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Original Article

Weighted DenseNet-121 for Osteoporosis Disease Detection using X-ray Images

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Abstract **-** *Osteoporosis is a bone-related disease that results in loss of bone minerals and medical-related complications. The diagnosis of Osteoporosis disease is a lengthy task and needs various procedures. The identification of this disease is a challenging task in remote areas because of due to the limited higher technological equipment. Medical radiography is still in practice to analyze and diagnose the health of bone for osteoporosis detection. However, due to the noise in X-ray images and there was a larger difference between the patient's bone shape when it is under lower contrast conditions. The existing models performed osteoporosis detection which was challenging to obtain a satisfactory outcome. They do not interact very strongly with lighter elements, so proposed DenseNet 121 based Convolutional Neural Network (CNN) classification method for osteoporosis disease detection. DenseNet diminishes the problem of vanishing gradient as it needs a few parameters for training the model. The proposed model will consider the feature propagation and takes care of the information that will build the DenseNet-121 architecture. The osteoporosis X-ray images are collected in the proposed DenseNet-121 based CNN method and have the advantage of segmenting vertebral body as well as vertebral foramen detection in the transverse slices, which improves the disease detection accuracy rate. The experimental result shows that the proposed classification using Weighted DenseNet-121 based CNN achieved an accuracy of 87.10%. Whereas, the existing U-net method showed an accuracy of 81.2% for osteoporosis disease detection.*

Keywords - *Convolutional Neural Network, Medical, Osteoporosis, Vertebral body, X-ray image.*

I. INTRODUCTION

Osteoporosis is a skeletal disease occurred due to loss of Bone Mineral Density (BMD) and results in bone fractures without any symptoms because of fragility and bone loss which equally affects men and women can occur at any age period. The bone fracture probability with the osteoporosis disease for those above the age of 50 is high in menopausal women [1]. The bones affected by osteoporosis disease get cracked because it is unable to accommodate the physical pressures and pain on bones. The common sites for fractures in individuals having osteoporosis disease are on the hip, back, and ankles [2]. There are various diagnostic imaging techniques for osteoporosis disease such as Dual Energy X-Ray Absorptiometry (DXA), Quantitative Ultrasound (QUS), and Quantitative Computed Tomography (QCT). The magnetic resonance identification of diagnosis includes Magnetic Resonance Imaging (MRI), Diffusion-Weighted Imaging (DWI), High-Resolution Magnetic Resonance Imaging (HRMR), Ultra Short Echo (UTE), and Magnetic Resonance Spectroscopy (MRS), etc. [3]. DXA is known as the gold standard osteoporosis diagnosis by utilizing bone minerals. For diagnosing osteoporosis disease, the standard process is to estimate the minerals in the lumbar spine and proximal femur with DXA [4]. The disadvantage of utilizing DXA is the presence of errors in relevant measurement caused due to the surrounding soft tissues. Further, DXA includes exposure to radiation and higher costs for devices which makes challenging for the diagnosis [5].

Low Dose of Chest Computed Tomography (LDCCT) is utilized for cancer diagnosis with lesser ionizing of radiation and is significantly reduces the mortality rate of cancer [6]. The bone structure is evaluated by understanding the variations of shapes and sizes in radiography of the proximal femur [7]. The analysis of QCT images needs manual operations frequently by including the localization of vertebral bodies and placement of volumes of interest that delivers reduplicative and heavy tasks in a larger scale of osteoporosis analysis [8]. The deep learning approaches enhanced the vertebrae identification and segmentation performance [9]. An automatic identification approach utilizes deep learning algorithms to classify osteoporosis disease [10]. However, problems include such as the images from patients having osteoporosis are similar to the healthy people which is difficult to identify directly from doctors and the texture features are not able to use for satisfactory classification [11]. So, the lower-cost system with effective performance for osteoporosis diagnosis is in high demand [12]. To solve such an issue, Convolutional Neural Network (CNN) based DenseNet 121 model was developed. The model diminished the problem of the vanishing gradient problem that requires lesser parameters for model training. The dynamic features are propagated that take care of the flow of information. The present research provides basic knowledge about the architecture of DenseNet-121. The osteoporosis dataset is collected from the hospital for disease detection. The pre-processing of images takes place to remove the noises in images and to enhance the intensity level. Then, the DenseNet-121 based CNN using DenseNet-121 is employed to classify the collected X-ray images. The present research work considers the CT images also for the evaluation of the results. The dense tissues are examined that can scan the CT images for bone capturing, blood vessels, and soft tissues all at the same time. The advantage of using X-ray-based images is that it is much less complex and smaller compared to the CT scan as the CT scanner is required to rotate around the patients scanned. Thus, the disadvantages such as exposure to radiation in contrast with most cases make the patients suffer from kidney problems.

The organization of the paper is shown as follows: Section 2 discusses the existing techniques involved for Osteoporosis detection. Section 3 discusses the proposed weighted DenseNet-121 based CNN model for performing osteoporosis disease classification. Section 4 is the results and discussion of the proposed research work. Section 5 is the conclusion and future work for the present research.

II. AREA OF STUDY

The existing researchers used various imaging diagnostic methods for osteoporosis that X-ray absorptiometry that required a curve for post-processing obtained bone mass per unit area. The BMD helped in calculating the measured values in presence of osteoporosis. The existing techniques were utilized for detecting Osteoporosis disease and the advantages of the models are discussed.

Tang [12] developed a CNN model to perform the detection of BMD for osteoporosis screening which includes two modules. The first module identifies and segments the region of interest diagnostic and the second module finds the type of BMD by utilizing region of interest features. The developed method was excellent for segmentation on shape preservations with various lumbar vertebras. The developed CNN achieved higher accuracy for detecting the BMD. The developed model was capable to maximize the accuracy for the complex data too and was able to model for the real-world relationships with variable interactions. However, the developed CNN method utilized lesser data and consumed more time by training the samples of data one by one.

Liu [13] developed a deep U-Net method for osteoporosis gradation and diagnosis. The original image was listed and utilized for dataset development. The normalized data was used for feeding it as the input at each layer to ensure the distribution of data in each layer is constant which achieved accelerated training. Finally, the functions of energy were calculated by joining the values for prediction. The prediction is done concerning the softmax class that is generated for each of the pixels for feature mapping. The developed U-Net model solved the problem of image interference for the process of BMD measurement. However, more iterations for the training data were needed and thus U-Net method showed limitations in localizing and segmenting the x-ray images.

Fang [14] developed a deep CNN-based approach for vertebral body segmentation and to measure BMD. A fully connected layer in CNN called U-Net was utilized for the segmentation of the vertebral body. The vertebral body regions are marked manually as the ground truth value for performing the comparison. The CNN model used DenseNet 121 for the BMD calculation. The developed method showed automatic identification of normal BMD, osteoporosis, and osteopenia in CT images. The developed deep CNN method excluded the vertebral bodies for classification. However, the capacity for balancing the high dimension data and incorporating it for non-linear interactions for various genetic variants or predictors was not addressed for conventional approaches.

Su [15] developed a hybrid CNN method with texture features such as gray level co-occurrence matrix, local binary pattern, and the encoded features for the detection of osteoporosis disease. The two kinds of features were used to classify among healthy and sick from X-ray images. The CNN features were obtained using deep CNN and handcrafted features were extracted which contains a set of standard textural features. The developed fusion method showed higher performance in selecting the features ensuring that the data distribution was not able to bias the statistical test results. The developed method was not accurately predicted osteoporosis by using X-ray images.

Fathima [16] developed a modified U-Net method combining the attention module for Osteoporosis disease screening. The developed various features-based method utilizes Artificial Neural Networks (ANN) or classification trees to develop an algorithm for disease detection. The developed U-Net with attention unit showed effectively better results in terms of classification accuracy and the Dice score for all the existing models validated the results for the similar datasets. The developed U-Net method showed limitations in localizing and segmenting the x-ray images.

Ping Wang [17] utilized computed tomography scans to detect osteoporosis in the thoracolumbar vertebral bodies. The CT attenuation and volumetric Bone Mineral Density (vBMD)values are measuring the correlation among the analyzed two measurements. The generated Receiver operator characteristic (ROC) curves determined the diagnostic optimal thresholds. The population included in the study was having the older subjects and middle-aged subjects about health. The developed model avoided a higher computational burden when the possible parameters have searched the model. It utilized a randomized approach for cross-validating the hyperparameters that sampled distinct parameter combinations for the given distribution. However, the results were affected in the scalability in terms of several samples.

Yijie Fang [18] performed Osteoporosis disease detection using multidetector CT images based on CNN. The fully connected NN was used for segmenting the vertebral body. The post-processed values are based on analyzing the standards using Quantitative Computed Tomography (QCT). The model was able to automatically exclude the vertebral bodies for calcification. The vertebral bodies were different from that of the actual situation identified had a significant effect during diagnosing. However, the developed model showed overfitting due to external validations to the required population.

From the study, the problem of overfitting is due to irrelevant features extracted from the X-ray images. Therefore, the proposed research work uses the CNN model that can develop a feature map on a transverse slice to filter out the irrelevant features solves the problem of overfitting.

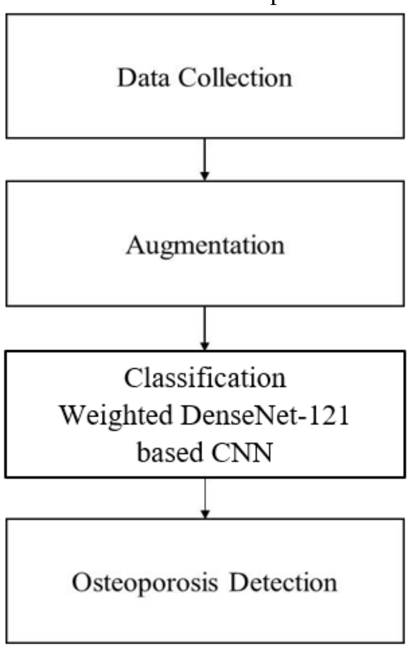

Fig. 1 The block diagram of proposed classification by using DenseNet-121 based CNN for osteoporosis disease detection

III. RESEARCH METHODOLOGY

The block diagram of the proposed classification process using the DenseNet-121 based CNN method for osteoporosis detection is shown in Fig.1.

A. Dataset Collection

a) XSITRAY

The osteoporosis X-Ray images were collected from the XSITRAY dataset. The 221 X-ray images were utilized for training and 174 images were utilized for the process of testing in which 81 total patients were observed as positive for osteoporosis disease [20]. The large-scale database consisted of images are used for supporting the BMD measurement from that of the DEXA images. There are a total of 441 DEXA images were used for distinct patients that are created and collected. The regions such as the spine, right femur regions are taken for the database creation. The dataset has a total 78 number of X-Ray scan images that are collected from distinct subjects. The X-SITRAY consists of 52 female images and 26 numbered male image subjects. The subject has Clavicle, Spine, Extremity & Femur, Extremity & Hand, Ankle, and Knee Bones X-Ray scan images.

b) American College of Radiology

The CT images are processed by using the QCT Pro Model 4 that analysis and controls the quality as used in the unified European Spine Phantom. The vertebral body has the central layer that selects and calculates the bone density average values. The guidelines are introduced for performing diagnosis were introduced concerning the International Society for Clinical Densitometry (ISCD) and American College of Radiology (ACR).

B. Augmentation

After pre-processing the images, the data augmentation process is undergone. The data augmentation techniques are utilized for performing random rotation, flipping transformation, and also for sharing the transformation. The networks used are profoundly performed on large data for avoiding the problem of overfitting. The dataset analysis is performed by creating the larger images that faced the major challenge in the system. Thus, the problem is overcome by utilizing data augmentation is carried improves the sample numbers for training the dataset. The image enhancement is performed on deep learning technology that increases the time for a certain level and generates the quality of an image as it is difficult for controlling. Thus, it is important for meeting the automatic training needs. Thus, the research has expanded the data collected when compared to the traditional data augmentation approaches. The traditional data augmentation technique such as rotation, flipping, flipping, translation, enhancing contrast, scaling, or brightness is performed. The brightness Y' for the proposed research is computed by using Eq. (1).

$$Y' = 0.299R + 0.587G + 0.114B \tag{1}$$

From the above equation, RGB is known as the standard Red Green Blue [sRGB] which coordinates concerning the International Telecommunication Union Radiocommunication (IT-R). Eq. (2) represents the question for the contrast.

$$Contrast = \frac{Change\ luminance}{Average\ luminance} \quad (2)$$

From the above equation, without any fixed angles, the images are repeated and are flipped vertically and horizontally. The vertical flipping is the same as that of rotating 180 degrees that performed horizontal flipping.

C. Classification

After augmenting the data, classification is carried out using DenseNet-121 based CNN. The proposed model has mainly 4 types of layers that are implanted as shown below. The augmented input images are fed for the convolution layers that compute the neurons and are connected with the local input regions.

The architecture of DenseNet 121 is shown in Fig. 2.

A CNN model starts with an input image that is pplied folayerilters fortruemp from the feature map. The l^{th} layer ets the ture maprom al preceding layers, and it is explained in Eq. (3).

$$Xl = H_l([X_0, X_1, ..., X_{l-1}]) \quad (3)$$

Where $[x_0, x_1 ... x_{l-1}]$ is the concatenation of feature maps produced in layers from $0, ... \ell - 1$

The ReLU function is applied for increasing the non-linearity to the pooling layer to each feature map. Every H_l function produces the k feature maps and it follows the l^{th} layer as shown in Eq. (4).

$$K_0 + K*(L-1) \quad (4)$$

From the above equation, K_0 is the overall number of channels in the input layer and hyperparameter is the growth rate of the network and every layer adds k feature maps to its state.

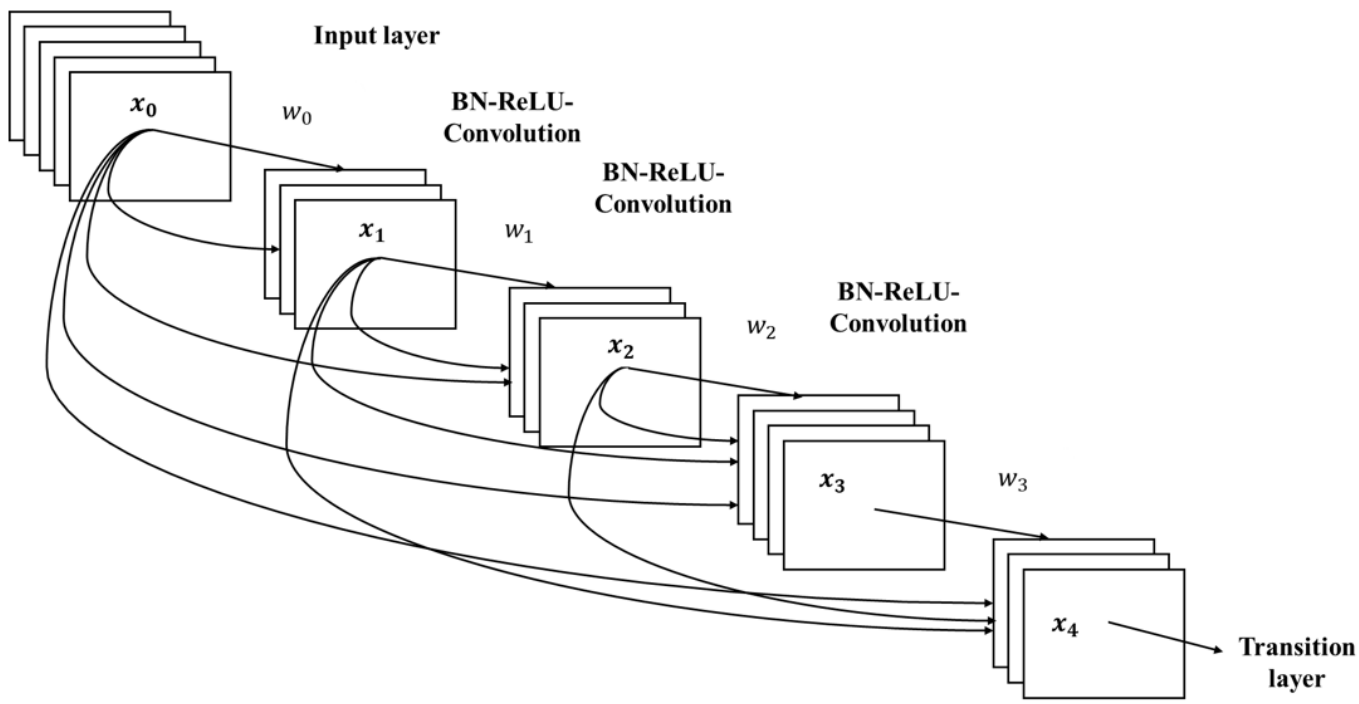

Fig. 2 Proposed Weighted Dense Net 121 architecture

Each neuron is calculated based on the smaller weights dot product and these regions are connected with the volume of input images. The activation function verifies the neurons whether it is correct or not based on the ReLU lrandom weights input layer assigns the rndom weigts represented a $w_0, w_1, w_2, ... w_n$ based on the resultant features. Where and W refers to the whole number. The output obtained is used to train the weights in every layer up to the Transition layer. The ReLU layer does not change the input image dimension. Therefore, the pooling layer utilizes to decrease the noise effect among the features that were extracted. The higher-end features are evaluated based on the outputs obtained by the FC layer. The proposed method pre-trained the deep CNN models that utilized DenseNet 121 to determine the position in the first 4 lumbar vertebral bodies. The DenseNet-121 network includes 5 convolutional layers, 13 learnable weight layers 4 FC layers, and 2 DenseNet layers. The proposed method includes a total of 3,462369 trainable parameters and zero non-trainable parameters. The DenseNet-121 utilizes dropout regularization in the FC layer which employed the ReLU activation unction fed on the convolution layers. The convolution layer detects the vertebral body from the images are shown in the below Eq. (5).

$$g_i^L = b_i^L + \sum_{j=1}^{m_1(L-1)} \psi_{i,j}^L \times h_j^{L-1} \quad (5)$$

where, g_i^L is the output layer of L, b_i^L is known as the base value, $\psi_{i,j}^L$ is known as having the filter connection that has the feature map feature,s and h_j is known as the output layer of $L-1$. The pooling layer performs vertebral foramen detection in the transverse slices and obtains responses from the convolution layer as the maximum that reduces the features that are unwanted solving the overfitting problem. The model overcomes the problem better when compared with the existing CNN model which is explained through Eq. (6-8).

$$m_1^L = m_1^{L-1} \quad (6)$$

$$m_2^L = \frac{m_2^{L-1} - F(L)}{S^L} + 1 \quad (7)$$

$$m_3^L = \frac{m_3^{L-1} - F(L)}{S^L} + 1 \quad (8)$$

The aforementioned Eq. (6 - 8) can develop a feature map based on a transverse slice to filter out the irrelevant features solving the problem of overfitting.

Where, S^L are the parameters from the neural network that changes the image movements expressed as m_1^L, m_2^L *and* m_3^L that are known as the feature, maps obtained from th filter, the other layers like ReLU and FC are explained in q. (9-10).

$$\mathrm{Re}_i^l = \max(h, h_i^{l-1}) \quad (9)$$

$$FC_i^L = f\left(z_i^l\right) with\, z_i^l = \sum_{j=1}^{m_1(l-1)} \sum_{s=1}^{m_2^{l-1}} \sum_{s=1}^{m_3^{l-1}} w_{i,j,r,s}^l \left(FC_i^{l-1}\right)_{r,s}$$

(10),

where, Re_i^l is known as the ReLU layer, h is known as the output layer, FC_i^L is known as the FC layer which follows the convolutional layer performed activation function at the FC layer for identifying the feature deeper. The osteoporosis X-ray images are classified into normal and abnormal patients.

IV. RESULTS AND DISCUSSION

Osteoporosis disease is a type of bone metabolism disease which is occurred due to a lack of minerals in the bone. Lack of strength leads to disc degeneration, low back pain, or an increase in the fracture at higher risk of the vertebral body. Thus, diagnosis of osteoporosis disease detection occurs as bone metabolism is decreasing the strength of the bone. Therefore, early diagnosis of the disease is important. Many osteoporosis disease detection methods were developed but showed limitations in localizing and segmenting the x-ray images. In this research, the proposed method uses DenseNet 121 based CNN model for detecting the disease. The proposed method evaluates for python 3 tool operating at windows 10, 16 GB RAM, i7 core processor, and 6GB 208- Ti NVDIA GTX edition working at GPU environments. The present research work is considered for evaluating the proposed method in terms of quantitative analysis and comparative analysis. The proposed method classification step is explained further.

A. Performance Metrics

The proposed method evaluates the results for the proposed weighted-based DenseNet-121 for osteoporosis disease detection. The results are explained below,

a) Accuracy

The term accuracy determines the mode quality. The accuracy term is expressed as shown below in Eq. 11).

$$Accuracy(\%) \frac{TP + TN}{TP + TN + FP + FN} \times 100 \quad (11)$$

b) Precision

Precision refers to the ratio of totally predicted positive observations to all positives as shown in Eq. (12).

$$\Pr ecision(\%) = \frac{TP}{TP + FP} \times 100 \quad (12)$$

c) Recall

Recall refers to the truly predicted values for all the fault modules as explained in Eq. 13).

$$\mathrm{Re}\, call = \frac{TP}{TP + FN} \times 100 \quad (13)$$

d) F-Measure

The mean of precision and recall is known as F-measure which is explained in Eq. 14).

$$F - measure(\%) = \frac{2PR}{P + R} \times 100 \quad (14)$$

B. Quantitative Analysis

The proposed quantitative analysis of the proposed classification using DenseNet-121 based CNN is explained in this section. The proposed method utilized 221 images for training, 174 images for testing the model and the number of osteoporosis patients observed is 81. The proposed method used DenseNet 121 for performing classification. DenseNet-121 based CNN for osteoporosis disease detection are shown in table 1 and it also has the results for evaluating the osteoporosis detection evaluated in terms of accuracy, precision, recall, and f-measure. The training and testing data images utilized in the proposed DenseNet-121 based CNN for osteoporosis disease detection are shown in Fig. 3 and Fig. 4. Table 1 shows the performance of the proposed classification using the DenseNet-121 based CNN method for osteoporosis disease detection that evaluates the performances. The accuracy for the proposed DenseNet-121 based CNN is 87.10%. The proposed classification using the DenseNet-121 based CNN method for osteoporosis disease detection achieved a precision of 73%, recall of 86%, and f-measure of 72% respectively. Whereas, the existing decision tree showed an accuracy of 41.96%, precision of 18%, recall of 3%, and f-measure of 24%. Further, Support Vector Machine achieved an accuracy of 87.10%, precision of 73%, recall of 86%, and f-measure of 29%. Therefore, it indicates that the proposed method showed higher performance than the existing method in osteoporosis disease detection. The plotted graph for evaluated values of proposed classification using DenseNet-121 based CNN for osteoporosis disease detection method is shown in Fig. 5. The training and testing of the dataset graph are shown in Fig. 6 and Fig. 7.

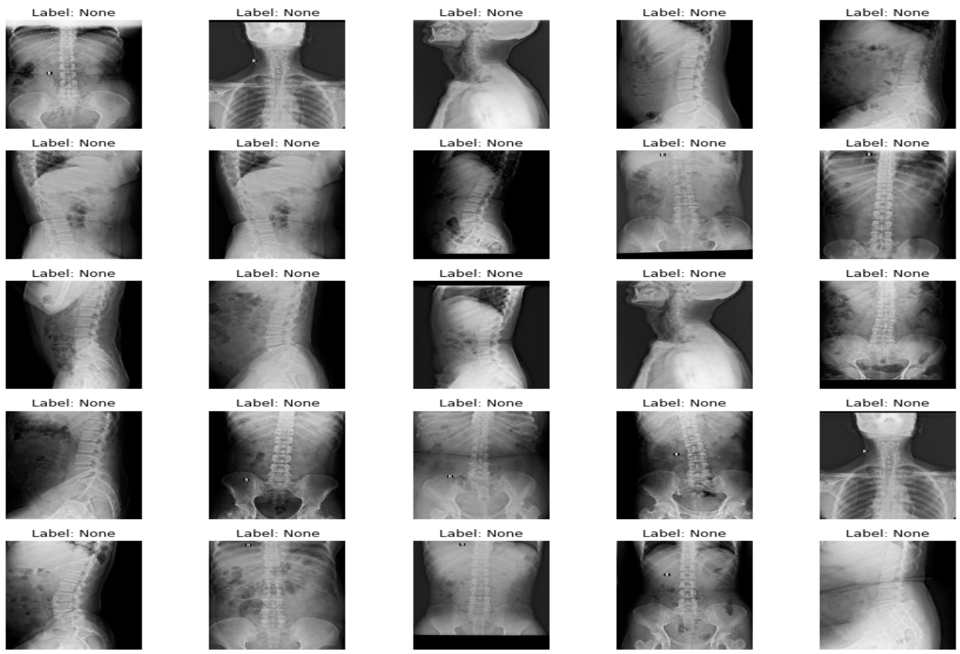

Fig. 3 The training data images utilized in proposed classification by using DenseNet-121 based CNN for osteoporosis disease detection

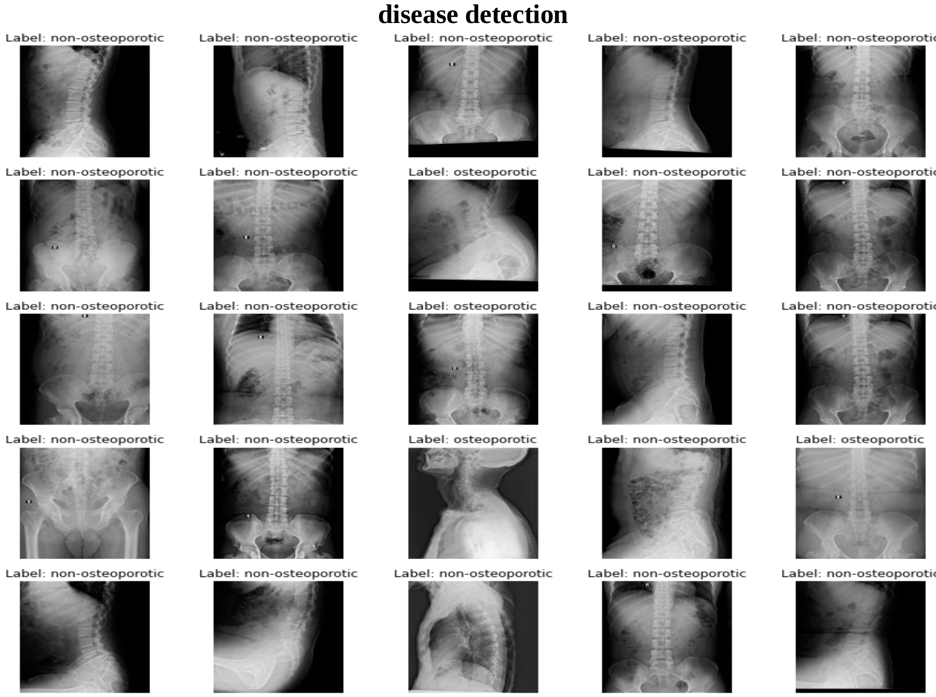

Fig. 4 The testing data images utilized in proposed classification by using DenseNet-121 based CNN for osteoporosis disease detection

Table 1. The quantitative analysis of proposed classification by using DenseNet-121 based CNN for osteoporosis detection with existing methods

Methods	Accuracy%	Precision%	Recall%	F-measure%
Decision Tree	41.96	18	35	24
SVM	45.23	21	37	29
ANN	47.8	24	45	34
CNN	54.56	29	54	38
DenseNet-121 based CNN	87.10	73	86	72

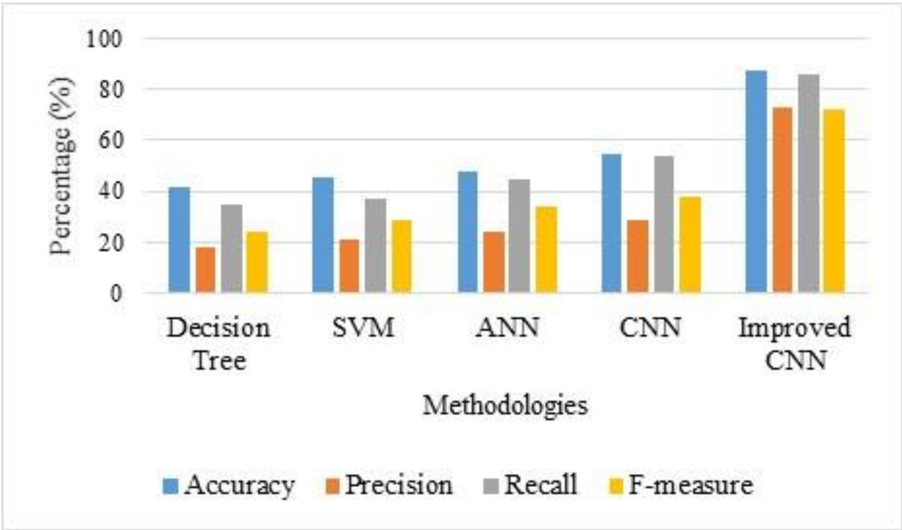

Fig. 5 The quantitative analysis result of the proposed DenseNet-121 based CNN method for osteoporosis disease detection

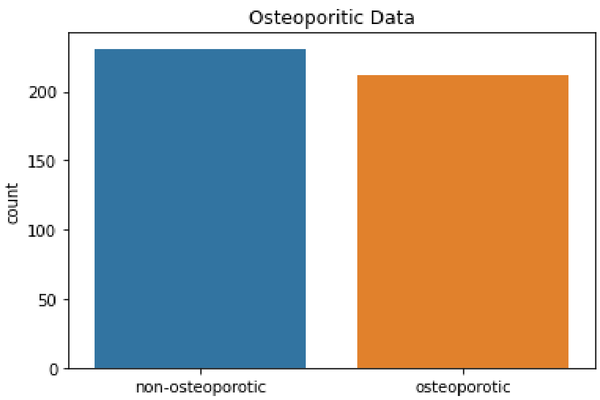

Fig. 6 The training data graph of the proposed DenseNet-121 based CNN method for osteoporosis disease detection

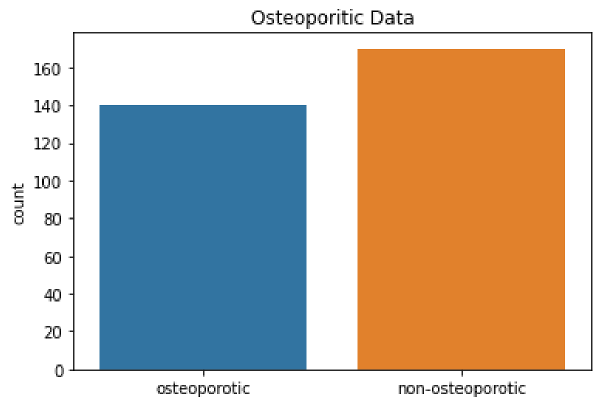

Fig. 7 The testing data graph of the proposed DenseNet-121 based CNN method for osteoporosis disease detection

Table 2. The comparison analysis of the proposed DenseNet-121 based CNN method with existing methods using X-ray images

Methods	Accuracy %	Sensitivity%	Specificity%
U-net [14]	81.2	74.3	72.3
CNN [16]	63.8	72.4	55.2
Proposed DenseNet-121 based CNN	87.1	86.0	73.0

Table 3. The comparison analysis of the proposed DenseNet-121 based CNN method with existing methods using CT images

Methods	Accuracy %	Sensitivity%	Specificity%
Hounsfield unit (HU) thresholding [18]	88	82.1	86.1
DCNN [19]	-	88.6	84.3
Proposed DenseNet-121 based CNN	90	89	86.9

Thus, the proposed method excluded the vertebral bodies and excluded them automatically with calcification. The BMD calculated for the vertebral bodies was different from that of the original scenario. Thus, a significant effect was seen on the clinical diagnosis for evaluation of results.

C. Comparative Analysis

The proposed DenseNet 121 based CNN model showed comparative results by comparing with existing methods such as U-net [14] and CNN [16] are described in this section. The comparison of the proposed method with existing methods in terms of accuracy, sensitivity, and specificity is described in table 2.

Table 2 shows the comparative analysis of proposed DenseNet-121 based CNN with existing methods such as U-net [14], CNN [16] in terms of accuracy, sensitivity, and specificity. The existing U-net method utilized 89 samples of X-ray images for the evaluation of results that obtained an accuracy of 81.2%, sensitivity of 74.3%, specificity of 72.3%. Similarly, the CNN method obtained an accuracy of 63.8 %, specificity of 55.2 % which trained 104 images that trained the model and 12 images were used for testing. The proposed DenseNet 121 achieved an accuracy of 87.1%, sensitivity of 86.0%, and specificity of 73.0% for osteoporosis disease detection. The proposed Dense-Net-based CNN model utilized 221 X-ray images for training and 174 images were utilized for the process of testing. Thus, the presence of more data results in better and more accurate models as there is pretty much information available in a large number of data that estimates the confidence in reaching better performances. The graphical representation of the proposed DenseNet-121 based CNN method with existing methods is shown in Fig. 8.

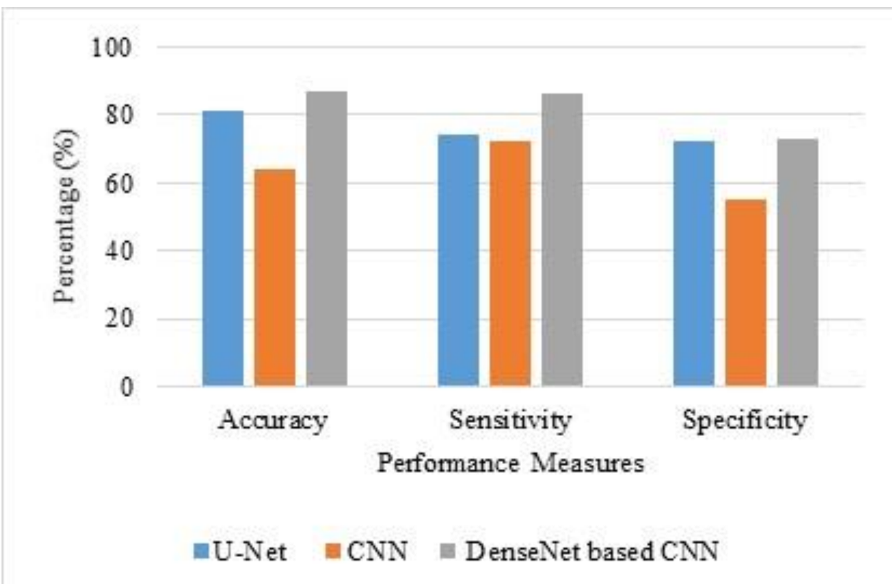

Fig. 8 The comparison graph of proposed Dense-Net-based CNN with existing methods for osteoporosis disease detection

Table 3 shows the comparative analysis of the proposed DenseNet-121 based CNN method with existing methods using CT images. The existing methods used volumetric bone mineral density obtained an accuracy of 88%, a sensitivity of 82.1%, and a specificity of 86.1%. Similarly, the DCNN model obtained an accuracy of 88.6 %, the sensitivity of 84.3 %, and the proposed DenseNet-121 based CNN model obtained an accuracy of 90%, the sensitivity of 89%, and specificity of 86.9%. The CT images results obtained in table 3 are better when compared to the X-ray images up to 2% to 3 %. The minute variation in percentage is negotiable as the X-ray images are more beneficial physically compared to the CT images. Thus, we have used X-ray images in the research.

V. CONCLUSION

In this research work, the DenseNet-121 based CNN classification method is proposed for osteoporosis disease detection. The collected osteoporosis X-ray image datasets are used in the proposed DenseNet-121 based CNN method for osteoporosis detection. Thus, the proposed method overcomes the problem of overfitting, data augmentation, flipping, transformation, shearing transformation, and random rotation. After augmenting the data, classification is carried out using DenseNet-121 based CNN. The DenseNet-121 was used to classify the x-ray images into normal and abnormal patients having osteoporosis disease. The proposed method has the advantage of segmenting the vertebral body and vertebral foramen detection in the transverse slices which improve the disease detection accuracy rate. The experimental result shows that the proposed classification using DenseNet-121 based CNN achieved higher accuracy of 87.10% classified the osteoporosis disease than existing methods U-net method showed an accuracy of 81.2% for osteoporosis disease detection. In the future, the location of the Osteoporosis Disease accurately will be determined.

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