expand contour curves in region-based level set procedures. These techniques resist noise and can handle images with uneven intensities. Operators rely on statistics as their foundation. However, obtaining the necessary background knowledge on the phase number may provide difficulties. We suggest using a weighted edge-based level set technique to overcome the constraints of conventional edge-based and region-based level set methods for segmenting noisy images. The approach aims to overcome the limitations of constant coefficients in noisy image segmentation using weighted coefficients for length and area terms. These coefficients are determined based on local normalized entropy and local fitting means [2].

Automated bone segmentation from computed tomography (CT) images is essential for the extensive use of computer-assisted diagnostics, which shows significant potential for assessing various spinal conditions. Active contour methods (ACM) are widely used for segmenting medical images and determining the region of interest (ROI). These solutions have limited automation since they need human interaction during setup or a global threshold. The work showcases the method of automatic contour initialization in ACM using spinal CT scans for medical picture segmentation. The Active Contour Model (ACM) starts with a collection of feature markers collected from the picture to construct the first contour. A novel corner measure based on intensity is suggested for detecting the feature markers that should be included in the form. The original form is derived from these indistinct corners, resulting in a concave hull. The suggested technique was evaluated compared to existing baseline methods and traditional feature detectors. The results demonstrate that the technique works consistently, even when subjected to higher levels of artificially generated Gaussian noise. This approach allows the ACM to achieve real-world segmentation quickly. The radiologist's annotated pictures were used as the standard for comparison, and the segmentation was evaluated using the Dice coefficient and Harsdorf distance measures [23].

Intervertebral disc degeneration, an age-related condition marked by chronic back pain, is the main indication for surgical intervention in the spinal column. Magnetic resonance imaging (MRI) is the main diagnostic modality for the clinical evaluation of disc degeneration. Our objective was to divide normal and deteriorated lumbar intervertebral discs in T2-weighted midsagittal MR images of the spine using a partially automated 2-D technique. This is further worsened by the partial volume effects and the overlapping grey-level readings in nearby tissues. Three iterations of atlas-based segmentation were created utilizing a probabilistic atlas of the intervertebral disc. The accuracy of these variations was subsequently evaluated quantitatively in comparison to manually segmented data. The atlas-robust-fuzzy c-means approach, which uses an accurately aligned disc atlas and combines fuzzy clustering with consistency constraints, showed excellent results in terms of both accuracy of segmentation and efficiency of time. As expected, the fuzzy segmentation metrics shown a decrease when the trained networks were applied to patients instead of healthy participants. [24].

Skull stripping is necessary for the analysis of brain MRI data. Despite being the most precise approach, manual segmentation is time-consuming. The aforementioned challenges have prompted the creation of multiple automated brain segmentation algorithms utilizing magnetic resonance imaging (MRI). However, there is currently no system that can consistently and universally address the challenge of extracting the full brain from various datasets. To overcome these restrictions, we suggest utilizing a 3D-Unet model for the purpose of skull stripping in brain MRI images. The 3D-Unet is a newly discovered approach that is widely employed for volumetric segmentation in medical imaging. This is an improved version of the proposed 2D-Unet, which is another convolutional neural network (CNN) based deep-learning network. When assessing several techniques for skull-stripping, we compare the outcomes

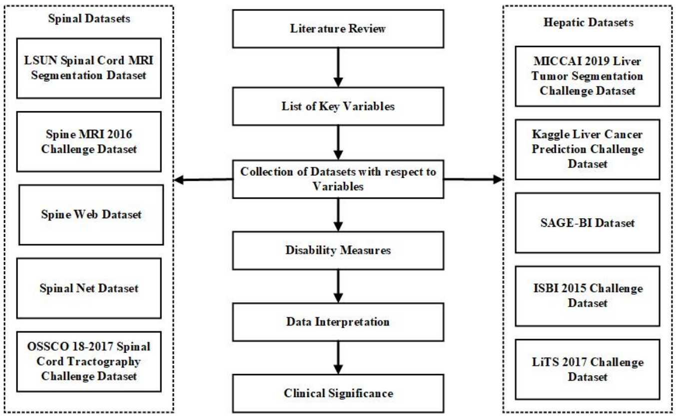

Figure 1: Flow case diagram of our work

obtained from our 3D-Unet method with those achieved using BSE, ROBEX, and Kleesiek's approach. Kleesiek's methodology utilizes deep learning, while BSE and ROBEX are mostly employed. The comparison utilizes MRI scans of individuals' brains due to their widespread availability on the Internet at no expense. [25].

III. ANALYSIS

Integrating with the Global Activity Limitation Indicator entails analyzing the impact and association of spinal and hepatic health issues on the overall activity restrictions encountered by people. Here are the methods to include these elements:

A. Key Variables

Precise indicators of impairment in both spinal and hepatic well-being are determined.

Spinal well-being encompasses various aspects that contribute to an individual's overall health. Pain, a key indicator, involves assessing the location, intensity, and duration of pain, including any radiating pain down the arms or legs and numbness or tingling. Range of motion is crucial, evaluating the ability to bend, twist, and move the spine, considering any limitations impacting daily activities. Motor function is assessed for weakness in the limbs and challenges with fine motor skills. Sensory changes, such as alterations in sensation or heightened sensitivity, are important indicators. Reflexes, including abnormalities like hyperreflexia or diminished reflexes, provide additional insights into spinal health. Lastly, balance and coordination are evaluated, with attention to difficulties maintaining balance and signs of coordination issues. These factors provide a comprehensive understanding of an individual's spinal well-being.

Hepatic (liver) well-being is crucial for overall health, and various indicators play a key role in assessing the liver's function. Elevated levels of liver enzymes such as AST, ALT, and ALP, along with abnormalities in bilirubin levels, can signal potential liver issues. Jaundice, characterized by yellowing of the skin and eyes, is a visible indicator of liver dysfunction. Abdominal pain, specifically in the upper right abdomen, may indicate liver-related discomfort. Ascites, the accumulation of fluid in the abdominal cavity, is another manifestation of liver impairment. Changes in stool and urine, such as pale-colored and dark urine, serve as additional indicators. Persistent fatigue and weakness, unexplained weight loss, and symptoms like persistent nausea and vomiting, especially with blood, are essential in evaluating hepatic health. Monitoring these signs aids in the early detection and management of potential liver disorders.

The Global Activity Limitation Indicator is a comprehensive measure for assessing overall functional impairment by considering limitations in various domains. It encompasses self-care, evaluating one's ability to independently perform activities of daily living (ADLs); mobility, which assesses the capacity to move around and engage in physical activities; cognition, encompassing mental functioning, thinking, reasoning, and memory capabilities; social interaction, gauging engagement in social activities and relationships; and work or productivity, measuring the ability to perform tasks related to employment or daily responsibilities. Evaluating these indicators involves a thorough assessment through medical history, physical examinations, laboratory tests, and imaging studies, providing a holistic understanding of an individual's functional limitations across diverse aspects of life.

B. Data Collection

Indeed, here are descriptions of various datasets related to spinal and hepatic issues:

Spinal Datasets:

1. LSUN Spinal Cord MRI Segmentation Dataset:
   - Includes over 20,000 spinal cord MRI slices with manual white matter, gray matter, and cerebrospinal fluid annotations. Accessible on the LSUN website.

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It encompasses self-care, evaluating one's ability to independently perform activities of daily living (ADLs); mobility, which assesses the capacity to move around and engage in physical activities; cognition, encompassing mental functioning, thinking, reasoning, and memory capabilities; social interaction, gauging engagement in social activities and relationships; and work or productivity, measuring the ability to perform tasks related to employment or daily responsibilities. Evaluating these indicators typically involves a thorough assessment through medical history, physical examinations, laboratory tests, and imaging studies, providing a holistic understanding of an individual's functional limitations across diverse aspects of life.

2. SpineMRI2016 Challenge Dataset:
   - Consists of MRI scans with clinical data and task-specific segmentations for spinal pathologies. Tasks include disc segmentation, vertebrae segmentation, landmark annotation, and vertebra fracture detection. Available on the GRAND Challenge website.
3. Spinal Net Dataset:
   - Contains MRI scans of lumbar spinal stenosis patients annotated for intervertebral disc and spinal canal segmentation and utilized for training the Spinal Net deep learning model. Available on the Spinal Net website.
4. OSSCO 18-2017 Spinal Cord Tractography Challenge Dataset:
   - Features diffusion MRI scans of healthy individuals and patients with spinal cord lesions and ground truth tractography data for specific white matter tracts. Helpful in evaluating tractography algorithms. Accessible on the OSSCO website.
5. Spine Web Datasets:
   - Offers diverse spinal datasets for disc degeneration, spondylolisthesis, and scoliosis research. Available on the Spine Web website.

Hepatic Datasets:

1. LiTS 2017 Challenge Dataset:
   - Contains CT scans of patients with liver lesions, segmented for tumours, metastases, and healthy liver tissue. Widely used for liver lesion segmentation research. Available on the LiTS website.

2. ISBI 2015 Challenge Dataset:
   - Provides MRI scans of patients with fatty liver disease, labelled for steatosis levels. Useful for studying and developing automated methods for fat quantification. Available on the ISBI website.
3. MICCAI 2019 Liver Tumor Segmentation Challenge Dataset:
   - Includes CT and MRI scans of patients with liver tumours, segmented for various tumour types and healthy liver tissue. Supports research on multi-modal and automatic segmentation techniques. Accessible on the MICCAI website.
4. Kaggle Liver Cancer Prediction Challenge Dataset:
   - Offers CT scans of patients with or without liver cancer and clinical data. Suitable for developing machine learning models for liver cancer prediction. Available on the Kaggle website.
5. SAGE-BI Dataset:
   - Comprises MRI scans of non-alcoholic fatty liver disease (NAFLD) patients, segmented for hepatic fat fraction and fibrosis stages. Aids research on NAFLD progression and diagnosis. Accessible on the SAGE-BI website.

Researchers should consider factors like data size, annotation quality, accessibility, and licensing terms when selecting a dataset.

C. Disability Measures

The study adopted a quantitative approach to measure the severity of disabilities and assess associated needs among adults aged 45 or over with intellectual disabilities (IDs). Utilizing the Inventory of Identification of Needs (IIN), the research identified and described staff perceptions of the participants' needs, analyzing their age, gender, and disability level. Noteworthy findings indicated that specific needs were more prevalent among older adults with IDs, with variations based on age, gender, and disability level. The development and psychometric properties of the assessment instrument (IIN) were addressed, showcasing satisfactory internal consistency, interpreter reliability, and construct validity. The study revealed numerous and diverse unmet needs, particularly in literacy, money handling, rights information, and self-care. The influence of disability level and age on certain needs was evident, guiding implications for service provision. These included recommendations for literacy learning experiences, information dissemination of rights and services, self-care assistance or training, and the organization of meaningful activities during regular periods, weekends, and holidays. The disability metrics employed encompassed functional. Limitations, activity limitation, participation restriction, health-related quality of life, severity and intensity, psychosocial aspects, and environmental considerations provide a comprehensive framework for understanding and addressing the needs of individuals with IDs.

D. Global Activity Limitation Indicator

The Global Activity Limitation Indicator (GALI) is integral to the European Union Statistics on Income and Living Conditions (EU-SILC), serving as a standardized measure to assess limitations in basic activities due to health issues or disabilities. In a study involving 232 Portuguese older adults with intellectual disabilities (mean age = 52, predominantly male), the Inventory of Identification of Needs (IIN) was employed as the assessment instrument. The study elucidated the psychometric properties of the IIN, affirming its reliability and validity in gauging the needs of older adults with intellectual disabilities. Perceived needs about age, gender, and disability level were analyzed, revealing diverse unmet needs such as literacy, financial handling, information on rights, and self-care. The study underscored the impact of disability level on specific needs, especially in individuals with moderate to severe disabilities, while age influenced mental health needs. The findings emphasize the importance of tailoring service provision to address identified needs, recommending literacy programs, rights awareness initiatives, self-care support, and meaningful activities during regular and leisure periods.

E. Data Interpretation

The correlation analysis conducted in this study delves into the intricate connections between global activity limitation indicators and disability measures among adults under 65 grappling with spinal and hepatic health issues. Employing robust statistical techniques, we systematically examined the strength and direction of correlations to discern the impact of these health conditions on overall activity restrictions. The positive or negative correlation coefficients provide valuable insights into the relationships between health status and functional limitations, aiding in identifying key patterns and trends within the data. By scrutinizing these correlations, we gain a nuanced understanding of the intricate global interdependencies. This analysis not only elucidates the immediate associations but also sets the stage for informed discussions on potential causal factors and broader implications for healthcare interventions. Our correlation analysis serves as a vital tool in unraveling the complex dynamics between spinal and hepatic health issues and the resulting constraints on individuals' activities, contributing to a more comprehensive comprehension of health outcomes in this population.

In the following table, the information from different countries is shown. Age groups are categorized to understand how health issues may vary with age. Spinal and hepatic health levels are assessed on a subjective scale (e.g., Excellent, Good, Moderate, Poor). Activity restrictions describe the limitations individuals may face due to their health issues. The everyday observations are as follows:

Age and Spinal Health Impact: One pattern we might notice is that in some cases, as people get older (move to higher age groups), their spinal health tends to decline. For instance, in Brazil, the spinal health level is moderate for the 35-45 age group.

Country and Activity Restrictions: There seems to be variability between countries. For example, individuals in China generally have excellent spinal health and experience no significant activity restrictions, suggesting a positive trend in spinal health in that country.

Hepatic Health and Activity Levels: In Germany, where hepatic health is excellent, individuals across different age groups seem to maintain normal activity levels. This suggests a positive correlation between good hepatic health and fewer activity restrictions.

Spinal Health Variation: The USA and Australia have a mix of spinal health levels across age groups. This diversity indicates that spinal health can vary widely in the same country.

F. Clinical Significance

Understanding how spinal and hepatic health issues affect activity limitations isn't just about numbers; it's about people's lives. This research sheds light on the real-world impact of these conditions, revealing how they can restrict everyday activities, hinder independence, and ultimately influence happiness and quality of life. By identifying these connections, we can pave the way for improved treatments and support systems, helping individuals with these conditions move beyond limitations and A life lived to the fullest. This research isn't just about statistics; it's about empowering people and rebuilding the possibilities for well-being.

Clinical Significance: This term means the practical importance of our medical research. It's about understanding how our study contributes valuable information that doctors and healthcare professionals can use to help real people with health issues.

Assessing Practical Importance: In simple words, we're evaluating our findings' usefulness in a practical, real-world sense. For example, suppose we discover a new treatment or identify factors that influence spinal and hepatic health. In that case, we want to know if doctors can apply this information to improve patient care.

Impact on Well-being: Well-being is all about how people feel and how healthy they are in their daily lives. In our study, we're trying to figure out if the things we learned about back and liver health positively impact how individuals feel physically and emotionally. For instance, if our findings lead to better treatments, it could mean less pain and more comfort for people.

Quality of Life: Quality of life refers to the overall satisfaction and happiness in someone's life. Our research aims to understand if the knowledge gained about spinal and hepatic health conditions translates into improvements in the daily lives.

Table 2: Comparative Analysis of Studies on Liver and Spinal Canal Segmentation Techniques

Paper Title	Focus of Survey	Newest Ref.	Survey Approach	Preprocessing Techniques	Features Selection	Techniques	Data Type	Performance Analysis
MRI Liver Segmentation with T2-Weighted Images	Liver Segmentation	[8]	T2-weighted MRI datasets, Contour assessment based on level set	No partial differential equations, Two-cycle segmentation approach	Not specified	Evaluation using four similarity metrics	MRI Data	Efficacy demonstrated against manual segmentation by radiologists.
Automated Hepatic Tumor Burden Calculation	Liver Segmentation	[9]	3-D Affine Invariant Shape, Geodesic Active Contour, Graph Cuts Segmentation	Local structure comparison, 3-D Affine Invariant Shape parameterization, Geodesic Active Contour, Graph Cuts Segmentation	Not specified	Geodesic Active Contour, Graph Cuts Segmentation, SVM, Feature Selection	CT Data	True Positive Rate: 100%, False Positive Instances: 2.3, Margin of Error: 0.9%
Abdominal MRI Liver Segmentation	Liver Segmentation	[10]	Artificial Neural Network, Iterative Watershed Algorithm	Anisotropic diffusion filter, Scale-specific gradient size filter, Fast-marching technique, Level-set technique, Geodesic-active-contour model	Not specified	Neural Networks, Watershed Algorithm	MRI Data	Utilizes a single segment of MRI data for precise liver segmentation.
Auto Context Model (ACM) for Liver Segmentation	Liver Segmentation	[11]	Auto Context Model (ACM), Mean-Shift, Multi-Atlases, Geodesic Active Contour	Mean-Shift, Multi-Atlases, Enhanced Mean-Shift	MICCAI 2007 datasets	Not specified	CT Data	Average Overlap Error: 8.3%, Average Surface Distance: 1.5 m
Uniform Framework for Liver Segmentation in CT and MRI	Liver Segmentation	[13]	Anisotropic diffusion filter, Scale-specific gradient size filter, Fast-marching technique, Level-set technique	Not specified	Not specified	Not specified	CT and MRI Data	High agreement with manual volumetry, Significant reduction in processing time.
Segmentation of Liver Images from CT Scans	Liver Segmentation	[14]	SKFCM Method, Grow Cut Approach	Fuzzy C-means clustering (FCM), Spatial Constraint and Kernel Function (SKFCM), Grow Cut	Abdominal CT images	Not specified	CT Data	Efficacy and precision demonstrated through segmentation data analysis.
3D MRI	Liver	[21]	3D Active	Anisotropic	CT	Not	CT and MRI	Dice

Liver Segmentation	Segmentation		Contour Model, Complete Difference Dual Methodology	diffusion filter, Fast-marching technique, Statistical model-based probability map	Database (18 liver donors), MRI Database (23 individuals)	specified	Data	Similarity Coefficient: 90.19, Accuracy: 98.89. High similarity to other advanced approaches.
Hough Transform for Spinal Canal Segmentation	Spinal Canal Segmentation in CT Imaging	Fu et al., 2018	Hough transform for image segmentation, detection of seed voxels and 3D region expansion.	Hough transform method	CT Imaging	Not specified	CT Imaging	Potential to enhance accuracy and feasibility of spinal canal segmentation in CT images.
Advanced Segmentation Techniques for Spinal Disease	Automated/semi-automated spine segmentation	Yao et al., 2016	Part-based, active shape, geometric and statistical anatomical models, deep learning	Part-based models, active shape models, deep learning	CT, MRI, PET Imaging	Part-based models, operational shape models, deep learning	CT, MRI, PET Imaging	Advancements in spine segmentation algorithms have greatly assisted in diagnosing spine abnormalities and guiding spine interventions.
AI Techniques for Lumbar Spine Disease Detection	Detection, segmentation, and diagnosis of spinal diseases using AI	Mushtaq et al., 2022	YOLOv5, HED U-Net architecture, object detection, vertebrae segmentation	YOLOv5, HED U-Net architecture	Medical Imaging	YOLOv5, HED U-Net architecture	Medical Imaging	Automation of vertebral localization and identification, enhancing diagnostic efficacy and reducing inconsistencies in human diagnosis.
Novel Level-Set Technique for Medical Image Segmentation	Image segmentation using level set-based techniques	Khadidos, Sanchez, & Li, 2017	Group set evolution based on an objective energy function, utilizing local edge characteristics for segmentation.	Level-set techniques based on local edge characteristics	MRI, CT, X-ray, Ultrasound Imaging	Level-set techniques based on local edge characteristics	MRI, CT, X-ray, Ultrasound Imaging	Efficacy in accurately identifying boundaries, especially at weak edges, surpassing state-of-the-art segmentation strategies.
Weighted Edge-Based Level Set Technique for Image Segmentation	Image segmentation method using a weighted edge-based level set technique	Liu, Liu, & Xing, 2019	Use of weighted coefficients for length and area terms to overcome limitations of traditional	Weighted edge-based level set technique	Image Segmentation	Weighted edge-based level set technique	Image Segmentation	I am overcoming the constraints of conventional edge-based and region-based level

			level set techniques					set methods for segmenting noisy images.
Automated Contour Initialization for Spinal CT Image Segmentation	Automatic contour initialization in ACM using spinal CT scans	Athertya & Kumar, 2016	Novel corner measure for detecting feature markers, automatic contour initialization	Automatic Contour Model (ACM)	Spinal CT Imaging	Automatic Contour Model (ACM)	Spinal CT Imaging	Consistent and automated ACM segmentation, even under higher noise levels, for improved real-world segmentation.
Image Segmentation of Spinal Canal in CT Imaging	Automated Spinal Canal Segmentation	Fu et al.	2018	Hough transform for image segmentation	CT Imaging	Hough transform for image segmentation	CT Imaging	We have enhanced the accuracy and feasibility of spinal canal segmentation in CT images.
AI Applications in Lumbar Spine Imaging	Lumbar Spine Imaging using AI	Mushtaq et al.	2022	Utilization of SegNet, Artificial Neural Networks (ANN), LOv5, HED U-Net architecture	CT Imaging	Utilization of SegNet, Artificial Neural Networks (ANN), LOv5, HED U-Net architecture	CT Imaging	High precision achieved in automated detection and segmentation of lumbar spine abnormalities using AI techniques.

VII. CONCLUSION

Incorporating computer image processing technology, primarily deep learning algorithms, has initiated a revolutionary period in medical imaging, particularly in the analysis and modification of spinal images. Using segmentation approaches and three-dimensional modelling, supported by deep neural networks, has dramatically improved the precision of diagnosing different spinal illnesses. This progress not only enhances medical training but also enhances our comprehension of intricate spinal anatomical processes. Furthermore, examining spinal and hepatic health conditions and the Global Activity Limitation Indicator offers a comprehensive method for evaluating total functional disability. A systematic approach is provided by the thorough assessment of critical factors about the health of the spine and liver, together with the gathering of data from specialist databases. Moreover, using a quantitative methodology in disability assessments, such as the Inventory of Identification of Needs, offers significant and informative perspectives on the requirements of persons with intellectual impairments. The use of the Global Activity Limitation Indicator in research with older persons with intellectual impairments highlights the need to provide customized services based on recognized requirements. To progress in this area, it is necessary to continue investigating improved imaging methods, improving deep learning algorithms, and creating specific therapies tailored to the requirements of persons with intellectual impairments. Moreover, it is essential to have cooperative endeavours among medical researchers, practitioners, and technologists to effectively convert these discoveries into practical implementations that improve patient care and overall healthcare results.

Table 3: Country Wise Record of Patients

Country	Age Group	Spinal Health Level	Hepatic Health Level	Activity Restrictions
USA	30-40	Moderate	Good	Difficulty lifting heavy objects, occasional back pain
India	45-55	Poor	Moderate	Limited mobility, discomfort in bending
Germany	50-60	Good	Excellent	Normal activity levels
Brazil	35-45	Moderate	Poor	Reduced ability to stand for long periods
China	40-50	Excellent	Good	No significant restrictions
Australia	55-65	Good	Moderate	Difficulty in strenuous physical activities

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