International Journal of Engineering Applied Sciences and Technology, 2021
Vol. 6, Issue 4, ISSN No. 2455-2143, Pages 115-123
Published Online August 2021 in IJEAST (http://www.ijeast.com)

DETECTION OF OSTEOPOROSIS IN DEFECTED BONES USING RADTORCH AND DEEP LEARNING TECHNIQUES

Mohsin Shahzad
Department of Electrical Engineering,
Islamia University of Bahawalpur, Pakistan

Talha Farooq Khan
Department of CS
Islamia University of Bahawalpur, Pakistan

Mohsin Bashir
Department of CS&IT
Riphah International University, Lahore, Pakistan

Muhammad Ayub
Department of Computer Science,
Government College University, Faisalabad

Fatima Ashraf
Department of Computer Science,
Government College University, Faisalabad

Shoaib Hashmi
Department of CS&IT,
Khwaja Fareed University of Engg. & IT, Rahim Yar Khan
Pakistan

Fareeha Zahoor
Department of Computer Science,
Islamia University of Bahawalpur, Pakistan

Fawwad Hassan Jaskani
Islamia University of Bahawalpur, Pakistan

***Abstract*— Osteoporosis is a bone issue which happens in light of low bone mass, debasement of bone smaller scale design and high powerlessness to break. It is a critical prosperity stress over the world, especially in more established people. In this paper a significant learning model reliant on a ResNet50 and XGBoost Classifier has been used for predicting gouts or osteoporosis in MURA V2 dataset by using RADTorch library in order to pre-process image of X-rays to identify the defects easily. The randomly provided images were of osteoporosis and the model predicted it correctly with a 99.9% confidence level. There are also some images that the model was not able to predict it with full confidence. Results shows that, the model predicted the Bones correctly and confidence level was impressive. These images show the model predictably the Bones correctly with the confidence level 98% and 91% respectively with ResNet50 and with Hybrid model of ResNet50 and XGBoost Classifiers. Similarly, our model does not only detect Bones, but it can also detect other osteoporosis with an impressive confidence level**

Keywords— **Deep Learning, Computer Vision, Osteoporosis**

I. INTRODUCTION

Osteoporosis can cause spinal or hip breaks that may provoke budgetary weight and high depressingness. As needs be, there is a prerequisite for the early examination of osteoporosis and anticipating the proximity of the break. Osteoporosis is a bone condition achieved by a lessening in bone mass and degeneration of bone structure that prompts high powerlessness to delicacy breaks. Osteoporosis-related crack is a vital overall prosperity danger, affecting one out of three women and one out of five men past 50 years of age. According to the Asia-Pacific Regional Audit in 2013, osteoporosis speaks to more hospitalization than diabetes, myocardial restricted rot, and chest threatening development, in women beyond 45 years old years. It is progressively inescapable among the old masses, especially postmenopausal women. With a rising in the developing people, there will be a liberal climb in the pace of Fractures. It is foreseen that by 2050, at any rate 33% of the all-out people will be developed over 50 years and in Asia alone, a 7.6-overlay increase in developing masses is ordinary that may realize over portion of the overall cracks to occur in Asia.

Bones are the unyielding organs in the human body which guarantee critical organs, for instance, mind, heart, lungs and other internal organs. The human body has 206 bones with various shapes, size, and structures. There are changed sorts of remedial imaging devices that are available to perceive different sorts of anomalies, for instance, Computed Tomography (CT), X-pillar and Magnetic Resonance Imaging (MRI). CT and X-shafts are most a great part of the time used for crack end since it is the least requesting and snappiest way for the specialists to examine the injuries of joints and bones.

International Journal of Engineering Applied Sciences and Technology, 2021
Vol. 6, Issue 4, ISSN No. 2455-2143, Pages 115-123
Published Online August 2021 in IJEAST (http://www.ijeast.com)

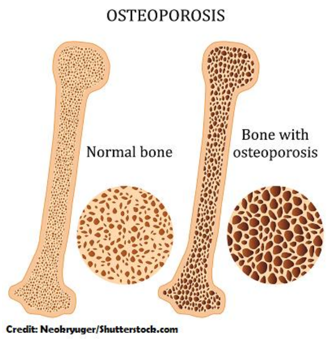


Figure 1 Basic Visualization of Osteoporosis

Surface Characterization of Bone radiograph images is a test in the osteoporosis finding. Osteoporosis can be portrayed as a skeletal issue depicted by an exchange off on bone quality slanting to an extension in case of crack. The most outstanding procedure for osteoporosis investigation is to measure Bone Mineral Thickness (BMD) by twofold essentialness X-bar absorptiometry.

In any case, BMD alone addresses only 60% of break desire. The depiction of trabecular bone microarchitecture has been seen as a huge factor and completes the osteoporosis finding using BMD, anyway it can't be routinely gotten by non-invasive procedures and requires a bone biopsy with histomorphometric examination. 2-D surface assessment offers a straightforward strategy to survey bone structure on standard radiography images. The appraisal of osteoporotic contamination from bone radiograph images presents an imperative test for instance affirmation and remedial applications. Completed images from the bone smaller scale engineering of strong and osteoporotic subjects exhibit a high degree of similarity, thusly drastically growing the issue of collection such surfaces.

Osteoporosis is a skeletal issue portrayed by traded off bone quality and subsequent increment in break chance. As per WHO report (2003) osteoporosis influences in excess of 75 million individuals in Europe, Japan and the USA. Overall evaluations surpass 200 million individuals influenced. Osteoporosis doesn't just aim breaks yet in addition purposes individuals to end up confined to bed with optional difficulties that can be perilous for the old.

CNN has been utilized in some orthopedically examines, creating great outcomes for instance in division of bone structure and determination of osteoarthritis. This examination tries to find if and how convolutional neural networks can anticipate osteoporotic breaks from spine Magnetic resonance images (MRI) images. It can realize new information the achievability of deep learning systems for MRI picture investigation. The investigation additionally endeavors to discover answers for down to earth deep learning difficulties, for example, low training rate and absence of straightforwardness.

In medical field, the X-rays, MRI and CT scan images are the basic source of detecting the bone diseases. Human eye may not be much efficient so that we have developed an algorithm to first take input MRI image, then segment this image into masked and unmasked image, then load the complete dataset (MURA from Stanford library) and apply CNN to test and predict the osteoporosis in the patients.

We present a ResNet50 model and XGB classifier for model training and testing afterwards used RADTorch to effectively detect osteoporosis in bone radiography data. Robotized assurance from automated radiographs is very testing since the outputs of sound and osteoporotic subjects appear alongside zero visual differentiations. In this paper, we have proposed a model to disengage sound from osteoporotic subjects using high dimensional textural feature depictions figured from radiography images. CNN Modified Model can empower us to bring the usage of assistant MRI estimations of bone quality into clinical practice for the recognizable proof of Osteoporosis as it gives high exactness. A grouping of these frameworks, including Artificial neural networks (ANNs), Bayesian Networks (BNs), Support Vector Machines (SVMs) and Decision Trees (DTs) have been commonly executed in helpful research for the structure and headway of insightful models, achieving careful and fruitful fundamental initiative. Notwithstanding the way that it is obvious that the usage of Machine Learning methodologies can improve our comprehension of Osteoporosis acknowledgment, a legitimate level of endorsement is required all together for these strategies to be considered in normal clinical practice. [1]– [3].

In [4], author discussed later and bleeding edge drives in imaging methods for the finish of osteoporosis and crack shot assessment. The maker has furthermore examined division methods used to section the region of interest and surface examination systems used for portrayal of osteoporotic and strong subjects.

Furthermore, challenges displayed by the current symptomatic instruments have been mulled over and down to earth answers for evade the confinements are discussed.

In [5] it has analyzed material science based models, using constrained part assessment (FEA) which have shown uncommon assurance in having the choice to non-prominently measure biomechanical measures of energy for the setting of osteoporosis. The imperative is that these models have high computational interest which confines their clinical gathering. The paper discusses a significant learning model reliant on a convolutional neural network (CNN) for predicting typical strain as an alternative as opposed to material science based techniques. [6], [7], [1], [8]–[16], [2], [17]–[22], [3]–[7], [7], [7]

The model is set up on a colossal database of falsely delivered cancellous bone life systems, where the target characteristics are handled using the material science based FEA model. [8], [9]

The display of the readied model [10], [11] was studied by taking a gander at the desires against material science set up together figuring as for an alternate test enlightening accumulation. Connection between's significant learning and material science based conjectures was phenomenal (0.895, $p < 0.001$), and no purposeful inclination were found in Bland Altman examination. [12], [13]. The CNN model in like manner performed better than anything the as of late introduced Support Vector Machine (SVM) model which relied upon high quality features (relationship 0.847, $p < 0.001$). Appeared differently in relation to the material science based estimation, typical execution time was decreased by an abundance of numerous occasions, provoking a consistent assessment of ordinary strain. [14], [15]

Authors in [16], [17], has inspected visual screening using Computed Radiography (CR) images is a practical strategy for osteoporosis, regardless, there are various equivalent afflictions that show a state of low bone mass. In this paper, we propose a programmed distinctive evidence methodology for osteoporosis from phalanges CR images.

In the proposed system, [18], [19] complete a classifier subject to Deep Convolutional Neural Network (DCNN), and recognize darken CR images as conventional or unusual. For getting ready and surveying of CNN, use pseudo colour images. In [20] Shinn, Hoo Chang has discussed the explanatory efficacies achieved by the utilization of a RBF parcel SVM showed that CAD system was precise and reasonable for separating women with low BMD. The maker attests the SVM technique can be a trustworthy choice for the proposed system since it is fast and express for request, using dental comprehensive radiographs, of postmenopausal women with low BMD.

In light of highly acceptable affectability and disposition results, the proposed system is required to be a helpful apparatus for gathering women with low BMD and is furthermore expected to give a second end that may diminish misdiagnoses. [21]– [23]

The treatment of osteoporosis is for the most part preventive. It plans to hinder further loss of bone or increment bone thickness. Subsequently, early conclusion or distinguishing proof of high hazard is vital for avoiding confusions. Exact imaging techniques give the premise to various conclusion and forecast models. The techniques are for the most part utilized for two purposes: distinguishing the nearness of osteoporosis, and figuring the bone thickness. [30]– [32]

Imaging techniques utilized for diagnosing osteoporosis incorporate customary radiography, Magnetic resonance images, quantitative registered tomography (QCT) and ultrasound strategies. Radiography requires about 30% bone misfortune to be clear on Intensities images and the examination is done physically by restorative master. It likewise opens the patient to a radiation portion, and is once in a while led without a particular explanation, for example, suspected crack [4] – [7]

X-ray can gauge the bone mineral thickness without a visual examination by master. It uses low vitality Intensities shafts diminishing the radiation add up to around one twelfth contrasted with ordinary radiography. This outcomes in lower goals, yet enough to figure BMD values for various joints. [8]– [10]

QCT is an augmentation of conventional registered tomography (CT) to deliver a picture as well as to quantify tissue thickness. It gives separate evaluations of the bone mineral thickness for trabecular and cortical bone. It has additionally demonstrated great outcomes in anticipating vertebral breaks. Be that as it may, QCT has its hindrances, for example, high radiation portion, poor exactness and high imaging expenses. [3]– [5]

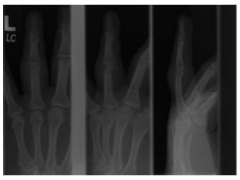
Quantitative ultrasound (QUS) is a nonexclusive term for ultrasound estimations of bone. In these systems, a sound heartbeat is transmitted through the bone site, more often than not the heel, and got in the opposite end. The technique requires no radiation and has points of interest like minimal effort of gadget and snappy

Estimations. It is capacity in break chance expectation has been seen as near BMD estimated by MRI. [22]–[25] Magnetic resonance images was presented in 1987 and is the most broadly utilized technique for diagnosing osteoporosis in clinical practice. X-ray can be applied to every skeletal site where osteoporotic cracks happen. These incorporate the lumbar spine, proximal femur, lower arm and calcaneus. In MRI framework, a radiation source is gone for a radiation locator set straightforwardly inverse the site to be estimated. The patient is set on a table and the source/identifier get together is then examined over the estimation area.

X-ray utilizes two distinctive vitality Intensities shafts to shape two images. From these images, the commitment of bone and delicate tissue can be comprehended numerically to figure bone thickness. The constriction coefficients of two delicate tissue segments, lean and fat tissue and their proportion specifically patient is first determined by estimating at an area adjacency to bone. X-ray gives the mass of bone mineral substance (BMC) in grams and the anticipated territory of the deliberate site in square centimeters. BMD is taken as the BMC isolated by the region and is given in units of g/cm2. Individual BMD qualities structure an advanced picture where every pixel speaks to an estimation point through the patient. [6]– [8], [10]

II. PROPOSED ALGORITHM

The publicly available MURA dataset is used for validation of the proposed method. The total number of images in the dataset is 1000. Out of which 11% images are of Normal while 67% images are of Osteoporosis.



International Journal of Engineering Applied Sciences and Technology, 2021
Vol. 6, Issue 4, ISSN No. 2455-2143, Pages 115-123
Published Online August 2021 in IJEAST (http://www.ijeast.com)

Figure 2 Sample Images of Joints taken from MURAV2 dataset

Performance metrics i.e. Accuracy and Confusion Matrix (CM) are used for validation of the model. Performance metrics of the procedure are determined as follows:

Performance parameters such as accuracy, sensitivity, specificity, and AUC are calculated for validation of the proposed technique. The accuracy is a measurement of a faithful representation of the truth, correctness. The accuracy can tell us immediately how the model is trained correctly. If the model is trained properly means that the system is accurate. In our research, we are comparing the accuracy of these techniques to find out the efficiency of each algorithm. The sensitivity contains the ability of a test to appropriately recognize with the abnormalities (true positive rate), whereas specificity is the ability of the test to properly categorize those without the anomalies (true negative rate).

The main objective of this research is Osteoporosis Detection using CNN and Keras by following steps:

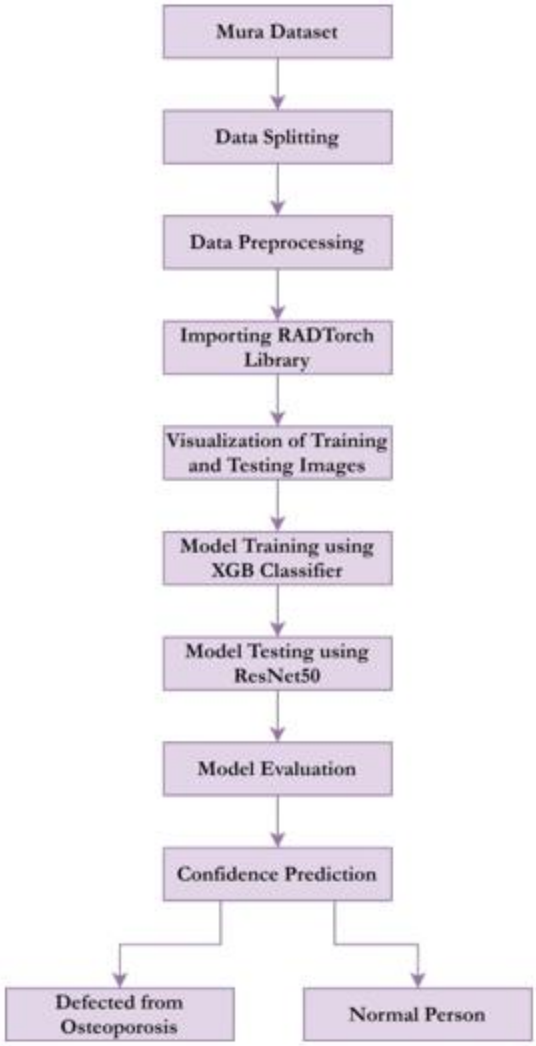


Figure 3 Proposed Methodology

We have used MURA dataset which is openly available to achieve segmentation and classification of osteoporosis in bones of human beings. Ultimately, we split our data into training, testing and validation with the ratio of 70%, 30% respectively. We can split our dataset in any ratio but we used this conventional ratio for the best classification of our model.
Training Dataset: The sample of data used to fit the model.
Test Dataset: The sample of data used to provide an unbiased evaluation of a final model fit on the training dataset.
As to validate our model properly, we have done some changes in the dataset in the pre-processing step. We create high quality, the balanced dataset for testing and validation as our downloaded dataset was unbalanced. We used to remove noise in pre-processing that was mainly due to bad light, noise and air bubbles. These steps provide us clear enhancement to further steps.

International Journal of Engineering Applied Sciences and Technology, 2021
Vol. 6, Issue 4, ISSN No. 2455-2143, Pages 115-123
Published Online August 2021 in IJEAST (http://www.ijeast.com)

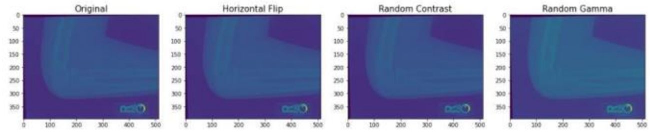


Figure 4 Preprocessing Steps using RADTorch

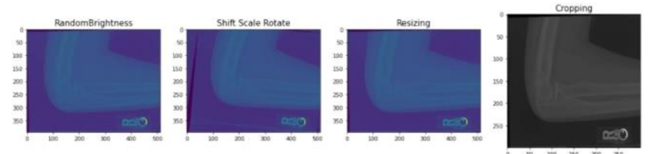


Figure 5 Cropping of the image using RADTorch

a. RADTorch

We have used the latest library released by Muhammad Elbanan* from MIT on 12th September, 2020. This a medical imaging handling library RADTorch provides a framework of higher level classes and functions that significantly reduce the time needed for implementation of different machine and deep learning algorithms on DICOM and non-DICOM medical images. RADTorch was built by radiologists for radiologists so they can build, test and implement state-of-the-art machine learning algorithms in minutes. RADTorch was developed and is currently maintained by Mohamed Elbanan, MD: a Radiology Resident at Yale New Haven Health System, Clinical Research Affiliate at Yale School of Medicine and Artificial Intelligence Advocate. RADTorch is built upon widely used machine learning and deep learning frameworks. These include: PyTorch for Deep Learning and Neural Networks. Scikit-learn for Data Management and Machine Learning Algorithms. PyDICOM for handling of DICOM data. Bokeh, Matplotlib and Seaborn for Data Visualization.

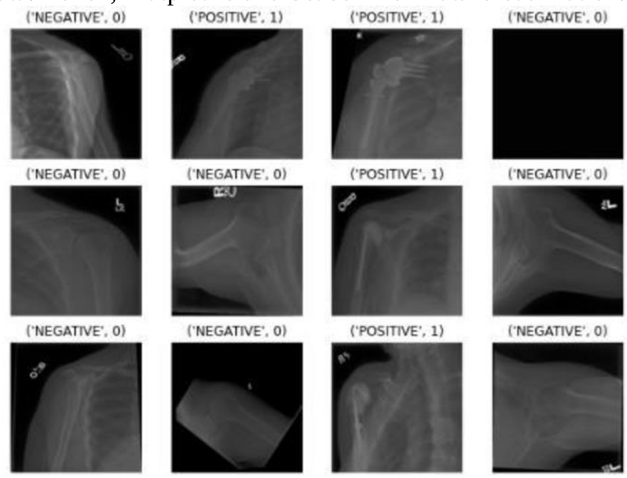


Figure 6 Preprocessed data visualization with RADTorch with true labels

III. Experimental Results

This section is about the model evaluation and the results of this research work. In this section, we will discuss the accuracy of our model and we will also test our model whether it can detect the osteoporosis with the highest accuracy or not.

a. Model Building

In our build model section, we have introduced ResNet Model Testing and XGB Model Training. We train the model on our training data and find the optimal learning rate.

b. Train Model for Detection of Osteoporosis

We have to train our model to find the optimal learning rate with XGB Classifier. Set our learning rate to the value where learning is fastest, and loss is still decreasing. We developed a function that uses our input as an anchor and sweeps through a range to search out the best local minima. The optimal learning rate of the model. We can see that losses decrease exponentially as the training of the number of batches increases.

c. Model Evaluation

A confusion matrix (CM) is often utilized to define the classification performance of a model on a test data or a set of data. Test data for which the accurate values are known are used. The CM itself is comparatively simple to know, but the associated terminology can be unclear.

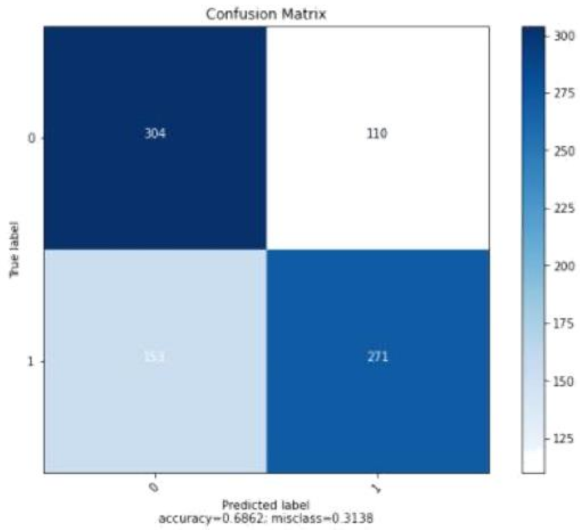


Figure 7 Confusion Matrix of our model training

Let's take a look at some of the samples that were most difficult for our model to detect. Figure 16 shows some of the random samples that were difficult for our model to detect. At every sub-image in fig. 16, some parameters are shown. These parameters are:

Prediction: osteoporosis predicted by the model

Actual: Actual image, could not predict.

Loss: Losses occur during predicting the random image.

International Journal of Engineering Applied Sciences and Technology, 2021
Vol. 6, Issue 4, ISSN No. 2455-2143, Pages 115-123
Published Online August 2021 in IJEAST (http://www.ijeast.com)

Probability: Probability of the model to predict the osteo correctly.

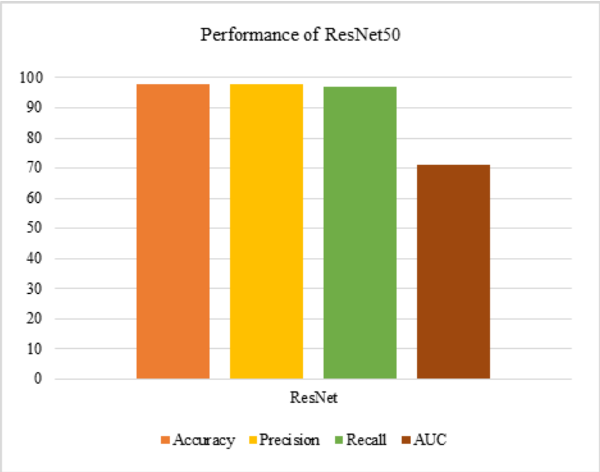


Figure 8 Model Testing using ResNet with ROC Random samples that were difficult to predict

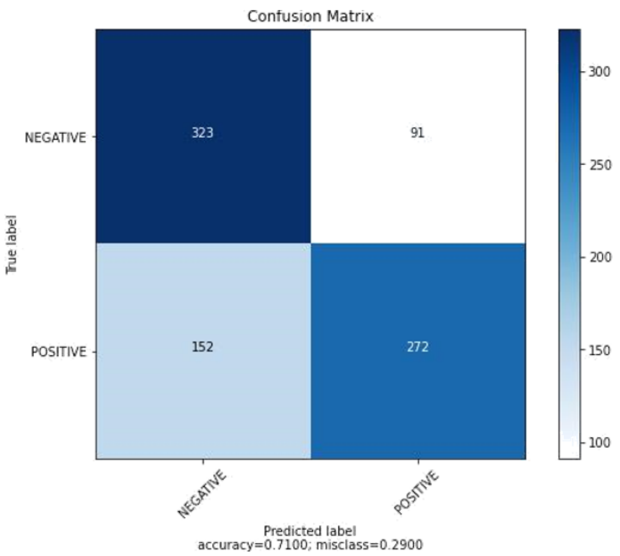


Figure 9 Accuracy of ResNet Model Prediction

d. Confidence Prediction

Finally, now it's time to test the model. We provided some random images one by one to the build model and let's look at the confidence predictions of some samples. Since our main focus was to detect Bones osteoporosis. The 'prediction interval' guesses in which value a future individual reflection will fall, whereas a 'confidence interval' displays the likely value of ranges related to the statistical constraint of the information, i.e., the mean of the population. So, we will see some random images of Bones and see the confidence predictions of the model. Two sample images are shown with a 100% confidence level.

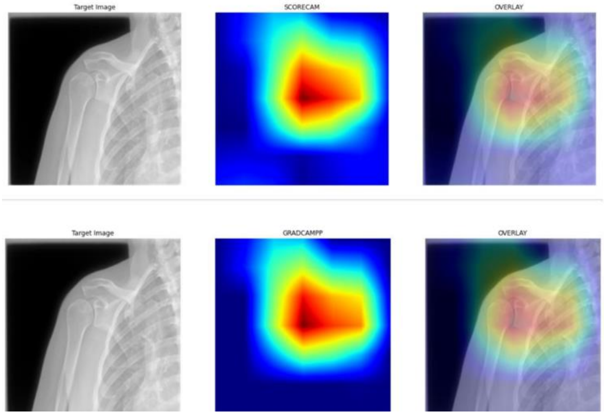


Figure 10 Target vs Predicted images

In the above Figures, the randomly provided images were of osteoporosis and the model predicted it correctly with a 99.9% confidence level. There are also some images that the model was not able to predict it with full confidence

In the above figures, the randomly provided images were of osteoporosis and the model predicted it correctly with a 99.9% confidence level. There are also some images that the model was not able to predict it with full confidence. Results shows that, the model predicted the Bones correctly and confidence level was impressive. These images show the model predictably the Bones correctly with the confidence level 98% and 91% respectively with ResNet50 and with Hybrid model of ResNet50 and XGBoost Classifiers. Similarly, our model does not only detect Bones, but it can also detect other osteoporosis with an impressive confidence level

IV. CONCLUSION

Portraying Osteoporosis by just considering the x-shaft images is incredibly problematic as the images obtained from the osteoporotic patient looks in a general sense equivalent to that of the sound patient. We have proposed CNN for course of action and evacuating features. Regardless, setting up a CNN requires a monster proportion of data. Nevertheless, we moved toward only few getting ready data, which is insufficient to set up a CNN. The outcomes bolster the promoted advantages of exchange learning, for example, quicker training rate and reasonableness for littler datasets. Then again, the visualizations from the pretrained models were too confounding to even think about drawing ends. The custom models created less noteworthy outcomes, yet through more clear visualizations, they gave better straightforwardness. This makes them exceptionally potential for further research.

V. REFERENCE

[1] B. Norman, "Use of 2D U-Net Convolutional Neural Networks for Automated Cartilage and Meniscus Segmentation of Knee MR Imaging Data to

Determine RelaxometryandMorphometry1,"no.March,2018,doi: 10.1148/radiol.2018172322.

[2] C. Florian, A. Vizitiu, F. Moldoveanu, C. Suciu, L. M. Itu, and A. T. H. Bone, "Towards Deep Learning Based Estimation of Fracture Risk in Osteoporosis Patients," pp. 659–665, 2017.

[3] D.Version,"Chapter1GeneralIntroduction,"2015,doi: 10.1016/j.medengphy.2014.02.016.

[4] C. R. Donoghue, "Analysis of MRI for Knee Osteoarthritis using Machine Learning," no. August, 2013.

[5] A. Horikawa, N. Miyakoshi, Y. Shimada, H. Kodama, and C. Report, "Case Report The Relationship between Osteoporosis and Osteoarthritis of the Knee : A Report of 2 Cases with Suspected Osteonecrosis," vol. 2014, no. Figure 1, pp. 1–7, 2014.

[6] S. S. Gornale, P. U. Patravali, and R. R. Manza, "A Survey on Exploration and Classification of Osteoarthritis Using Image Processing Techniques," vol. 7, no. 6,
2016.

[8] R. Maini, "Study and Comparison of Various Image Edge Detection Techniques," vol. 147002, no. 3, pp. 1–12

[9] M. K. Liukkonen, M. E. Mononen, O. Klets, and J. P. Arokoski, "Simulation of
Subject-Specific Progression of Knee Osteoarthritis and Comparison to Experimental Follow-up Data : Data from the Osteoarthritis Initiative," *Sci. Rep.*, no. March, pp. 1–14, 2017, doi: 10.1038/s41598-017-09013-7.

[10] I. Stajduhar, "Semi-Automated Detection of Anterior Cruciate Ligament Injury from MRI."

[11] C. M. Deniz, S. Xiang, S. Hallyburton, A. Welbeck, K. Cho, and G. Chang, "Segmentation of the Proximal Femur from MR Images using Deep Convolutional Neural Networks," pp. 1–13.

[12] C. M. Deniz *et al.*, "Segmentation of the Proximal Femur from MR Images using Deep Convolutional Neural Networks," no. October, pp. 1–14, 2018, doi: 10.1038/s41598-018-34817-6.

[13] M. Kazemi, Y. Dabiri, and L. P. Li, "Recent Advances in Computational Mechanics of the Human Knee Joint," vol. 2013, 2013.

[14] A. Guermazi *et al.*, "Prevalence of abnormalities in knees detected by MRI in adults without knee osteoarthritis : population based observational study (Framingham Osteoarthritis Study)," vol. 5339, no. August, pp. 1–13, 2012, doi: 10.1136/bmj.e5339.

[15] M. Boesen *et al.*, "AC SC," *Osteoarthr. Cartil.*, 2017, doi: 10.1016/j.joca.2016.12.009.

[16] K. Harrar, L. Hamami, S. Akkoul, E. Lespessailles, and R. Jennane, "Osteoporosis Assessment Using Multilayer Perceptron Neural Networks."

[17] "Osteoporosis detection using x-ray bone image ooi mei hong universiti teknologi malaysia."

[18] K. S. Basaruddin, N. Takano, and T. Nakano, "Numerical Study on the Morphology and Mechanical Role of Healthy and Osteoporotic Vertebral Trabecular Bone *," no. April 2014, 2011, doi: 10.1299/jbse.6.270

[19] A. Abbas, G. Campoli, and H. Weinans, "Neural network prediction of load from the morphology of trabecular bone," *Appl. Math. Model.*, vol. 37, no. 7, pp. 5260– 5276, 2013, doi: 10.1016/j.apm.2012.10.049.

[20] "Neural networks for analysis of trabecular bone in osteoarthritis," pp. 1–11, 2014.

[21] H. Shin, N. A. Tenenholtz, J. K. Rogers, C. G. Schwarz, and C. V Sep, "Medical

[22] Image Synthesis for Data Augmentation and Anonymization using Generative Adversarial Networks

[23] L. M. Shapiro, E. J. Mcwalter, M. Son, B. A. Hargreaves, and G. E. Gold, "NIH Public Access," vol. 39, no. 6, pp. 1346–1356, 2015, doi: 10.1002/jmri.24562.Mechanisms.

[24] A. L. Heureux and G. S. Member, "Machine Learning With Big Data : Challenges and Approaches," vol. 5, 2017.

[25] A. L. Heureux, K. Grolinger, H. F. Elyamany, and M. A. M. Capretz, "Machine Learning with Big Data : Challenges and Approaches," 2017, doi:10.1109/ACCESS.2017.2696365.

[26] G. N. Duda, S. Checa, M. Cilla, E. Borgiani, and J. Martı, "Machine learning techniques for the optimization of joint replacements : Application to a short-stem hip implant," pp. 1–16, 2017.

[27] C. Kruse, P. Eiken, P. Vestergaard, C. Kruse, P. Eiken, and P. Vestergaard,

[28] "Machine Learning Principles Can Improve Hip Fracture Prediction," *Calcif. Tissue Int.*, vol. 100, no. 4, pp. 348–360, 2017, doi: 10.1007/s00223-017-0238-7

[29] F. Cabitza, A. Locoro, and G. Banfi, "Machine Learning in Orthopedics : A
Literature Review," vol. 6, no. June, 2018, doi: 10.3389/fbioe.2018.0007

[30] F. Jaskani, S. Manzoor, M. Amin, M. Asif, and M. Irfan, "An Investigation on Several Operating Systems for Internet of Things," *EAI Endorsed Trans. Creat. Technol.*, vol. 6, no. 18, p. 160386, 2019, doi: 10.4108/eai.13-7-2018.160386.

[31] M. Riaz, F. Jaskani, and T. Awan, "An Artificial Neural Network Based Digital Differential Protection

Scheme for Synchronous Generator Stator Winding Protection," *EAI Endorsed Trans. Creat. Technol.*, vol. 6, no. 18, p. 160837, Jan. 2019, doi: 10.4108/eai.30-1-2019.160837.

[32] M. Arshad *et al.*, "Hybrid Machine Learning Techniques to detect Real Time Human Activity using UCI Dataset," *EAI Endorsed Trans. Internet Things*, p. 170006, 2018, doi: 10.4108/eai.26-5-2021.170006.

[33] M. U. Ghani, T. M. Alam, and F. H. Jaskani, "Comparison of Classification Models for Early Prediction of Breast Cancer," *3rd Int. Conf. Innov. Comput. ICIC 2019*, no. Icic, 2019, doi: 10.1109/ICIC48496.2019.8966691.

[34] S. Manzoor, F. Jaskani, and O. Riaz, "A Comparative View Of Applying Linear And Non-Linear Visualisation Approaches To Protein Dataset," *EAI Endorsed Trans. Creat. Technol.*, vol. 6, no. 19, p. 161109, Apr. 2019, doi: 10.4108/eai.13-7-2018.161109.

[35] M. Iqbal, M. Iqbal, F. Jaskani, K. Iqbal, and A. Hassan, "Time-Series Prediction of Cryptocurrency Market using Machine Learning Techniques," *EAI Endorsed Trans. Creat. Technol.*, p. 170286, 2021, doi: 10.4108/eai.7-7-2021.170286.

[36] I. Z. Memon, S. Talpur, S. Narejo, A. Z. Junejo, and F. Hassan, "Short-term prediction model for multi-currency exchange using artificial neural network," *Proc. - 3rd Int. Conf. Inf. Comput. Technol. ICICT 2020*, no. August, pp. 102–106, 2020, doi: 10.1109/ICICT50521.2020.00024.

[37] S. Manzoor, F. Jaskani, and O. Riaz, "A Comparative View Of Applying Linear And Non-Linear Visualisation Approaches To Protein Dataset," *EAI Endorsed Trans. Creat. Technol.*, vol. 6, no. 19, p. 161109, 2019, doi: 10.4108/eai.13-7-2018.161109.

[38] W. Abbas *et al.*, "Lungs Nodule Cancer Detection using Statistical Techniques," no. January 2021, 2020, doi: 10.1109/INMIC50486.2020.9318181.

[39] I. Z. Memon, S. Talpur, S. Narejo, A. Z. Junejo, and F. Hassan, "Short-term prediction model for multi-currency exchange using artificial neural network," *Proc. - 3rd Int. Conf. Inf. Comput. Technol. ICICT 2020*, pp. 102–106, Mar. 2020, doi: 10.1109/ICICT50521.2020.00024.

[40] M. Riaz, F. Jaskani, and T. Awan, "An Artificial Neural Network Based Digital Differential Protection Scheme for Synchronous Generator Stator Winding Protection," *EAI Endorsed Trans. Creat. Technol.*, vol. 6, no. 18, p. 160837, 2019, doi: 10.4108/eai.30-1-2019.160837.

[41] H. Shaikh, F. H. Jaskani, F. Khuhawar, K. Khan, M. A. Azam, and M. Aqeel, "Comparative Analysis of Urdu Parts Of Speech Taggers using Machine Learning Techniques," no. September, 2020, doi: 10.13140/RG.2.2.21875.35366.

[42] W. Abbas *et al.*, "Lungs Nodule Cancer Detection using Statistical Techniques."

[43] M. Aqeel, K. B. Khan, M. A. Azam, M. H. Ghouri, and F. Hassan, "Detection of Abnormal Events in Videos Using Convolutional Autoencoder and Generative Adversarial Network model," no. November, 2020.

[44] L. Mughal, K. Bhatti, F. Khuhawar, and F. Jaskani, "Comparative Analysis of Face Detection Using Linear Binary Techniques and Neural Network Approaches," *EAI Endorsed Trans. Creat. Technol.*, vol. 5, no. 17, p. 159712, 2018, doi: 10.4108/eai.18-10-2018.159712.

[45] L. Mughal, K. L. Bhatti, F. Khuhawar, and F. H. Jaskani, "EAI Endorsed Transactions Comparative Analysis of Face Detection Using Linear Binary Techniques and Neural Network Approaches," vol. 5, no. 17, pp. 1–7, 2018.

[46] I. Z. Memon, S. Talpur, S. Narejo, A. Z. Junejo, and F. Hassan, "Short-term prediction model for multi-currency exchange using artificial neural network," in *Proceedings - 3rd International Conference on Information and Computer Technologies, ICICT 2020*, Mar. 2020, pp. 102–106, doi: 10.1109/ICICT50521.2020.00024.

[47] F. Jaskani, S. Manzoor, M. Amin, M. Asif, and M. Irfan, "An Investigation on Several Operating Systems for Internet of Things," *EAI Endorsed Trans. Creat. Technol.*, vol. 6, no. 18, p. 160386, Jan. 2019, doi: 10.4108/eai.13-7-2018.160386.

[48] W. Abbas, K. B. Khan, M. Aqeel, M. A. Azam, M. H. Ghouri, and F. H. Jaskani, "Lungs Nodule Cancer Detection Using Statistical Techniques," Jan. 2021, pp. 1–6, doi: 10.1109/inmic50486.2020.9318181.

[49] M. U. Ghani, T. M. Alam, and F. H. Jaskani, "Comparison of Classification Models for Early Prediction of Breast Cancer," in *3rd International Conference on Innovative Computing, ICIC 2019*, Nov. 2019, doi: 10.1109/ICIC48496.2019.8966691.

[50] M. Faisal, R. Fawwad, H. Jaskani, and T. Awan, "EAI Endorsed Transactions An Artificial Neural Network Based Digital Differential Protection Scheme for Synchronous Generator Stator Winding Protection," pp. 1–13.

[51n] F. H. Jaskani, S. Manzoor, M. T. Amin, and M. Asif,

"EAI Endorsed Transactions An Investigation on Several Operating Systems for Internet of Things," pp. 1–7.