Classification of Scoliosis based on Multiclass SVM Model

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Abstract: **Scoliosis is defined as a sideways curvature of the vertebral column. The current clinical approach uses radiographic images to determine the type of spine deformity and the severity of scoliosis is assessed by Cobb's Angle. There are different types of scoliosis based on the region of bend such as thoracic, thoracolumbar, lumbar, and double major. Classification of scoliosis is of utmost importance for guiding the treatment of scoliosis. This paper proposes an automated scoliosis classification system based on a multiclass SVM model that uses pretrained deep neural networks as a feature extractor and a multi svm model to classify the scoliotic images into three categories Thoracic, Thoracolumbar, and Lumbar. A comparison was done using three pre-trained DNN.Statistical measures such as accuracy, Precision, Recall, and F1score were calculated and tabulated for each of them for performance evaluation.**

IndexTerms **-Cobb's angle, Classification, Deep Neural Networks, Feature Extraction, Multiclass SVM model, Scoliosis**

I. INTRODUCTION

Scoliosis is a deformity of the spine. It is defined as a sideways curvature of the vertebral column. It is a combination of angular and lateral displacement the curve is usually S or C shaped over three dimensions. Conventionally, X-ray imaging has been used for detection, categorization and monitoring of scoliosis. [1].
Classification of scoliosis helps in guiding the treatment of the scoliotic patients Scoliosis can be classified based on the region of the bend such as thoracic, thoracolumbar and lumbar as shown in Fig 1.Some of the existing classification algorithms that have been developed proposes the application of advanced image processing techniques to automate quantification of spinal curvature [1]. In [2] Lin proposes a multilayer feed forward artificial neural network that was implemented to identify the classification patterns of the scoliotic deformity. In [3], Deep learning has been used to develop an automatic scoliosis diagnosis and measurement
In [4] semi-automated approach was proposed for accurate estimation of Cobb angles from scoliosis radiographs using a difference matrix. Vaibhav Tiwari et al implemented a modified version of VGG16 model to classify an image into one of the categories like living and non-living.
V. Pomponiu et al in [6] proposed the use of pretrained deep neural network (DNN) for the detection of skin lesion malignancy.
From [6] it can be inferred that DNN can be combined with a classifier as feature extractor. In this paper, we investigate a classification system that employs a pretrained DNN, to extract features from the scoliotic spine imagery and classify them as thoracic, thoracolumbar or lumbar.The contents of this paper are organized into five sections. Section I gives an introduction about scoliosis and its different types, Section II deals with the architecture of the pretrained DNN. Section III briefs about the proposed methodology and Section IV consist of performance evaluation and Section V concludes the paper.

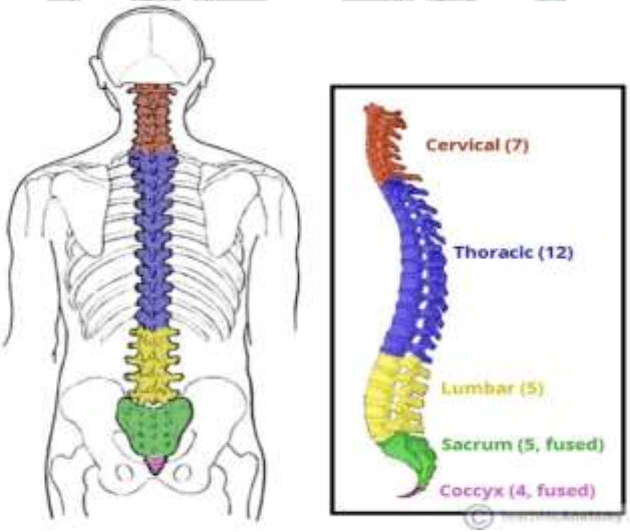

Figure 1:Illustrating the different regions of spine

II. PRETRAINED DEEP NEURAL NETWORK

In the proposed work three pre-trained DNN's have been applied. The features extracted from the earlier layers of these networks are passed on to the multiclass SVM classifier

ALEX NET

Alex Net is a 8 layers deep network consisting of 5 convolutional layers and 3 fully connected layers having an image input size of 227x227. Figure 2 represents the architecture of Alex net.

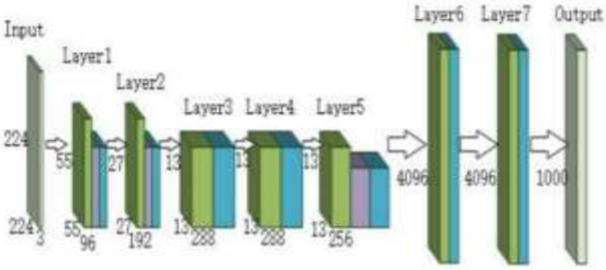

Figure 2:structure of alex net

SQUEEZE NET

Squeeze net is a convolutional neural network with a depth of 18 layers It has a smaller architecture that uses fewer parameters while maintaining competitive accuracy. The fire modules are applied to squeeze the parameters. Fire-modules are used to squeeze in the parameters. Figure 3 represents the architecture of squeeze net

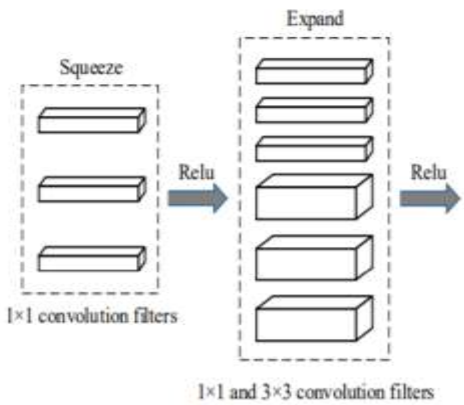

Figure 3:Squeeze Net Architecture

VGG-19

VGG-19 convolutional network having a depth of 19 layers with image input size 224 x224.It is a series network with 16 convolutional layers and 3 fully connected layers. There are five variants of VGG networks. Figure 4 shows the architecture of VGG 19 network.

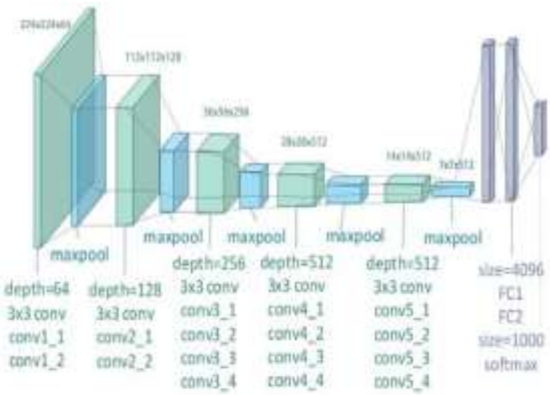

Figure 4:VGG 19 Architecture

III. PROPOSED METHODOLOGY

This study has been performed on the scoliotic image database downloaded from the Kaggle repository. A total of 54 spine x ray imageries have been used for the study which were categorized into three folders labelled thoracic, thoracolumbar and Lumbar by observing the apex of the spine imagery .23 of them were categorized under thoracic,16 of them under thoracolumbar and 15 of them under lumbar. A pretrained deep neural network (DNN), is used as a feature extractor for the scoliotic x ray image dataset. The features extracted are passed on to the multiclass SVM model for classification. The main reason to use this method is due to the small size and different kind of dataset used.

Figure 5 represents the block diagram of the overall methodology.

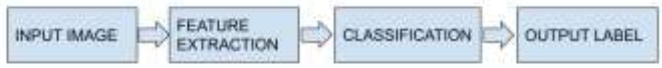

Figure 5:Overall Methodology

Load the data

The database was downloaded from the Kaggle website were used for the study. The images are unzipped and stored as an image datastore. The images are automatically labelled by the image datastore based on folder names and the data is stored as an image datastore object. The data is splitted into 70% training and 30% testing. The fig 6 and fig 7 represent the number of images used for training and testing.

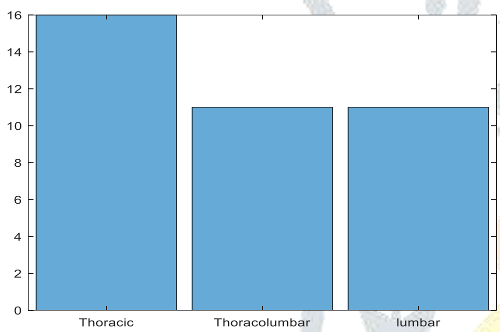

Figure 6: Training images

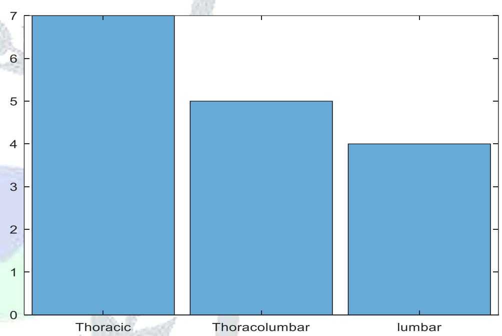

Figure 7: Test images

Load the Pretrained Network

A pretrained network which is trained on more than 1000 images i.e., Alex net, VGG 19, squeeze net is loaded into the MATLAB workspace and a prerequisite of the deep learning toolbox support package is needed

Feature Extraction using the pretrained DNN

The input images are resized to the image input of the pretrained DNN. As the pretrained networks are not trained with the spine imageries, the features are extracted from the earlier layers for better accuracy. The features of the layers are extracted from the activations.

Fitting the Image classifier

The extracted features calculated from the training images are used as the predictor variables and fits a multiclass support vector machine (SVM) using error correcting output model which minimizes the categorization of three classes to a set of binary classification problem ECOC classification requires a coding design, which determines the classes that the binary learners train on, and a decoding scheme, which determines how the results (predictions) of the binary classifiers are aggregated.Learner 1 trains on observations in Class 1 or Class 2, and treats Class 1 as the positive class and Class 2 as the negative class. The other learners are trained similarly.Table-1 shows the coding design of the learners

Table 1:Coding design matrix

	AB	AC	BC
Thoracic(A)	1	1	0
Thoracolumbar(B)	-1	0	1
Lumbar (C)	0	-1	-1

Classification of the test images

Classify the test images using the trained SVM model using the shallower features from the test images

IV. RESULTS AND DISCUSSIONS

The proposed work uses pretrained DNN for feature extraction and the extracted features are passed on to the multiclass support vector machine using ECOC model.38 scoliotic x ray images were used for training and 16 images were used for testing. Alex net, squeeze net and vgg19 networks were deployed for feature extraction and the extracted feature were passed on to the classifier to classify the spine imagery into thoracic, thoracolumbar and lumbar. Statistical parameters precision, recall, f1score and accuracy has been tabulated and plotted for each of the networks as shown in fig 8. The statistical parameters are calculated from the confusion matrix as shown in fig 9.

Accuracy

Accuracy is measured as a proportion of number of correctly predicted samples to the total number of samples. The accuracy of each model has been tabulated as shown in Table 2.

Table 2:Accuracy tabulated for each model

DNN	Accuracy		
	Thoracic	Thoracolumbar	Lumbar
Alexnet	57.14	28.57	28.57
Vgg19	28.57	57.14	28.57
Squeezenet	42.86	28.57	42.86

Precision

Precision is also called the Positive Predictive Value (PPV). It is measured as the ratio of correct positive prediction to total number of predicted positive. Precision of each model has been tabulated as shown in Table 3

Table 3:Precision values tabulated for each model

DNN	Precision		
	Thoracic	Thoracolumbar	Lumbar
Alexnet	57.14	33.33	66.66
Vgg19	66.66	44.44	50
Squeezenet	75	28.57	60

Recall

Recall also known sensitivity is measured as the ratio of correct positive predictions to the total positives samples. Recall has been tabulated for each model as shown in Table 4.

Table 4:Recall tabulated for each model

DNN	Recall		
	Thoracic	Thoracolumbar	Lumbar
Alexnet	57.14	40	50
Vgg19	28.57	80	50
Squeeze net	42.85	40	60

F1 Score

F1 score is the harmonic mean of the model's Precision and Recall. The F1 score for each of the model is tabulated as shown in Table 5.

Table 5:F1 score for each of the model

DNN	F1 Score		
	Thoracic	Thoracolumbar	Lumbar
Alexnet	57.14	36.36	66.66
Vgg19	40	57.14	50
Squeezenet	54.54	33.33	66.66

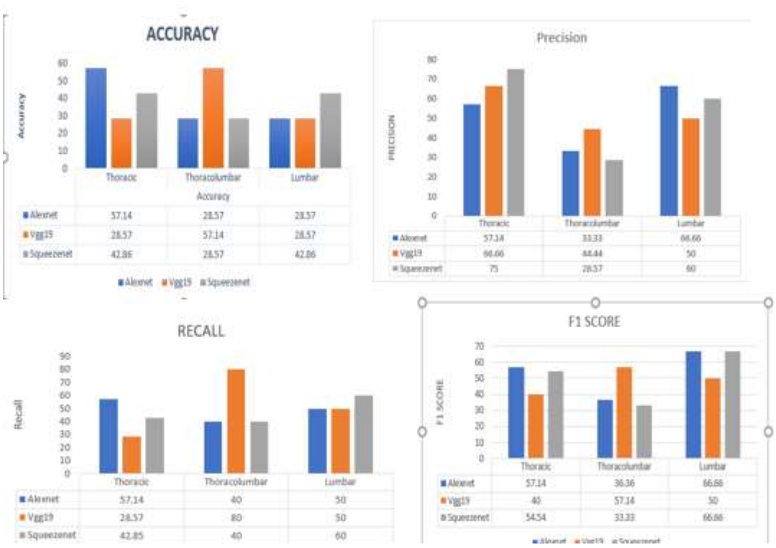

Figure 8 :Statistical parameters plotted for each model

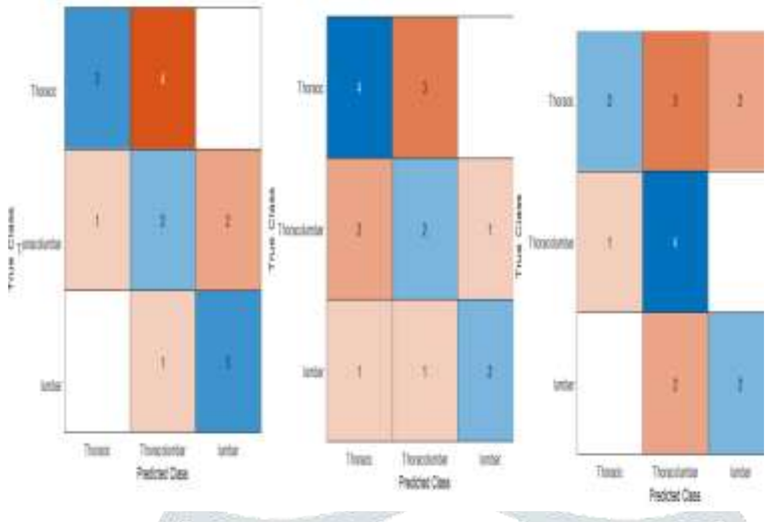

Figure 9: confusion matrix for each of the models

V. CONCLUSION

Alex net and Squeeze Net showed higher accuracy for thoracic and lumbar type of scoliosis. VGG-19 net showed higher accuracy for thoracolumbar type of scoliosis. Squeeze Net and Vgg 19 showed higher precision for thoracic type of scoliosis .Alex Net showed higher precision for lumbar type of scoliosis Alex Net and Squeeze Net showed higher sensitivity for Thoracic type of scoliosis. Vgg 19 showed higher sensitivity for thoracolumbar type. Squeeze Net showed higher sensitivity for lumbar type of scoliosis. An overall accuracy of 50% was achieved. It can be concluded that a better accuracy can be obtained by using a larger dataset

VI. ACKNOWLEDGMENT

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