

EXPLORATION OF ARTIFICIAL INTELLIGENCE AND BLOCKCHAIN TECHNOLOGY IN SMART AND SECURE HEALTHCARE

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PREFACE

From the last decade onward, a considerable amount of research and developments in technology have taken place especially in the healthcare industry, with the involvement of technologies like Artificial Intelligence (AI), Machine Learning (ML), Deep Learning, Blockchain, Communication Systems, Internet of Things, Multisensory Systems, *etc.* The purpose is only to make smart and secure healthcare possible. Machine Learning techniques and algorithms are required to give a boost to the aim of smart healthcare. Hence, to fulfill the vision of smart healthcare, the tools and applications based on Artificial Intelligence and Machine Learning are becoming extremely popular for producing more accuracy (in terms of values) in predicting results (without being explicitly programmed) in the healthcare industry. However, Artificial Intelligence-based algorithms are quite helpful for the transformation of physiological data into clinical information of real values, but for processing such big data from a set of medical images and identifying or extracting characteristic patterns of health function, then translating these patterns into clinical information definitely requires an adequate knowledge base of physiology, advanced digital signal processing capabilities, and machine learning. The domain of Artificial Intelligence can be taken into three main groups *viz.* Artificial Slight Intellect, Artificial Overall Intelligence, and Artificial Super Intelligence, and undoubtedly all these groups work in an absolute manner in the presence of fundamental or advanced Machine Learning techniques. There are a number of categories existing concerning the AI/ML algorithms used for fulfilling the objective of smart healthcare such as supervised (regression, decision-tree, classification) and unsupervised (clustering, association analysis, hidden Markov model, *etc.*). Although the preparation of intelligent algorithms or systems based on AI/ML combined with novel wearable portable devices (especially sensors *etc.*) offers unprecedented possibilities and opportunities for remote patient monitoring, traditional sharing schemes cannot guarantee the security and immutability of data. Machine Learning along with Artificial Intelligence is quite helpful towards the research and development in health care, but still lacking somewhat especially in security and privacy related to healthcare information of all categories *i.e.* the dream of smart healthcare is far behind. So to make the dream of smart healthcare come true, the emerging Blockchain technology is spreading its feet in the healthcare industry having revolutionized results. The Blockchain is helping in numerous perspectives in health care such that for managing the security, the integrity of data *i.e.* electronic health records (EHRs), electronic medical records (EMRs); preserving immutability of data, tracking the origin, spreading of data, the authenticity of data, data sharing, protection against data spoofing, *etc.*, as compared to traditional security mechanism *i.e.* a single technology having a number of features. In simple words, smart healthcare will only be possible if both the accuracy in results, security and privacy of such results will be equally maintained. In a nutshell, the primary goal of this book is to offer a variety of techniques for a broad readership, ranging from computing and methodologies to business analytics in the health sciences.

In the chapter titled, “Blockchain Associated Machine Learning Approach for Earlier Prognosis and Preclusion of Osteoporosis in Elderly”, the authors discuss a fully automated mechanism for suspecting osteoporosis patients, which uses machine learning techniques to improve prognosis and preciseness through various processes. Here, we created an automated method that combines principal component analysis (PCA) and the weighted k-nearest neighbors algorithm (wkNN) to effectively detect, predict, and categorize BMD scores as normal, osteopenia, and osteoporosis.

In the chapter titled, “Online Detection of Malnutrition-Induced Anemia from Nail Color using Machine Learning Algorithms”, the author proposed a noninvasive online-based

malnutrition-induced anaemia detection using a smartphone App for remotely measuring and monitoring anaemia and malnutrition in humans. This painless method enables user-friendly measurements of human bloodstream parameters such as haemoglobin (Hb), iron, folic acid, and vitamin B12 by embedding intelligent image processing algorithms that will process photos of fingernails captured by the camera in the smartphone, thereby providing a contact-free measurement system during this Covid 19 pandemic.

In the chapter titled, “Artificial Intelligence and Bioinformatics Promise Smart and Secure Healthcare: A Covid-19 Perspectives”, the authors elaborate on the principle, procedure and applications of AI equipped with bioinformatics knowledge to create opportunities, and prospects and answer the challenges met by academicians, researchers, students and industry professionals from the background of computer science, bioinformatics, and healthcare.

In the chapter titled, “Detection of Breast Cancer using Context-Aware Capsule Neural Network”, the authors' primary focus in this work is on the extraction of the features of the images and to accomplish this work, 3D mammogram images are pre-processed. Noise is removed and these preprocessed images are further passed through different convolution layers. After convolution process is done, images are fed to the capsule layers for final classification.

In the chapter titled, “Enhancement of Breast Cancer Screening through Texture and Deep Feature Fusion Model using MLO and CC View Mammograms”, the authors' proposed model is more concentrated on the extraction and fusion of deep features from the two views to improve screening efficacy. The efficacy of the model is evaluated on mammogram images taken from MLO view and CC views of the DDSM data set. Medical imaging-based ML techniques are commonly used for breast cancer detection and diagnosis, but they are time-consuming.

In the chapter titled, “Artificial Intelligence Assisted Colonoscopy in Diagnosis of Colorectal Cancer”, the authors discuss how AI has gained attention for its potential to improve standard clinical practice. One such use is in diagnostic colonoscopy, where it can help identify precancerous lesions early and permit appropriate care.

In the chapter titled, “Developing a Smart Device for the Manufacturing of Health Products for Patients Using the Internet of Things”, healthcare analytics in a connected world were briefly discussed. In this study, the causes of the creation of contemporary healthcare are methodically examined, along with its causes, methods, and effects.

The authors of the chapter titled, “Blockchain Security in Healthcare” discuss the security and privacy needs, threats, and solution strategies in healthcare Blockchain for the exchange of electronic medical data, which further aids healthcare professionals, healthcare service developers, and healthcare consumers in gaining a thorough understanding of the security and privacy requirements and technologies for enabling a secure and decentralized EMR data sharing.

In this chapter titled, “Enhancing the Communication of Speech Impaired People using Embedded Vision Based Gesture Recognition through Deep Learning”, the author proposes to employ an image-based recognition system for American Sign Language (ASL) namely, (i). classification of handcrafted features using Machine Learning methods, (ii) classification utilising a pre-trained model *via* transfer learning, and (iii) classification of deep features derived from a specific layer by machine learning classifiers.

The chapter titled, “Advancing Data Science: A New Ray of Hope to Mental Health Care” examines the contributions of AI/ML and Blockchain to several mental healthcare system domains and discusses its potential in many additional unexplored frontiers in this discipline.

The chapter titled, “Machine Learning Based Techniques for Pneumonia Disease Identification in the Health Industry”, discusses the applications of one of the AI sub-disciplines, ML, and the difficulties and obstacles that researchers encounter when identifying early-stage pneumonia disease. In conclusion, Blockchain technology combined with ML and DL may be useful to create safe diagnostic systems as cloud systems have grown to be a possible hazard due to the accumulation of data stored there.

In the chapter titled, “Framework towards Smart Healthcare Tourism based on the Internet of Medical Things (IoMT)”, the authors provide the outlines of the Internet of Things-based health monitoring system that may be helpful for foreign visitors and hotel management throughout maintaining the health of both its guests and staff. The system will identify and examine the body’s many vital signs before telling the operator of the condition of each person’s health.

This chapter titled, “Unmasking the Sentiments of People Towards Pandemic: Twitter Sentiment Analysis in Real Time”, aims at examining and assessing people’s feelings and sentiments throughout the coronavirus outbreak. The study analysed people’s sentiments on the COVID-19 pandemic among Indians using sentimental analysis from tweets collected on Twitter.

In the chapter titled “Application of Industry 4.0: AI and IoT to Improve Supply Chain Performance”, the author briefs about how Artificial Intelligence and the Internet of Things play a vital role in enhancing supply chain management specifically in the healthcare industry. The businesses may streamline operations, cut expenses, and enhance decision-making by utilizing such emerging technologies.

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CHAPTER 1

Blockchain Associated Machine Learning Approach for Earlier Prognosis and Preclusion of Osteoporosis in Elderly

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Abstract: Osteoporosis (OP), or porous bone, is a severe illness wherein an individual's bones weaken, increasing the likelihood of fractures. OP is caused by micro-architectural degradation of bone tissues, which raises the probability of bone fragility and can result in bone fractures even when no force is placed on it. Estimating bone mineral density (BMD) is a prevalent method for detecting OP. For women who have reached menopause, prompt and precise forecasts and preventative measures of OP are essential. BMD can be measured using imaging methods like Computed Tomography (CT) and Dual Energy X-ray Absorptiometry (DEXA/DXA). Blockchain (BC) is a revolutionary technique utilized in the health sector to store and share patient information between clinics, testing centres, dispensaries, and practitioners. The application of Blockchain could detect drastic and even serious errors. As an outcome, it may improve the confidentiality and accessibility of medical information interchange in the medical field. This system helps health organizations raise awareness and enhance the evaluation of health records. By integrating blockchain technology with machine learning algorithms, various bone ailments, including osteoporosis and osteoarthritis, can be identified earlier, which delivers a report regarding the prediction of fracture risk. The developed system can assist physicians and radiologists in making more rapid and better diagnoses of the affected ones. In this work, we developed a completely automated mechanism for suspicious osteoporosis patients that uses machine learning techniques to improve prognosis and precision *via* different processes. Here, we developed a computerized system that effectively integrates princi-

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pal component analysis (PCA) with the weighted k-nearest neighbours algorithm (wkNN) to identify, predict, and classify the BMD scores as usual, osteopenia, and osteoporosis. The ranked results are validated with the DEXA scan results and by the clinicians to demonstrate the efficacy of the machine learning techniques. The laboratories use BC to safely and anonymously share the findings with the patients and doctors.

Keywords: Blockchain (BC) technology, Bone mineral density (BMD), Dual energy X-ray absorptiometry (DEXA/DXA), Osteoporosis (OP), Principal component analysis (PCA), Weighted k-nearest neighbours algorithm (wkNN).

INTRODUCTION

Healthcare records encompass the physical information concerning our bodies and are essential for diagnosing and treating diseases. Medical data includes several patient-related archives necessary for proper care and areas for further study. Moreover, it must be kept securely and distributed to safeguard the data's confidentiality [1]. With the fast progress of artificial intelligence (AI), healthcare information has emerged as a valuable asset that can support the creation of AI diagnostic modelling techniques that could help therapists diagnose. Even though medical data documentation has progressed from paper files to electronic health records, which are more useful for accessing data and retrieval, more consideration should be given to data security. Numerous hospitals and organizations have already whittled down the transfer and sharing of data to mitigate personal data breaches, resulting in the development of a repository as health records are dispersed within and between diverse healthcare centres [2]. The data-sharing operation among external organizations benefits patients by allowing them to analyze their data using the latest methodologies and tools to detect a disorder.

Moreover, patients are concerned about the lack of openness in the information exchange procedure because their records could be revealed to a third person. This demonstrates the necessity for a technological system that helps eliminate intermediary entities, reduces expenses, and boosts patient honesty and trust. Blockchain is a technological advancement that may effectively and reliably share data using its decentralized paradigm to address this issue [3]. A problematic situation arises when accessing and evaluating the patient's vital information, which is housed across many healthcare systems. Blockchain implementation can address this issue with health information exchange platforms by backing reliable and decentralized databases. Fig. (1) depicts the various types of Blockchains.

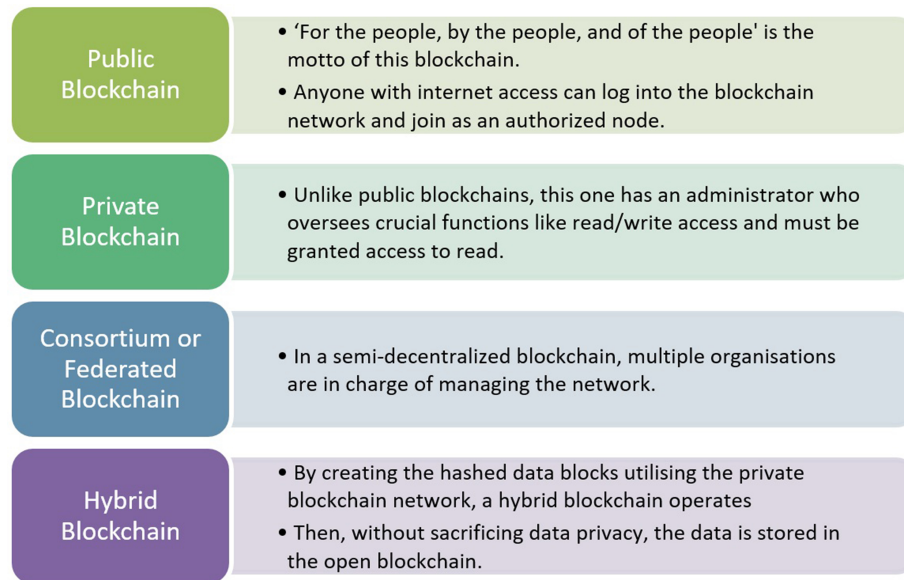


Fig. (1). Types of blockchain.

BLOCKCHAIN IN HEALTHCARE

Securing patients data
Streamline care and prevent costly mistakes
Breakthrough in Genomics
Point of care Genomics management
Managing Electronic Medical/Health Record (EMR/EHR)
Interoperable Electronics Health Records
Medical supply chain management
Ease in drug traceability
Remote patient monitoring
Personal health record data management
Diseases and outbreaks being tracked
Claims for health insurance
Mobile health Apps
Easy access and storage of patient information
Data collection and analysis
Cybersecurity
Clinical trials
Personalized healthcare
Accelerating Research & Development
Giving patients control of their data
Neuroscience studies
Telemedicine and E-Healthcare

Fig. (2). Applications of blockchain in healthcare.

Because of its decentralized and tamper-proof characteristics, blockchain (BC) technology is extensively utilized in the healthcare industry to manage records. In the medical system, the BC network stores and shares patient forms among

clinics, diagnostic and testing centres, pharmaceutical enterprises, and healthcare professionals [4]. Implementing BC in the medical system can detect intense and serious errors reliably. By delivering immutable data from clinical studies and findings, BC technology could assist in reducing the number of fraudulent activities and errors in clinical study documents. Furthermore, blockchain-enabled technology can address transition and specific disclosure in clinical studies. Then, without sacrificing data confidentiality, the data is stored on the open Blockchain [5]. Blockchain technology has several applications and is utilized in health care services. The administration of the medicine supply chain, the decryption of genetic information, and the safe transfer of medical information about patients are all made possible by distributed ledger technology [6]. A technology suitable for safety applications is Blockchain, which has the propensity to keep an eternal, decentralized, and seamless record of every patient's data.

Moreover, whereas Blockchain is translucent, it is also secret, trying to conceal any individual's identity with intricate and secure codes capable of protecting the responsiveness of health information. It generally requires time to get access to a patient's medical information, which exhausts employees' resources and slows down the delivery of care. To deal with these issues, blockchain-based medical databases have been developed. The decentralized framework of the system offers a single ecosystem of patient data that can be efficiently accessed by doctors, hospitals, pharmacies, and anyone else involved in the treatment by securely and rapidly exchanging data. The Blockchain can, therefore, result in improved diagnostics and tailored treatment initiatives [7]. Fig. (2) illustrates the numerous applications involved in healthcare using Blockchain.

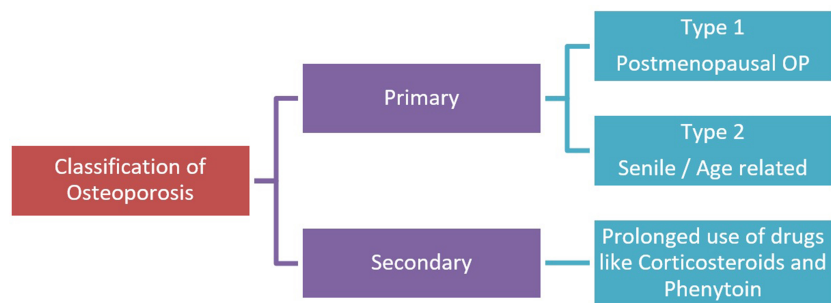


Fig. (3). Classification of osteoporosis.

The condition, osteoporosis, weakens bones, making them more brittle and prone to fracture. OP steadily worsens over time and is typically only discovered after a minor accident that results in a bone fracture [8]. Among those who have osteoporosis, wrist, hip, and vertebral fractures are the most frequent wounds. Throughout one's life, bone tissue is consistently absorbed and supplanted.

Whenever the absorption rate exceeds the production rate, bone density diminishes; this usually happens with older people. The average age at which peak bone mass is obtained is 20. People who develop their bone mass less rapidly before this age are more likely to have OP [9]. Osteopenia is a severe illness wherein bone tissue's protein and mineral content is whittled down, but not as severely as in OP. Sarcopenia is an age-related deficit of skeletal muscle mass and strength. OP is classified into two categories and is portrayed in Fig. (3).

OP is underrated and medicinally silent because the repercussions are only experienced when a fracture occurs. Such a subclinical illness is an incredibly complicated problem that affects women worldwide, with postmenopausal women accounting for 80% of cases. It lowers the quality of life for older women unless addressed or prevented. Osteoporosis is a prevalent and eerily quiet disorder unless fractures aggravate it. According to estimates, 20% of men and 50% of women over 50 will suffer from an osteoporosis-related fracture at some point in their lives. The condition occurs primarily in postmenopausal women over the age of 50. Following menopause, bone loss accelerates due to decreased estrogen and other sex hormone secretions. It is estimated that one-fourth of the world's female population over 60 has OP [10]. Osteoporosis medications can increase bone density; although the gains may seem mild, they can significantly impact fracture rates.

Medicines may significantly boost BMD in the hip by approximately 1-3% and in the spine by around 4-8% during the initial three to four years following therapy. Hip fractures and spinal fractures are both reduced by 30–50% and 30–70%, respectively, by the drug. After starting medication, promising benefits may show as soon as 6 to 12 months later. The best defence against osteoporosis is a healthy diet rich in phosphorus, vitamin D, and calcium throughout life, especially in the early postmenopausal years. Exposure to sunlight produces vitamin D in the skin, which is also consumed through diet. Physical activity that is moderate and consistent helps to prevent bone loss. Weight-bearing exercises (weightlifting, walking, and running), balance exercises, postural exercises, and exercises for strengthening and flexibility should all be part of physical therapy for those with osteoporosis or osteopenia [11]. A significant public health issue that millions of older people face is osteoporosis. In addition to leading to fractures, the disease has severe mental and economic ramifications for the sufferer. An inter-professional team of healthcare professionals is best-suited to address the disorder because it has numerous risk factors. Osteoporosis is treated using medicine to strengthen bones and treat and prevent fractures. Bisphosphonates, prescribed to both genders at greater risk of breakage, are one of the most prevalent OP medications. Before a fracture, suspicious osteoporosis can be detected or confirmed with a bone density examination.

An estimation of bone mass and quality, particularly bone mineral density (BMD), is used to determine the presence of OP. Computed Tomography (CT), Single Energy X-ray Absorptiometry (SEXA), Dual Energy X-ray Absorptiometry (DEXA), Quantitative Ultrasound (QUS), bone densitometer, and Magnetic Resonance Imaging (MRI) are some of the techniques that can be used to evaluate BMD. Of these, doctors consider DEXA the gold standard method to assess BMD. QUS, which uses sound waves rather than radiation for testing, is another commonly used approach to assessing BMD [12]. The metrics Speed of Sound (SoS) and Broadband Ultrasound Attenuation (BUA) are used to determine a patient's T-score who has undergone a QUS evaluation. The most beneficial bone density test is DEXA scan, which uses both high- and low-energy X-rays of the hip and spine, two areas where significant fractures are most likely to occur [13]. Doctors can compute bone density using the difference in x-ray findings between low- and high-energy scans. A T-score is given as a result, comparing the subject's bone density to that of a healthy individual of the same gender, race, and ethnicity at the time of peak bone mass, around age 30. The T-score decreases when bone density decreases [10]. The Z-score contrasts an individual's bone density with a typical person's age and gender. DXA scans take 10 to 15 minutes to complete, are painless, and expose the patient to very little radiation. In addition to helping with diagnosis, they might also help track treatment responses. The T-score and Z-score ranges are mentioned in Fig. (4).

Category	T - Score Range	Remarks	Category	Z - Score Range	Remarks
Menopausal Women & Men ≥ 50 years	+1 to -1	Healthy bone density	Premenopausal Women & Men < 50 years	≤ -2	Below the expected range for age
	-1 to -2.5	Osteopenia			
	-2.5 to -3.0	Osteoporosis		> -2	Within the expected range for age
	Less than -3.0	Severe Osteoporosis			

Fig. (4). T-Score and Z-Score rating system.

With the help of AI and ML, the data can be easily categorized into three different classes. The features of three distinct courses are initially extracted using feature extraction [14]. Turning highly dimensional data into a valuable representation of lower dimensions is known as feature extraction. Principal Component Analysis (PCA) is the best feature extraction technique that transforms raw data into processable numerical features that retain the information from the original input dataset. PCA yields superior results when compared to explicitly utilizing machine learning over the initial data set. The extracted representations frequently reduce computational complexity and raise the classifier's accuracy. Once the

features are removed, the data can be clustered based on the similarity and the distance measurement and classified using the neural network classifier. The k-nearest neighbours algorithm (kNN) is a non-parametric, supervised training classifier that uses proximity to categorize or predict how a particular data point will be clustered. The experimental results on three high-dimensional datasets show the value of our approach. The novel technique that combines PCA and weighted kNN performs well in classifying different classes with high accuracy. The results are stored and safely transferred or shared through the internet to other hospitals or diagnostic centres using blockchain technology [15].

The following is how the manuscript is organized: Section 1 addresses the connotation of BC in healthcare, osteoporosis detection using Artificial Intelligence and machine learning, and the way it assists healthcare professionals in diagnosing and treating bone ailments earlier. Recent research about BC and OP is reviewed in Section 2. The explanation of the datasets utilized in this work is described in Section 3. The implementation and outcomes of the developed system are explained in Section 5. The impact of developments in healthcare data is concluded in Section 6.

Related Studies

With the advent of machine learning and Artificial Intelligence, the ailments or anomalies existing in medical images or data sets can be accurately extracted or classified—the information and data obtained from the outcomes aid in the early prediction and diagnosis of the disease. Recently, numerous researchers have examined BMD scores collected from CT, X-rays, and DEXA images to diagnose bone disease as osteopenia or osteoporosis [16]. Fang *et al.* recommended a fully automated system to dissect the vertebral body and assess the BMD score from CT images acquired from 1449 patients [17]. The U-Net was employed for segmentation, and DenseNet-121 type DCNN was utilized for evaluating the BMD score. The segmented vertebral body was compared and validated with the manually sketched portion of the vertebral body, which was accepted as ground truth. Tomita *et al.* made an LSTM network to find and group the radiological features of osteoporotic vertebral fractures (OVFs) in 1432 CT scans of the pelvis, abdomen, and chest [18]. Incorporating deep CNN in predicting ailments in CT has achieved 89.2% accuracy and a 90.8% F1 score. Such a fully automated detection method may shorten the consumption of time and stress on radiologists for inspection of OVF, as well as the possibility of false negatives. Yamamoto *et al.* tested five CNN models to predict and assess osteoporosis from 1131 hip radiography DXA images collected during 2014–2019 [19]. Out of five CNN models, EfficientNet b3 and GoogleNet performed better than others and attained

the best precision, accuracy, and specificity values. Clinical covariates such as gender, age, body mass index, and fracture history were recorded in this study, and the same was included in the ensemble model at the time of detecting osteoporosis in DXA images. Using a deep learning algorithm, Jang *et al.* suggested a model to predict osteoporosis from DXA hip images of 1001 patients [20]. Out of 1001 images, 800 were allotted for training, 100 for validation, and 100 for testing. Based on VGG16 equipped with a non-local neural network, the DNN was utilized, and it achieved 81.2% accuracy, 91.1% sensitivity, and 68.9% specificity.

Lee *et al.* introduced an automated system for screening OP from dental panoramic radiographs (DPRs) by examining the BMD using DCNN. Four study groups were utilized to assess the effect of various transfer learning strategies on DL [21]. Using the gradient-weighted class activation mapping method, the visual representation of the best features in the mandibular region is found and noted. Shim *et al.* developed an automated model to predict OP in postmenopausal Korean women [22]. The backward stepwise variable selection technique was employed for selecting the features. This study utilized seven neural network classifier models to assess OP values from continuous and categorical-based values. Overall, the ANN model perfectly predicts the OP in the dataset and achieves the best area under the region of the curve value compared to others. Using DCNN, Nakamoto *et al.* devised a way to predict OP by looking for low bone mass in dental panoramic X-rays of the femoral neck and lumbar spine [23]. The average accuracy in predicting OP in the femoral neck and lumbar spine was 76% and 73%, respectively. Zhang *et al.* established a model for classifying OP and osteopenia from X-ray images of 1616 patients examined at the lumbar spine [24]. T-score values derived from DXA images were used as references for the classification. Using DCNN, the category of standard and low-bone mass data was obtained. Many researchers have attempted to predict OP in CT and X-ray images, but only a few have tried DEXA images. Traditional approaches, particularly CNN, provide better classification accuracy when looking for OP in multimodal images. However, there is a scope for further improvement by using some other variations of a neural network classifier to increase classification accuracy while minimizing error rates. To estimate and categorize three different classes of data from the entire data set, we propose the weighted k k-nearest neighbour (kNN) method. One of the most commonly used data classification and clustering techniques is kNN. In tests on various data sets, it was discovered that the kNN algorithm operated quite efficiently. To achieve high classification accuracy with less computing time, the weight factor is combined with traditional kNN.

Numerous methods, including convolutional neural networks (CNNs), require extensive and diverse datasets for optimal performance. There is a need for more comprehensive and representative databases, including medical images. Using gender, age, and ethnicity as variables in the training data can introduce biases and inaccuracies into predictive models, impeding the findings' generalizability across different demographic groups. The predictions generated by black-box algorithms, such as deep learning models, pose challenges in terms of interpretability. The significance of interpretability concerns is pronounced in medical contexts since healthcare professionals necessitate unambiguous information to facilitate informed decision-making. Medical images are comprised of confidential patient information. Disclosing such data on external platforms, such as blockchains or cloud-based solutions, can potentially violate patient confidentiality. Labelled training data for atypical medical scenarios or disorders is scarce. The limited data availability poses challenges in developing precise models for identifying and categorizing uncommon medical conditions. Well-labeled training data is a prerequisite for the effective functioning of deep learning models. The process of annotating medical images has challenges in terms of complexity and time requirements, perhaps resulting in errors or discrepancies that can impact the performance of the models.

In summary, using machine learning and artificial intelligence in medical image analysis is promising. However, it is imperative to recognize and confront the associated challenges to guarantee the secure, efficient, and morally sound implementation of these technologies in clinical settings.

METHODOLOGY IN THE PROPOSED WORK

Large datasets are becoming more common in many fields of study. These records need to reduce their dimensionality to be interpreted while retaining most of the data's information.

Principal Component Analysis (PCA)

Principal component analysis (PCA), one of the earliest and most extensively utilized unsupervised learning algorithms, has been developed specifically for this purpose, among many other techniques [25]. It is an empirical method that uses orthogonal transformations to turn measurements of related features into a list of features that are not related linearly. These are called the principal components. This tool is most commonly used for explorative data analysis and predictive modelling [26]. The number of these PCs is equal to or less than the original features in the dataset. First, PCA calculates the covariance matrix and determines the eigenvalues and vectors. The data are then projected along the eigenvectors. If the original data is n -dimensional, it can be reduced to k -dimensionality, where $k \leq n$.

The steps involved in the PCA technique,

1. Are the range of continuous initial variables.
2. In this procedure, the range of variables is determined and standardized to examine the impact of each variable. The variables influencing the other variables in short scope can be categorized with the initial variables' computation. As an outcome, the analysis's final results will be more subjective. Utilizing the formulas given below, the variable transformation can be achieved.

$$z = \frac{(Value - \mu)}{\sigma} \quad (1)$$

$$\mu = \frac{(\text{Sum of the terms})}{(\text{Total Number of terms})} \quad (2)$$

$$\sigma = \frac{(x - \mu)^2}{N} \quad (3)$$

Where,

z Standardized values

μ = Mean

σ = Standard Deviation

x_i = initial value

N = Number of values

1. Computation of covariance matrix

The covariance matrix helps in identifying the values that are not highly related to the dataset,

by contrasting it with the mean value. A 2-D covariance matrix is given as

$$\text{Covariance Matrix} = \begin{bmatrix} \text{COV}(X, X) & \text{COV}(X, Y) \\ \text{COV}(Y, X) & \text{COV}(Y, Y) \end{bmatrix} \quad (4)$$

Where,

$$\text{Covariance} = \frac{\sum (X - \mu_x)(Y - \mu_y)}{(\text{Number of data points})} \quad (5)$$

The covariance of a number with itself is its variance, like,

$$\text{COV}(X, X) = \text{Var}(X) \text{ and } \text{COV}(Y, Y) = \text{Var}(Y) \quad (6)$$

The Covariance Matrix's entries will also be symmetric because the covariance is commutative at the diagonal elements.

$$\text{COV}(X, Y) = \text{COV}(Y, X) \quad (7)$$

The data points are correlated if the covariance matrix value is positive. The negative value of the matrix represents the data points are inversely related. At last, it can be identified which pair of variables correlate with each other, which will help categorization.

1. Calculate the eigenvectors and eigenvalues of the covariance matrix to find the principal components. Let a square matrix be represented as A. The non-zero vector, v, is an eigenvector of A if,

$$Av = \lambda v \quad (8)$$

Where $\lambda = \text{eigenvalue}$

1. Form a feature vector to finalize the principal component.
2. Reorganize the data along the main component axes.

$$\text{Final - dataset}(X_{ij}) = \text{Standardized original dataset} * \text{Feature vector} \quad (9)$$

Blockchain technology can be integrated to enhance the security and transparency of PCA results. Blockchain's decentralized and tamper-resistant nature ensures the integrity of PCA computations and results. After calculating the covariance matrix

and determining eigenvalues and eigenvectors, these critical components of PCA could be securely stored on a blockchain. This integration ensures the PCA process is open, auditable, and cannot be changed without permission. This makes the analysis results for predicting disease more reliable.

Weighted kNN

An easy-to-use supervised learning technique is the KNN, which has the potential to overcome classification and regression issues [27]. A directed learning system produces the required output after receiving new unlabeled data and uses labelled input data to train a function. Based on the distance measurements, it modifies the training data and classifies the recently received test data. It identifies the test data's k-nearest neighbours and most class labels, then types. For a data analyst, choosing the best K value to achieve the highest accuracy is an ongoing challenge. Weighted KNN is an amended version of the KNN. The KNN model's performance is affected by several variables, including the choice of the hyper parameter k [28]. If k were selected as being too small, the classifier could become more prone to outlier data values.

If k is smaller, the neighbourhood might keep fewer points from other categories. Weighted kNN is employed to circumvent this drawback. The closest k points are given a weight in weighted kNN. The idea behind a weighted KNN is to provide facts closer together, more weight and less to the issues that are farther apart. The primary function employed is the inverse distance function, which implies that weight significantly reduces as distance level increases and rises as distance decreases. The steps to be followed in kNN are mentioned below:

1. Load the unclassified training and testing data (X_{ij}) – mentioned in Chapter 4 eq (9).
2. Compute the distance from the new data to all previously classified data using the Euclidian, Minkowski, Manhattan, or Weighted distance method.
3. The k value should be chosen by evaluating the square root of the total number of data points.
4. Compute the distance between test and training data in each row by any length measuring method.
5. Sort the values in ascending order as per their distance value.
6. Choose the top k rows from the sorted values in the array.
7. Based on the most prevalent class of these rows, a class type is allocated to the test point.
8. Classifies the new data with the class.

and sensitivity to outliers, can affect the performance of the kNN. To address these concerns, blockchain technology can be applied. Each kNN classification instance and its corresponding distance metrics can be recorded on the Blockchain. This record-keeping provides an immutable history of decisions, improving the algorithm's transparency and traceability. Also, adding Blockchain can allow authorized parties to share training data securely, protecting data privacy and ensuring compliance with data protection laws and other requirements for operations or processes that use BMD scores to predict disease.

Proposed PCA-wkNN

Integrating a neural network approach with feature extraction techniques aids in identifying and classifying the disease precisely and with better accuracy [29, 30]. In this study, we combine PCA with weighted kNN, which reduces data dimensionality to expedite kNN computation and reduces redundant data while maintaining helpful information to enhance kNN predictive accuracy. The distinctive features noticed through PCA are then provided for classification. The data was divided into testing and training for the classification task. By supervised learning, 30% of the data was used for testing and 70% for training. Fig. (5) demonstrates the proposed block diagram that employs Blockchain in healthcare.

Blockchain technology can play a vital role in enhancing this approach. After performing PCA to extract distinctive features, these features can be hashed and securely stored on the Blockchain. Subsequently, when applying weighted kNN for disease classification, the distances and weights of neighbouring instances can be recorded on the Blockchain. This creates an auditable trail of decisions and ensures that the classification process is transparent and resistant to tampering. Additionally, Blockchain can facilitate the secure sharing of disease-related data among healthcare providers, researchers, and patients while maintaining data integrity and privacy.

Dataset Description

Obtaining a vast quantity of BMD scores is very difficult because most hospitals in Tamil Nadu are not equipped with DEXA equipment. The BMD score of patients from DEXA images was obtained from the Tamil Nadu Government Multi Super Specialty Hospital, Omandurar Estate, Chennai, Tamil Nadu, after a drawn-out process on request through the appropriate procedures. This dataset presented BMD scores of patients aged 25 to 74. DEXA images are taken at a spine location from all patients. The clinicians classified the patient's BoneBone as usual, osteopenic, or osteoporosis based on the BMD score value attained. The 64-detector Hologic Discovery Wi DXA bone densitometry system was used to collect the information. High-definition Instant Vertebral Assessment creates a