Analysis and Classification of Abnormal Vertebral Column by Convolutional Neural Network Algorithm
การวิเคราะห์และการจำแนกกระดูกสันหลังที่ผิดปรกติด้วยขั้นตอนวิธีโครงข่ายประสาทสังวัฒนาการ

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ABSTRACT

This research applied the convolutional neural network (CNN algorithm) to determine the misalignment of vertebral column from the processed image. The raw data was the 3D-computerized tomography (CT) provided by the Suranaree University of Technology Hospital, Nakhon Ratchasima, Thailand. There were 93 data sets that comprised 40 data of misalignment vertebral columns. These studies first extracted front, rear, left, and right images of the vertebral column from 3D CT images by RadiAnt Program (Version 2020.2). In the second step, the images were processed by the Ridge detection algorithm with various parameters. The combinations processed were of sigma 1, 4, 7, and 10 with the two low-high thresholds, 10-30 and 20-20. The last step was about the Python code development (with Tensorflow, Numpy, and Sklearn libraries) for creating the model to classify the normal and abnormal vertebral column image sets by the CNN algorithm. The best model could perform very well. The model with Ridge detection preprocessing of parameters sigma=7, low threshold=20, and high threshold=20 performed faultlessly. The performance was accuracy 100 percent, precision 100 percent, and recall 100 percent.

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Ridge detection (ขั้นตอนการตรวจหาสันภาพ),
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บทคัดย่อ

งานวิจัยนี้เป็นการประยุกต์ใช้ขั้นตอนวิธีของโครงข่ายประสาทเทียมแบบสังวัฒนาการ (CNN algorithm) กับภาพทางการแพทย์ เพื่อใช้ในการจำแนกและวิเคราะห์การเรียงตัวของกระดูกสันหลังมนุษย์ด้วยภาพเอกซเรย์คอมพิวเตอร์ CT (Computerized Tomography) ข้อมูลที่ใช้ในการวิจัยเป็นภาพเอกซเรย์คอมพิวเตอร์และข้อมูลการวิเคราะห์ความผิดปรกติกระดูกสันหลังของผู้ป่วยได้รับการสนับสนุนจากโรงพยาบาลมหาวิทยาลัยเทคโนโลยีสุรนารี นครราชสีมา ประเทศไทย การศึกษานี้มุ่งเน้นไปที่การจัดเรียงตัวของกระดูกสันหลังโดยเฉพาะกระดูกสันหลังส่วนคอ (C1-C7) วิธีการดำเนินการประกอบด้วย 2 กระบวนการหลัก กระบวนการแรกคือการประมวลผลภาพ เพื่อเลือกลักษณะสำคัญของภาพทางการแพทย์ออกมา ภาพ 3D เอกซเรย์คอมพิวเตอร์ทั้งหมดใช้โปรแกรม RadiAnt ในการศึกษาลักษณะของภาพในสี่ มุมมองได้แก่ ด้านหน้า ด้านหลัง ด้านขวา และด้านซ้าย หลังจากนั้นนำภาพที่ได้เข้าสู่การตรวจหาสัน (Ridge detection) เพื่อแสดงลักษณะสำคัญของการจัดเรียงตัวของกระดูกสันหลังจากภาพ โดยการปรับพารามิเตอร์ที่แตกต่างกันในแต่ละแบบจำลอง จำนวน 8 แบบจำลอง พารามิเตอร์ประกอบไปด้วยซิกมา 1, 4, 7 และ 10 ตามลำดับ ค่าเกณฑ์ต่ำและค่าเกณฑ์สูงคือ 10-30 และ 20-20 ตามลำดับ ในขั้นตอนสุดท้ายคือการสร้างแบบจำลองขั้นตอนวิธีโครงข่ายประสาทสังวัฒนาการด้วยภาษา Pythonร่วมกับไลบารี (Tensorflow, Numpy, & Sklearn) ที่ได้รับการพัฒนาเพื่อจำแนกการจัดแนวกระดูกสันหลังของมนุษย์ที่ปรกติและผิดปรกติจากภาพที่ผ่านการประมวลผล จากผลการศึกษาการสร้างแบบจำลองการวิเคราะห์และการจำแนกกระดูกสันหลังที่ผิดปรกติด้วยขั้นตอนวิธีของโครงข่ายประสาทเทียมแบบสังวัฒนาการพบว่าแบบจำลองที่ดีที่สุดสามารถทำงานได้ดีมาก อีกทั้งยังเป็นแบบจำลองที่สามารถทำนายได้อย่างไม่มีข้อผิดพลาดด้วย 7 Sigma 20 low threshold และ 20 high threshold ซึ่งประสิทธิภาพการวิเคราะห์และจำแนกความผิดปรกติประกอบไปด้วยความแม่นยำร้อยละ 100 ความถูกต้องร้อยละ 100 และค่าเรียกคืนร้อยละ 100

Introduction

A vertebral column is built up of 24 small bones, which are called vertebrae. They are stacked on each other to from a column. A proper vertebral column is typically curved. The curves help the column absorb stress from both movement and gravity in the human body (Miele, Witiw, Badhiwala, & Fehlings, 2012 .(When a vertebral column malformation occurs, the natural curvatures of the vertebral column misalign in a certain area, as the occurrence with lordosis, kyphosis, and scoliosis (Rochester, 2009).

The abnormality of the human vertebral column can be predicted and identified by an orthopedic doctor. Sometimes, the process of vertebral column diagnosis can be done by a variety of techniques in medical imaging such as x-ray imaging, computerized tomography (CT) imaging, and magnetic resonance imaging (MRI) (Preim & Botha, 2014). The most appropriate technique used is the CT image, which is capable of indicating the abnormal point of computerized tomography and provides an identifiable root cause to an issue (Goel, Yadav, & Singh, 2016). This valuable information helps the doctor in the rapid treatment and recovery of the patient's injury. Conversely, the traditional diagnosis relies solely on the specialist. However, the patients still face a shortage of doctors in the orthopedic department and a lack of such in rural areas (Miller, 2019). In attempting to address this problem, many researchers try to use artificial intelligence (AI) as an established platform. The platform combines big data and systematic analysis (Dey, 2016; McCoy, Dupont, Gros, Cohen-Adad, Huie, Ferguson, Duong-Fernandez, Thomas, Singh, Narvid, Pascual, Kyritsis, Beattie, Bresnahan, Dhall, Whetstone, & Talbott, 2019). The advantages of AI are thinking as human thinking, without human error. Many researchers are interested in using AI for detecting an abnormal organ in the patient. Padhy et al. (2019) reviewed the use of AI in the diagnosis of diabetic retinopathy. Romiti, Vinciguerra, Saade, Anso Cortajarena, & Greco (2020) reviewed the AI techniques such as machine learning and deep learning to help in cardiovascular imaging. Pankhania (2020) reviewed the use of AI in Musculoskeletal radiology, which is a radiological technique for the diagnosis of muscle damage, bone fractures, bone tumors, musculoskeletal infection, and other diseases. Tanzi, Vezzetti, Moreno, & Moos (2020) reviewed the research of different deep learning techniques to classify bone fractures. Kokkotis, Moustakidis, Papageorgiou, Giakas, and Tsaopoulos (2020) also provided a variety of Machine Learning techniques on the diagnosis and predictions of knee osteoarthritis. Larhmam, Benjelloun, & Mahmoudi (2013) used the K-means clustering algorithm for classifying the abnormal cervical vertebrae column. Many reviews show that even though AI is a powerful tool in the medical imaging diagnosis process, it still relies on many image processing techniques. There are also many applications of image processing to medical images. Staal et al. (2004) applied image ridge detection to retinal images, which were able to screen for diabetic retinopathy. Nerysungnoen and Tanthanuch (2015) classified noises in computed radiography images. That helps in the digital image enhancement. In addition, Das, Nirmala, & Medhi (2016) applied 3 image processing techniques, which were mathematical morphology, regional glowing, and watershed transformation, to diagnose glaucoma (a chronic eye disease that causes blindness).

In this study, we focused on developing the process for the classification of abnormal vertebral column CT scan images. The preprocessing part concerned the Ridge Detection technique. The process used a well-known AI algorithm, Convolutional Neural Network (CNN), to make a model to identify between the normal and misaligned columns from the prepared information. The obtained models would be analyzed for performance regarding the accuracy, precision, and recall values.

Demographics of the abnormal vertebral column

The researched demographics were consented to by all patients admitted for cervical vertebrae injury (fracture-dislocation injury) at Suranaree University of Technology Hospital between January 2017 and January 2020 (3 years). The research implementation complied with the international guidelines for human research protection. All aspects were approved by the Suranaree University of Technology Human Research Ethics Committee. The CT images were 93 images in total, of which 53 were normal patients (Alignment characteristics) and 40 abnormal patients (Misalignment characteristics). The detail of the patient demographics and the vertebral characteristics were summarized in Table 1. The CT image and clinical report displayed the alignment characteristics of the cervical vertebral column. Inclusion criteria of the research were the following: 1) cervical vertebral column, 2) alignment of vertebral criteria, 3) the CT image of the cervical vertebral column, and 4) the monitoring record of the SUT orthopedic physician. Exclusion criteria were the following: 1) other vertebral column parts, and 2) other vertebral column monitoring record.

Table 1. Vertebral column characteristics of patient demography were supported by Suranaree University of Technology Hospital

No.	Vertebral Characteristics	Number of patients
1.	Alignment	53
2.	Misalignment	40

Materials and Methods

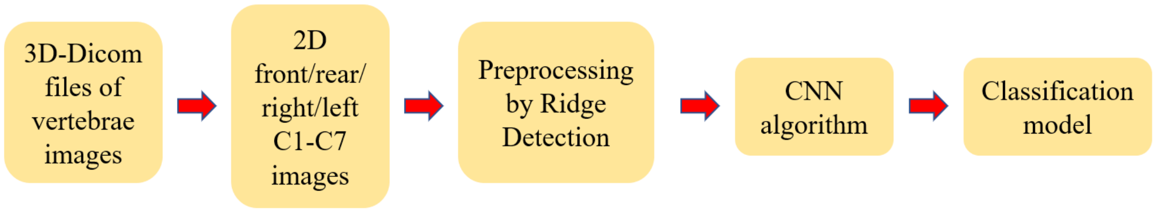

Figure 1 Overall classification methods schematic

CT-Images

The CT image was created by using RadiAnt Program. The program displayed a medical image file that was digital imaging and communications in medicine (DICOM). We gained a 3D image. Then, we set the point of the viewer for analysis and classification. The viewer position was front, rear, right, and left side (PNG File). All CT imaging of the research was performed on a multi x-ray scanner with CT Application Software (APPS) Version 15HW25.2_SP2-0-1.H40-P2_SS64_G_GMV (General Electric, USA). Only the front, rear, right, and left sides of C1 - C7 vertebral columns were used for image analysis. It was performed with the following parameters: axial C1 - C7; slice thickness 2.5 mm, echo - train length 16, FOV *32, nominal in - plane pixel size 512*512 mm^2. Other non-specified alignment performance values of the CT images were not evaluated for inclusion in this research.

Image processing by Ridge Detection

The CT image was extracted by the Ridge Detection technique. This technique emphasized the essential characteristics of the CT image. The technique captured the structure image and was reflected via ridges, valleys, and critical points. This study used Ridge detection algorithms from the Ridge Detector program (Sage & Unser, 2003). The parameters of Ridge Detection were adjusted by the hysteresis thresholds which were sigma, high and low thresholds. In the study, we designed eight models. 8 models were shown in Table 2. By the preliminary process, it was found that each step-up of sigma provided similar Ridge detection images. Then, for sigma of 1, 4, 7, and 10, the processed images are significantly different. Figure 6 represented alignment characteristics and misalignment characteristics for the generating model.

Table 2. The hysteresis thresholds of Ridge Detection consisted sigma, high and low thresholds

Models	Sigma	Threshold	
		Low	High
1	1	10	30
2	1	20	20
3	4	10	30
4	4	20	20
5	7	10	30
6	7	20	20
7	10	10	30
8	10	20	20

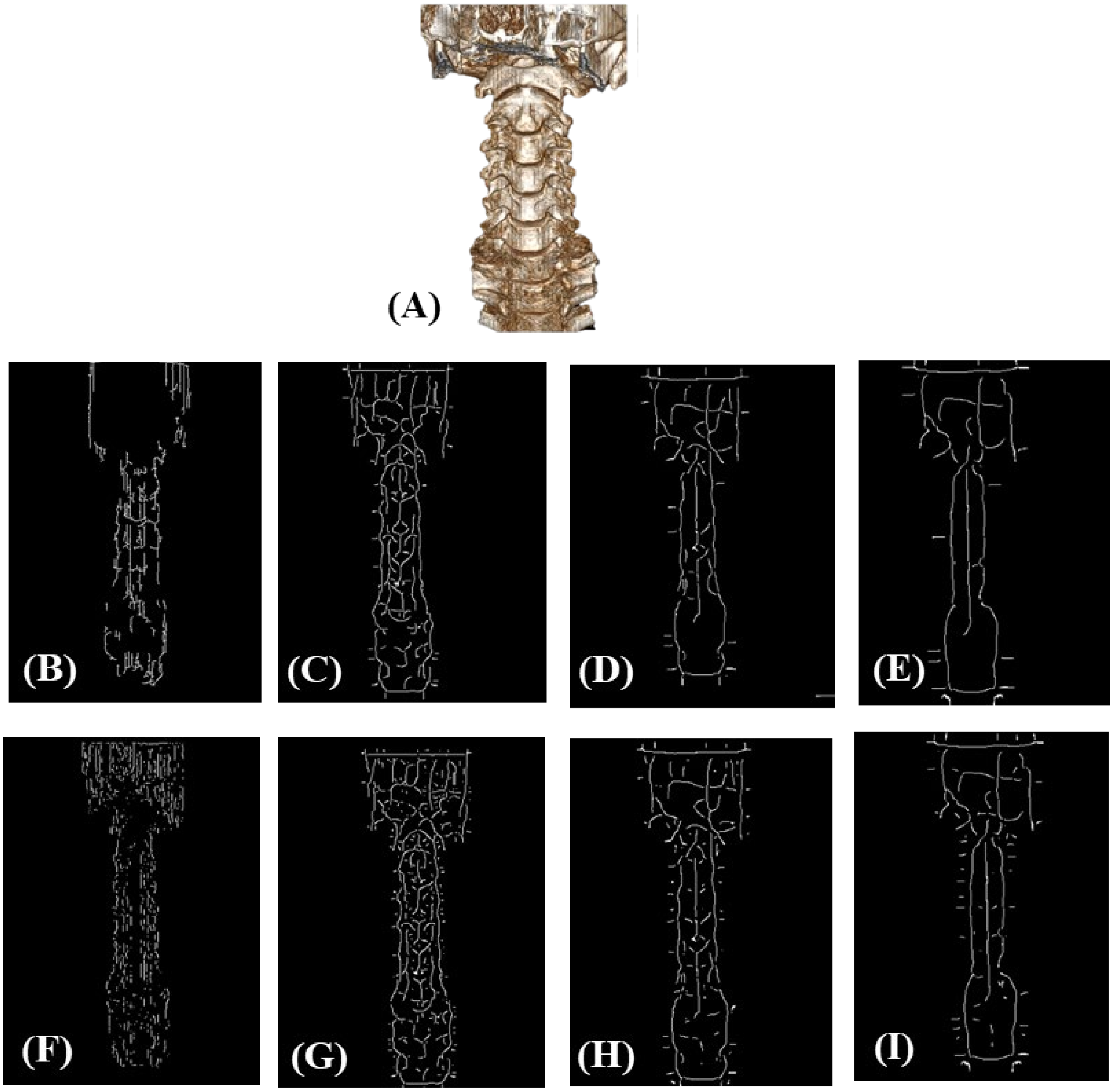

Figure 2 Ridge Detection technique generated the extracted images. 8 models were demonstrated in the front view ((A) CT scan image, (B) model 1, (C) model 2, (D) model 3, (E) model 4, (F) model5, (G) model 6, (H) model 7 and (I) model 8, respectively)

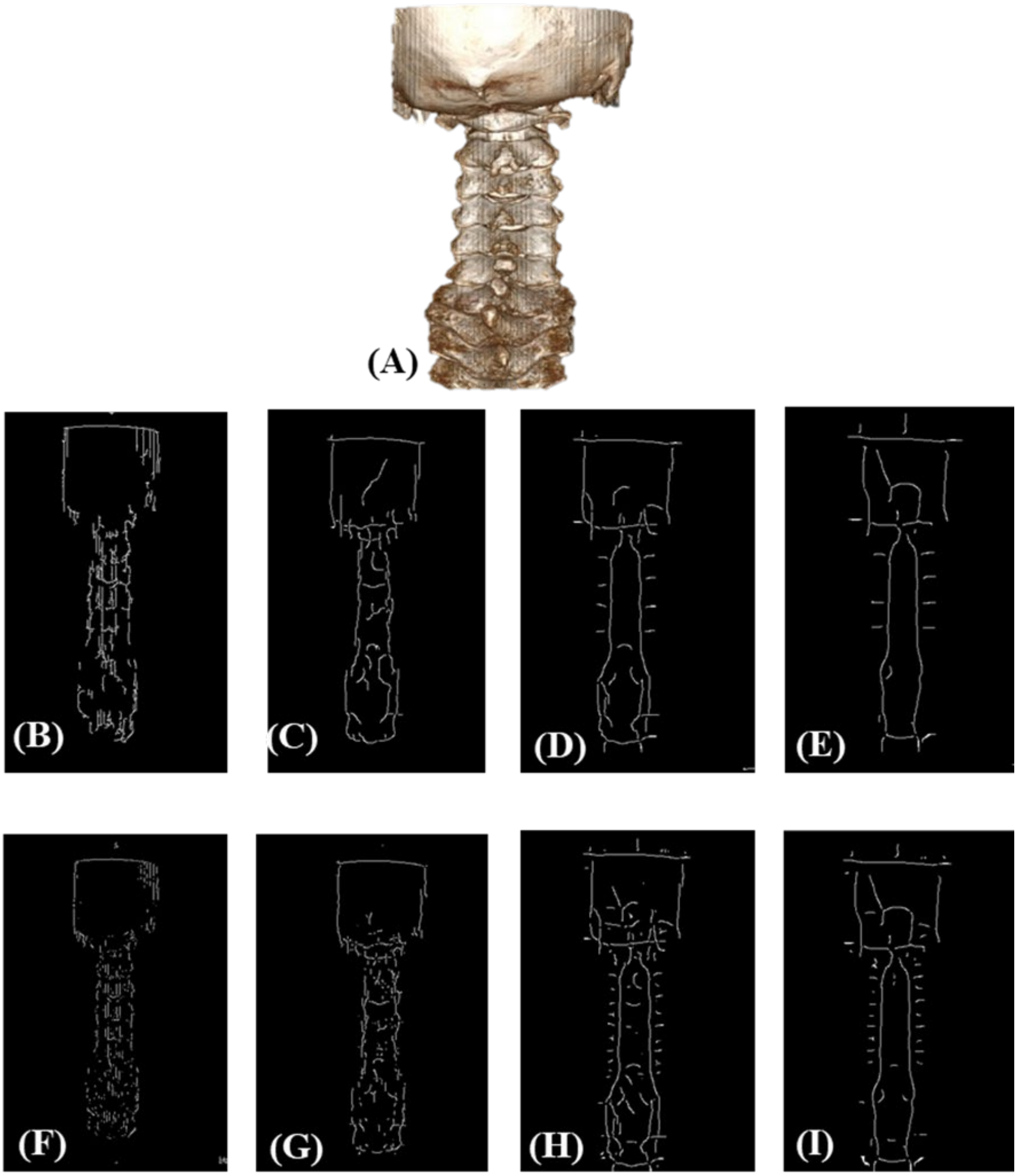

Figure 3 Ridge Detection technique generated the extracted images. 8 models were demonstrated in the rear view ((A) CT scan image, (B) model 1, (C) model 2, (D) model 3, (E) model 4, (F) model 5, (G) model 6, (H) model 7 and (I) model 8, respectively)

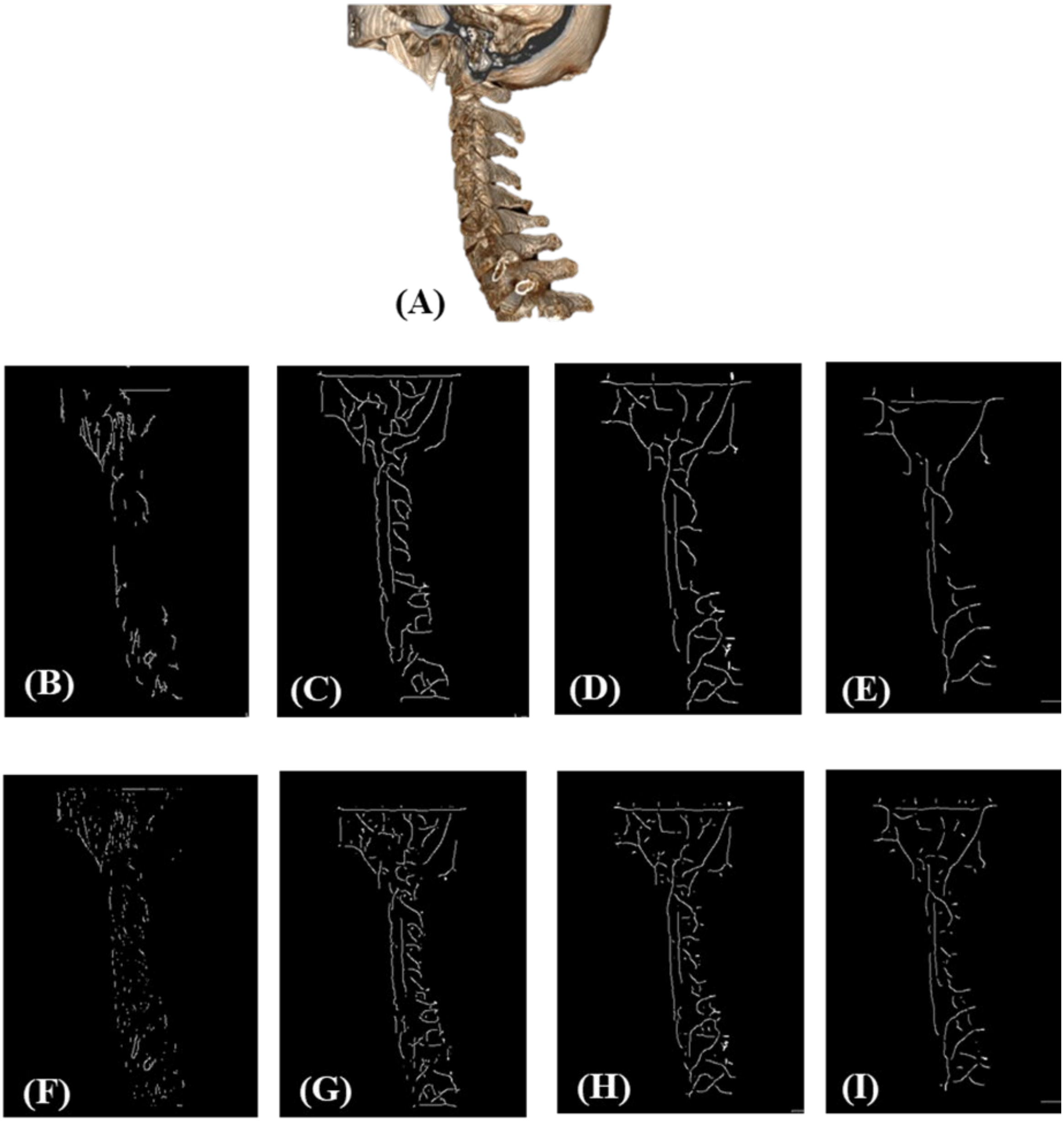

Figure 4 Ridge Detection technique generated the extracted images. 8 models were demonstrated in the left view ((A) CT scan image, (B) model 1, (C) model 2, (D) model 3, (E) model 4, (F) model5, (G) model 6, (H) model 7 and (I) model 8, respectively)

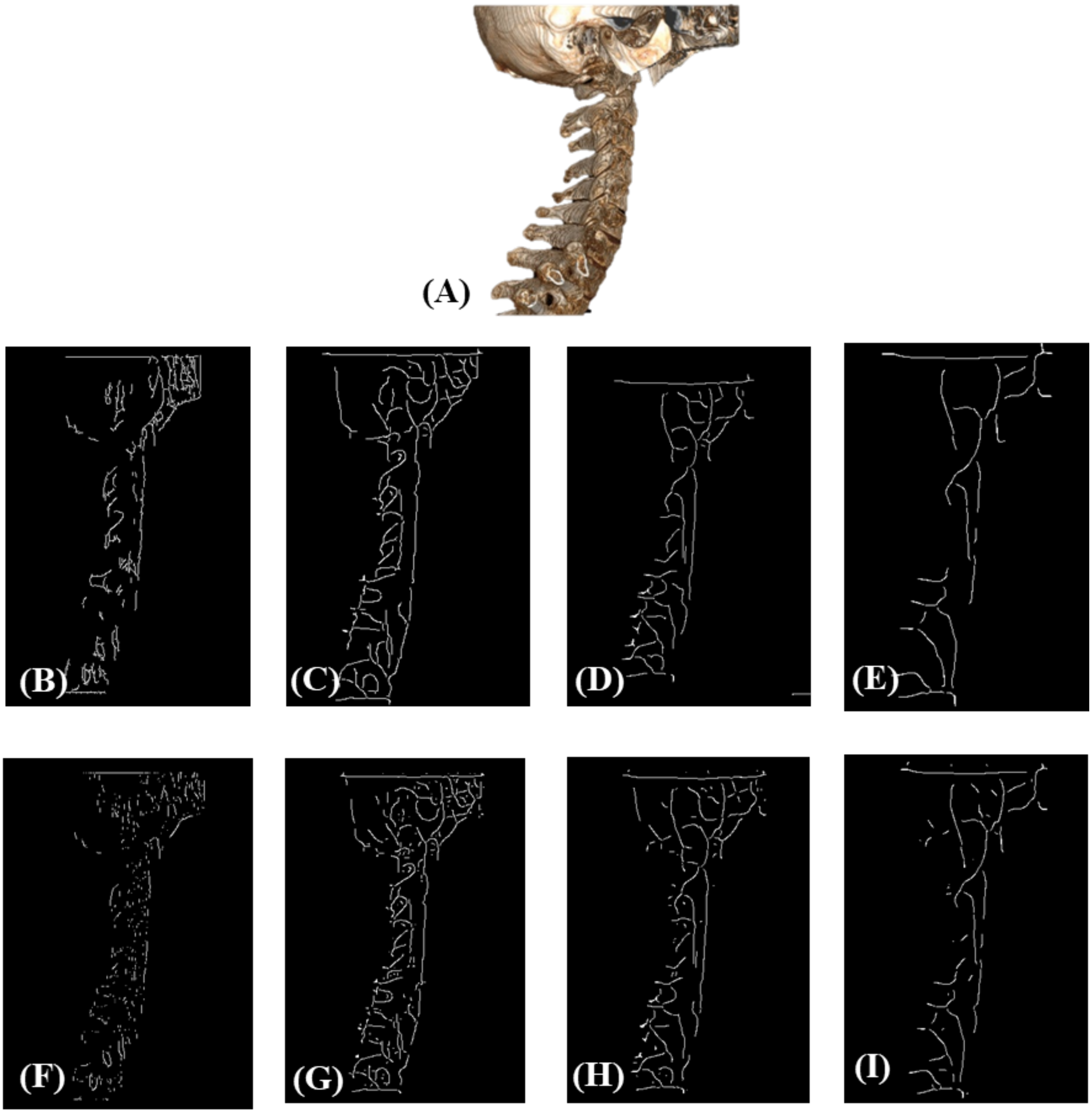

Figure 5 Ridge Detection technique generated the extracted images. 8 models were demonstrated in the right view ((A) CT scan image, (B) model 1, (C) model 2, (D) model 3, (E) model 4, (F) model5, (G) model 6, (H) model 7 and (I) model 8, respectively) Instruments

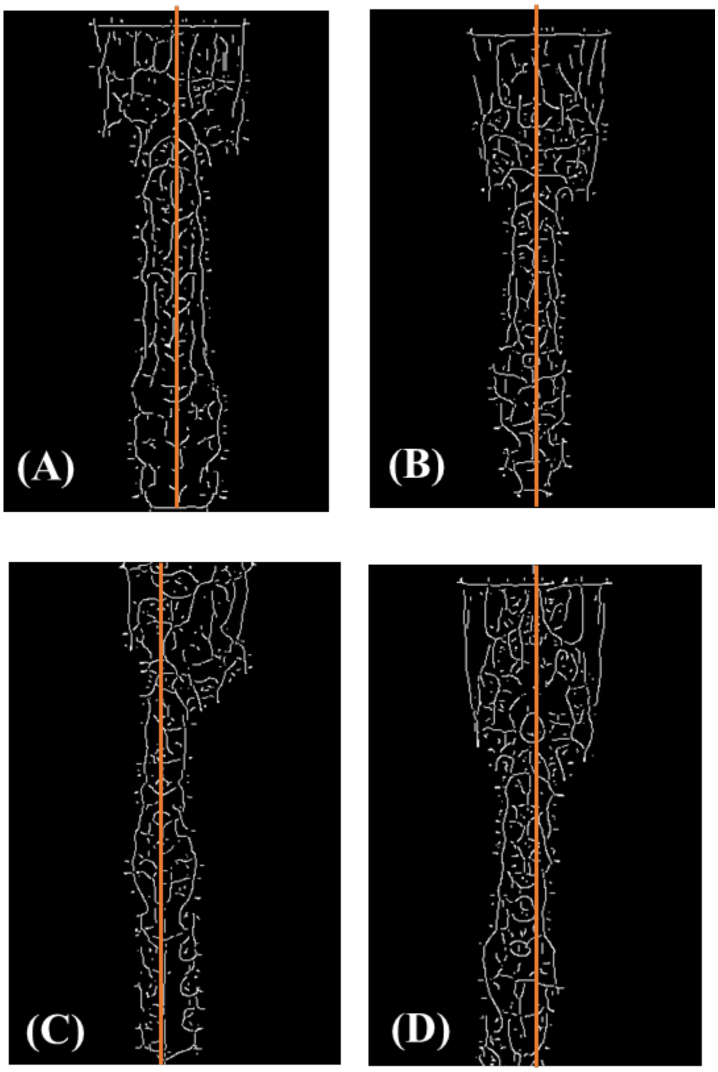

Figure 6 The images indicate the different characteristics of the vertebral columns. ((A) Alignment characteristic, (B) Alignment characteristic, (C) Misalignment characteristic, and (D) Misalignment characteristic, respectively)

Training and Testing Process

The research used the python languages (with Tensorflow, Numpy, and Sklearn libraries), a convolutional neural network (CNN) algorithm for the analysis and classification of abnormal vertebral columns. The data sets were the 93 CT images. The CT images consisted of 53 alignment characteristics and 40 misalignment characteristics. We managed the images for generating the model that consisted of the training process (X train 40 image and Y train 30 image) and the testing process (X test = 13 images and Y test = 10 images). The description of X train and test mean the image of alignments vertebral characteristic. Also, the description of Y train and test mean the image of misalignment vertebral characteristic. The model was built up of hidden layers. This research had 3 hidden layers. The first layer was 2 - dimensional matrices or 2D. The number of nodes was 64 in the first layer, 32 nodes in the second layer, and 16 nodes in the last layer. The input shape section was 512*512 pixels in the first layer, 128*128 pixels in the second layer, and 1*1 pixels in the last layer. The parameters of the CNN model were training cycles=1000, verbose=1, and epoch=1. The validation steps were eight steps in all.

Results and Discussion

The implementation of the ML model was built up by the Ridge Detection and Convolutional Neural Network (CNN) algorithm. All the processes had an adjustive parameter for the best condition in the machine learning (ML) model. We investigated eight models that were different detailing lines in the study image. Insight into the processes used in the extraction program, which was Ridge Detection, was an essential feature to be extracted from the CT image. We found that model 6 was the best performing of the ML models. The accuracy of model 6 indicated 1.000 that equates to 100.000 % correct predictions out of 93 total examples. The precision of model 6 values shown indicate 1.00 or 100.00% and recall 1.000 or 100.00%, respectively. It meant that our model was the excellence model for analysis and classification alignment of the vertebral column. Model 6 was created by Ridge Detection as an essential extractable feature of the CT image. The values of the Ridge Detection regarding this were sigma of 7, low threshold 20, and high threshold 20. The model 6 image was used as a clear example of alignment and detail. The number of sigma and threshold parameters provided indicates better potential than the other models, as shown in Table 2, and more complete than the previous study (Larhmam, Benjelloun, & Mahmoudi, 2013) because this study used the supervisor algorithm for training models and CT images for model classification. Other model results were shown in Table 3.

Table 3. The results shown indicate the performance of the models

Models	Accuracy	Precision	Recall
1	0.444	0.000	0.000
2	0.556	1.000	0.200
3	0.556	0.556	1.000
4	0.889	0.833	1.000
5	0.556	0.556	1.000
6	1.000	1.000	1.000
7	0.889	0.833	1.000
8	0.556	0.556	1.000

We investigated the receiver operating characteristic curve (ROC curve) of the ML model by using the graph followed in Figure 7. Figure 7 shows the relationship between the sensitivity (True position rate) of the ML model (x axial) with the specificity (False position rate) (y axial). We found that the trend of the scoring rate led to 1 (y axial) as model 6. Model 6 was adjusted by hysteresis thresholds in the Ridge detection (sigma=7, low threshold=20, and high threshold=20). It was apparent that the hysteresis thresholds of model 6 were appropriate parameters for this endeavor. It built suitable image segmentation. The accuracy, precision, and recall increased the percent of score in each ROC graph. On the other hand, if the image values were adjusted differences in outcome occurred to those of model 6. For example, model 1(sigma=1, low threshold=10, and high threshold=30). This process provided merely a few lines of image segmentation. The performance of model 1 was low. This result supported the previously published models (Staal et al., 2004). A previously published image ridge detection of retinal images that identified diabetic retinopathy assisted Tanzi et al. (2020) publish research on different deep learning techniques to classify bone fractures. Kokkotis et al. (2020) also published a variety of Machine Learning techniques on the diagnosis and predictions of knee osteoarthritis. In summary, our model using a machine learning and ridge detection approach identified similar factors as being associated with abnormal organ outcomes as previous models have found that used convolutional neural network (CNN) algorithm.

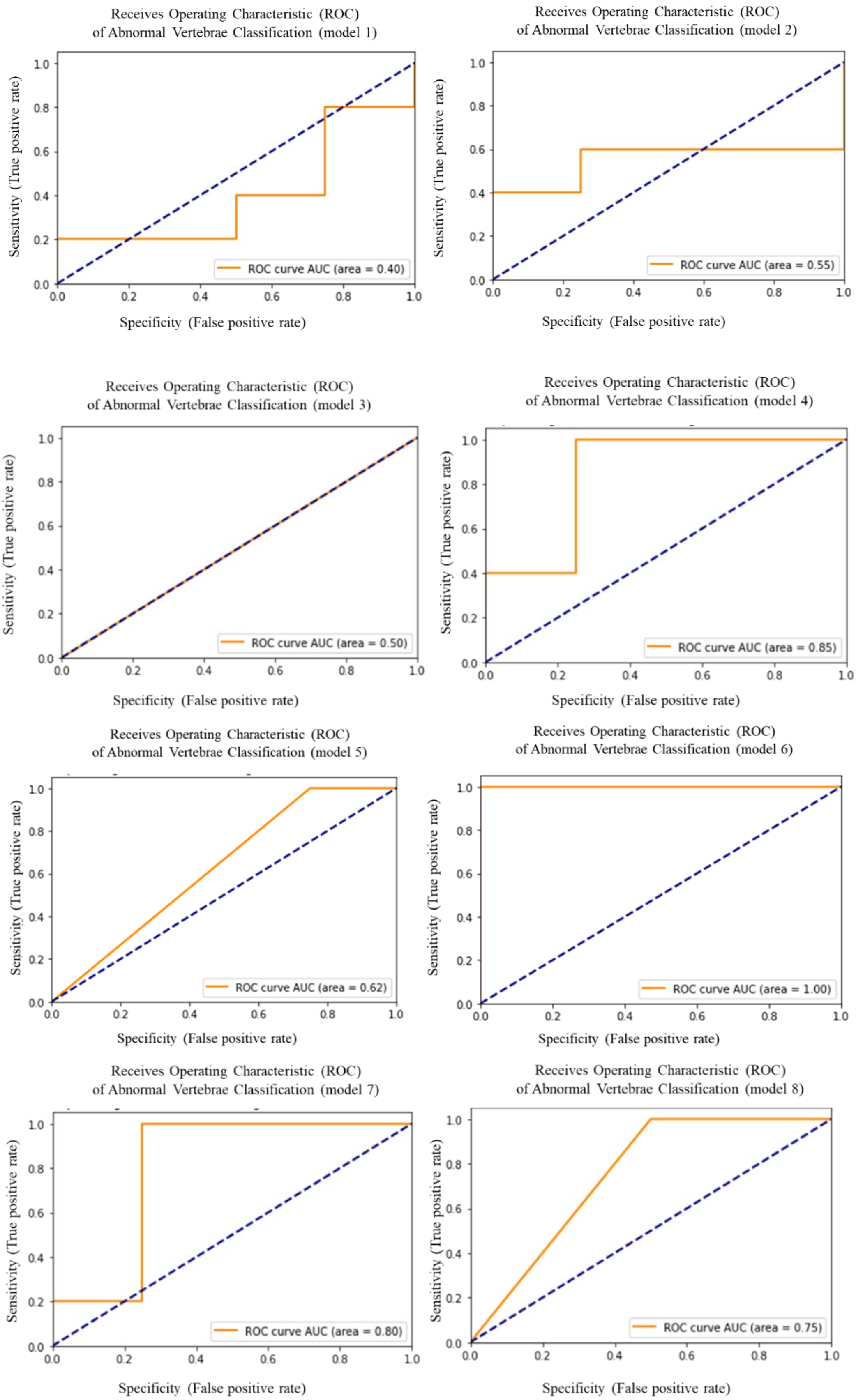

Figure 7 ROC graph shows the relationship between true position rate and false position rate. (A) ROC of model 1, (B) ROC of model 2, (C) ROC of model 3, (D) ROC of model 4, (E) ROC of model 5, (F) ROC of model 6, (G) ROC of model 7, (H) ROC of model 8.

The flowchart and code model for analysis and classification of abnormal vertebral column in CT images as shown in Figure 8 and Figure 9, respectively.

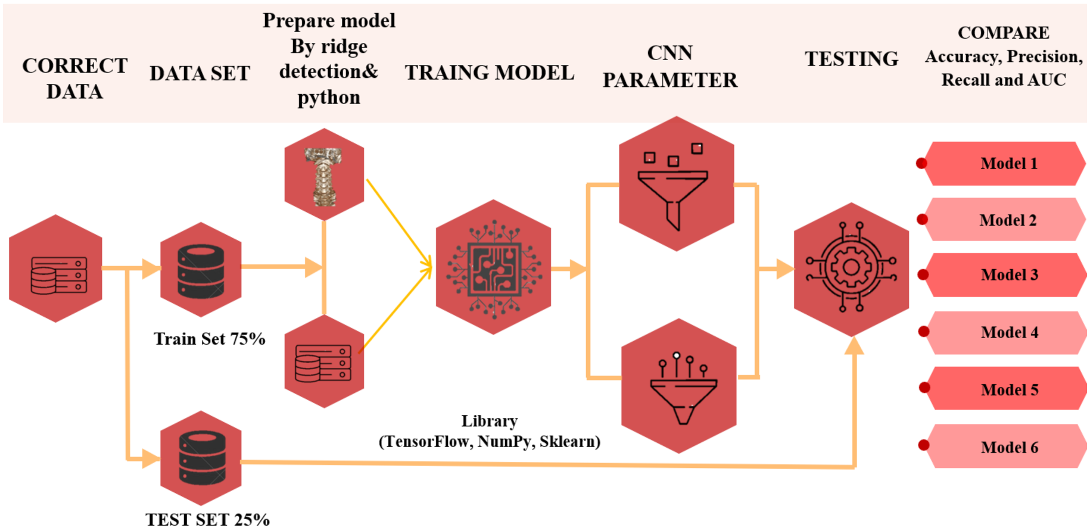

Figure 8 The flowchart of the summary analysis and classification of abnormal vertebral column model by convolutional neural network algorithm

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# All images will be rescaled by 1./255
train_datagen = ImageDataGenerator(rescale=1/255)
validation_datagen = ImageDataGenerator(rescale=1/255)

# Flow training images in batches of 120 using train_datagen generator
train_generator = train_datagen.flow_from_directory(
        '/tmp/train/',  # This is the source directory for training images
        classes = ['Alignment', 'Misalignment'],
        target_size=(512, 512),  # All images will be resized to 200x200
        batch_size=120,
        # Use binary labels
        class_mode='binary')

# Flow validation images in batches of 19 using valid_datagen generator
validation_generator = validation_datagen.flow_from_directory(
        '/tmp/valid/',  # This is the source directory for training images
        classes = ['Alignment', 'Misalignment'],
        target_size=(512, 512),  # All images will be resized to 200x200
        batch_size=120,
        # Use binary labels
        class_mode='binary',
        shuffle=False)

import tensorflow as tf
import numpy as np
from itertools import cycle

from sklearn import datasets
from sklearn.metrics import roc_curve, auc
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import label_binarize
from sklearn.multiclass import OneVsRestClassifier
from scipy import interp
from sklearn.metrics import roc_auc_score

model = tf.keras.models.Sequential([tf.keras.layers.Flatten(input_shape = (512,512,3)),
                                    tf.keras.layers.Dense(128, activation=tf.nn.relu),
                                    tf.keras.layers.Dense(1, activation=tf.nn.sigmoid)])

model.summary()


model.compile(optimizer = tf.optimizers.Adam(),
              loss = 'binary_crossentropy',metrics=['accuracy',f1_m,precision_m, recall_m])

#metrics=['accuracy',f1_m,precision_m, recall_m]

from keras import backend as K

def recall_m(y_true, y_pred):
    true_positives = K.sum(K.round(K.clip(y_true * y_pred, 0, 1)))
    possible_positives = K.sum(K.round(K.clip(y_true, 0, 1)))
    recall = true_positives / (possible_positives + K.epsilon())
    return recall
```

Figure 9 The analysis and classification of abnormal vertebral column model by convolutional neural network algorithm code

Conclusion

This study demonstrated the performance of the ML model using CNN combine with the Ridge detection process. The ML model was the analysis and classification of abnormal vertebral columns. The model with Ridge detection preprocessing of parameters sigma=7, low threshold=20, and high threshold=20 performed faultlessly. Our model performed favorably in our cohort of patients with the abnormal vertebral column. The ML model has shown the ability of characteristics detection that were related to misalignment vertebral column. The ML application was the significant model. Ultimately, the application will potentially advance and enhance monitor CT image quality for both research and the healthcare system.

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