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Deep Learning Approach for Predicting Bone Disorder Using DenseNet

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Abstract. Osteoporosis is a medical condition that affects the structure and strength of bones. Osteoporosis is an asymptomatic disease of the bone that affects a significant proportion of the world's elderly, leading to increased fragility of the bone and an increased risk of fracture. This paper's key objective is to provide a critical review of the main artificial intelligence-based systems for detecting populations at risk of osteoporosis or fractures. Skeletal deformities, fractures, twisted knees, inherited bone defects, and other bone disorders affect millions of individuals as a result of a variety of bone disorders. These may help to prevent a variety of possible complications if diagnosed and treated early. We discussed deep neural networks in this paper, including recognition, segmentation, and classification. The architecture and concepts of the deep learning algorithm we used to detect bone density were also discussed. As a result, we'll use a variety of deep learning algorithms to build a model that can detect a person's bone mass density and recognize any potential threats that have occurred or could occur.

Keywords: Bone Mass Density, Convolution Neural Network, Machine Learning, Musculoskeletal Radiographs.

1. Introduction

Bigdata Low bone density and bone tissue damage characterize osteoporosis, which leads to increased bone fragility and fracture risk. When the body's capacity to regenerate bone mass outpaces the ability to absorb it, bone strength deteriorates. It affects all of the body's bones and causes no symptoms or a sign until a fracture occurs. A fractured bone is also the first symptom of osteoporosis, which is why it's often known as "the silent crippler" since patients don't realize they suffer from it until the time runs out. Osteoporosis is characterized by low bone mineral density and poor bone architecture, which increases the risk of fracture [1]. Calcium and vitamin D, bisphosphonates [2], estrogen, and selective estrogen receptors, modulators, calcitonin, parathyroid hormone, balance, and fitness rehabilitation programs, and the marginally invasive spine procedures vertebroplasty and kyphoplasty are also part of a multidisciplinary method to treating osteoporosis [2]. Osteoporosis and its main complication, osteoporotic fracture, which affects both men and women, cause a large amount of morbidity and mortality worldwide [3]. Males had a greater rate of morbidity and death following osteoporotic fractures than females, even though women are at higher risk of osteoporosis. As the world's population ages, osteoporosis has become a serious public health concern. By 2050, the global incidence of hip fractures is anticipated to increase thrice in males and twice in women.

BMD (bone mineral density) has been used to diagnose osteoporosis since 1994 [4]. The World Health Organization defines osteoporosis as a BMD of 2. 5 or more standard deviations below that of a young healthy woman [5]. BMD [6] is the single most effective predictor of initial osteoporotic fracture. Each standard deviation decline in BMD is associated with a 1. 5 to threefold increase in fracture risk [7], depending on the bone region assessed, type of fracture, and ethnicity of the research group. The most common osteoporosis fractures are hip, vertebral, and wrist fractures. There are 2 types of osteoporosis [8]: primary osteoporosis and postmenopausal osteoporosis, which is a common condition in women after menopause has occurred. Secondary osteoporosis is a form of osteoporosis that can affect someone who has hormonal imbalances or other chronic diseases. Gluco corticoid osteoporosis is the name given to this form of osteoporosis. The most prevalent metabolic bone disorder, osteoporosis, is a growing problem that affects 200 million people around the world. Osteoporosis is often misdiagnosed and under-treated. It is critical to recognize the disease and provide adequate medical and non-medical care.

According to the data, medical care for osteoporosis is improving annually as physician awareness grows. Non-medical therapy with osteoporosis should be used in conjunction with effective pharmacologic treatment to improve outcomes for people with osteoporosis. Despite their positive impact on bone mineral density and short-term outcomes, minimally invasive spine operations such as vertebroplasty and kyphoplasty, as well as fracture data for intravenous bisphosphonates, have yet to be established. [9].

The under-treatment of osteoporosis patients is a severe problem. Patients can not undergo enough medical attention after being diagnosed with osteoporotic fractures. Just 24% of 1160 women with distal radial fractures had a surgical test, 2. 9% volunteered for a bone density scan, and22. 8%were afflicted with at least one anti-osteoporotic drug, according to the report. Men could be undervalued even more than women when it comes to osteoporosis care. In a survey of approximately 360menandwomendiagnosedwithhipfractures [9], only 27% of males had any osteoporosis treatment, according to the study in comparison to 70% of women. Appropriate medical treatment, on the other hand, seems to be improving. According to the report, 11 percent, 13 percent, 24 percent, and 29 percent of 75 patients were prescribed osteopenia medicine in 1997, 1998, 1999, and 2000, respectively, indicating a substantial rise in the rate of care.

Patients who have had an osteoporosis fracture are at a higher risk of developing another osteoporosis fracture. For eg, sustaining one or more vertebral fractures increases the chance of having another vertebral fracture by five times. Fractures of the shoulder, wrist, and spine have a 39% chance. A woman's average likelihood of hip fracture is 15%, and the risk increases as she gets older. Hip fractures affect 21% of women [10] over the age of 75, and 50% of women around the age of 85. Females over 85 are eight times more likely to be run to the hospital for a hip injury than women in the middle of the ages of 65 and 74. Furthermore, patients with osteoporosis have a higher risk of morbidity and mortality. Deep learning algorithms, especially deep convolutional neural network architecture, have gained widespread recognition in recent years as a reliable method for learning the classification of features directly from original medical images. Deep CNNs are a form of deep neural network that can learn high-dimensional features to improve the network's ability to distinguish anomalies within images, as opposed to ML methods that focus on specifically categorized features. There are a variety of CNN architectures for image processing and identification. The number and scale of layers, the interfaces between these layers, and the total network depth are all different in both of these architectures. Since various network architectures are better adapted for different problems and it is impossible to predict the architecture is best for a particular challenge in advance, the analytical examination is often regarded as the best way to make these decisions.

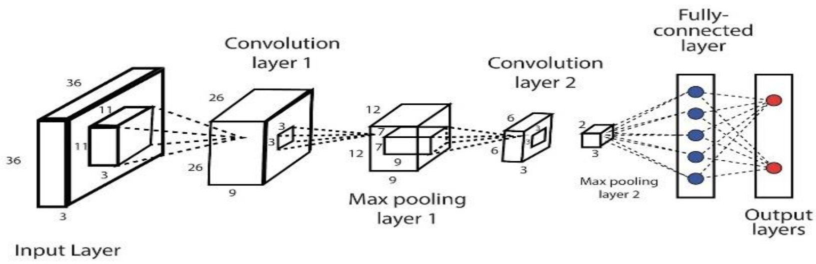

Figure 1. CNN architecture.

A Convolutional Neural Network (CNN) is a biologically based version of a multi-layer feed-forward architecture that is commonly used in image detection and recognition tasks today. A CNN's layers are divided into four categories: layers, processes, and layers. The convolutional layer is the first layer, and it is founded on the mathematical concept of convolution, which involves applying a kernel to all sections of an input picture that are used to generate a filtered picture. The second procedure, pooling, reduces the dimensionality of the function map while saving the vital input for the following convolution layer. The activation function layer is the third layer, and it applies the activation function element by element, deciding the output by determining whether or not the neurons are active [11-15]. The final layer is a completely connected layer, in which all neurons from previous layers are connected to all nodes in subsequent layers, similar to a fully connected multilayer perceptron. CNN architecture is shown in Fig. 1.

The proposed regression convolution neural network (CNN) for automated bone disorder from wrist and shoulder X-ray provides a completely automatic deep learning method for analyzing X-ray images of hips and shoulder for bone calculation. It also focuses on the attention module and complex attention deficit, all of which have been shown to improve bone age reading accuracy. Another method proposed is deep learning in microscopy image processing, which offers quantitative support for enhancing disease Characterization. The other suggested approach is an enhanced and optimal predictor of bone disease based on risk factors, with the key goal of predicting the risk natures present in the human body by analyzing electronic health data based on various characteristics. It attempts to predict the prevalence of bone-related diseases using structural terminologies such as bone loss rate and osteoporosis risk. T-scores are used to report the outcome of the bone density analysis. A t-score is a measurement of a patient's bone density and how it differs from that of a typical 30-year-old adult.

2. Motivation

Disorders of the bones and joints can take multiple types, ranging from a catastrophic leg injury to progressively deteriorating arthritis of the hands. Bone and joint disease can lead to chronic pain if not treated properly [16]. Bones are at risk as a result of delayed disease diagnosis, which contributes to a difficult and inefficient existence. Bones are essential for mobility and often serve as a cage for internal organs. As a result of the late diagnosis, not only bones but also other organs are at risk. As the world evolves, new findings on bone disorders emerge, increasing the risk. To combat this, we will develop a machine-learning algorithm to recognize and diagnose different bone disorders based on bone density. Wrists, elbows, knees, ankles, and finger joints are all examples of healthy joints that allow the body to move freely. The femur (thighbone) and humerus (upper arm) are both involved in the movement. A picture of bone disorder is shown in Fig. 2.

Figure 2. Bone Disorder.

3. Literature Review

Using a Convolutional Neural Network (CNN), a pediatric bone age assessment can be automated by a hand radiograph. Researchers suggest a fully automated deep learning method for processing X-ray images of joints for determining bone age in this article. This paper proposes a regression convolution network to be specific to assess the age of the bone using hand radiographs. The first attention module is used to process all the images present and generate a fine attention map which acts as input for the regression network. The regression convolution network then undergoes a loss during training enabling it to assess the bone age of the outlier images more efficiently. Deep Learning in Microscopy Image Processing: Microscopic image analysis aids in the better characterization of diseases such as breast cancer, lung cancer, brain tumors, etc. This paper provides us with a brief overview of this fast-growing field of computerized microscopy image analysis. Here we are introduced to the deep neural networks and discuss the current achievements in this sector such as detection, classification, and segmentation in the image analysis. The architecture and main concepts of the convolution neural network stacked autoencoders, and recurrent neural networks and their modeling related to specific tasks are discussed on various microscopy images.

Improved and Optimal Bone Disease Prediction Using Risk Factors: The main purpose of this research is to analyze electronic health records and forecast the risk natures that occur in the human body using different forms of online features. This is achieved based on the similarities that exist between the various structures that are available on the internet. The aim is to predict the prevalence of bone-related diseases in the system using a range of risk elements like bone loss rate, osteoporosis risk feature sets, and so on. Improved diagnosing of bone-related disease prediction using Deep Belief Network (DBN) to estimate bone loss rate by adjusting the learning process in terms of applicable factors.

The objective of "Artificial intelligence on the identification of risk groups for osteoporosis, a general review" paper is to introduce to us a basic review of the fundamental frameworks that use computerized reasoning to distinguish the danger of osteoporosis or cracks. The frameworks considered for the examination were those that satisfied the accompanying prerequisites: scope of inclusion, minimal expense, and ability to recognize more huge physical elements. The paper's main aim is to gather and describe the main techniques used to point out the risk groups for osteoporosis and recognize their trends as well as their challenges. The techniques used are some of the most upcoming and latest branches in science like Artificial Intelligence Concepts, Some Advanced Algorithms, and Input Parameters.

The paper "Deep Multimodal Representation Learning: A Survey", talks about bridging the gap between various modalities. They play an important role in the utilization of multimodal data. Because of its various levels of abstraction, it has garnered a lot of attention in recent years. To start the discussion on how to bridge the gap, a deep multimodal representation is used with three major frameworks which include coordinated representation, joint representation, and encoder-decoder. This paper talks about the major problems of new technologies and the attention mechanism used. Different model has been described and each model talks about its objective, structure, issues, advantages, applications, and disadvantages.

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4. Model Design and Architecture

As MURA (musculoskeletal radiographs) is a massive set of X-rays of the bones. The task is of deciding whether the X-ray is natural or abnormal. More than 1.8 billion people in the world are affected by musculoskeletal diseases, which are the leading cause of long-term pain and disability, with over 25 million emergency room visits per year rising. We hope that our research will lead to major developments in medical imaging technology that can help at the specialist level, thus expanding healthcare access in areas where professional radiologists are scarce.

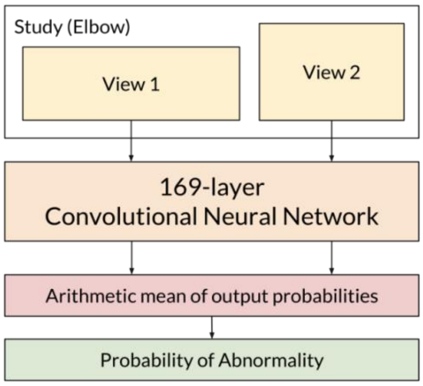

Figure 3. Model Design and Architecture.

DenseNet is a network design in which each layer (within each dense block) is feed-forward connected to all other layers. Previous layers' feature maps are read as separate inputs for each layer, while the layer's feature maps are taken on as inputs for future levels.On the CIFAR10/100 and SVHN platforms, this networking trend delivers state-of-the-art accuracies. DenseNet achieves equivalent accuracy as ResNet on the large-scale ILSVRC 2012 (ImageNet) dataset, but with fewer parameters and almost half the FLOPs.

We suggest a routing pattern to increase information transfer between layers: We create direct ties from any layer to the layers below it As a result, all previous layers' function maps, y0,..., y(l-1), are fed into the lth sheet: Z (Equation 1)

$$y_l = T_l([y_0, y_1 \dots, y(l-1)]) \tag{1}$$

The combination of the feature maps produced in layers 0... l-1 is denoted by [y0, y1... y(l-1)]. This network design is known as a Dense Convolutional Network because of its dense connectedness. We concatenate Tl's various inputs into a single tensor for ease of execution.

4.1. Pooling Layers

As the scale of feature maps increases, the concatenation operation used in the equation is no longer feasible. Convolutional networks, on the other hand, depend on sampling layers for changing the size of feature maps. Our architecture divides the network into several closely connected dense blocks to make down sampling easier. Layers between blocks are referred to as transformation layers, and they perform convolution and pooling

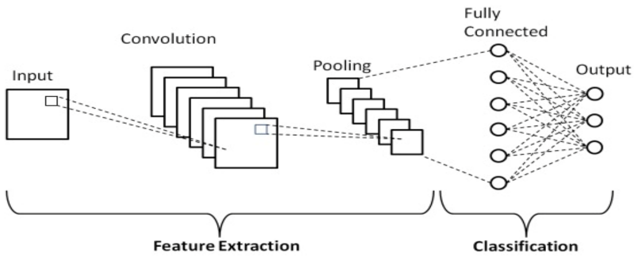

Figure 4. CNN Layers.

4.2. Growth Rate
The fact that DenseNet may have very thin layers distinguishes it from current network designs. The network's growth rate is referred to as the hyper-parameter y. Each layer is provided access to existing feature maps in its block that came before it, as well as the network's "collective awareness." The feature maps can be seen as the network's overall condition. The rate of growth determines how much is the new information added to the overall state.

4.3. Transition Layer
A transition layer controls the model's sophistication. It uses a11 convolutional layers to cut the number of channels in half and a stride of 2 to cut the height and width of the typical pooling layer in half, further reducing the model's complexity. DenseNet concatenates all of the feature maps. Concatenating function maps of varying sizes will be impossible. As a result, the function maps of each sheet in each dense block are the same height.

4.4. Batch Normalization
Batch normalization helps to minimize internal covariate change and, as a result, speed up deep neural net training. It accomplishes this by adjusting the means and variances of layer inputs via a normalization stage. Since gradients are less dependent on the size of the parameters or their initial values, batch normalization improves gradient flow across the network. This enables much higher learning speeds to be used without the possibility of divergence. Furthermore, batch normalization makes the model more consistent and eliminates the need for Dropout.

4.5. Dense Block
The DenseNet system is made up of dense bricks. The layers of such blocks are tightly interconnected: The previous layers' output function maps are fed into each layer.

5. Model Implementation
The MURA detection model is a binary classification assignment where the input is an upper extremity sample with 1 or more views and the result is a binary mark y is 0 or 1 showing whether the study is natural or abnormal respectively. We gathered de-identified, HIPAA-compliant photographs from Stanford Hospital's PACS. A large dataset was downloaded the elbow, finger, thumb, side, humerus, back, and wrist are seven normal upper extremity radiographic research forms. Our attention is drawn to two categories based on the images: wrist and shoulder. Board-certified radiologists from Stanford Hospital manually labeled each sample as normal or abnormal during clinical radiographic analysis in the diagnostic radiology department. The dataset was divided into two parts: training (2300 steps) and validation (199 steps). In this article, we support this observation and introduce DenseNet, a feed-forward network that connects each layer to the next. Each layer uses the feature maps from the previous layers as inputs, and each layer's feature maps are used as inputs into all subsequent layers:

- DenseNets offer several persuasive benefits.
- They solve the problem of vanishing gradients.

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- Function dissemination can be improved.
- Encourage people to reuse functionality.
- A substantial reduction in the number of parameters is needed.

With the help of four intensely competitive object detection benchmark tasks, we test our proposed architecture. On the majority of them, DenseNets outperform the current state-of-the-art by using less computing power to achieve high performance.

The following steps are the technique by which we will be approaching our problem:

- For the study and model, the data was downloaded from compiled Stanford database and was uploaded on google collaboration. The data was then unzipped on google collaboration.
- The necessary libraries and functions were defined and called.
- The data was viewed for abnormality and later were labeled as 0 or 1 which indicated normal or abnormal respectively.
- The data was then labeled for valid data and train data after which a CSV file was created for the same.
- After the file creation Image processing was done in which shoulder and wrist images were considered. The train function was performed using shoulder images, while the valid function was performed using wrist images.
- The 169 layers dense model was imported and later compiled after image analysis and pre-training.
- After compiling the model, weights were produced, and the model was fit.
- After the working accuracy for the train and test functions was generated and gained.
- A graph for accuracy and loss was plotted until the accuracy was gained.

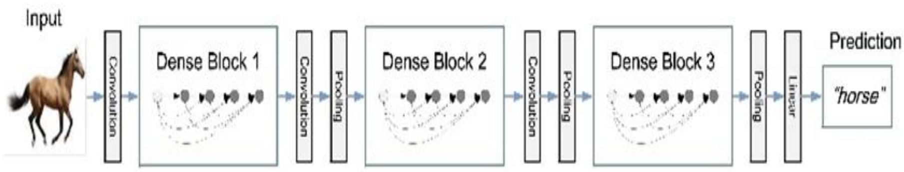

Figure 5. Denseness Prediction.

6. Results and Analysis

It is observed that our model takes a total of 15 epochs where each epoch takes a total of 730 seconds with 2300 training steps. Through every epoch, our modulation accuracy has increased. Model accuracy is 83.38% Validation accuracy is 78.20%. Model loss is 0.4198 and validation loss is 0.5008. We also calculated model accuracy by using another method defined by evaluate generator. The accuracy is 77.73% and the loss is 0.49041296860809326 via this method. Our main aim was to increase the accuracy of the dataset containing shoulder images. To create a standardized model this can run for all the available images present under the MURA Dataset. During our experiment, we made sure to prevent over-fitting and under-fitting of data and tried to make the model as real-time as possible. When changing the epoch values and the training and validation steps we also noticed fluctuations in the accuracy of the data. After a lot of reading, researching and experimentation we were able to finally able to decide on the number of epochs, training, and validation steps that would suit our model. For further enhancements, more images from the dataset can be used to increase the accuracy of the image. But, special care has to be taken to prevent over-fitting and under-sitting of data when using the MURA Dataset. The Study Provided a feasible approach to the detection of bone disorder using X-ray images. The proposed Neural Network-based system for the detection of abnormal bone X-ray images is promising and has an end-to-end segmentation strategy convenient for practical or real-life usage. The proposed system also achieves very good accuracy and can be further improved by using more images.

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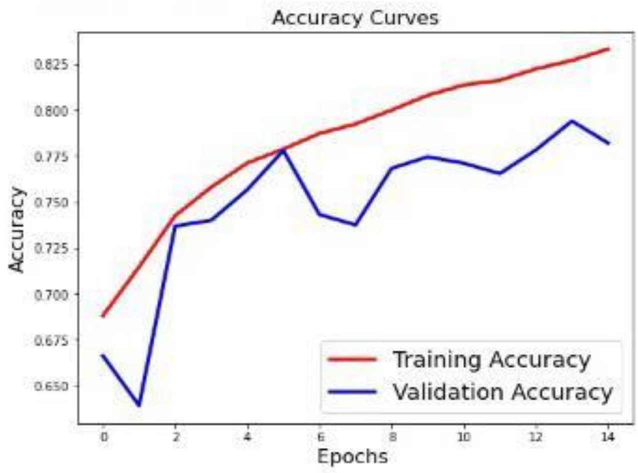

Figure 6. Accuracy.

From Fig. 6., it can be observed that as the Epoch Increases the training accuracy increases while using the training dataset and it can be depicted using the red line. The blue line represents the accuracy we achieved after validating our model. As the number of epochs increases the accuracy increases and sometimes there is also a fall representing the real-time nature of our model.

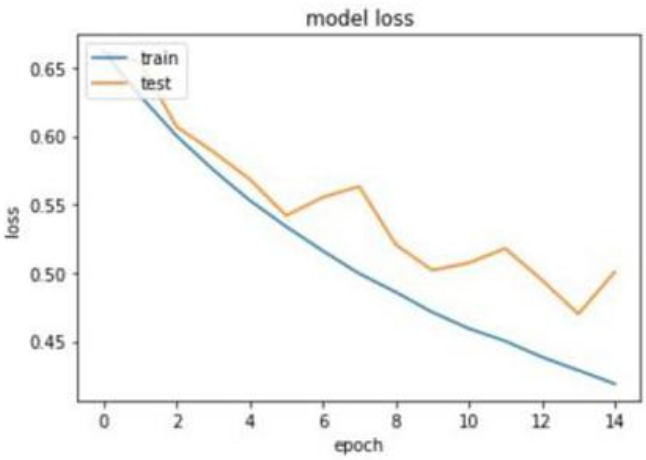

Figure 7. Model Loss.

From Fig. 7, we can conclude that as the number of epochs increases the model loss decreases which is a good thing because the model loss should be as less as possible. As represented in the above graph, the blue line depicts the model loss which occurred during training and the yellow line depicts the model loss which took place while performing testing.

7. Conclusion and Future Work

We propose a Convolution Neural Network to process X-Ray images of Abnormal and Normal Bone. DenseNet has been seen to be an appropriate model for our use which helped us improve the accuracy of our model. Our model achieved its accuracy in a period of 1 and ½ months of continuous research, training, and validation. Therefore, the said model is more efficient. More initiative can be taken to carry our forward. Currently, existing systems are very generic and do not work for specific disorders, and hence as future scope of this problem, we can continue to work on this system for specific disorders like osteoporosis. Being a problem that is related to the medical field we would like it to be as correct and precise as possible and hence we can work more on the training accuracy and the testing accuracy. This software can be installed in hardware and can be used as a device in hospitals and other medical institutions for the betterment of society. Working on X-ray images can also help us learn and explore the study of various other issues, disorders, infections, etc. that can be easily determined with the help of X-ray images. Using more powerful hardware we can also increase the efficiency of our model as it would enable us to carry out the experiment training and testing more extensively.

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