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Using Artificial Intelligence Algorithms to Recognize Osteoporosis: A Review

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ABSTRACT

Osteoporosis is a silent disease that usually occurs due to bone mineral deficiency (BMD), which leads to increased bone porosity, thus weakening the bones and increasing their porosity, which increases the risk of fractures in those with this disease. Bone porosity is defined as an increase in internal spaces in the bone structure, which reduces its density and strength and makes it more susceptible to fractures. Many parts of the skeleton are exposed to osteoporosis, such as the hip, thigh, jaw, knee, forearm, spine, and others. The incidence of osteoporosis increases in the elderly, and women are more affected by it than men. There are also other factors such as genetic predisposition and lifestyle. The use of artificial intelligence-based technical programs has received wide attention in the medical field to diagnose and classify various medical images, such as images of cancerous tumors, arthritis, osteoporosis, and others, as artificial intelligence provides accurate and rapid tools for the early detection of osteoporosis through the analysis of medical images, outperforming traditional methods, which improves treatment opportunities and reduces diagnostic costs. However, these techniques face challenges such as algorithmic bias and the need for diverse databases to ensure a balanced assessment of different cases.In addition, despite the advances in computer technologies for the early detection of osteoporosis, the disease remains a challenge in healthcare due to the absence of clear symptoms until fractures occur, the difficulty of early detection, the variability in disease progression, and the need for personalized treatment plans, which leads to increased mortality. The paper presents a review of studies that have addressed osteoporosis in skeletal parts such as the knee, spine, hip, and teeth. It also reviews the techniques and methods used in diagnosis, with a focus on the role of artificial intelligence in improving accuracy and speed of detection. The review shows how deep learning algorithms, especially convolutional neural networks (CNNs),have been effectively used to classify osteoporosis through the results and achieve high accuracy rates in different studies.

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1. INTRODUCTION

The scientific and technological progress and development that the world is witnessing in all different fields, including the medical field, such as the development of advanced imaging technologies that have become more accurate and of higher quality, as well as remote health care and work to diagnose the appropriate treatment for each patient based on his health condition, has brought about a qualitative shift in improving diagnosis and treatment through improving the provision of health services to people in different parts of the world, as advanced technologies such as artificial intelligence and modern medical devices have helped increase the accuracy of diagnosis and also reduce medical errors [1], [2].

The use of artificial intelligence in healthcare began in the mid-twentieth century through computers, as it was limited to analyzing medical data. With the development of technologies and the increase in computer computational power and storage capacity in the nineties, it became possible to analyze huge amounts of medical data, which led to the emergence of machine learning techniques that enabled computers to recognize patterns and predict outcomes [3]. Work is currently underway on emerging trends, such as developing medical imaging techniques that focus on accurate analysis of panoramic images as well as the use of digital biomarkers extracted from medical images, which has greatly contributed to enhancing the quality of health services and raising the level of care provided to patients [4], [5]. This progress has led to an increase in life expectancy and a decrease in mortality rates in many countries of the world compared to previous years and decades. As a result, it has led to an increase in the proportion of elderly people in society , as the elderly are more susceptible to osteoporosis than other age groups [6]- [9].

Osteoporosis is considered a silent disease, as many patients often do not know that they have the disease, because they do not show any prior symptoms of this disease until after they are exposed to fractures, in addition to the fact that some patients may suffer from symptoms indicating the presence of osteoporosis, such as chronic back pain, easy exposure to fractures, and muscle weakness, which is a source of great concern for those interested in the medical field as well as those infected with this disease, as bone fractures affect the movement of the body and osteoporosis of the spine, as it leads to a curvature in the body's straightness and affects its movement, in addition to psychological effects such as depression and anxiety, and economic effects including health care expenses and loss of productivity that affect patients and accompany exposure to bone fractures as a result of osteoporosis [10]-[12].

Osteoporosis is a major health problem, with a higher incidence in women than in men. The development of osteoporosis depends on lifestyle, such as physical activity and diet, which increases the deterioration and exacerbation of the condition according to the known levels of osteoporosis [13]. However, the development of osteoporosis can be reduced and its symptoms alleviated by following a healthy, balanced lifestyle, such as eating foods rich in calcium and vitamin D, practicing bone-strengthening exercises regularly, and maintaining a healthy weight. Regular consultation with a doctor and following up on prescribed treatment also play an important role in managing the disease [14], [15].

Given the challenges in the early detection of osteoporosis, machine learning, profound learning, has become an increasingly important tool in diagnosing osteoporosis. Deep learning is characterized by its ability to analyze large amounts of medical data with great accuracy and extract complex patterns that are difficult for traditional methods to recognize, making it suitable for dealing with medical images such as X-rays or CT scans, thus improving the accuracy and speed of diagnosis in cases of osteoporosis [16]. As a result, reliance on machine learning techniques and algorithms has increased in recent years. The latter has witnessed major developments and a qualitative leap, especially deep learning algorithms that rely on artificial neural networks [17].

2. OSTEOPOROSIS RECOGNITION

Osteoporosis is a common bone disorder that results from the deterioration of the internal bone tissue and increased porosity in the bones. This disorder is usually associated with aging, and as a person ages, the likelihood of developing osteoporosis increases, as osteoporosis is a chronic disease that makes bones weak and brittle, and thus the likelihood of these affected bones being exposed to fractures increases [19], [20].

Osteoporosis is a disease known since ancient times, such as the Greek and Roman civilizations, where some cases similar to the modern symptoms of osteoporosis were described by Hippocrates, the father of medicine. In the Middle Ages, weak bones were diagnosed with old age. In the nineteenth and twentieth centuries, with the development, microscopic studies and understanding the relationship between menopause and low bone density contributed to understanding the disease, with the development of treatments based on calcium and vitamin D. In addition to the development of medical imaging techniques in the second half of the twentieth century, the diagnosis became more accurate. In the twenty-first century [21], [24]. With the scientific and cognitive progress witnessed by the world, scientific knowledge of the causes of the disease has increased, and methods of treatment have also developed. Several factors have been diagnosed that play a role in increasing the incidence of osteoporosis, such as age, which increases the incidence of osteoporosis with age, and gender, as females are more susceptible to the disease, as well as lack of physical activity, calcium and vitamin D deficiency, heredity, and side effects of some medications, in addition to lifestyle and diet [18], [25]. The incidence of this disease increases among women more than men, especially after menopause, as statistics indicate that women over the age of seventy suffer from osteoporosis at different levels of the disease [26], [27].

Global statistics also indicate that more than 200 million people suffer from osteoporosis around the world, as in the United States of America, reports from health organizations indicated that about 44 million people in the population have bone density below the normal rate, which increases their risk of developing osteoporosis, in addition to 10 million people suffering from osteoporosis [28], [29]. From a health perspective, estimates indicate that 3.5 million cases of fractures resulting from osteoporosis occurred in the European Union in 2010. These cases included 1,800,000 cases of different types of fractures, 520,000 cases of spinal fractures, 620,000 cases of hip fractures, and 560,000 cases of forearm fractures. By 2025, 4.5 million osteoporotic fractures are expected to occur annually [30], [31]. Fig. 1 shows images of normal bones and others affected by osteoporosis.

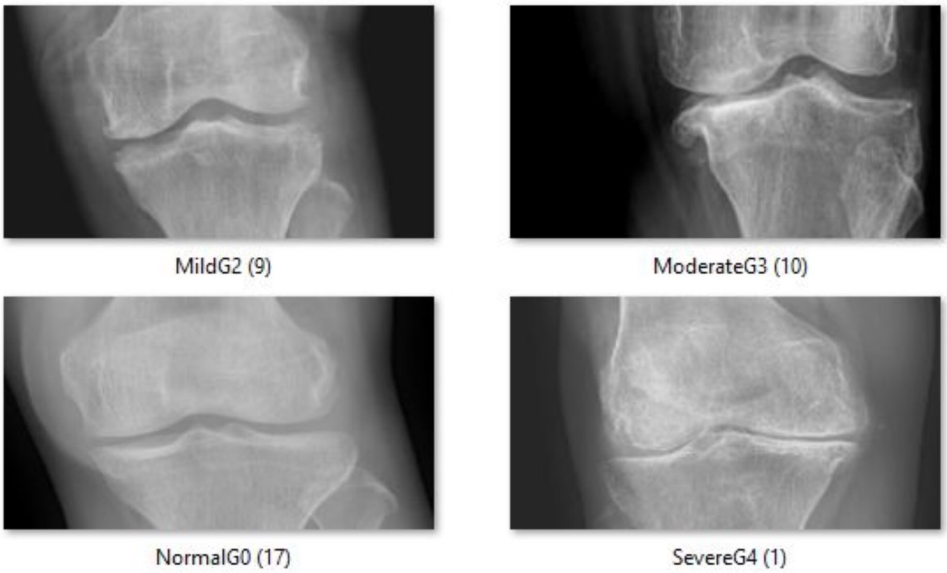

Fig. 1. Images of Normal Bones and others Affected by Osteoporosis.

3. TRADITIONAL METHODS USED TO DETECT OSTEOPOROSIS

There are many methods and techniques used to detect osteoporosis, which represent a combination of traditional techniques and advanced techniques used in the medical field that help in diagnosing bone health, including the well-known bone density test (DEXA), which is one of the most widely used tests in diagnosing osteoporosis by measuring bone mineral density using low-energy X-rays, which is considered the main standard in diagnosing osteoporosis with great accuracy, but it is limited in detecting subtle changes in the structure [32], [33]. The traditional X-ray imaging method is also used to detect fractures and osteoporosis, as traditional X-rays provide an available and inexpensive means of detecting fractures, but they are less accurate compared to the well-known bone density test (DEXA) [34]-[36]. There is also the magnetic resonance imaging (MRI) method used to evaluate bones and surrounding tissues, which is characterized by an accurate evaluation of tissues and bones without radiation, but it is expensive, in addition to the use of computed tomography (CT) to evaluate bone density, which provides a three-dimensional view but requires higher radiation doses and greater cost. Vitamin D, calcium, and parathyroid hormone levels are also measured, in addition to other hormones related to bone health [37]-[39]. Finally, genetics, family medical history, and diet play a role in the disease, in addition to the level of physical activity, which helps in detecting any pain or weakness. Muscular or skeletal abnormalities [40], [41]. In addition, the field of osteoporosis diagnosis has witnessed great development in many techniques, such as magnetic resonance imaging and computed tomography, which work to provide high-resolution, three-dimensional images of bones and joints, which contributes to early diagnosis and more accurate assessment. The use of artificial intelligence in analyzing medical images with high accuracy contributes to improving early diagnosis and effective treatment [42].

4. INTELLIGENT TECHNIQUES USED IN OSTEOPOROSIS RECOGNITION

Many smart methods and techniques are used to deal with medical images, such as osteoporosis images, as medical images differ from normal images in that they provide information about the functional status of different internal organs in the body, which is very important for detecting and predicting between normal and abnormal conditions [43], [44], [52].

Medical image datasets for training machine learning models include many main types such as magnetic resonance imaging (MRI) images that require precise pre-processing because they are characterized by high accuracy and also face challenges related to patient privacy, as well as X-ray images, which are often large but vary in quality depending on the device used, as well as computed tomography (CT) images that provide precise details but require complex processing to balance between different pathological conditions, and ultrasound images, whose quality varies greatly. The main challenges in obtaining medical images include the lack of public data due to privacy restrictions, the lack of sufficient data diversity to generalize models, and the need for pre-processing to improve quality and correct errors, which increases the complexity of the training process [45]-[47].

With the continuous development in healthcare, the volume of big data has increased significantly, and medical images and medical imaging constitute a large part of it [51]. Dealing with these platforms that contain very large and huge data has helped increase the speed of prediction, diagnosis, and detection using computer technologies based on the concept of artificial intelligence in dealing with this big data to process this huge amount of medical images and work on analyzing images by extracting features from them and identifying the extracted patterns from them [48], [49].

Artificial intelligence-based techniques can also be used to determine the presence of osteoporosis through input images such as X-rays and the well-known bone density test (DEXA) and others, with different levels of accuracy [35]. The rapid development of artificial intelligence has led to the creation of applications for screening and diagnosis with the help of artificial intelligence, which is used in recognizing medical images, such as diagnosing and predicting osteoporosis [50]. Among the smart methods that can be used to diagnose and distinguish osteoporosis are different machine learning methods Such as the use of deep learning models that are used in analyzing X-ray images or computed tomography (DXA) to assess bone density [47], [49].

5. MACHINE LEARNING

One of the primary subfields of artificial intelligence is machine learning that aims to program, improve, and develop software and technologies that can make decisions and improve performance based on available information and data without the need to write and program each task [53], [54]. This is done by relying on the principle of learning through experience, so that the more data the designed system or machine learning algorithm deals with, the more this leads to improved performance and the ability to make decisions and make predictions. With the huge and enormous amount of data that is accumulating and generated at present, the need has become necessary to find algorithms and systems capable of learning on their own through experience [54], [55].

Machine learning differs from traditional programming, as in traditional programming the system or pre-programmed algorithm performs the tasks required of it according to the instructions specified in advance for it, while in machine learning, the designed system or algorithm is trained through a set of data, and then the system, after training, makes the appropriate decision for the new data based on what it has learned from the training [56], [57].

Machine learning is generally divided into three main sections: supervised learning, unsupervised learning, and reinforcement learning [58]. In supervised learning, algorithms are trained on labeled data, i.e., the data has known inputs and outputs, where the target output is known to the algorithm. The most famous examples of algorithms used in this type are linear regression and support vector machines (SVM) [58], [59]. Unsupervised learning deals with unlabeled data and does not have known outputs or target outputs. Rather, the algorithm tries to discover hidden patterns, analyze the data it deals with, and discover relationships in it. The most famous examples of algorithms of this type are clustering algorithms in dealing with large data and extracting useful information and features from it [60]. In reinforcement learning, learning and decision-making are based on the environment in which the algorithm operates, based on the principle of reward or punishment based on its results, where it will receive a reward if it achieves a correct and positive result and a penalty in the event of inappropriate performance [58]. For example, in self-driving car systems, the work is rewarded if it reaches the specified location safely, and otherwise it will be punished if it deviates from the specified path. The customer in the self-driving car will be rewarded for reaching the location safely, but the customer will be punished if he deviates from the road and does not reach the desired location [56], [58]. The concept of deep learning falls within the field of machine learning, which includes various technologies, which in turn falls within a broader and more comprehensive field known as artificial intelligence, where these concepts are used to develop and improve the performance of systems and applications in dealing with information and data and in implementing complex tasks [61], [62]. Fig. 2. the Shows the relationship between artificial intelligence, machine learning and deep learning [63].

5.1. Artificial Neural Network (ANN)

Despite the great and rapid growth witnessed by smart technologies and machine learning, many complex problems have emerged, such as very large data, which has become an obstacle to traditional methods and approaches in dealing with them [53], [54]. This has necessitated the construction and design of systems and models that are more efficient in dealing with complex problems, as models have been built that attempt to simulate the natural system in organisms such as humans, including artificial neural networks, which are computational algorithms that simulate the method and way biological neural networks work in the brain in dealing with data, as well as learning, solving difficult problems, and making decisions [55], [57].

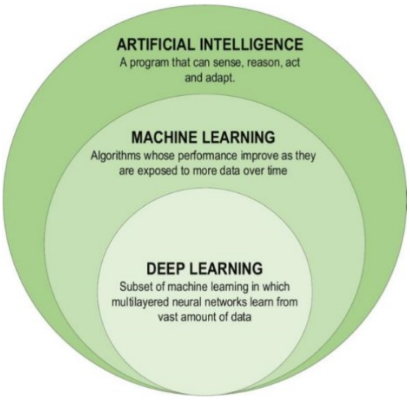

Fig. 2. Relationship Between Artificial Intelligence, Machine Learning and Deep Learning.

The general structure of the artificial neural network consists of a group of neurons in the form of simple computational units arranged through several layers, such as the input layer and a hidden layer, and ending with the output layer. These layers are connected through links, and each link has a weight that plays an important role in training and influencing the final results, as the number of layers depends on the type and purpose of the network design, as they cooperate to implement the required work such as predictions, data analysis, and obtaining conclusions [66]-[69].

There are several kinds of neural networks, be typical of multi-layer neural networks (MLP), which represent the simplest kinds of neural networks, as well as convolutional neural networks (CNNs) used in computer vision and recurrent neural networks (RNNs) used to process successive data, such as natural language processing [64], [65]. Artificial neural networks constitute an important and large field in the field of artificial intelligence, as they represent the basic building blocks of many technologies, such as deep learning, which is used and relied upon extensively in the medical field and medical image analysis [64], [70].

5.2. Deep Learning (DL)

It is one of the branches of machine learning that can deal with very large and complex data that other traditional algorithms and methods cannot deal with, and its operating principle is based on artificial neural networks that are characterized by being multi-layered, as they consist of several hidden layers that work to simulate the work of the human brain through multiple levels of representations and abstraction, and the deeper the hidden layer, the more learning and complexity it will encounter [71] - [73] . The information and data are dealt with in the upper layers, which are simpler, and then the output of these upper layers is transferred to the layers that follow, which are more complex than the previous layer and deal with more complex data as well [71]. Deep learning models are trained by dealing with very large and massive data, then processing and analyzing this data and also working to extract features from it, which enables the deep learning models used to learn on their own without any human intervention [71], [74].

Many deep learning models have been developed that are used in different fields, such as image recognition and different data, by training the model by following several steps, such as the pre-processing stage, the feature extraction step, and then the recognition and data matching stage or plan [75]. The deep learning model, convolutional neural networks (CNN), is considered one of the first models who was developed in 1988 by Yan Andre, which simulates the work of the biological neural network for the human brain and was used in computer vision to recognize handwritten numbers. The CNN model consists of several layers, which are the convolution layer, the pooling layer, and the fully connected layer [76] - [78]. Fig. 3. shows traditional machine learning and how it differs from deep learning [76], [77].

The use of deep learning models and techniques faces many challenges, such as the need for a large database in the training phase of the models, which is often expensive and difficult. Also, deep learning models

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lack clarity on how to reach the solution, which makes interpreting their results complex. Also, the results may be subject to bias if the data is unbalanced, leading to questionable results. In addition, training requires a lot of time and computational resources for the training process of the model [78].

Deep learning models and structures based on artificial neural networks have been designed to perform many complex and diverse tasks such as classification, prediction, speech recognition, and data analysis [71]. With the increase in the size and type of data, neural network structures have also evolved significantly to suit the diversity and amount of data, as each structure is used for specific purposes and according to the nature of the data it deals with and the problem that the model is trying to solve [79].

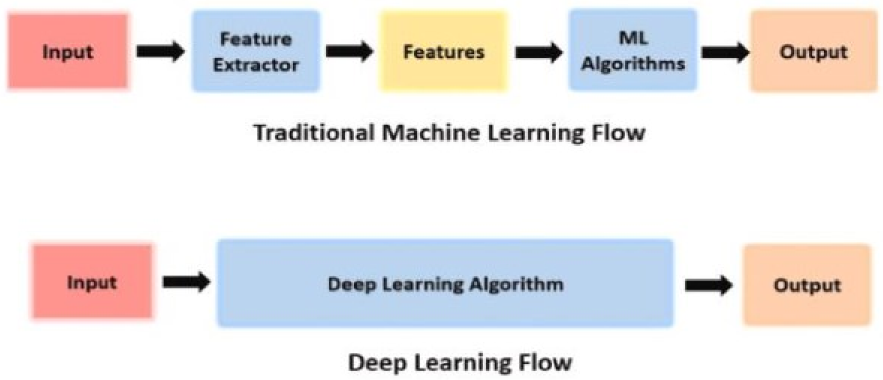

Fig. 3. Traditional Machine Learning and How it Differs from Deep Learning.

5.2.1. Convolutional neural network (CNN)

CNNs are mostly used for recognition of speech and computer vision tasks. They can handle jobs involving spatially related datasets, where the rows and columns cannot be switched out. According to the specific modeling job, their network design consists of several steps that enable hierarchy feature learning [80]-[83]. For instance, when it comes to object discrimination in images, the initial layers of the network are in charge of extracting fundamental properties like corners and edges. These are then gradually combined to create increasingly intricate details in the final layers that mimic the real items of Importance, such as vehicles, houses, or animals. The auto-generated attributes are then utilized for prognosis to identify important objects in fresh images [81]-[84]. Fig. 4 shows the CNN architecture for image classification [63].

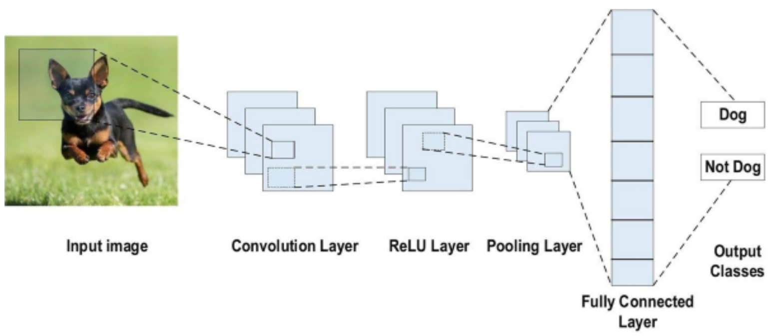

Fig. 4. CNN Architecture for Image Classification.

5.2.2. Autoencoder

It is a type of unsupervised network. Since autoencoders creates an intensive representation of the input data features, these architectures often have two stages: an encoding stage where a low-dimensional representation is used as input, and a decoding step where the network attempts to rebuild the original input using the learned features. This forces the network to discard unnecessary noise and preserve the important information in the latent representation [85]-[87]. Autoencoders are often used in conjunction with other post-learning systems for dimensionality reduction and unsupervised feature learning. However, they can also be used for anomaly detection, such as fraudulent activity in financial markets, because they can identify rebuilding errors, who are thought to be much larger for anomaly samples compare normal example [88] – [90]. Fig. 5 shows the basic architecture of an autoencoder [90].

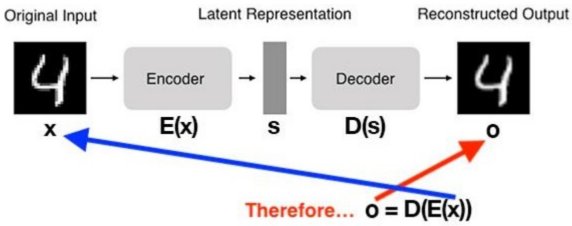

Fig. 5. Basic Architecture of an Autoencoder.

5.2.3. Distributed representation

Distributed representation is one of the methods used in deep learning to represent a set of information and data in the form of a unified model instead of using the representation of the information individually, as distributed representations play a fundamental function in learning features and modeling language in natural language processing jobs, where words, phrases, and sentences are projected into numerical representations as embeddings inside a single semantic space [91]-[93]. This technique enables neural networks to understand complex data, as it can be a multidimensional numerical representation that reflects the meaning of the word in addition to clarifying the relationship of the word with words, which helps facilitate understanding the relationship between words [94]-[96].

5.2.4. Recurrent neural network (RNN)

Recurrent neural networks are specifically designed to handle successive data such as time sequence analysis data, event successive, and natural language. With the interior feedback loops provided by their architecture, temporal dependencies can be modeled using sequential pattern learning, which creates a memory that allows them to retain information. The problem with simple RNN architectures is that they have vanishing gradients, meaning that early memories have little effect [97]-[99]. It is through complex structures that work to address this problem, such as long short-term memory (LSTM) networks. with sophisticated attention processes. RNNs are popular used for natural language processing applications including neural machine translation and sequence transfer, as well as time series prediction and process behavior prediction [100]-[102].

5.2.5. Generative adversarial neural network (GAN)

It is a subset of generative models that seek to learn the splitting probability so that the network can generate new data samples on a set of training data randomly and with some diversity. Generative neural networks consist of two competing subnetworks for this purpose. The generator network is the first network that generates new examples from the original data by capturing the distribution of the inputs. The discriminator network, a second network, aims to recognize between original and fake cases. Until the discriminator becomes indistinguishable between the two types of data [103]-[105]. the two networks are trained so that the gain of one network equals the loss of the other. However, when misused with malicious intent, such methods can pose serious risks with societal consequences. of particular concern is when “fake” content in the form of hate speech and false information is produced in an attempt to influence public opinion or distort financial markets [106]-[108].

6. LITERATURE REVIEW

State-of-the-art outcomes in illness diagnosis have been demonstrated using machine learning techniques, particularly with deep convolutional neural networks Numerous scientists have effectively constructed an osteoporosis diagnostic system from various images kinds using machine learning techniques [109].

In 2020, Yamamoto *et al.* integrated patient and image characteristics and statistically examined the distinction that resulted from the addition of these factors. While the study demonstrated increases in performance, many CNN models did not demonstrate the same gains. After being assessed in the model, the effect size a measurement of the actual impact sized by an experience or the degree of the correlation between variables—was found to have a substantial effect size, with a value of 0.871,Additionally, DPR and six ensemble CNN models—ResNet-18, 50, and 152, as well as EfficientNet-b0, b3, and b7—were used to screen for osteoporosis. The performance of the ResNet-152 and EfficientNetb7 models was comparable [110].

In 2020, Lee *et al.* with the use of CNN architectures, retrieved the features from the spine x-rays and sent them to machine learning classifiers for classification. Using random forest for classification and VGG for feature extraction, they were able to attain the highest possible accuracy in classification of 71% [111].

In 2020, Yousfi *et al.* presented a technique that used artificial intelligence, genetic algorithms, and texture analysis to differentiate between instances of osteoporosis and healthy, normal cases using two-dimensional bone X-ray scans. The number of gray levels employed prior to processing and the co-occurrence matrix coefficients (also known as the distance coefficients or pixel separation) were both enhanced via genetic algorithms. The optimal collection of features taken from GLCM and RLM matrices was also chosen using genetic algorithms. The findings demonstrated that the classification rates (ACC = 87.50%) attained using GLCM (ACC = 77.8%) alone might be enhanced using genetic algorithms in combination with GLCM and BSIF characteristics [112].

In 2022, Sukegawa *et al.* studied DPRs using CNNs through the Ensemble CNN model to detect osteoporosis. Clinical variables were also used which further improved the classification performance achieving acc: 84% [113].

In 2022, a pre-trained deep convolutional neural network (DCNN) consisting of six basic structures was employed by Dzierzak *et al.* to develop their model. Of these models, the VGG-16 model performed better than the others, with an ACC of 95% and an AUC of 0.985, Moreover, an ACC of more than 90% was attained by three models (InceptionResNetV2, VGG-19, and VGG-16). The implementation of fine-tuning and pre-training procedures, Who have shown very success in spite of the restricted quantity of accessible data are responsible for the notable improvement in performance.VGG-16 turned out to be the best model for managing tiny datasets [114].

In 2022, Sollmann *et al.* studied spine CT images and used CNN to assess volumetric bone mineral density. When they contrasted the findings with volumetric bone mineral density measured from standard CT scans, they discovered that CNN provides excellent diagnostic precision. The AUC for the applied model was 0.862 [115].

In 2022, Nakamoto, T., Taguchi, A., & Kakimoto, N.) researchers presented a way to create computer-aided screening systems that can forecast osteoporosis in 2022. Three types of convolutional neural networks with deep layers (CNNs)—Alexnet, VGG-16, and GoogLeNet—were used to develop the systems using panoramic images of women 50 years of age and older. The systems' performance was then assessed. All of the CNNs' findings agreed rather well with the oral radiologist's assessment, ranging from 86.0% to 90.7%. The sensitivity, specificity, and accuracy of the three systems' predictions for lumbar spine osteoporosis were 78.3%–82.6%, 71.4%–79.2%, and 74.0%–79.0%, respectively. The sensitivity, specificity, and accuracy of the prediction scores for femoral neck osteoporosis were 80.0%–86.7%, 67.1%–74.1%, and 70.0%–75.0%, respectively [116].

In 2023, Zhang *et al.* presented an end-to-end multi-task framework that includes location, classification, and segmentation by U-Net, which is required for this framework to work. the learning rate of 10e-3, the framework outperformed modern DL models in diagnosing osteoporosis, with the highest results (ACC: 0.957, F1-score: 0.975, specificity: 0.922, sensitivity: 0.962). In the field of deep learning, transfer learning has become more and more popular because of its capacity to draw on prior task experience, enhance generalization, and create more accurate results with less data input [117].

In the year 2023, the researcher (Widyaningrum, R.) and colleagues performed a comparison between K-means and fuzzy C-means and published a technique for automated cancellous bone segmentation to identify osteoporosis using a Decision tree and color graph, naive Bayes, machine learning (ML), and multilayer receiver machine learning techniques were utilized to segment the bone utilizing the pixel distribution derived from fuzzy C-means and K-means. (The results of this study were obtained using the test dataset. The best diagnostic performance of the osteoporosis detection technique was the segmentation using the multi-class classifier combined with K-means, with sensitivity, specificity, and accuracy of 90.00%, 90.90%, and 90.48%, respectively. This was based on the performance evaluation of the two segmentation methods using fuzzy C-means and segmentation using K-means combined with the three ML methods [118].

In 2024, Yen, T., and colleagues published a model to investigate the potential use of X-ray images for the prediction of the density of bone minerals (BMD) and the classification of patient groups at risk. A deep learning model named DeepDXA-KUB was put out; it uses the input X-ray images to predict BMD values for lumbar vertebrae and the left hip. For the lumbar vertebrae, the model had an accuracy of 84.7%, a specificity of 86.6%, and a sensitivity of 81.6%; for the left hip, the corresponding percentages were 84.2%, 91.2%, and 81%. With an AUROC of 0.947 for the left hip and 0.939 for the lumbar spine, the model showed adequate performance in screening for osteoporosis [119].

The paper summarizes the related work in Table 1. The table below shows several techniques that use artificial intelligence and algorithms to detect and classify osteoporosis, which have been used for different datasets of osteoporosis-related medical images. The main criterion for comparing these methods is the results obtained for each method, as many factors affect the accuracy rate, such as feature selection, image quality, and the algorithm used. Based on this, we can say that CNN models have shown accurate classification of osteoporosis. It is also possible to enhance the performance of CNN models by combining them with other techniques, such as support vector machines, to improve classification accuracy through dynamic feature exploration or with generative deep learning models (GANs) to generate high-quality synthetic medical images that support training and improve model performance.

Table 1. Summary of techniques used to detect and classification osteoporosis.

No.	Authors	Year	Imaging Modality	Human Site	Methods	Dataset	Result
1	Yamamoto *et al.*	2020	X-RAY	Hip	ResNet-18, ResNet-34 EfficientNet-b3, GoogleNet, EfficientNetb4	1131 Images	CC: 0.89 Recall: 0.899 F1 score: 0.89 AUC: 0.94
2	Lee *et al.*	2020	X-RAY	Spine	Vgg-16, Random forest	334 Images	AUC: 0.858
3	Yousfi *et al.*	2020	X-RAY	Hip	GLCM method. RLM method. BSIF method. Genetic Algorithms (GAs) for feature selection	174 .images	GAs combined with GLCM and BSIF features can improve the classification rates ACC = 87.50%) obtained) using GLCM (ACC = 77.8%) alone
4	Sukegawa *et al.*	2022	X-RAY dental panoramic radiographs	Dental panoramic	Ensemble CNN	778 images	ACC: 84%
5	Dzierzak *et al.*	2022	CT	Spine	VGG-16, VGG-19, DCNNs MobileNetV2, Xception, ResNet-50, InceptionResNetV2	400 images	AUC: 0.98 ACC: 0.95 TPR: 0.96 TNR: 0.95
6	Sollmann *et al.*	2022	CT	Spine	DCNN	144 patients	AUC: 0.862
7	Nakamoto *et al.*	2022	X-RAY	spine and femoral neck	used for transfer learning in three CNNs (Alexnet, GoogLeNet, and .(VGG-16	1500 images	spine osteoarthritis showed a sensitivity of 78.3%–82.6%, a specificity of 71.4%–79.2%, and an accuracy of 74.0%–79.0%. femoral neck osteoarthritis showed a sensitivity of 80.0%–86.7%, a specificity of 67.1%–74.1%, and an accuracy of 70.0%–75.0%
8	Zhang *et al.*	2023	CT	spine	U-net	1048 patients	CC: 0.96 Sensitivity: 0.96 Specificity: 0.92 F1-score: 0.98
9	Widyaningrum *et al.*	2023	X-RAY dental panoramic radiographs	Dental panoramic	using three ML methods: decision tree, naive Bayes, and multilayer perceptron	102 .images	achieved 90.48% accuracy for osteoporosis detection. Specificity and sensitivity were 90.90% and 90.00%, respectively
10	Yen *et al.*	2024	X-RAY	lumbar vertebrae and left hip	proposed DeepDXA-KUB, a deep learning model	8923 images	The model showed accuracy, sensitivity and specificity for detecting osteoporosis of 84.7%, 81.6% and 86.6% for the lumbar vertebrae and 84.2%, 91.2% and 81% for the left hip, respectively. The AUROC was 0.939 for the lumbar vertebrae and 0.947 .for the left hip

7. CONCLUSION

The detection and classification system for osteoporosis medical images is considered one of the advanced systems that can be relied upon and used in the detection and classification processes of medical images of different body organs through the results achieved based on several measures such as accuracy, precision, recall, and F1 score. The process of applying and using artificial intelligence technologies in the field of medical services also requires the provision of technical infrastructure in addition to large investments to develop the technologies on an ongoing basis, as well as training specialized personnel and financial costs for ongoing maintenance purposes, and also from an ethical perspective, such as data security and patient privacy, which requires setting fixed and strict policies for users. In this work, the techniques and methods used by artificial intelligence technologies were presented based on previous research to detect osteoporosis images. The process of detecting and classifying images includes several main steps, such as pre-processing the input images, extracting features, training the models used, and then testing them to evaluate their efficiency and performance according to approved standards. It is important to work on supporting and enhancing health care for people who are more susceptible to osteoporosis than others, such as the elderly, postmenopausal women, or those with diseases such as diabetes, such as implementing regular osteoporosis screening programs, educating with information about the disease, and clarifying the methods followed in preventing it and reducing its symptoms for early treatment of the disease and avoiding their exposure to fractures.

Future work: Work can be done to follow the method of integrating multiple medical imaging data to provide a more accurate diagnosis by exploiting the unique advantages of each type of data, such as combining X-rays and magnetic resonance imaging or computed tomography, and it is also possible to work on choosing an ideal and global model for detection and classification by working to unify the database used by researchers by cooperating to overcome the challenges they face in collecting and exchanging data to unify it in a globally approved database and apply different methods and models to them and choosing the best efficiency and performance to be the approved model, which can contribute to reducing costs and helping those interested in the field of health care.

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