# Sequential and Parallel CNN Structures for the Classification of Lumbar Herniated Disc in MRI

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## ABSTRACT

The purpose of present study was to detect the lumbar herniated disc in lumbar spine MRI using Convolutional Neural Network with sequential and parallel models. We performed CNN classification technique for detecting the normal and herniated disc using sequential (single-input) and parallel (multi-input) models, while capturing the effect of dropout ratios and L2 regularizers on the overall accuracy of the model. To overcome the problems of overfitting of CNN model and to enhance the overall performance, we applied data augmentation to our dataset. After evaluating the 87 patients MRI data using sequential and parallel CNN structures, the sequential CNN structure provides the higher accuracy 99.31% (training accuracy) and 96.86% (test accuracy), and when we apply parallel CNN structure, the classification accuracy is also high i.e., 99.52% (training accuracy) and 95.38% (test accuracy). We conclude that, the overall sequential and parallel CNN structures provides higher accuracy for the classification of normal or herniated disc in lumbar spine MRI, as compared to when we add dropouts and regularizers in CNN model. The results demonstrate that our proposed CNN structures significantly outperforms the state-of-the-art methods.

**Key words:** CNN. Sequential. Parallel. Dropout. L2 Regularizer. Herniated. Lumbar spine.

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## INTRODUCTION

The medical imaging technology plays very important role in a wide range of diagnosing diseases using patient's data and most of the interpretations of the medical images are carried out by medical experts and physicians (Huang et al., 2020). Low back pain is the major problem throughout the world, and it is getting worse, mostly mainly due to the aging and increasing world population. Most people with low back pain could not correctly identify the exact nociceptive source of their pain. That's why most of the patients with low back pain treated in a manner that is not consistent with the best practice treatment guidelines. Lumbar pain syndrome is the second cause of reporting to a doctor. It's thought that 15 percent of absences from work come from pain at the trunk, and it leads as a cause of sick leave in the people below the age of 45 years (Peulić et al., 2020). More than just one individual in ten global suffer low back pain, and it was the motive for 60.1 million disabilities in 2015, an increase of 54% since 1990, with the maximum growth occurring in low-income and low nations.

In Pakistan context, a study has been conducted to find out the prevalence of lower back pain in the bankers with a sample data of 164 bankers with the age group of 22 – 58 years. Their findings showed that the chances of occurrence of lower back pain were 52.4% in bankers, and it is more prevalent in males as compared to females (Tauqeer et al., 2018). The frequency of low back pain is superior in more prosperous countries than in developing countries, i.e., 42% and 35%. The prevalence of lower back pain causes high levels of care utilization and disability (Nurul et al., 2010). There is an alarming fact 80%population in the whole world indeed experienced low back pain (Rubin et al., 2007). Besides, to the enormous health problem, low back pain that is mainly occurring from the lumbar disc herniation is also a socioeconomic problem that substantially burdens the health and social budget of the Governments, due to allocation for medical expenses and payment for sick leave (Stephens et al,, 1992). Although there are several global initiatives to address the global burden of low back pain as a public health problem, there is a need to identify cost-effective and context-specific strategies for managing low back pain to mitigate the consequences of the current and projected future burden.

In 1995, an international forum held to discuss the various methods for the management of lower back pain (Delitto., 1995), (Bowling et al., 1997). In this forum, different possibilities for the possible classifications of lower back pain discussed and the existence of these classifications helps to develop a Computer-Aided Diagnostic system because of the central concept behind using an automatic system based on the set of features derived from the images.

The anatomy of the human lumbar spine consists of 33 vertebrae, and these vertebrae connected each other with discs. The most well-known strategies utilized for the perception of the spine are Magnetic Resonance Imaging (MRI) and Computer Tomography (CT). A lumbar herniated disc characterized as restricted prolapse of the plate material past the limits of the intervertebral circle space. Approximately, 75% of the lumbar flexion and augmentations acted in the lumbosacral joint at the level L5-

S1, 20% at L4-L5, and remaining 5% at upper lumbar levels. In this manner, the lumbar plate herniation is limited in 90% of cases to the lower two levels, with those at the L5-S1 level being twice as basic as the following upper level (Peulić et al., 2020). Most of the abnormalities in the lumbar spine identified by the radiologist with the help of MRI scans of the patients intended for further referring to the specialized doctors for their treatment. The radiologist uses both the axial and sagittal MRI images of a patient's lumbar spine for diagnostic (Unal et al., 2015). Fig.1 shows the Axial and Sagittal MRI views of the lumbar spine.

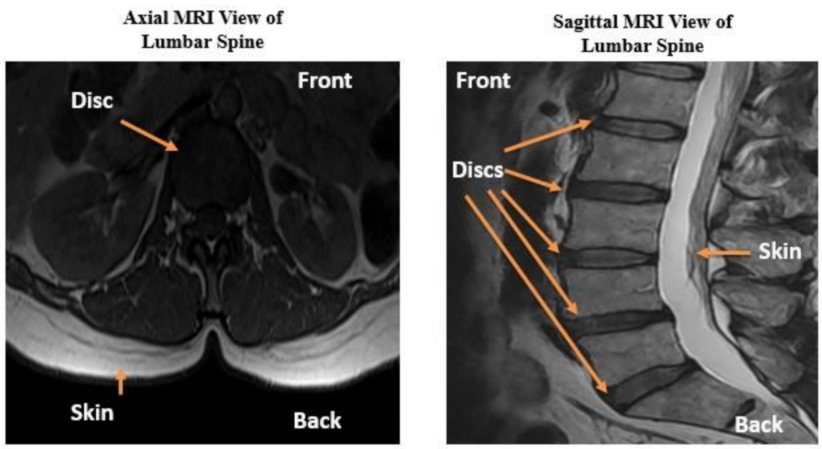


**Figure 1:** Axial and sagittal view MRI of lumbar spine

The detection of different types of diseases or injuries in the body parts of humans in MRI images is the central part of the diagnosis of many diseases and the most challenging work for radiologists. Generally, the work comprises doing the localization and identification of the MRI images in some parts of the full images. Many researchers applied different computer-aided diagnostic systems for the detection of the lumbar herniated disc through MRI images. Previously, the researchers have used a high-resolution surface coil imaging technique for a lumbar herniated disk and found the comparison of computed tomography (Unal et al., 2015). By analyzing the data of 17 patients, they discovered that surface coil MR imaging will become established as the procedure of choice for MR imaging of lumbar disc disease, and MR is the best alternative of CT and Myelography (Edelman et al., 1985).

Detection of lumbar herniated disc in MRI images is a big challenge for radiologist in today's world. Because the correct and early detection of this disease can safe human life and working patterns. MRI is the imaging modality of choice to evaluate the lumbar herniated disc and allows to identify the position, aetiology, and severity of these frequent diseases and report level-by-level these findings to referring physicians. To address this complicated challenge, the detection of lumbar herniated disc in MRI, a variety of computer-aided diagnosis techniques have been explored over the past decade for potential applicability. Many of them use various techniques including, computer aided diagnosis systems, histogram of orientated gradients, neural networks, probabilistic models, support vector machines etc., (Ghosh et al., 2012) , (Guinebert et al., 2022); (Lootus et al., 2014) and (Corso et al., 2008). However, in current study we utilize Convolutional Neural Network (CNN) models in different parameters and achieved maximum accuracy in the detection of lumbar herniated disc.

Mainly this study is conducted to answer the question that whether CNN model with parameters i.e., sequential and parallel, provides the maximum accuracy in the detection of lumbar herniated disc in MRI images? Therefore, the objective of our study was to develop an automatic system based on CNN parameters for the detection of lumbar herniated disc in MRI images.

The organization of this paper is scheduled as follows. The significance of our work and some fruitful medical image classifications are organized in the "Introduction" section. Section 2, describes the relevant literature review. Patients, data and proposed convolutional neural network with data augmentation technique, dropout, L2 regularization, accuracy and loss are explained in the "Methodology" section 3. Experiment results and evaluations tested on the MRI dataset are arranged in the "Results and Discussion" section 4 and finally, conclusions are proposed in the "Conclusion" section 5.

## LITERATURE REVIEW

Due to the incredible improvements in the field of information technology and the handling of big data, the current approaches of the detection of diseases from images using features or pattern recognitions make the use of machine learning methods essential for data analysts. In the early 1970s to 1990s, the medical image analysis performed using different types of techniques such as edge and line detectors, region growing, ellipses, and circles and fitting lines. At the end of 1990s, these techniques used training data to develop a system, were becoming increasingly popular in medical image analysis and which become much popular in the field of medical imaging (Litjens et al., 2017). Examples include Active Shape Models (ASM) for segmentation, Atlas methods, where Atlases fitted to the data from trained data, and the concept of using feature extraction and classifiers for developing computer-aided diagnostic (CAD) systems to detect different diseases. The first CAD system was a mammography device made by R2 Technology, which was also approved by the United States of America Food and Drug Administration (FDA) in 1998. After that, the commercialization of CAD systems has continued in the diagnostic imaging field (Fujita et al., 2020).

The machine learning approach is still trendy and serves as the basis of many practical, commercially available medical image analysis systems. The deep learning is an evolutionary form of an artificial neural network, which artificially models the neural network of the human brain with a computer. Deep learning has a structure that is called a CNN, which has three types of layers in it, i.e., convolution, pooling, and total connection, and staked in multiple layers. The main advantage of using deep learning in imaging analysis is that it can create features by itself through its learning process. Thus use of deep learning saves much time and provides significant accuracy (Fujita et al., 2020).

Deep learning has attracted significant attention in the medical image field; for instance, Wang and Yeung (2013) focused on the automatic detection of various diseases and tracked problems using deep learning. Some recent studies suggest that fully automated analysis of the lumbar spine is technically reasonable because the rapid inventions and developments in machine learning algorithms using computers achieve higher accuracy (Sun et al., 2017), (H. Wu et al., 2018). Some authors trained networks to detect the lumbar vertebras on labeled images with bounding boxes and positions (Kim et al., 2017) and (Oktay et al., 2013). Most deep learning methods of detecting and locating vertebras in medical images rely on an annotated dataset (Celik et al., 2013). Making preparing datasets requires different manual works. Additionally, the preparation dataset marked by their group impacts to some degree on the exactness of identification and area (Forsberg et al., 2017).

A study was conducted to automatically diagnose the disc herniation on Axial MRI. They applied CNN model with four classes, i.e., normal, extrusion, protrusion and bulge. The quality of the images has been improved using USM and CLAHE filters and the overall accuracy of the CNN model has been improved by applying Xavier parameter and batch normalization layer (Salehi et al., 2019). Concerning system structures, this study aims to classify the lumbar herniated disc in MRI data of patients using two different types of CNN structures i.e., Sequential (single-input) and Parallel (multi-input), while also capturing the effect of dropout ratio and L2 regularizers on the proposed CNN structures.

Use of neural network provided medical imaging a new and innovative way to accurately detect different types of diseases. For example, automatic detection of spinal degeneration of discs, a system was proposed by to extract silent features from MRI images of lumbar spine (Schlemper et al., 2017). In fact, CNN has led to deep learning approaches where algorithms automatically learn the relevant features from raw data at multiple different levels of abstraction to perform classification with high accuracy (Gulshan et al., 2016), (Bejnordi et al., 2017) and (Esteva et al., 2017).

In this study, we tried to build a simple and effective CNN models using parallel and sequential modeling to detect the lumbar herniated disc in MRI images. Our approach is simple and unique in many ways, i.e., nether study uses this methodology for the purpose of detection of lumbar herniated disc in MRI images, however some authors applied this technique for the detection of other diseases (Park et al., 2020), (Bae et al., 2016) and (Gao et al., 2019). Our CNN model with sequential and parallel parameters provides better data visualization and accuracy as compared with previous models. Further in this study, we use spine five vertebras in MRI images to detect the lumbar herniated disc for obtaining more clear results and accuracy.

## MATERIALS AND METHODS

### *3.1 Patients*

This study was approved by the local ethics committee (Reference number: INMOL/PA/2019). We performed a retrospective search in the INMOL hospital (Institute of Nuclear Medicine & Oncology Lahore, Pakistan) for lumbar herniated disc patients that underwent an MRI examination of the hospital MRI scanners between

January 2017 and October 2017. All consecutive 87 patients that met the inclusion criteria were included in our study, there were no exclusions. The inclusion criteria of patient's dataset in this study consists of lumbar spine sagittal MRI, which include five vertebrae. The images of separate discs are obtained by segmentation for further processing in CNN models.

### *3.2 Data and Image acquisition*

The MRI examinations performed using magnetic field 1.5 T. The dataset was in the original form of DCOM images. The sample data contains 38 patients' detailed attributes, i.e., patient sex, patient weight and age, and Echo time, etc. Signa HDxt of manufacturer GE Medical Systems scanner was used to extract MRI images of patients in a computer system. Scanning performed with 3157 Repetition Time (TR), 100 Echo Time (TE), and a Flip Angle of 90. The radiologist with vast experience (Head, Radiology, INMOL) reviewed all the data images thoroughly and gave his opinion for training and testing datasets.

### *3.3 CNN Architecture*

Deep learning is the part of machine learning as its subfield and an assortment of algorithms that are invigorated by the structure of the human brain and attempt to duplicate the elements of the human mind, which is the explanation these algorithms are a large portion of the occasions additionally named as NEURAL NETWORKS. These algorithms called DEEP as the info goes through a progression of non-direct changes before it turns into a yield. Convolutional neural network (CNN) is one such profound learning calculation in which the changes are finished utilizing an activity called "convolution".

CNN is the specifically defined structure Deep Neural Network (DNN) that uses conceptually identical training and parameter estimations. The difference of CNN and DNN lies in what happen in convolution and pooling layers, where each layer of CNN model conducts different tasks. Generally, CNN includes four types of layers in its architecture, input layer, convolutional layer (Convo+ReLU), pooling layer, and fully connected layer. Every neuron of the layer connected with a little neighborhood input, which resembles the open field in the human visual framework (Lee et al., 2019). The input layer in CNN model contains the image data which is represented by three-dimensional matrix. Convolutional layer or Convo layer is the feature extractor layer because features of the input images are extracted in this layer. Convo layer also use ReLU activation function for making all values to zero. Pooling layer (Max pooling) is used within two Convo layers for reducing the spatial volume of the input image. Once the pooled featured map is obtained from max pooling layer, the final step is to flatten it. The Flatten layer involves in transforming the whole pooled feature map matrix into a single column that is then fed to the neural network for further processing (Wu et al., 2017).

In this study, a new automatic method for detecting the lumbar disc herniation is proposed. The proposed method consists of two models shown in figure 2 and 3. Figure 2 shows model 1 of the study with single input for classification of normal and herniated disc. The proposed CNN model has input image of lumbar spine disc in 200×100 dimensions and contains three Convolutional layers followed by Maxpooling and Flatten layer. The batch size of model is 10 and 20 epochs have been selected to execute the model. Similarly figure 3, shows the architecture of the CNN model 2 of the study with multiple input (parallel). The input of model comprises of two images, one is original and other is segmented image with 200×100 dimensions each. Each model input has its own Convolutional, Maxpooling and Flatten layers. The batch size of model is 10 and 20 epochs have been selected to execute the model.

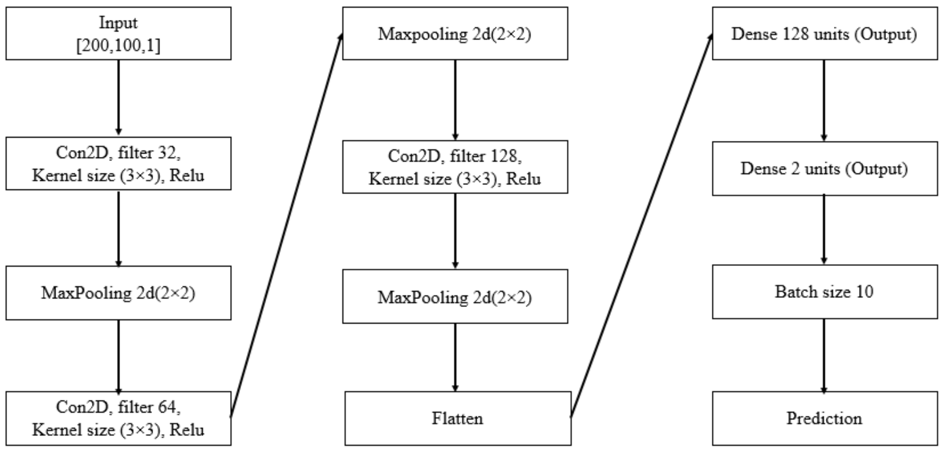


**Figure 2:** Model 1 CNN architecture diagram

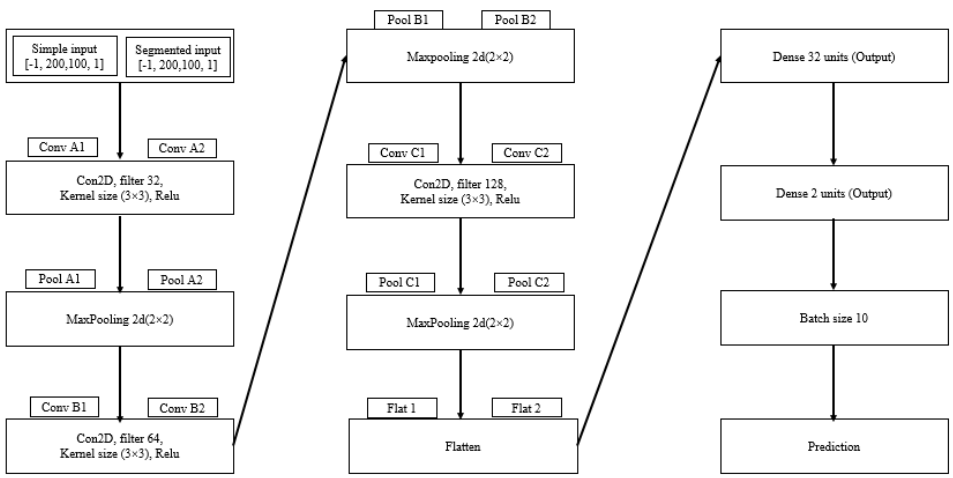


**Figure 3:** Model 2 CNN architecture diagram

### *3.4 Data Augmentation*

In order to effectively run the model, deep convolutional neural networks require a large number of training data. However the collection of such real time data is laborious and expensive and most of the large datasets are not publicly available (Taylor et., 2017). This problem can be overcome with the data augmentation technique (Yaeger et al., 1996). Data augmentation is a regularization scheme that artificially inflating the training dataset with label preserving transformations to add more invariant dataset. Data augmentation is a scheme to boost the overall convolutional neural network performance and prevent the overfitting of the CNN model

(Perez et al., 2017). The use of data augmentation technique is well suited when

the training data is limited and difficult to collect i.e., in our case, we have 87 patients MRI data for detecting the lumbar disc herniation. The 87 lumbar spine images further divided into 5 parts (L1-2, L2-3, L3-4, L4-5 and L5-S1). Thus the total number of real time image data of patients are 87×5 = 435. To overcome the problems of overfitting of CNN model and to enhance the overall performance, we applied data augmentation to our dataset. After data augmentation, we have total 9951 images out of which 2186 are herniated, and 7765 are normal disc images of 200×100 dimensions. The number of training and test images after data augmentation are 7960 and 1991 respectively.

### *3.5 Dropout*

Dropout is a well-known regularization method and has been successfully used in CNN models (Hinton et al., 2012); (Srivastava et al., 2014). The major problem arises using the small training dataset is that the trained models do not generalize well data from the test and validation data and the CNN model suffers the overfitting problem. The use of dropout ratios provides state of the art performance on CNN models and avoids overfitting (Dahl et al., 2013). Dropout prevents the overfitting of the CNN model and provides a way of about combining exponentially various network architectures efficiently. The dropout in CNN model works by dropping certain connection or probabilistically removing a neuron from the designated layers during the training process (Kubo et al., 2016). Dropout in CNN model refers to dropping out or removing the units,

temporary from the network along with all its incoming and outgoing connections. The choice of dropping the units from the network is random, where each unit is retained with a fixed probability *p* independent for other units. We use dropout 0.2, 0.3 and 0.5 in our CMM model, where optimal probability of retention is usually closer to 1.

### *3.6 L2 Regularization*

Generally, the complexed relationships among input and output pattern can be learned by deep neural networks which have many hidden layers and large number of parameters. However, the generalization ability of the CNN model is limited due to the limited data and single train criterion. To overcome this problem, we use regularizes in CNN model and improve the generalization ability. The one common way to limit the capacity of model is adding a penalty on the model parameters as the regularization term. Most common such type of parameters are L1 and L2 regularization on the weight parameters of neural networks (Shi et al., 2019). The L1 regularizer tends to shrink coefficients to zero, whereas L2 regularizer tends to shrink coefficients evenly. The L1 regularizer is useful for feature selection, whereas L2 regularizer is a useful method when we have codependent features. As in our case the features of lumbar herniated discs images are collinear or codependent, we applied L2 regularizer i.e., 0.001, 0.01 and 0.1.

### *3.7 Accuracy and Loss of CNN Model*

Accuracy is the one of matrices to measure

the performance of CNN model, such as, false positive rate, true positive rate, positive prediction value, negative prediction value, overall error rate and overall accuracy (Lever et al., 2016). Accuracy of CNN model is measured as described in equation 1.

$$Accuracy\ of\ classification = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions}\ .(1)$$

Loss in CNN model is defined as the difference between the true value and predicted value of our model. The most common loss function used in deep learning is cross-entropy (Huotari et al., 2018), shown in equation 1. Cross-entropy is also known as log loss, which measures the performance the classification of a model whose outputs are in probability values ranging between 0 and 1. The loss of CNN model increases when the predicted probability diverges from the actual label and a perfect CNN model would have a loss of 0 (Glossary, 2017). The cross-entropy is measured as indicated in equation 2.

$$Cross\text{-}entropy = -\sum_{i=1}^{n}\sum_{j=1}^{m} y_{i,j}\ log(p_{i,j})\ .(2)$$

Where $y_{i,j}$ represents true value such as , if the sample i belongs to class j and 0, otherwise and $p_{i,j}$ shows the predicted probability of

your model of the sample i belongs to class j.

## RESULTS AND DISCUSSION

We evaluated training and test accuracy and loss for single and multi-input CNN model for the classification of herniated and normal lumbar spine disc. We run the model for 20 epochs and have shown results for accuracy in Figure 4 and 5. Figure 4 shows that training accuracy of multi-input (parallel) model is 99.52% and the training accuracy of single input (sequential) model is 99.31% at 20 epochs. We can see that both the model performs almost equally in terms of training accuracy with a slight improvement in case of parallel model.

We tested our model performance for test images out of our dataset and it appears that single input (sequential) model performs better (97.16% accuracy) than multi-input (parallel) model 97.07% accuracy) slightly. This may be due to (Agarwal et al., 2020), where CNN model with single input having 3 layers is better than the other traditional detecting mechanisms like, machine learning, support vector machines, naïve bayes, random forecast, logistic regression and decision trees etc. Figure 5 shows the results of training and test loss for single

input (sequential) and multi-input (parallel) CNN model. We can see that the maximum training loss of sequential model is 0.66.9 at epoch 1 and the minimum training loss is 1.6% at epoch 18. The maximum training loss of parallel model is 46.67% at epoch 1 and the minimum training loss is 0.74% at epoch 19. Whereas on epoch 20, the test loss of sequential model (16.29%) is better than the parallel model (26.13%). We can say that the sequential CNN model also performs better in terms of minimum training and test loss.

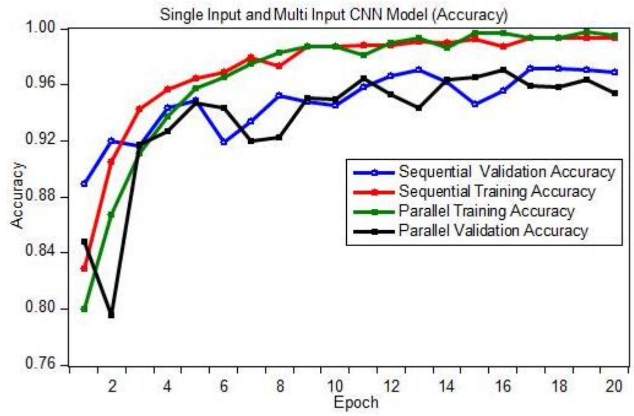


**Figure 4:** Training and test accuracy for sequential and parallel CNN model

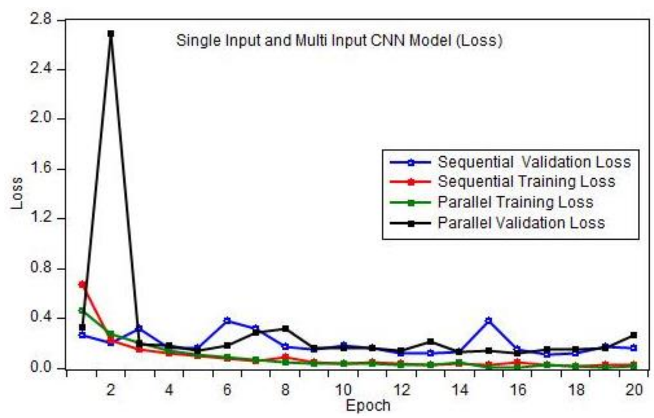


**Figure 5:** Training and test loss for sequential and parallel CNN model

In next phase, we capture the effects of the dropouts on the sequential CNN model for detecting the herniated and normal lumbar spine disc in MRI images. Figure 6 and 7 describe the accuracy and loss results of the sequential and sequential with dropouts CNN model. Figure 6 shows the accuracy of sequential and sequential model with dropouts of 0.2, 0.3 and 0.5 with 20 epochs. We can see that in terms of training accuracy, the maximum accuracy of sequential model at epoch 20 is 99.31%, and with dropouts 0.2, the training accuracy is 98.9%, with dropout 0.3, the training accuracy is 98.14% and finally with dropout 0.5, the training accuracy is 94.96%. We confirmed the same results with test accuracy i.e., sequential model test accuracy is 96.86%, and with dropout 0.2, 0.3 and 0.5, the test accuracy is 97.31%, 96.06% and 94.71% respectively. Figure 7 show the results of training and test loss of sequential and sequential model with dropouts 0.2, 0.3 and 0.5 at 20 epochs. The results indicate that sequential model with dropout 0.2 has minimum training and test loss i.e., 31.3% and 67.3%. We can see that the sequential model with dropout 0.2 performs better in terms of both accuracy and loss than other dropout ratios. This may be due to (Zhang et al., 2018), where CNN model with dropouts improves the detection accuracy of multiple sclerosis disease.

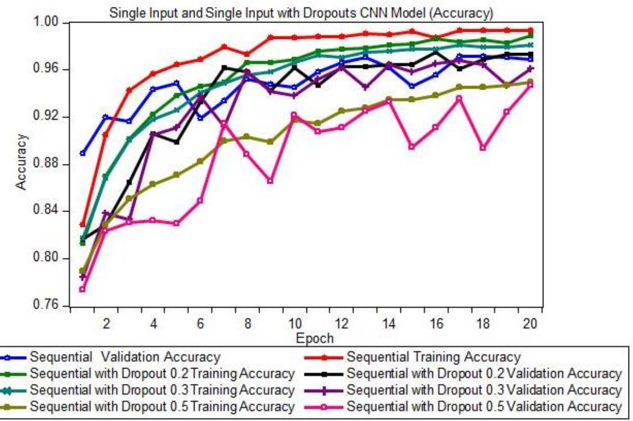


**Figure 6:** Training and test accuracy for sequential and sequential with dropout CNN model

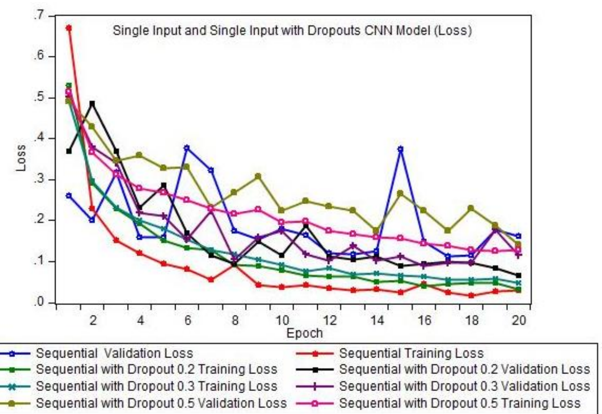


**Figure 7:** Training and test loss for sequential and sequential with dropout CNN model

Figure 8 and 9, describes the effect of L2 regularizer on accuracy and loss of sequential CNN model. For this purpose, we designed different CNN models with L2 regularizer 0.1, 0.01 and 0.001 and compare with the sequential model. Figure 8 show the results of the training and validation accuracy of sequential model and sequential model with L2 regularizers 0.1, 0.01 and 0.001. We can see that in terms of training accuracy, the maximum accuracy of sequential model at epoch 20 is 99.31%, and with L2 regularizer 0.001, the training accuracy is 97.44%, with L2 regularizer 0.01, the training accuracy is 93.39% and finally with L2 regularizer 0.1, the training accuracy is 85.86%. We validate the same results with test accuracy i.e., sequential model test accuracy is 96.86%, and with L2 regularizers 0.1, 0.01 and 0.001, the test accuracy is 94.71%, 84.83% and 85.18% respectively. Figure 9 show the results of training and test loss of sequential and sequential model with L2 regularizers 0.1, 0.01 and 0.001 at 20 epochs. The results indicate that sequential model with L2 regularizer 0.001 has minimum training and test loss i.e., 22.12% and 30.09%. We can see that the sequential model with L2 regularizer

0.001 performs better in terms of both accuracy and loss than other L2 regularizers ratios. This may be due to (Albahar, 2019), where CNN model with L2 regularizer improves the accuracy of skin lesion classification.

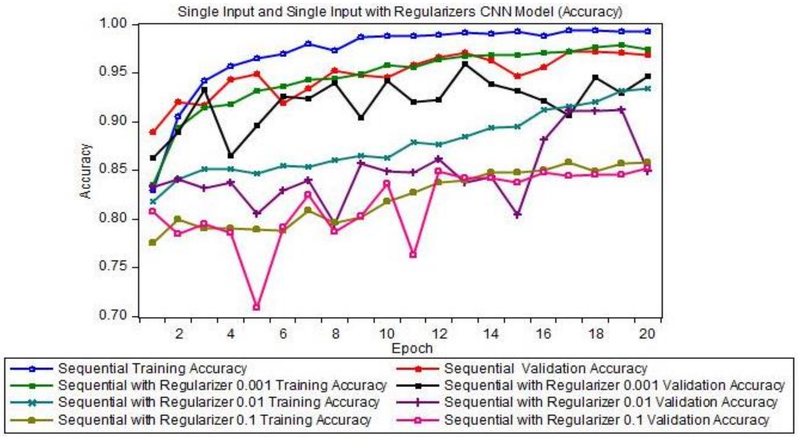


**Figure 8:** Training and test accuracy for sequential and sequential with L2 regularizers CNN model

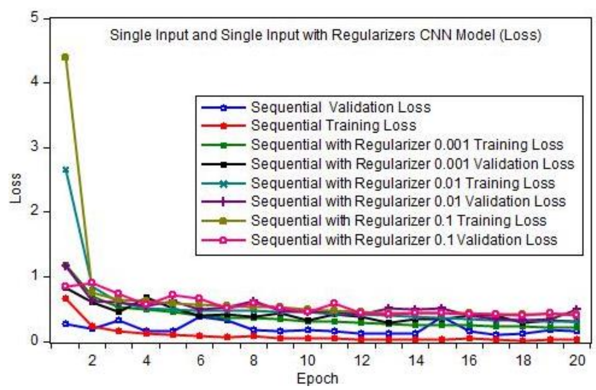


**Figure 9:** Training and test loss for sequential and sequential with L2 regularizer CNN mode

Next, we capture the effects of the dropouts on the parallel CNN model for detecting the herniated and normal lumbar spine disc in MRI images. Figure 10 and 11 describes the accuracy and loss results of the parallel and parallel with dropouts CNN model. Figure 10 show the accuracy results of parallel and parallel model with dropouts of 0.2, 0.3 and 0.5 with 20 epochs. We can see that in terms of training accuracy, the maximum accuracy of parallel model at epoch 20 is 99.52%, and with dropouts 0.2, the training accuracy is 92.9%, with dropout 0.3, the training accuracy is 92.66% and finally with dropout 0.5, the training accuracy is 89.75%. We validate the same results with test accuracy i.e., parallel model test accuracy is 95.38%, and with dropout 0.2, 0.3 and 0.5, the test accuracy is 88%, 83.93% and 77.5% respectively. Figure 11 show the results of training and test loss of parallel and parallel model with dropouts 0.2, 0.3 and 0.5 at 20 epochs. The results indicate that sequential model with dropout 0.2 has minimum training and test loss i.e., 48.71% and 58.87%. We can see that the parallel model with dropout 0.2 performs better in terms of both accuracy and loss than other dropout ratios.

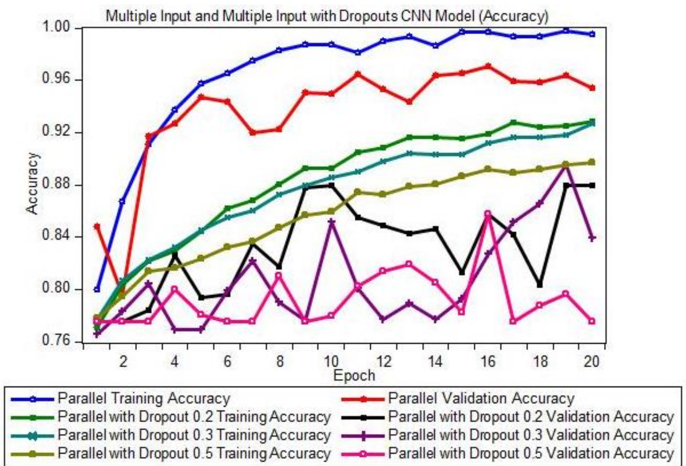


**Figure 10:** Training and test accuracy for parallel and parallel with dropouts CNN model

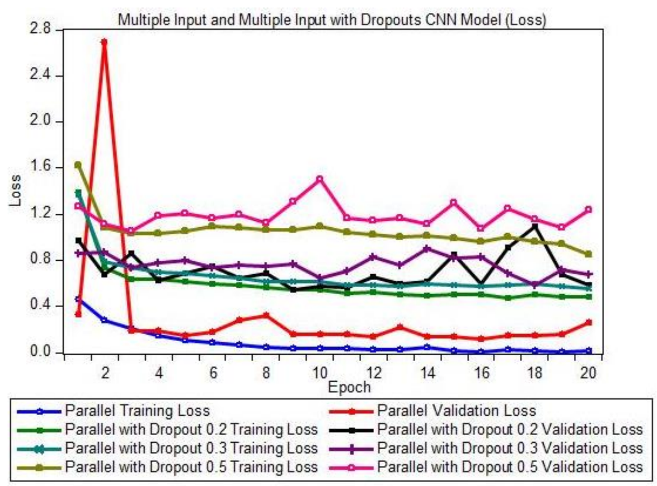


**Figure 11:** Training and test loss for parallel and parallel with dropouts CNN model

Figure 12 and 13, illustrates the effect of L2 regularizers on the training and test accuracy and loss of parallel CNN model. For this purpose, we designed different parallel CNN models with L2 regularizers 0.1, 0.01 and 0.001 and compare with the parallel model.

Figure 12 show the results of the training and test accuracy of parallel model and parallel model with L2 regularizers 0.1, 0.01 and 0.001. We can see that in terms of training accuracy, the maximum accuracy of parallel model at epoch 20 is 99.52%, and with L2 regularizer 0.001, the training accuracy is 97.84%, with L2 regularizer 0.01, the training accuracy is 94.47% and finally with L2 regularizer 0.1, the training accuracy is 86.39%. We validate the same results with test accuracy i.e., parallel model test accuracy is 95.38%, and with L2 regularizers 0.1, 0.01 and 0.001, the test accuracy is 92.11%, 95.13% and 85.28% respectively. Figure 13 show the results of training and test loss of parallel and parallel model with L2 regularizers 0.1, 0.01 and 0.001 at 20 epochs.

The results indicate that sequential model with L2 regularizer 0.001 has minimum training and test loss i.e., 17.89% and 35.50%. We can see that the parallel model with L2 regularizer 0.001 performs better in terms of both accuracy and loss than other L2 regularizers ratios.

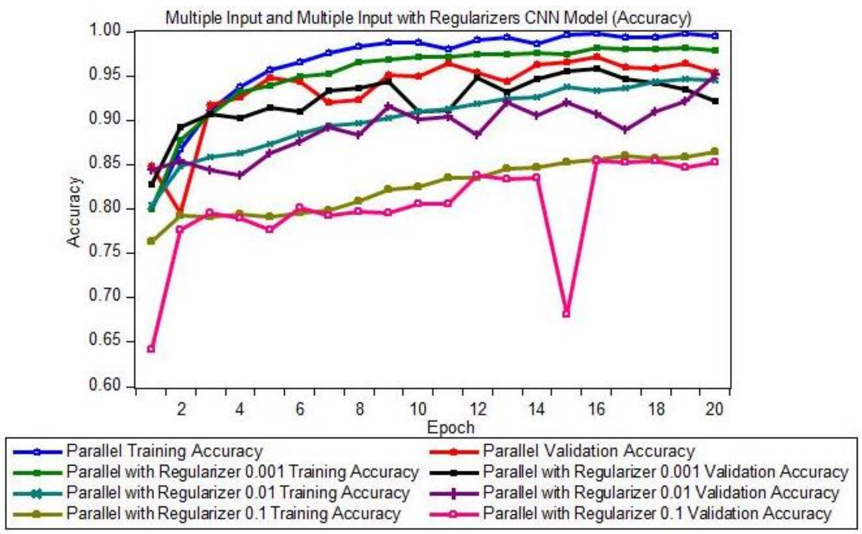


**Figure 12:** Training and test accuracy for parallel and parallel with L2 regularizer CNN model

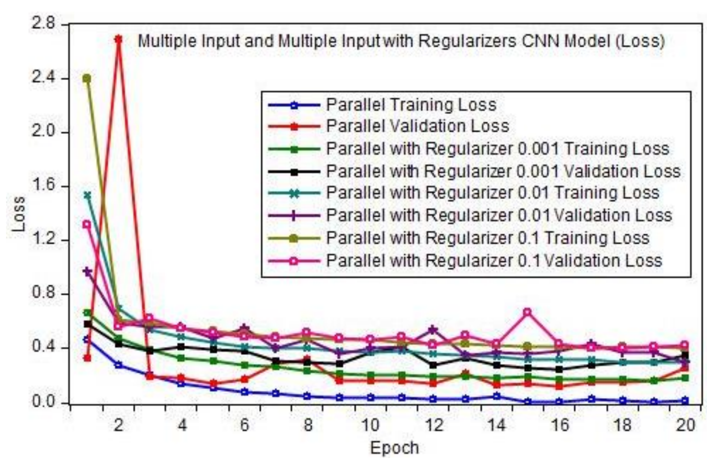

**Figure 13:** Training and test loss parallel and parallel with L2 regularizer CNN model

Finally, we combine the results of models from figure 4 to 13 and choose the best model with accuracy and loss with dropouts and L2 regularizer and shown in figure 14 and 15. Figure 14 illustrates the accuracy of CNN models under different parameters i.e.,

sequential, parallel, sequential with optimal dropout (0.2), sequential with optimal L2 regularizer (0.001), parallel with optimal dropout (0.2) and parallel with optimal L2regularizer (0.001). We can see that in terms of training accuracy parallel CNN

model is best having 99.52% training accuracy of the classification of normal and herniated disc at 20 epochs. The second-best training accuracy after parallel CNN model is 99.31% of sequential model and after that 98.9% training accuracy of sequential model with dropout 0.2 and 97.84% of parallel model with L2 regularizer 0.001 at 20 epochs. For validating the results, we can see that the best test accuracy is 97.31% of sequential CNN model with dropout 0.2 at 20 epochs. After that sequential and parallel CNN models provides the best test accuracy i.e., 96.86% and 95.38% respectively. By concluding the results, we found that sequential and sequential CNN model with dropout 0.2 provides the optimal accuracy both in terms of training (99.31%, 98.9%) and test (96.86%, 97.31%) for the classification of normal and herniated disc. Figure 15 describe the results of training and test loss of sequential, parallel, sequential with optimal dropout (0.2), sequential with optimal L2 regularizer (0.001), parallel with optimal dropout (0.2) and parallel with optimal L2 regularizer (0.001) CNN models. We found that parallel (14.5%), sequential (29.4%) and sequential CNN model with dropout 0.2 (31.3%) provides the minimum training loss. Whereas in terms of test loss, the sequential model with dropout 0.2 (67.3%), sequential (16.29%) and parallel (26.13), CNN models have minimum test losses. By summarizing the results, we found that as we increase the L2 regularizers in the CNN model the training and test loss increases and the accuracy of the model decreases and vice versa. Similarly, if we increase dropout ratio of the CNN model the training and test loss increases and the accuracy of the model decreases and vice versa.

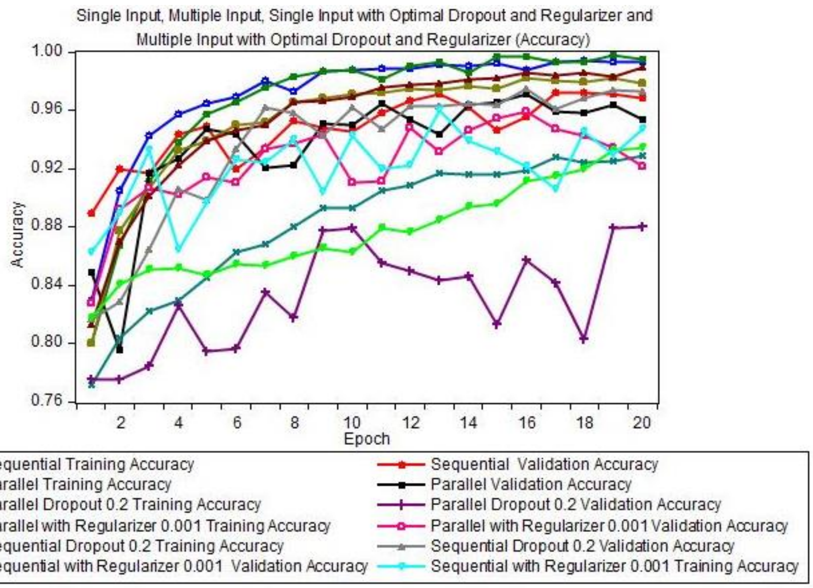


**Figure 14:** Training and test accuracy for single input and single input with L2 regularizer CNN model

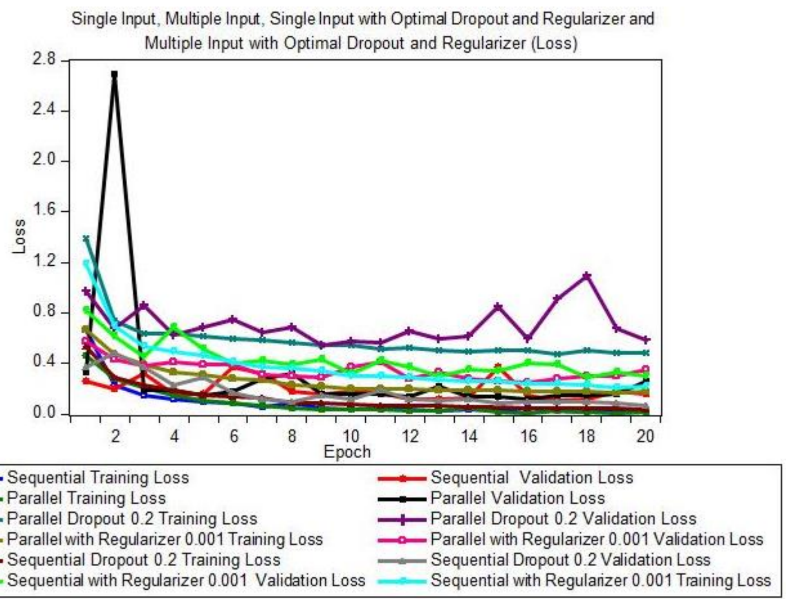


**Figure 15:** Training and test loss for single input and single input with L2 regularizer CNN mode

## CONCLUSION

The objective of this study was to develop an automatic system for the detection of lumbar herniated disc in MRI images and the use of CNN architecture under parallel and sequential parameters for obtaining maximum accuracy in disease detection. For more clarity and accurate in the detection process, we use five vertebra of human lumbar spine. The purpose of this study is to create a decision system that can help the physicians in terms of accuracy and speed of diagnosis of the lumbar herniated disc. Our proposed CNN models are employed to produce the two classes of lumbar spine MRI (Normal or Herniated). We conclude that when we apply simple 3 layers CNN model to augmented dataset of lumbar spine discs images, the results show higher accuracy 99.31% (training accuracy) and 96.86% (test accuracy) both in terms of training and test, and when we apply parallel model, the classification accuracy is also high i.e., 99.52% (training accuracy) and 95.38% (test accuracy) as compared to when we add dropouts and regularizers in CNN model. We can further improve the classification accuracy by executing our model in more than 20 epochs. Moreover, we can improve the accuracy our parallel CNN of model, by adding real dataset images instead of augmented images. In future, we can apply parallel CNN model to detect different types of diseases.

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